A Computational Framework for Life-Cycle Management of Wind Turbines incorporating Structural Health Monitoring

Kay Smarsly[1*], Dietrich Hartmann[2] and Kincho H. Law[1]

[1]*Stanford University, Department of Civil and Environmental Engineering, 473 Via Ortega, Stanford, CA 94305, USA*

[2]*Ruhr University Bochum, Department of Civil and Environmental, Universitätsstr. 150, 44801 Bochum, Germany*

Abstract

The integration of structural health monitoring into life-cycle management strategies can help facilitating a reliable operation of wind turbines and reducing the life-cycle costs significantly. This paper presents a life-cycle management (LCM) framework for online monitoring and performance assessment of wind turbines, enabling optimum maintenance and inspection planning at minimum associated life-cycle costs. Incorporating continuously updated monitoring data (i.e. structural, environmental and operational data), the framework allows capturing and understanding the actual wind turbine condition and, hence, reduces uncertainty in structural responses as well as load effects acting on the structure. As will be shown in this paper, the framework integrates a variety of heterogeneous hardware and software components, including sensors and data acquisition units, server systems, Internet-enabled user interfaces as well as finite element models for system identification and a multi-agent system for self-detecting sensor malfunctions. To validate its capabilities and to

demonstrate its practicability, the framework is deployed for continuous monitoring and life-cycle management of a 500 kW wind turbine. Remote life-cycle analyses of the monitored wind turbine are conducted and case studies are presented investigating both the structural performance and the operational efficiency of the wind turbine.

Keywords: Life-cycle management, structural health monitoring, wind turbines, long-term monitoring, wind turbine operational efficiency, wind turbine structural performance, statistical analysis

1 Introduction

In 2012, the globally installed wind energy capacity has reached 282 GW, as the Global Wind Energy Council (GWEC) reports [1]. According to GWEC, the worldwide clean energy investments, having more than doubled in the past five years, have reached a new record with US$ 260 billion last year [2]. However, according to the International Energy Agency (IEA) US$ 380 trillion are needed to meet the projected worldwide energy demand until 2035 [3]; a significant portion is due to maintenance and operation of wind energy systems.

Cost-efficient maintenance and reliable operation of wind turbines are among the major concerns of owners and operators. Therefore, research on life-cycle management (LCM) of wind turbines has considerably been fostered in the past several years, enabling operators and owners to efficiently organize, analyze, and manage information and life-cycle activities. Leading companies have recognized that LCM can be used to minimize environmental and socio-economic burdens while maximizing the economic values of their investments [4]: On the one hand, LCM is used to calculate and to reduce the carbon, material and water

footprints, the energy and material use, and the direct and indirect greenhouse gas emissions. On the other hand, opportunities of improvements in the maintenance and operation of wind turbines are realized. To this end, methodologies have been proposed to enable life-cycle costing (LCC) for calculating the total costs of a structure (caused during its life-cycle from raw material extraction to recycling and disposal) and life-cycle assessment (LCA) for assessing current and potential environmental impacts, as standardized in ISO 14040:2006 and 14044:2006 [5, 6].

Although offering wind turbine operators and owners predictive views of cost, safety and condition [7], operational LCM strategies do not consistently include structural, environmental and operational data collected by structural health monitoring (SHM) systems. Typically, the operation of wind turbines is monitored and controlled through integrated supervisory control and data acquisition (SCADA) systems that collect environmental and operational data, e.g. wind speeds, wind directions, and revolutions of the rotor [8, 9]. The main feature of a SCADA system is its ability to communicate with wind turbine control equipment in order to facilitate control actions, such as adjustments of blade pitch angles or yaw angles of the nacelle [10]. Unfortunately, common SCADA systems do not integrate structural data, which is needed for life-cycle analyses that consider – in addition to the operational wind turbine performance – the structural wind turbine integrity. Furthermore, SCADA systems are primarily real-time control systems and, as such, require to make compromises: For example, as reported in [11], sensor sampling rates provided by commercial SCADA-based monitoring and control solutions are not high enough to conduct life-cycle analyses under consideration of the structural dynamic behavior of a wind turbine. Another well-known issue is the lack of security in SCADA systems, i.e. inadequate data protection and insufficient authentication, which is a matter of current research [12].

In related disciplines, such as life-cycle management of bridges or naval ship structures [13, 14], it has been demonstrated that incorporating automatically collected and continuously updated structural data provided by SHM systems can significantly improve the quality of LCM. The benefits of coupling LCM strategies and SHM systems are several: Damages can reliably be identified before reaching critical levels, and owners and operators are provided with detailed and accurate information on the monitored structures for decision making and for scheduling maintenance work (*predictive maintenance*). Despite the substantial progress being made in deploying state-of-the-art SHM systems, which have proven to be accurate and easy to install [15-21], periodic inspections, which are time-consuming and costly, remain a common practice in the life-cycle management of wind energy systems [22-24]. In the wind energy industry, the current state of practice is characterized by *reactive maintenance*, where wind turbine components are replaced or repaired after failure, and by *preventive maintenance* based on regular intervals according to manufacturer specifications [25].

In this paper, an integrated life-cycle management framework for wind turbines is presented. The framework is designed to support the structural assessment of wind turbines and to facilitate decision making with respect to maintenance and operation. Integrated into the LCM framework, a SHM system provides continuously updated structural and environmental data. In addition, the LCM framework takes advantage of the SCADA system installed in the wind turbine, without suffering from the previously described deficiencies of SCADA systems: The data sets collected by the wind turbine SCADA system, in the following referred to as "operational data", are modularly integrated into the LCM framework complementing the structural and environmental data recorded by the SHM system. The framework also serves as an online information platform that automatically processes the heterogeneous data sets

originating from the different sources; it provides the processed data, transmitted via secure connections through the Internet, to human users in charge of LCM.

This paper is organized as follows: First, an overview of the integrated LCM framework and its components is given. Then, two pivotal components of the framework – the "SHM system" and the "management module" – are described in detail. Next, two studies on the structural performance and operational efficiency of a 500 kW reference wind turbine are presented, illustrating the practicability and the effectiveness of the LCM framework. Finally, concluding remarks are made on the capabilities of the LCM framework as well as on the key findings achieved in the studies, and future research directions are discussed.

2 An Integrated Life-Cycle Management Framework for Wind Turbines

The integrated life-cycle management framework is primarily composed of five interconnected components that are installed at spatially distributed locations:

1. **Structural health monitoring system:** A prototype SHM system is installed on a wind turbine located in Germany. The SHM system includes sensors installed inside and outside the wind turbine as well as data acquisition units continuously collecting and pre-processing monitoring data. The data acquisition units are connected to an on-site computer located in the maintenance room of the wind turbine.

2. **Decentralized software system for automated data processing:** A decentralized software system is installed on different computers at the Institute for Computational Engineering (ICE) in Bochum, Germany. The monitoring data recorded from the wind

turbine is continuously forwarded to the decentralized software system, which is designed to serve three basic purposes: First, it provides a persistent storage for the monitoring data; second, it supports automated data management and processing; third, it enables remote access to the data sets. Specifically, the software system comprises of a central server for automated data synchronization, data aggregation, and conversion of the raw monitoring data into an easily interpretable data format. In addition, a MySQL database is deployed for persistent data storage, and RAID-based storage systems are used for periodic data backups. Furthermore, Internet-enabled user interfaces allow authorized personnel (and software programs) remotely accessing, analyzing, and visualizing the monitoring data.

3. Multi-agent system for detecting sensor malfunctions: A multi-agent system, capable of autonomously detecting system malfunctions, is designed to ensure reliability and availability of the SHM system. For real-time SHM systems, malfunctions of sensors and data acquisition units are common. If not detected timely, the malfunctions may cause interruptions in data acquisition that lead to a loss of valuable measurement data and decisive information needed for structural assessment and life-cycle management. Typical reasons for such malfunctions are communication problems when using long-distance lines, temporary power outages, or simply breakdowns of sensors due to harsh environmental conditions. The multi-agent system is composed of several collaborating software entities, referred to as “software agents”, which are also installed at ICE. Once a malfunction is observed, the software agents – capable of executing autonomous actions without human intervention – enable corrective actions and inform the responsible personnel through email alerts about the detected malfunctions; the

affected data acquisition unit can remotely be restarted and defective sensors can be replaced immediately.

4. Model updating module for system identification and damage detection: A model updating module couples finite element wind turbine models with the monitoring data recorded from the physical structure. For model updating, the modal parameters of the individual numerical models are varied by adjusting stiffnesses, masses, geometries, elements of the inertia tensor and damping values until the computed structural responses of the models, i.e. accelerations, velocities and displacements, approximate closely the measured responses of the monitored wind turbine. Free vibration analyses are conducted to determine the modal parameters (such as natural frequencies and mode shapes) from the finite element models, and operational modal analysis (OMA) is employed to calculate the modal parameters from the monitoring data. In the model updating module, two OMA methods are used, the enhanced frequency domain decomposition (EFDD) technique and the stochastic subspace identification (SSI) [26]. For model-based damage detection, synthetic damage patterns are imposed on the finite element models. The models' structural responses to these damage patterns are calculated, analyzed, and archived in a "damage catalog" (or "look-up table"). Using this catalog, it is possible to assess deteriorations and damages, that may occur in the physical wind turbine structure, in near real time.

5. Management module for life-cycle analyses: A management module, installed on a computer at the Engineering Informatics Group (EIG) at Stanford University, USA, supports the wind turbine life-cycle management through remote analyses of structural, environmental and operational wind turbine data. Program modules are specifically

designed for decision support and for the analysis of the structural performance and operational efficiency of the wind turbine.

This paper focuses the discussion on component 1 ("SHM system") and component 5 ("Management module") of the LCM framework, which are described in detail in the following subsections. Details on the other LCM framework components have been presented in [26-30].

2.1 Structural Health Monitoring System

The SHM system is installed on a 500 kW wind turbine located in Germany (Figure 1). The wind turbine has a hub height of 65 m and is in operation for about 15 years [31]. Made of reinforced epoxy, the 40.3 m-diameter rotor is equipped with three synchronized blade pitch control systems. Both the steel tower and the foundation of the wind turbine are instrumented with a network of sensors that is complemented by two anemometers. The first anemometer, a cup anemometer directly connected to the wind turbine SCADA system, is installed on top of the nacelle at a height of 67 m; the second anemometer, a three-dimensional ultrasonic anemometer, is mounted on a telescopic mast adjacent to the wind turbine at 13 m height. The ultrasonic anemometer, shown in Figure 1a, continuously monitors the horizontal and vertical wind speed (0...60 m/s), the wind direction (0...360°) as well as the air temperature (–40...60°C).

As illustrated in Figure 2, six three-dimensional accelerometers (labeled B_1...B_6) are installed in the wind turbine tower. The accelerometers, mounted at five different levels in the tower, provide acceleration measurements with a sensitivity of 700 mV/g at sampling rates up to

100 Hz and measurement ranges of ±3 g. In addition to the accelerometers, six displacement transducers (W_1...W_6) with a nominal range of ±5 mm are installed at two levels in the tower. To capture temperature influences on the displacement measurements, every displacement transducer is complemented by a Pt100 resistance temperature detector (RTD) with a temperature range from –60°C to 200°C (T_1...T_6). Figure 1b shows the assembly of accelerometers, displacement transducers, and temperature detectors at the 21 m level (level E) in the wind turbine tower. Temperature detectors (T_7...T_{10}) are also installed at two further levels both inside and outside the tower to adequately measure temperature gradients. At the foundation of the wind turbine, three single-axis seismic accelerometers (B_7...B_9) are placed (Figure 1d). The seismic accelerometers have a measurement range of ±0.5 g and a sensitivity of 10,000 V/g, which allows recording relatively small accelerations, as expected at the foundation.

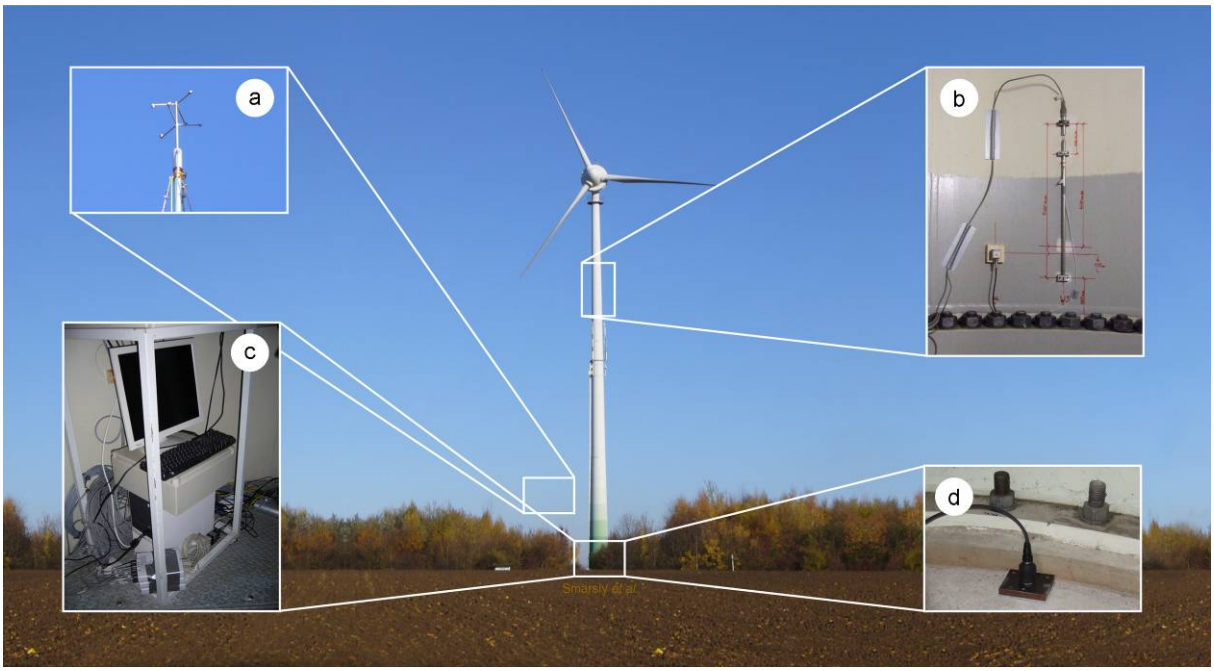


Figure 1 Monitored wind turbine and hardware of the SHM system: (a) three-dimensional ultrasonic anemometer, (b) three-axis accelerometer, displacement transducer, and RTD surface sensor, (c) on-site computer and data acquisition units, (d) seismic accelerometer.

To collect and pre-process the sensor data, data acquisition units (DAUs) are installed in the maintenance room of the wind turbine (Figure 1c). For the prototype implementation of the SHM system, two types of data acquisition units are deployed: First, for the temperature measurements sensed by the RTD surface sensors, Picotech Pt104 units are used. The Pt104 units – four-channel temperature data loggers – employ high-performance 24-bit A/D converters achieving a 0.001°C resolution. Second, for the acceleration and displacement measurements, HBM Spider8 multi-channel data acquisition units are installed, which allow for parallel data acquisition on eight channels at sampling rates up to 9,600 Hz using separate A/D converters for each channel. In addition, the digital data output of the ultrasonic anemometer is recorded by the on-site computer using a RS-422 connection.

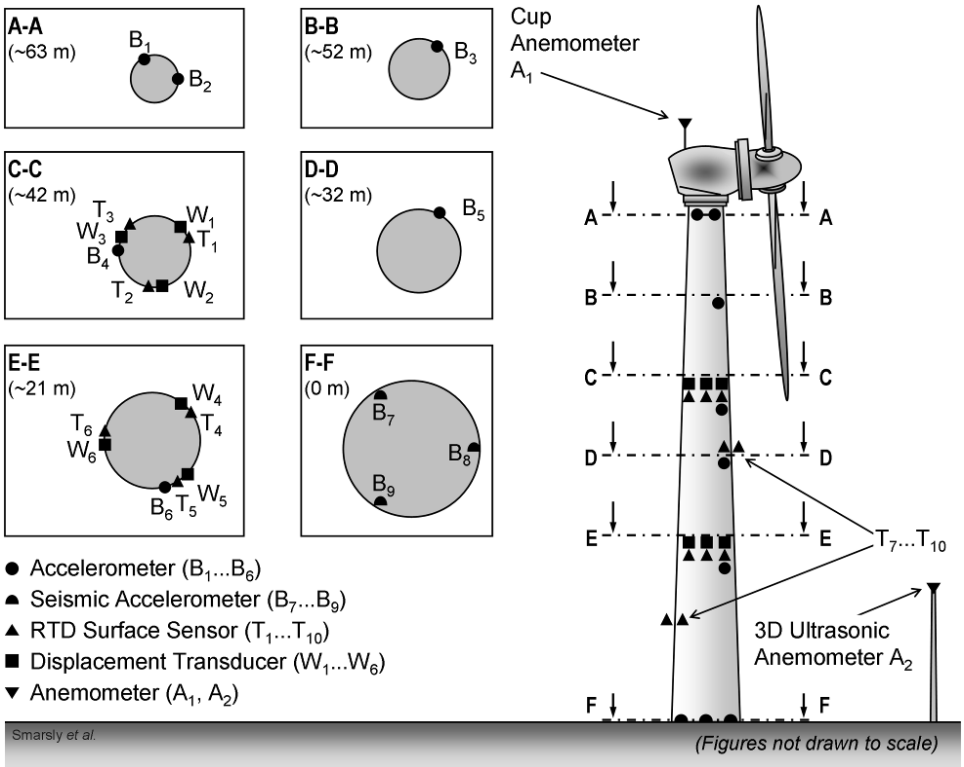


Figure 2 Prototype structural health monitoring system.

All data sets recorded from the wind turbine, being sampled and digitized, are continuously forwarded from the DAUs to the on-site computer, also placed in the maintenance room, for

temporary storage. In addition to the structural and environmental data collected by the DAUs, operational wind turbine data is logged. Taken from the wind turbine SCADA system and synchronized with the structural and environmental data, the relevant operational data includes revolutions of the rotor, pitch angles of the blades as well as yaw angles and power production of the wind turbine. The on-site computer creates local backups of the data sets (referred to as "primary monitoring data") and, through a permanently installed DSL connection, transfers the data to a central server being part of the decentralized software system (LCM framework component 2) installed at ICE in Bochum.

The periodic data transmission from the SHM system (i.e., from the on-site computer at the wind turbine) to the decentralized software system (i.e., the central server at the ICE) is automatically executed by the software running on the on-site computer. When transferring the primary monitoring data to the central server of the decentralized software system, metadata is added to provide information on installed sensors, DAU IDs, output specification details, date and time formats, etc. ("secondary monitoring data"). Upon being synchronized, aggregated and converted, the data sets are persistently stored in a central monitoring database, a MySQL database also installed at ICE in Bochum. During the conversion process, "tertiary monitoring data", summarizing the basic statistics of the data sets such as quartiles, medians and means, is computed at different time intervals and also stored in the monitoring database (further details on the sensor data management and on the wind turbine instrumentation are provided in [32] and [33]). Once being stored in the database, the monitoring data is available in the LCM framework for life-cycle analyses, and it is remotely accessible by authorized personnel and software programs for further data processing and evaluation.

2.2 Management Module

The management module, LCM framework component 5, is installed at the Engineering Informatics Group (EIG) at Stanford University to support wind turbine life-cycle management based on remote analyses of the monitoring data. Structural performance and operational efficiency of the wind turbine are analyzed through a variety of specifically designed analysis methods and engineering algorithms provided by the management module. Current implementations include methods

- to construct wind turbine power curves,
- to compute power coefficients,
- to calculate tip speed ratios, or
- to analyze wind speed distributions, turbulence intensity, and wind shear.

Furthermore, the management module allows remotely studying coherences and correlations in the monitoring data in order to detect significant changes in structural and operational wind turbine conditions. For that purpose, statistical methods are implemented, such as regression analysis techniques, analysis of variance (ANOVA), and analysis of covariance (ANCOVA). In addition, statistical hypothesis testing, also implemented into the management module, supports decision making with respect to potential changes in the structural or operational conditions.

Figure 3 shows the software architecture and the core classes of the prototype implementation illustrated using the Unified Modeling Language (UML). To ensure conceptual integrity and extensibility of the management module, written in Java, its architecture combines several

software design patterns and software architectures commonly adopted in software engineering – primarily the "three-tier model" and the "adapter pattern" [34]. The three-tier model, both a software architecture and a software design pattern, ensures a concise separation of the module into three logical layers, the user interface ("presentation"), the monitoring data ("data access"), and the functional process logic ("controller"). This logic allows any of the three tiers to be upgraded, changed, or replaced independently from each other, thereby improving scalability, integrity and performance of the management module.

The first tier, the *presentation*, gives a user access to the management module and presents the monitoring data as well as the analysis results to the user. The presentation tier can be installed on any PC, laptop, and on Java-enabled mobile devices such as cell phones and smart phones. The second tier, the *data access* tier, is designed to remotely access the monitoring database of the LCM framework in order to request data obtained from the wind turbine. The connection to the database is realized through a programming interface based on the Java Database Connectivity (JDBC), an industry standard for database-independent connectivity between Java applications and database systems [35]. JDBC enables the management module to remotely connect to the monitoring database and provides protocols for sending database queries and for processing the retrieved data sets. In particular, JDBC connections between the management module and the monitoring database ensure the execution of database queries that are relevant to monitoring-based life-cycle analyses, such as "SELECT" statements used to request specific data sets from the database. The selection of data sets and the proper specification of relevant parameters (e.g. sensor IDs or time intervals of interest) are facilitated by the management module, which translates user requests into statements that can be processed by the monitoring database. The security of database requests and data transmissions is provided by the database itself and requires secure drivers

as well as password and username to be specified when automatically accessing the monitoring database. The third tier, the *controller*, contains specific methods and algorithms to be used for structural as well as operational analyses and for life-cycle management of the wind turbine.

The analysis methods and engineering algorithms in tier three, as shown in Figure 3, are integrated into the management module in terms of adapters. Using the concept of adapters, additional algorithms and existing software tools can easily be integrated into the management module. As can be seen from Figure 3, both wind *turbine-specific methods* and general *statistical methods* are modularly implemented, including, e.g., fast Fourier transforms (FFT), calculations of tip speed ratios (TSR), wind shear coefficients (WSC) and power coefficients (PC) as well as a number of statistical methods.

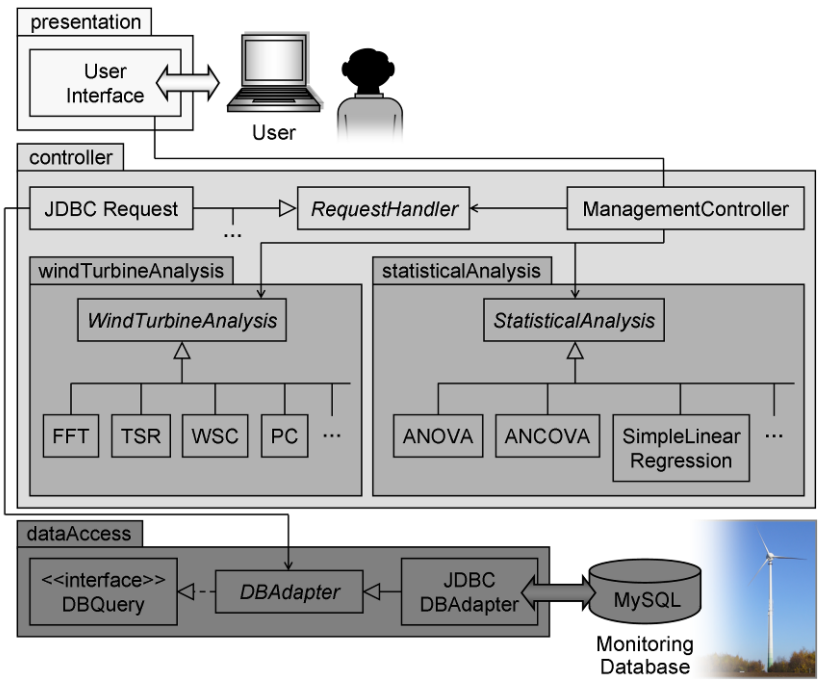


Figure 3 Architectural overview of the management module.

3 Wind Turbine Efficiency and Performance Analyses

To illustrate the practicability and the effectiveness of the LCM framework, online efficiency and performance analyses are conducted through the management module using the monitoring data taken from the wind turbine. This section presents two illustrative case studies: The first case study analyses the operational and structural wind turbine response to varying wind field characteristics; the second case study investigates the long-term operational efficiency of the wind turbine over a 2-year period.

3.1 Diurnal Variations of Wind Field Characteristics and Wind Turbine Responses

Diurnal variations of environmental conditions and wind field characteristics are investigated. It is well known that variations of the wind field characteristics (such as wind shear and turbulence intensity) can considerably affect the operational efficiency [45], cause different structural responses and, hence, contribute differently to fatigue damage of the wind turbine [46]. While varying wind field characteristics and the effects on operational and structural response of wind turbines have been studied in laboratory experiments and computer simulations [47, 48], there is still limited scientific knowledge gained from long-term monitoring data taken from wind turbines in operation. In this study, the diurnal variations of actual wind field characteristics, i.e. the loads acting on the wind turbine, as well as the corresponding structural and operational responses of the wind turbine are investigated.

Diurnal Variations of Wind Field Characteristics

Environmental, structural, and operational data collected by the LCM framework during the 6-month summer season from April 2012 to September 2012 serve as the basis for the study. The 30-minute mean values and 30-minute standard deviations of measurement data, which are available in the monitoring database as tertiary monitoring data, are analyzed. Data access and analysis are executed in the management module. Specifically, the horizontal wind speed at 67 m height (recorded by the cup anemometer A_1) as well as the horizontal wind speed at 13 m height and the air temperature (recorded by the ultrasonic anemometer A_2) are used for the analysis. The basic statistics of the recorded wind speed and temperature data are summarized in Table 1.

Table 1 Wind speed and air temperature statistics from April 2012 to September 2012

	Mean wind speed at 67 m height (m/s)			Mean wind speed at 13 m height (m/s)			Mean air temperature (°C)		
	Min.	Max.	Avg.	Min.	Max.	Avg.	Min.	Max.	Avg.
April 2012	1.63	13.43	5.57	0.33	8.19	3.16	0.00	25.49	9.24
May 2012	1.62	11.01	4.82	0.31	7.55	2.46	2.94	27.25	16.44
June 2012	1.55	11.82	5.04	0.38	6.65	2.34	8.02	28.26	15.91
July 2012	1.62	11.72	4.93	0.26	5.58	2.15	11.58	30.59	18.64
August 2012	1.59	11.52	4.70	0.32	5.66	2.15	12.41	35.41	20.86
September 2012	1.59	14.76	5.22	0.31	8.24	2.40	7.27	28.53	15.64
Average			5.05			2.44			16.12

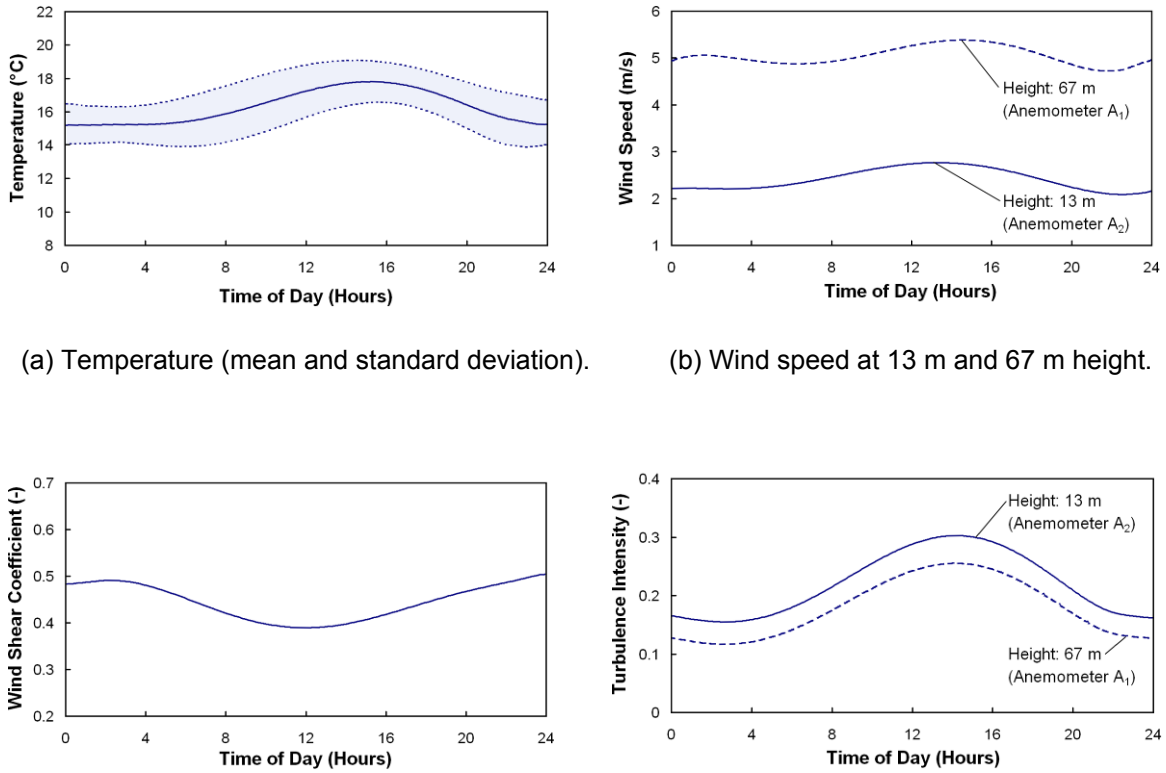
Taking the mean horizontal wind speed and temperature data as the basis, the diurnal variations of temperature, wind speed, wind shear and turbulence intensity are calculated. While the diurnal variations of temperature and wind speed are directly extracted from the tertiary monitoring data, obtaining the wind shear and the turbulence intensity requires additional calculations that are supported by the management module. The wind shear coefficient α, or Hellmann exponent, that expresses the degree of atmospheric stability, is extrapolated from the wind speed measurements based on the power law that is commonly used in wind energy research to calculate the wind shear coefficient [49]:

$$\frac{V_{A1}}{V_{A2}} = \left(\frac{h_{A1}}{h_{A2}}\right)^{\alpha} \tag{1}$$

where V_{A1} and V_{A2} are the mean horizontal wind speeds at the heights $h_{A1} = 67$ m and $h_{A2} = 13$ m. As proposed in [50], the turbulence intensity I_V, which reflects horizontal turbulence fluctuations in the wind field, is calculated for both heights h_{A1} and h_{A2} from the mean horizontal wind speeds V and the standard deviations σ_V of V as:

$$I_V = \frac{\sigma_V}{V} \tag{2}$$

The diurnal variations are plotted in Figure 4. Figure 4a and Figure 4b show typical patterns of temperature and wind speed variations, with maxima in the afternoon and minima at night. As can be seen from Figure 4c, it is evident that the heating and cooling cycle of the air also influences the wind shear. During the night, relatively high wind shear coefficients are observed indicating a stable atmosphere, whereas during the day the wind shear coefficients reach a minimum indicating a more unstable or neutral atmosphere. Correspondingly, the diurnal variations of turbulence intensity, illustrated in Figure 4d, show higher values during the day and smaller values during the night. Furthermore, higher turbulence intensities are in general observed near the ground.



(a) Temperature (mean and standard deviation). (b) Wind speed at 13 m and 67 m height.

(c) Wind shear. (d) Turbulence intensity at 13 m and 67 m height.

Figure 4 Diurnal variations from April 2012 to September 2012 based on 30-minute average values.

As the result of the calculations described above, Table 2 summarizes the inflow statistics representing typical site-specific daytime and nocturnal conditions within the considered 6-months period. Representative daytime and nocturnal wind profiles, calculated from the inflow statistics, are shown in Figure 5. As can be seen from the representative wind profiles, the horizontal mean wind speed is, on the average, smaller at night than during the day. However, due to the higher nocturnal wind shear, the wind speed differences between the lowermost and the uppermost part of the wind turbine rotor, which have a significant effect on rotor fatigue [51], are on the average 10% higher at night ($V_{\Delta R,n}$ = 1.55 m/s) than during the day when the atmospheric boundary layer is more unstable ($V_{\Delta R,d}$ = 1.41 m/s).

Table 2 Site-specific daytime and nocturnal inflow statistics

	Daytime	Nocturnal
Mean wind speed at 67 m height (m/s)	5.17	4.93
Mean wind speed at 13 m height (m/s)	2.62	2.25
Wind shear coefficient (-)	0.41	0.48
Turbulence intensity at 67 m height (%)	45%	39%
Turbulence intensity at 13 m height (%)	48%	45%
Mean air temperature (°C)	17.0	15.4

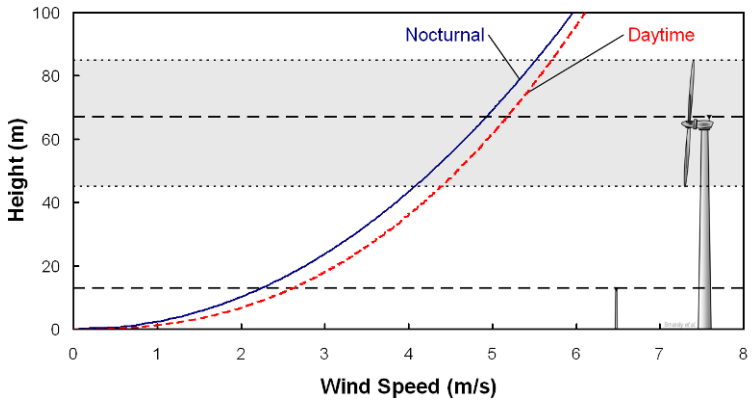


Figure 5 Representative site-specific daytime and nocturnal wind profiles.

Operational and Structural Wind Turbine Response

The wind turbine power curves calculated from the monitoring data obtained in the 6-months period show that the daytime and nocturnal power outputs of the wind turbine (relative to the wind speed) are almost identical (Figure 6). Minor differences are detected when comparing the operational efficiency by means of the wind turbine power coefficients, as shown in Figure 7. The curves in Figure 7 reveal that the operational efficiency is minimally higher at night than during the day. The increased nocturnal efficiency is likely the consequence of the more stable atmosphere at night. This finding agrees with recent studies investigating atmospheric stability effects on wind turbine efficiency [52].

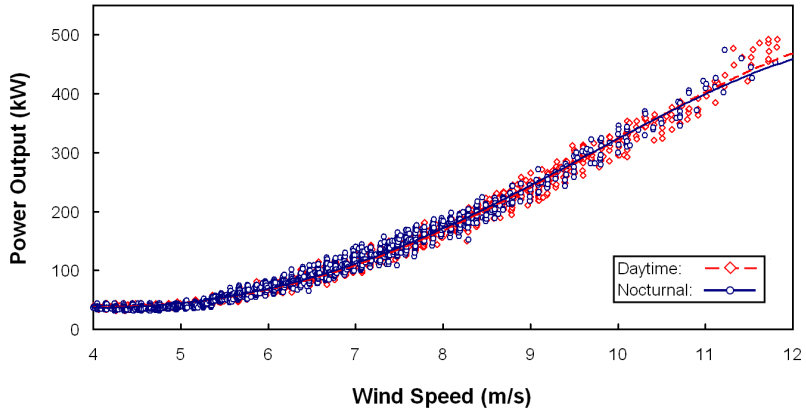


Figure 6 Comparison of daytime and nocturnal power curves.

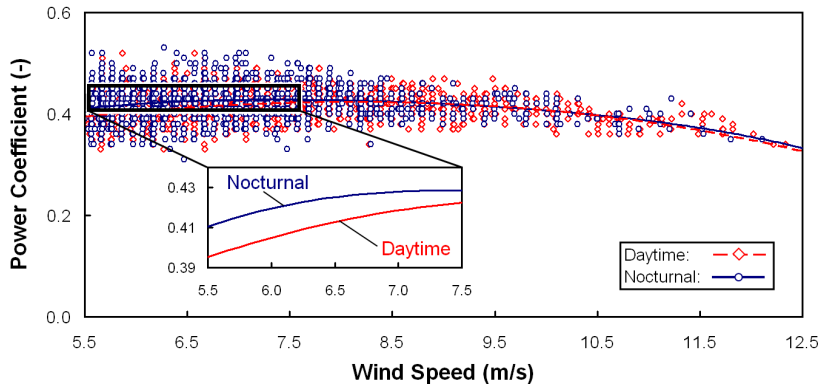


Figure 7 Comparison of daytime and nocturnal power coefficients.

To investigate the relationship between varying wind inflows and structural wind turbine response, two representative points in time, at which the characteristic daytime and the characteristic nocturnal conditions were present, are selected through a search in the monitoring database. Considering similar wind directions and nacelle orientations, two representative cases are found: (1) the nocturnal, stable case occurred on September 17, 2012, at about 05:00 CEST, whereas (2) the daytime, more unstable case occurred on September 18, 2012, at about 11:00 CEST. The structural responses for both illustrative cases are shown in Figure 8 and Figure 9. Exemplarily, the horizontal acceleration response of the wind turbine tower (recorded by accelerometer B_4) and the longitudinal strain response (computed from the

displacement measurements recorded by displacement transducer W_3), both taken at the 42 m level (level C) with a sampling rate of 100 Hz, are depicted.

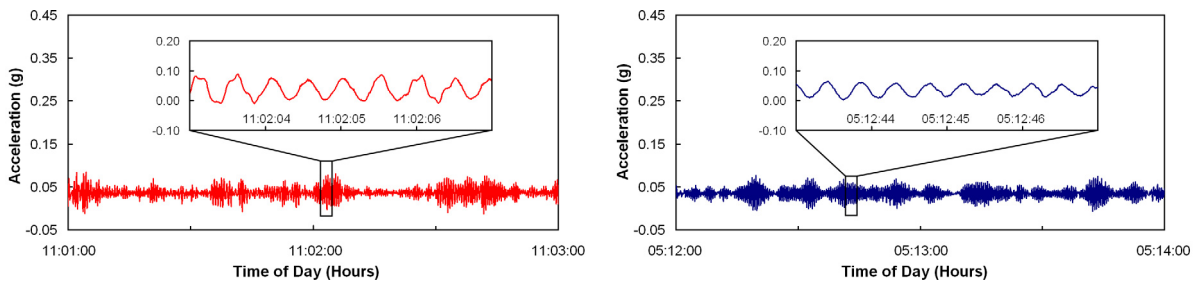


Figure 8 Horizontal tower acceleration at 42 m height (left: daytime; right: nocturnal).

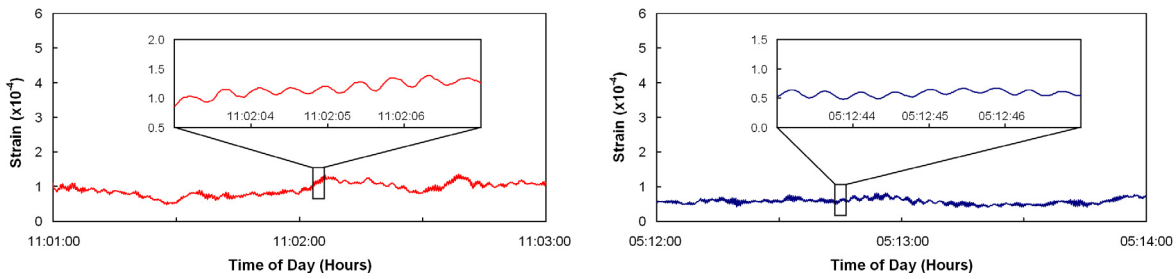


Figure 9 Longitudinal strain of the tower at 42 m height (left: daytime, right: nocturnal).

As this study shows, there are only marginal differences between the daytime and nocturnal responses of the wind turbine. The frequency response functions, calculated from the acceleration response data using the Cooley-Tukey FFT algorithm [53], show very close agreement between the two data sets (Figure 10), and the natural frequencies obtained match almost exactly (the frequency peaks at $f = 2.3$ Hz reflect the second mode that is distinctively captured at 42 m height). As shown in Figure 11, also the damage-relevant amplitudes of the wind turbine longitudinal strain time series, as computed through the rainflow counting method [54], show close agreement. Insignificant differences are observed that are possibly attributable to the higher turbulence at daytime. Finally, it is worth mentioning that when comparing the representative daytime and nocturnal data of September, 2012, with data sets

recorded in previous years [26, 27], no significant changes in the structural response are detected.

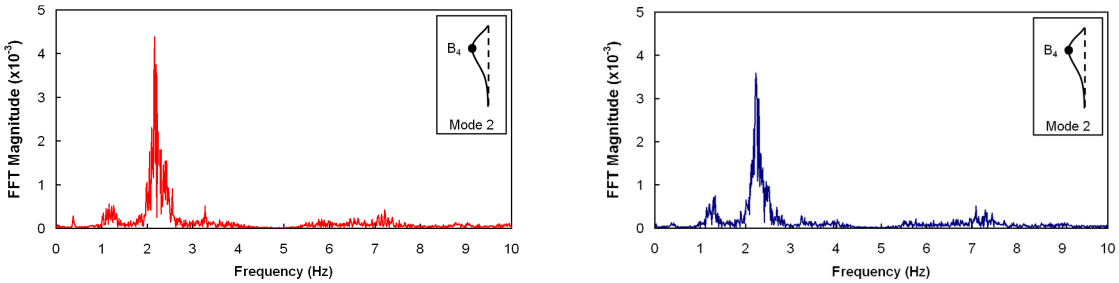


Figure 10 FFT results obtained from the acceleration response at 42 m height (left: daytime, right: nocturnal).

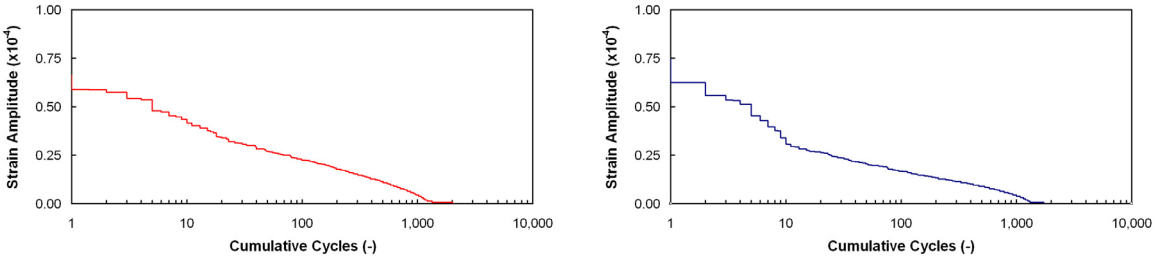


Figure 11 Rainflow counting applied to the strain time series (left: daytime, right: nocturnal).

3.2 Long-term Operational Efficiency of the Wind Turbine

In the second case study, the long-term operational efficiency of the wind turbine, which is of critical economic importance, is exemplarily analyzed based on comparisons of monitoring data recorded in the second quarters of the years 2010, 2011, and 2012. To evaluate the operational efficiency of the wind turbine, the data sets are analyzed with respect to (statistically) significant changes for each of the three time periods. In addition to the monitoring data taken from the wind turbine, data sets provided by the manufacturer are included serving as control variables that allow comparing the power outputs of the three time periods consistently.

Wind Turbine Efficiency Analysis

The monitoring data of interest is first transferred from the monitoring database to the management module through the remote database connection. Representing tertiary monitoring data, 30-minute mean values of wind speed as well as 30-minute mean values of power output are taken for the analyses. Figure 12 shows the wind speed time histories and the power output time histories for the 3-month periods in 2010, 2011, and 2012. Based on these data sets, the actual power curves, fitted to polynomial functions, are plotted in Figure 13. Calculated from the manufacturer's data that is persistently stored in the management module, the theoretical power curve is also shown in Figure 13 for comparisons. It should be noted that the monitoring data used in the following sample calculations is provided by the integrated LCM framework, rather than by extensive instrumentations deployed for power performance tests (for compliance with IEC 61400-12-1 [36]). The wind speed data, for example, is recorded by the cup anemometer A_2 on top of the nacelle (Figure 2) instead of employing external anemometers mounted on meteorological masts. Nevertheless, nacelle anemometry, as emphasized in [37], has shown to be a reliable and cost-effective alternative for verifying power performance and operational efficiency of wind turbines.

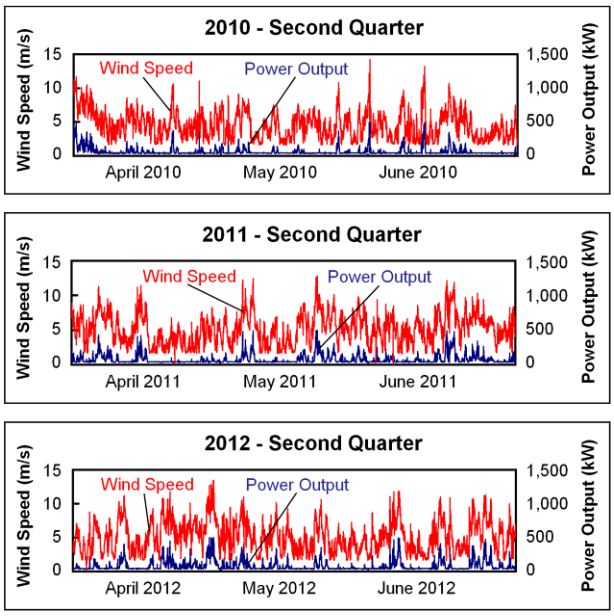


Figure 12 Wind speed and power output in 2010, 2011, and 2012.

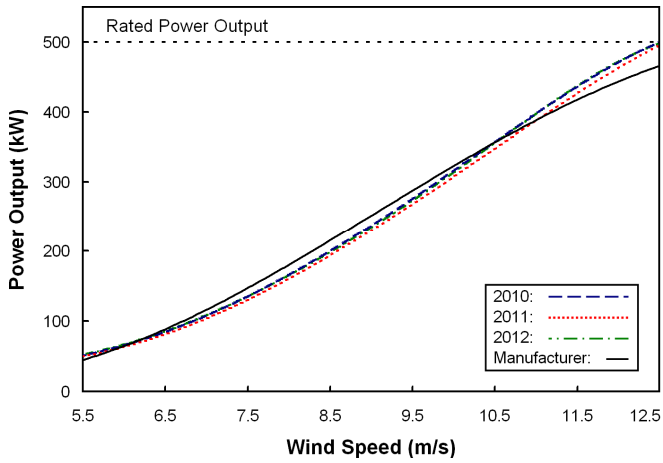


Figure 13 Power curves constructed from the monitoring data.

To assess the actual wind turbine efficiency, power coefficients are calculated by the management module for each of the three periods (Figure 14). The power coefficients $C_P = P/P_{wind}$ are calculated from the power produced by the wind turbine P divided by the total power available in the wind

$$P_{wind} = \frac{1}{2}\rho A V^3 \tag{3}$$

where ρ is the air density assuming a sea-level air density of $\rho = 1.225$ kg/m^3, $A = \pi d^2/4$ is the swept area with d, the rotor diameter of the wind turbine, and V is the wind speed. In addition to the C_P curves, the Betz limit is shown in Figure 14. The Betz limit defines the theoretical maximum power coefficient, implying that no wind turbine, independent of its design, can convert more that 59.3% of the kinetic energy of the wind into mechanical energy. As a result of this sample calculation, the maximum efficiency of the wind turbine is found for all three time periods between $V = 7.5$ m/s and $V = 8.5$ m/s, which agrees with previous investigations of the wind turbine efficiency [38-40].

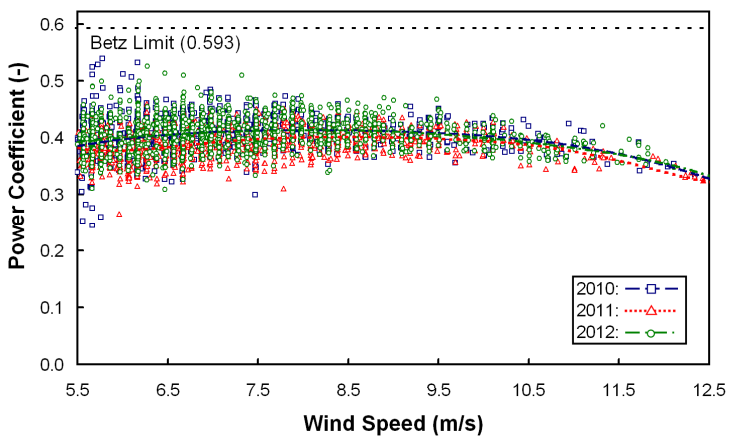


Figure 14 Power coefficients in 2010, 2011, and 2012.

Inferential Statistics for the Wind Turbine Efficiency

The power curves and the power coefficients indicate that there have been no significant changes in the wind turbine efficiency in 2010, 2011 and 2012. In other words, the mean power outputs (relative to the wind speed) apparently remain the same over the 2-year period from 2010 to 2012. To verify this hypothesis and to ensure the level of statistical confidence

of the assessment, analysis of covariance (ANCOVA) and statistical hypothesis testing are carried out.

The power output P, as illustrated in Figure 13, is a function of the wind speed measurements V. To compare the power outputs, i.e. to describe the degree of similarity between the groups $P_{2010}(V)$, $P_{2011}(V)$ and $P_{2012}(V)$, the power outputs $P_i(V)$, where i denotes the group, and the theoretical (reference) power output $X(V)$, calculated from the manufacturer's data, are paired based on the wind speed measurements. The (X_i, P_i) pairs for every group are plotted in Figure 15. Assuming a linear relationship between X_i and P_i, the correlation coefficients are computed as $r_{2010} = 0.994$, $r_{2011} = 0.996$ and $r_{2012} = 0.995$, which are not only high, but also relatively similar in every group – an important assumption underlying the use of ANCOVA. The homogeneity of the regression line slopes is demonstrated in Figure 15 as the slopes match almost completely with each other as well as with the slope of that regression line, which incorporates the data from all three periods. When taking these results as a basis for further calculations, it should be emphasized that *correlation* between two variables does not imply *causation*; claiming a "cause-and-effect" relationship between X and P would be a logical fallacy frequently being made [41].

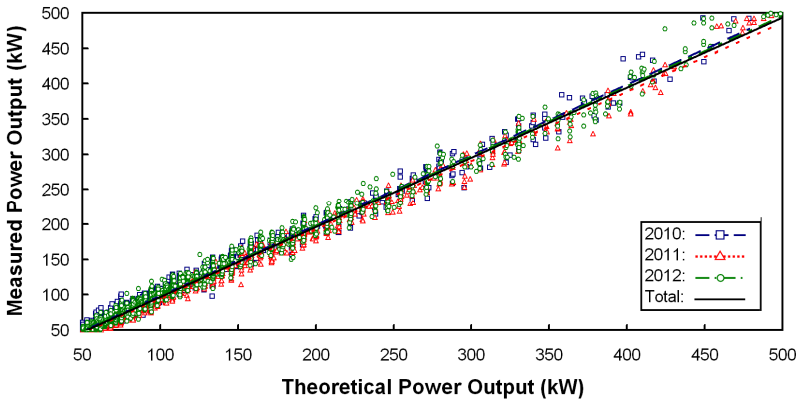


Figure 15 Correlation between measured and calculated power output.

Importantly, a direct comparison of the mean power outputs $\overline{P_i}$ of the regarded groups would be biased because of the corresponding $\overline{X}_i$ – which can be interpreted as control variables or covariates – being different. For a meaningful comparison of the power outputs, each mean power output is adjusted by applying a computational efficient ANCOVA procedure. The results are summarized in Table 3. In a final step, a statistical test, an F-test, is performed for the aforementioned hypothesis. As a result, the null hypothesis that all mean power outputs are equal is rejected. With the result being significant at the 1% significance level, it can be concluded that there is evidence that the considered power outputs in 2010, 2011 and 2012 differ. However, the statistical trend in the mean power outputs indicates that there is no decrease of the wind turbine efficiency over the 2-year period. In contrast, the mean power output in the second quarters of 2011 and 2012 is about 2% higher than in the second quarter of 2010, as shown in Table 3.

Table 3 Analysis results (summary).

	2010	2011	2012
Mean power output	101.1 kW	111.6 kW	121.3 kW
Adjusted mean power output	113.1 kW	115.4 kW	115.4 kW

Assessment of the Site Characteristics

Besides analyzing the wind turbine operational efficiency, the LCM framework is employed for verifying the assumptions being made when planning and implementing wind energy projects and for gaining new, useful information to be used for future projects. When choosing optimal wind turbines for specific sites, several significant parameters are of importance. These parameters are, among others, cut-in wind speed (i.e. the minimum wind speed at which the wind turbine will generate usable power) and cut-out wind speed (i.e. the wind speed at which the turbine's rated speed is exceeded so that a further increase in wind

speed would not lead to increased power output). Typically, the Weibull distribution, the most widely accepted distribution for wind speed [42-44], is used to characterize wind speeds and to estimate wind turbine power outputs. Such estimations are necessary in wind engineering because actual wind speed distributions are usually not available. Using the LCM framework, actual wind speed distributions are available; the wind speed distributions for the 3-month periods in 2010, 2011 and 2012 are shown in Figure 16 based on 30-minute mean values calculated from the wind speed measurements. Also plotted in Figure 16, the Weibull probability density functions

$$f(V;k,c) = \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-\left(V/c\right)^{k}} \tag{4}$$

are fitted to the measured wind speed measurements. In Eq. (4), V is the horizontal wind speed, k is the non-dimensional Weibull shape parameter, and c is the Weibull scaling parameter with the same unit as V. The probability density functions shown in Figure 16 describe the relative likelihood for the wind speed to take on a given value V. Figure 17 depicts the Weibull cumulative distribution functions

$$F(V;k,c) = 1 - e^{\left(V/c\right)^{k}} \tag{5}$$

derived from the wind speed measurements, which describe the probability that the wind speed will be found at a value less than or equal to V. In total, as calculated from the cumulative distribution functions, the wind speed in the regarded time period in 2010 was greater than the wind turbine's cut-in wind speed of 2.5 m/s with a probability of 90%, and of 93% in 2011 and 2012. The statistical analysis confirms that the 500 kW wind turbine, with

the cut-in wind speed of 2.5 m/s and a cut-out wind speed above 25 m/s, represents an appropriate choice for the given site characteristics.

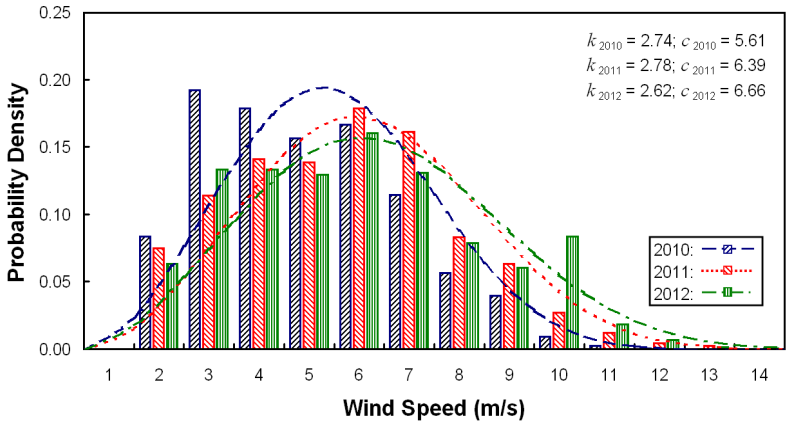


Figure 16 Measured wind speed distributions and calculated Weibull probability density functions.

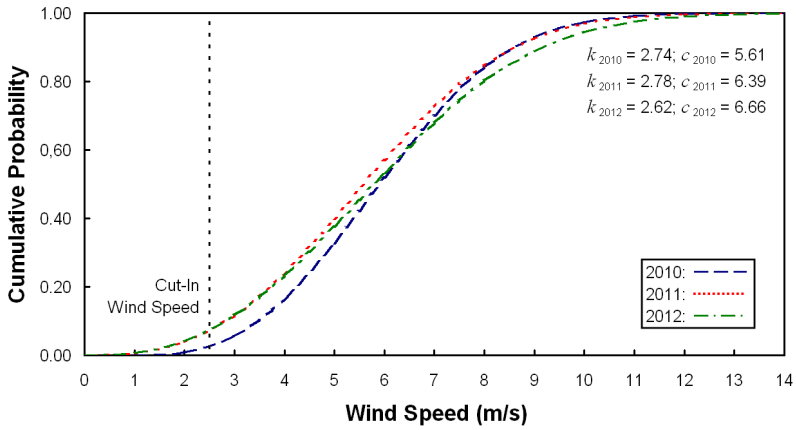


Figure 17 Calculated Weibull cumulative distribution functions.

4. Summary and Conclusions

Reliable and efficient life-cycle management strategies of wind turbines are best implemented based on integrated LCM frameworks that incorporate continuously recorded monitoring data. In this paper, an integrated life-cycle management framework has been presented that facilitates online monitoring and performance assessment of wind turbines. The LCM framework has been prototypically deployed on a 500 kW wind turbine located in Germany.

Integrated into the LCM framework, a SHM system provides continuously updated monitoring data, i.e. structural and environmental data. In addition, operational data taken from the wind turbine SCADA system is integrated into the LCM framework.

As demonstrated, the LCM framework, serving as an online information platform, automatically processes the heterogeneous monitoring data and provides the processed data through secured Internet connections to authorized personnel. The practicability and the effectiveness of the LCM framework have been demonstrated by means of (remote) analyses of the site characteristics. Furthermore, life-cycle analyses of the wind turbine considering structural performance and operational efficiency have been presented in details in two case studies. Using one of the integrated LCM framework components, the management module, performance indicators have been calculated from the monitoring data and statistical analyses have been performed to support decision making.

The results of the case studies have brought valuable insights into the life-cycle performance and the operational efficiency of the monitored wind turbine. The findings are summarized as follows: In the first case study, clear diurnal patterns of actual wind field characteristics and wind turbine responses could be computed from the monitoring data, although a relatively simple (but computationally efficient) concept of using averaged measured values has been applied for constructing representative daytime and nocturnal cases. The second case study has revealed that, according to the analyses conducted, the wind turbine is in an excellent condition and that the selected wind turbine model is an appropriate choice with respect to the given site characteristics. The investigations conducted have shown that both the operational and the structural wind turbine responses differ slightly between daytime and nighttime. In essence, it can be concluded from the above results that, on the one hand, the operational

efficiency of the wind turbine is higher at night than during day due to the more stable atmosphere. On the other hand, the contribution to fatigue particularly of the rotor is higher at night because of larger wind speed differences across the rotor blades as a result of increased nocturnal wind shear. Finally, comparing the current (operational and structural) response data to data recorded in previous years indicates that there is no decrease in operational efficiency or structural integrity of the wind turbine based on the knowledge gained from the life-cycle analyses presented herein.

Although the presented LCM framework can serve as a practical tool for wind turbine owners and operators, several opportunities exist to further improve the proposed LCM approach. Continuing research is underway, for example, to increase the reliability and the availability of SHM systems, which represent the basis for a robust and accurate life-cycle management. In addition, research efforts exploring the transfer of the proposed concepts from single wind turbines to wind farms will be an important next step that would provide new insights into the overall wind farm performance and would allow detecting new structural and operational coherences on the network level.

Acknowledgements

This research is partially funded by the German Research Foundation (DFG) under grants SM 281/1-1 and SM 281/2-1, awarded to Dr. Kay Smarsly, and under grant HA 1463/20-1, awarded to Professor Dietrich Hartmann. This research is also partially funded by the U.S. National Science Foundation (NSF) under grant CMMI-0824977 awarded to Professor Kincho H. Law. Any opinions, findings, conclusions, or recommendations are those of the

authors and do not necessarily reflect the views of the German Research Foundation and the U.S. National Science Foundation.

References

[1] "Global Wind Statistics 2012", 2013. Report. Brussels, Belgium: Global Wind Energy Council (GWEC).

[2] "Global Wind Report – Annual market update 2011", 2012. Report. Brussels, Belgium: Global Wind Energy Council (GWEC).

[3] "IEA Quotes", 2012. Press Release. Paris, France: International Energy Agency (IEA). Online: https://www.iea.org/publications/worldenergyoutlook/pressmedia/quotes (Accessed: September 12, 2012).

[4] "Life Cycle Management", 2009. Issue brief. Paris, France: United Nations Environment Programme (UNEP).

[5] "ISO 14040:2006 - Environmental management -- Life cycle assessment -- Principles and framework", 2010. Geneva, Switzerland: International Organization for Standardization (ISO).

[6] "ISO 14044:2006 - Environmental management -- Life cycle assessment -- Requirements and guidelines", 2010. Geneva, Switzerland: International Organization for Standardization (ISO).

[7] Liberman, E.J., 2003. A Life Cycle Assessment and Economic Analysis of Wind Turbines using Monte Carlo Simulation. M.Sc. Thesis (AFIT/GEE/ENV/03-16). Wright-Patterson Air Force Base, OH, USA: Air Force Institute of Technology.

[8] Zaher, A., McArthur, S.D.J., Infield, D.G. and Patel, Y., 2009. Online Wind Turbine Fault Detection through Automated SCADA Data Analysis. Wind Energy, 12(6), 574-593.

[9] Spinato, F., Tavner, P.J., van Bussel, G.J.W and Koutoulakos, E. Reliability of wind turbine subassemblies. IET Renewable Power Generation, 3(4), 1-15.

[10] Figueiredo, J.M.G., 2010. PLC based Structure for Management and Control of Distributed Energy Production Units. In: Guedes, L.A. (ed.). Programmable Logic Controller. Manhattan, NY, USA: InTech.

[11] Yang, W., Tavner, P.J. and Wilkinson, M.R., 2008. Condition monitoring and fault diagnosis of a wind turbine with a synchronous generator using wavelet transforms. In: Proceedings of the 4th IET Conference on Power Electronics, Machines and Drives. York, UK, April 2-4, 2008.

[12] Hentea, M., 2008. Improving Security for SCADA Control Systems. Interdisciplinary Journal of Information, Knowledge, and Management, 3(1), 73-86.

[13] Okasha, N.M. and Frangopol, D.M., 2012. Integration of structural health monitoring in a system performance based life-cycle bridge management framework. Structure and Infrastructure Engineering, 8(11), 999-1016.

[14] Frangopol, D.M., Bocchini, P., Decò, A., Kim, S., Kwon, K., Okasha, N.M. and Saydam, D., 2011. Integrated life-cycle framework for maintenance, monitoring, and reliability of naval ship structures. In: Proc. of the Fleet Maintenance & Modernization Symposium (FMMS) 2011. San Diego, CA, USA, August 30-31, 2011.

[15] Swartz, R.A., Lynch, J.P., Zerbst, S., Sweetman, B. and Rolfes, R., 2010. Structural Monitoring of Wind Turbines using Wireless Sensor Networks. Smart Structures and Systems, 6(3), 183-196.

[16] Smarsly, K., Law, K.H. and König, M., 2011. Resource-Efficient Wireless Monitoring based on Mobile Agent Migration. In: Proceedings of the SPIE (Vol. 7984): Health Monitoring of Structural and Biological Systems 2011. San Diego, CA, USA, June 3, 2011.

[17] Smarsly, K. and Hartmann, D., 2010. Agent-Oriented Development of Hybrid Wind Turbine Monitoring Systems. In: Proceedings of the International Conference on Computing in Civil and Building Engineering. Nottingham, UK, June 30, 2010.

[18] Mittrup, I., Smarsly, K., Hartmann, D. and Bettzieche, V., 2003. An Agent-based Approach to Dam Monitoring. In: Proceedings of the 20th CIB W78 Conference on Information Technology in Construction. Auckland, New Zealand, April, 23, 2003.

[19] Smarsly, K., Lehner, K. and Hartmann, D., 2007. Structural Health Monitoring based on Artificial Intelligence Techniques. In: Proceedings of the International Workshop on Computing in Civil Engineering. Pittsburgh, PA, USA, July 24, 2007.

[20] Ghoshal, A., Sundaresan, M.J., Schulz, M.J. and Pai, P.F., 2000. Structural health monitoring techniques for wind turbine blades. Journal of Wind Engineering and Industrial Aerodynamics, 85(3), 309-324.

[21] Ciang, C.C., Lee, J.-R. and Bang, H.-J., 2008. Structural health monitoring for a wind turbine system: a review of damage detection methods. Measurement Science and Technology, 19(12), 122001.

[22] D'Souza, N., Gbegbaje-Das, E. and Shonfield, P., 2011. Life Cycle Assessment of Electricity Production from a V112 Turbine Wind Plant. Final Report. Copenhagen, Denmark: PE North West Europe ApS.

[23] Besnard, F. and Bertling, L., 2010. An Approach for Condition-Based Maintenance Optimization Applied to Wind Turbine Blades. IEEE Transactions on Sustainable Energy, 1(2), 77-83.

[24] LaPuma, P.T. and Liberman, E.J., 2006. A Life Cycle Assessment and Economic Analysis of Wind Turbines Using Monte Carlo Simulation. In: Proceedings of the International Life Cycle Assessment & Management 2006. Washington, DC, USA, October 4-6, 2006.

[25] Barber S. and Golbeck, P., 2006. Wind Turbine Maintenance & Condition Monitoring. WIND ENERGY - Technology and Planning. Bonn, Germany: The World Wind Energy Association (WWEA). Online: http://www.wwindea.org/technology/ch03/en/3_4_3.html (Accessed: September 14, 2012).

[26] Hartmann, D., Smarsly, K. and Law, K.H., 2011. Coupling Sensor-Based Structural Health Monitoring with Finite Element Model Updating for Probabilistic Lifetime Estimation of Wind Energy Converter Structures. In: Proceedings of the 8th International Workshop on Structural Health Monitoring 2011. Stanford, CA, USA, September 13-15, 2011.

[27] Smarsly, K., Law, K.H. and Hartmann, D., 2012. A Multiagent-Based Collaborative Framework for a Self-Managing Structural Health Monitoring System. ASCE Journal of Computing in Civil Engineering, 26(1), 76-89.

[28] Smarsly, K., Hartmann, D. and Law, K.H., 2012. Structural Health Monitoring of Wind Turbines Observed by Autonomous Software Components – 2nd Level Monitoring. In: Proceedings of the 14th International Conference on Computing in Civil and Building Engineering. Moscow, Russia, June 27-29, 2012.

[29] Smarsly, K., Law, K. H. and Hartmann, D., 2011. Implementation of a multiagent-based paradigm for decentralized real-time structural health monitoring. In: Proceedings of the 2011 ASCE Structures Congress. Las Vegas, NV, USA, April 14-16, 2011.

[30] Smarsly, K., Law, K.H. and Hartmann, D., 2011. Implementing a Multiagent-Based Self-Managing Structural Health Monitoring System on a Wind Turbine. In: Proceedings of the 2011 NSF Engineering Research and Innovation Conference. Atlanta, GA, USA, January 4-7, 2011.

[31] Höffer, R., Lachmann, S. and Hartmann, D., 2012. Conceptual Study on Instrumentation for Displacement-based Service Strength Checking of Wind Turbines. In: Proceedings of the 14th International Conference on Computing in Civil and Building Engineering. Moscow, Russia, June 27-29, 2012.

[32] Law K.H., Smarsly, K. and Wang, Y., 2013. Sensor Data Management. In: Wang, M. L., Lynch, J.P. and Sohn, H. (eds.). Sensor Technologies for Civil Infrastructures: Performance Assessment and Health Monitoring. Sawston, UK: Woodhead Publishing, Ltd. (in print).

[33] Lachmann, S., Baitsch, M., Hartmann, D., Höffer, R., 2009. Structural lifetime prediction for wind energy converters based on health monitoring and system identification. In: Proceedings of the 5th European & African Conference on Wind Engineering. Florence, Italy, July 19-23, 2009.

[34] Gamma, E, Helm, R., Johnson, R. and Vlissides, J., 1995. Design Patterns: Elements of Reusable Object-Oriented Software. Boston, MA, USA: Addison-Wesley.

[35] "JDBC Technology Guide", 2011. Redwood Shores, CA, USA: Oracle Corporation. Online: http://docs.oracle.com/javase/6/docs/technotes/guides/jdbc/getstart/GettingStartedTOC.fm.html (Accessed: September 21, 2012).

[36] IEC 61400-12-1 ed1.0, Wind turbines – Part 12-1: Power performance measurements of electricity producing wind turbines, 2005. International Standard. Geneva, Switzerland: International Electrical Commission (IEC).

[37] Smith, B., Link, H., Randall, G, and McCoy, T., 2002. Applicability of Nacelle Anemometer Measurements for Use in Turbine Power Performance Tests. In: Proceedings of the AWEA WINDPOWER 2002 Conference. Portland, OR, USA, June 2-5, 2002.

[38] Smarsly, K., Hartmann, D. and Law, K.H., 2012. Integration of Structural Health and Condition Monitoring into the Life-Cycle Management of Wind Turbines. In: Proceedings of the 4th Civil Structural Health Monitoring Workshop (CSHM-4). Berlin, Germany, November 6-8, 2012.

[39] Smarsly, K., Hartmann, D. and Law, K.H., 2013. An Integrated Monitoring System for Life-Cycle Management of Wind Turbines. International Journal of Smart Structures and Systems (in press).

[40] Smarsly, K., Law, K.H. and Hartmann, D., 2012. Towards Life-Cycle Management of Wind Turbines based on Structural Health Monitoring. In: Proceedings of the First

International Conference on Performance-Based Life-Cycle Structural Engineering. Hong Kong, China, December 5-7, 2012.

[41] Aldrich, J., 1995. Correlations Genuine and Spurious in Pearson and Yule. Statistical Science, 10(4), 364-376.

[42] Manwell , J.F, McGowan, J.G. and Rogers, A.L., 2002. Wind Energy Explained. Chichester, UK: John Wiley & Sons.

[43] Celik, A.N., 2004. On the distributional parameters used in assessment of the suitability of wind speed probability density functions. Energy Conversion and Management, 45(11), 1735-1747.

[44] Takle, E.S. and Brown, J.M., 1978. Note on the use of Weibull statistics to characterize wind-speed data. Journal of Applied Meteorology, 17(4), 556-559.

[45] Wharton S. and Lundquist, J.K., 2012. Atmospheric stability affects wind turbine power collection. Environmental Research Letters 7(1), 014005, DOI:10.1088/1748-9326/7/1/014005.

[46] Sathe A. and Bierbooms, W., 2007. Influence of different wind profiles due to varying atmospheric stability on the fatigue life of wind turbines. Journal of Physics: Conference Series, 75, 012056, DOI:10.1088/1742-6596/75/1/012056.

[47] Sum, C., Basu, S. and Manuel, L., 2009. The Influence of Stable Boundary Layer Flows on Wind Turbine Fatigue Loads. In: Proceedings of the 47th AIAA Aerospace Sciences Meeting Including The New Horizons Forum and Aerospace Exposition. Orlando, FL, USA, January 5-8, 2009.

[48] Park, J., Smarsly, K., Law, K.H. and Hartmann, D., 2013. Wind Turbine Load Prediction using Online Convex Optimization. In: The 9th International Workshop on Structural Health Monitoring 2013, Stanford, CA, USA, September 9, 2013.

[49] Gualtieri, G. and Secci, S., 2011. Comparing methods to calculate atmospheric stability-dependent wind speed profiles: A case study on coastal location. Renewable Energy, 36 (2011), 2189-2204.

[50] "Wind Resource Assessment Handbook – Fundamentals for Conducting a Successful Monitoring Program", 1997. Handbook (NREL Subcontract No. TAT-5-15283-01). Golden, CO, USA: National Renewable Energy Laboratory (NREL).

[51] Eggers, A.J., Digumarthi, R., Chaney, K., 2003. Wind Shear and Turbulence Effects on Rotor Fatigue and Loads Control. Journal of Solar Energy Engineering, 125 (4), 402-409.

[52] Wharton S. and Lundquist, J.K., 2012. Atmospheric stability affects wind turbine power collection. Environmental Research Letters, 7(1), 014005, DOI:10.1088/1748-9326/7/1/014005.

[53] Cooley, J.W. and Tukey, J.W., 1965. An Algorithm for the Machine Calculation of Complex Fourier Series. Mathematics of Computation, 19(90), 297-301.

[54] Matsuishi, M. and Endo, T., 1968. Fatigue of metals subjected to varying stress. In: Proceedings of the Kyushu District Meeting of the Japan Society of Mechanical Engineers. Fukuoka, Japan, March, 1968.