# An Integrated Approach for Smart Monitoring, Inspection and Life-Cycle Assessment of Wind Turbines

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# An Integrated Approach for Smart Monitoring, Inspection and Life-Cycle Assessment of Wind Turbines

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## ABSTRACT

In this paper we present a new integrated approach for assessing the structural health and life-cycle of wind turbines. A major challenge in efficient condition assessment and residual life prediction for such systems lies in their continual exposure to highly stochastic loadings due to non-stationary environmental conditions, gravity, and inertial effects. Furthermore, wind turbines suffer from significant degree of interaction amongst their components comprising a variety of materials, which bears a large influence on the measured condition/health monitoring data. The challenge is compounded by the presence of advanced control systems trying to extract maximum power from the wind while maintaining the operating loads within the design limits. The objective is thus to develop methods and tools, which are able to account for the lack of precise loading information as well as operational, environmental and modelling uncertainties, toward the structural health monitoring, damage detection and life-cycle assessment for wind turbine components across two temporal scales, namely the short-term (gusts, extreme turbulence, faults) and long-term (fatigue). To this end we propose a novel framework that combines a easily deployed and relatively cheap sensor network, with state-of-the-art data processing methodologies and "near-real time" Aero-elastic simulations, with the standard stream of condition monitoring data (SCADA). We present the main thesis of this framework and illustrate one aspect of it, namely the data driven modelling part.

## NOMENCLATURE

| | | |
|---|---|---|
| *SHM* | = | Structural Health Monitoring |
| *CMS* | = | Condition Monitoring Systems |
| *WT* | = | Wind Turbine |
| *PCE* | = | Polynomial Chaos Expansion |
| *O&M* | = | Operation and Maintenance |

## INTRODUCTION

There is a major challenge in efficient condition assessment and residual life prediction when wind turbine components are subjected to strongly varying loads, both on the short-term scale (seconds) due to varying rotor speed, gravitational, aerodynamic and inertial forces, and long-term scale (days, weeks) due to temperature, gusts, turbulence and seasonal variations. Furthermore, due to the narrow gap amongst their natural frequencies, wind turbines suffer from significant degree of interaction amongst their components, comprising a variety of materials, which bears a large influence on the measured condition/health monitoring data. This challenge is to some level compounded by the presence of advanced control systems aiming to extract maximum power from the wind, while maintaining the operating loads within the design limits. The current practice of monitoring and diagnostics of the health of wind turbine structures involves (1) Visual inspection which is subjective, labor-intensive, time-consuming, and periodic, (2) Non-Destructive Evaluation which is costly, labor-intensive, time-

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consuming, periodic and requires trained personnel, and finally (3) Supervisory Control And Data Acquisition (SCADA) and/or component specific Condition Monitoring Systems. The motivation of this work stems from the obvious lack of decision making framework for O&M and lack of integration of SHM for both short-term damage detection and long-term Life-Cycle Management. Furthermore, uncertainties in measurements, wind turbine operation and environmental conditions are rarely considered in SHM, and finally "Near-real time" Aero-elastic simulations are rarely integrated into an SHM framework. The ERC funded WINDMIL project aims to develop appropriate performance assessment methodologies, which are able to account for the lack of precise input (loading) information as well as environmental and modeling uncertainties, toward the assessment of structural performance, damage detection and life-cycle assessment across two temporal scales, namely the short- and long-term one. The former refers to the handling of sudden anomalies typically linked to extreme events (strong winds, waves, earthquake), while the latter refers to deterioration processes that evolve across a lengthier time span and which form an adverse factor for extending the life-cycle of these structural components, as fatigue damage. To this end, we propose a novel framework that fuses multiple sources of information including: (1) a easily deployed and relatively cheap sensor network to capture the structure response, (2) with state-of-the-art data processing methodologies and "near-real time" Aero-elastic simulations, with (3) the standard existing stream of condition monitoring data and SCADA. We present the main thesis of this framework and illustrate one aspect of it, namely the data driven modelling part.

## METHODOLOGY

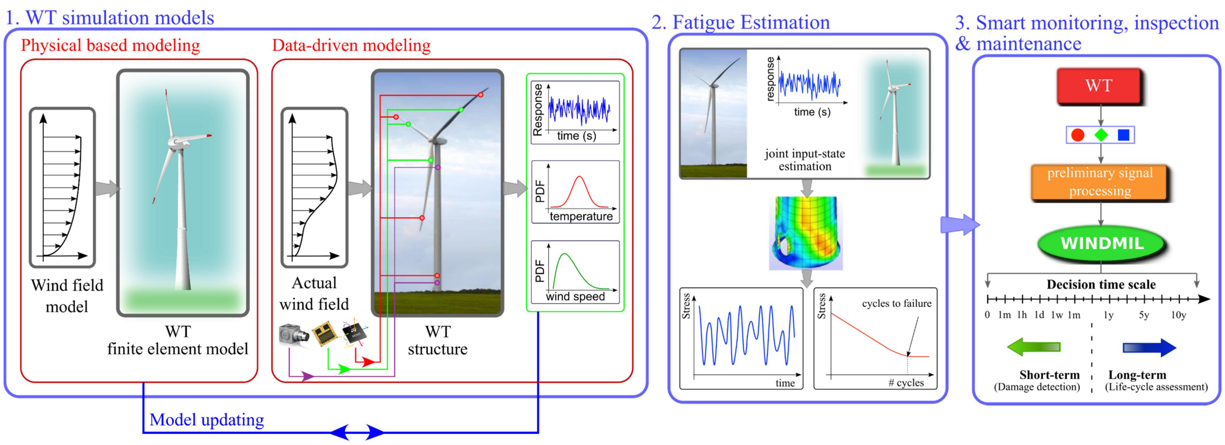



**Figure 1.** Integrated framework for Monitoring, inspection and life-cycle Assessment of wind turbines.

Figure 1 illustrates the integrated framework for Monitoring, inspection and life-cycle Assessment of wind turbines, which is defined on the basis of two separate time scales, one short-term and one long-term. The short-term assessment aims to provide early warning of the onset of damage or to register an extreme event (i.e. abnormal operation). The long-term framework is linked to the prediction of fatigue accumulation and the evidence of deterioration in the derived performance indicators.

The first level of the integrated approach is to establish the wind turbine simulation models, both physical (simulations) and data driven. In the physical based modeling a refined representation of the wind turbine components and their geometry and material properties is established. The refined model serves as a link between the system's characteristics (geometry, materials) and properties (stiffness, strength) and the resulting aero-servo-hydro-elastic response, which is the quantity measured in the field via sensors. Data-driven modeling relies on dynamic response measurements for extracting mathematical representations of the system. These representations can be delivered in a modal, regression or wavelet based form. Since the model is inferred from measurements of the response without necessarily a-priori knowledge of the system itself, this step comprises a task of inverse engineering. When the WT is parked, the structure is excited by ambient wind loads. During power production, the dynamics of the WT becomes non-stationary due to the rotation of the rotor, which induces a "periodic variability". This may be attributed to the effects of aerodynamic, gravitational and inertial forces [1], [2]. Time Varying Auto Regressive (TVAR) models constitute a suitable tool for tracking the time evolution of the dynamics using a compact parametric formulation:

$$y[t] + a_1[t]y[t-1] + a_2[t]y[t-2] + \cdots + a_n[t]y[t-n] = e[t], \quad e[t] \sim NID(0, \sigma_e^2[t])$$

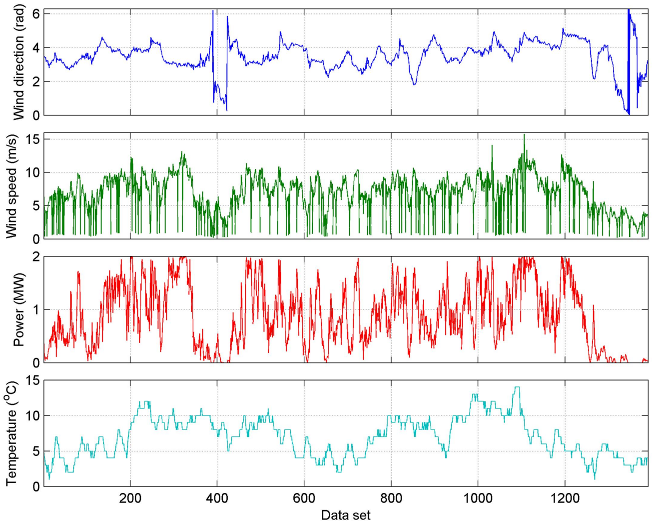
where $t$ designates discrete time, $y[t]$ the observed non-stationary signal, $e[t]$ the residual sequence, that is the un-modeled part of the signal, which is assumed to be normally identically distributed with zero mean and time-varying variance $\sigma_e^2[t]$, and $a_i[t]$ the time-varying AR parameters.

The second level builds onto the physics and data driven models for the prediction of fatigue accumulation. Toward this end, the physical and the data-driven models developed in Level 1 will be used in a synergistic way. The data-driven models will be used for the loading estimation through very recently developed system identification methods, which allow to infer the states of the system, i.e., its displacement and velocity time histories, under an unknown dynamic excitation (unknown input) via a limited number of sensors. This is known as a joint input-state estimation problem [3], [4], [5], [6] for fatigue prediction in civil structures. The extension of this theory to WTs, although not straightforward due to once again the particular dynamics involved, is a crucial task for treating the most commonly identified bottleneck for these systems, namely failure due to fatigue. In a next stage, the predicted response quantities will be linked to physical properties of the system, via use of the physics based models, leading to the estimation of strain time histories in hot-spot locations of the WT structures. The use of a physics based model in this case is vital for transiting from vibrational response data into strain information in unmeasured locations of the structure. The integration of appropriately adapted deterministic and stochastic fatigue theories will generate fatigue damage accumulation maps based on actual operational conditions. This in turn enables prediction of the residual fatigue lifetime and reliability of the structure minimizing down time, lowering the frequency of sudden breakdowns and associated maintenance and logistic costs. A subcomponent of this step necessarily entails the definition of suitable sensor configurations, able to monitor those quantities that are critical for allowing fatigue estimation in absence of load information [7]. In this sense, a successful sensor setup should ensure the realization of inference, numerical verification, and experimental validation of the developed simulation models, as well as, damage detection and prediction of fatigue accumulation. The measurement system delivered from this study should come as a complimentary low cost solution to the information standard SCADA systems routinely provided for WTs.

The third level, Smart Monitoring, Inspection and Maintenance, relies on the treatment of the data collected from the suggested monitoring system, which will inevitably deliver diverse information contaminated with a significant amount of uncertainties. Indeed, due to reasons relating to material properties, ageing processes, loading conditions, boundary conditions, and others, every structural system is characterized by uncertainty. As a result, we may only have a limited degree of confidence in a WT physical model, when the latter has to be employed for the assessment of the WT's reliability and safety through its life-cycle. A fundamental question that therefore arises is how does one deal with a system that is probabilistic in nature and continually changing? In this case we refer to "macro-temporal variability" which pertains to the loading and environmental conditions which are continually changing within the range of hours, or even minutes [8]: (i) non-periodic, stochastic loads caused by wind gusts and turbulence (within the order of minutes), (ii) changes in the input wind flow profile (within the order of minutes) and (iii) environmental conditions variation (temperature, humidity, solar radiation, wave loading and others; within the order of hours). For modeling the evolution of the system as a function of changing conditions, the parameters of the non-stationary representations obtained in Level 1 will be projected onto the stochastic spaces of the recorded operational and environmental conditions of the WT [9], [10]. In this way, a statistical model may be built, incorporating the effects of environmental and operational conditions and alleviating the danger of misinterpreting these as damage. A Polynomial Chaos Expansion (PCE) method, coupled with the TVAR models enables the transition from micro (structure on its own) to macro (structure in interaction with its environment) delivering performance indicators that ensure enforcement of this scheme in a uniform and repeatable manner. The formulation of performance indicators (indices) essentially requires a training period after which these are able to predict performance within regular. Deviations of these indices from normal bounds, indicate irregularity in the operation of the WT and serve as a warning/alarm. This "macro-temporal" stochastic framework provides a means of quantifying the uncertainty pertaining to the evolution of the dynamic behaviour of a WT during its complete operational spectrum. Once variability due to environmental conditions is quantified, damage detection may be accomplished by identifying within the robust performance indices distinct patterns that evidence different types of damage, from component failures to fatigue accumulation or material deterioration. A feature extraction approach will be pursued to this end [11].

## RESULTS

In the context of this framework we will present the data-driven result of the framework. The WT under study is a V90 2MW Vestas generator of a wind farm in Lübbenau in northern Germany owned by Repower Deutschland GmbH. The vibration response of the WT were measured by triaxial accelerometers at five distinct locations of the WT tower. A 10-minute-long dataset was recorded every half hour for 29 days. The signals recorded at 200 Hz were low pass filtered and down sampled to 12.5 Hz (cutoff frequency at 5 Hz). An example of the SCADA signals is shown in Figure 2. Figure 3 shows the non-stationary SP-TARMA model of the tower accelerations tracks with good accuracy the evolution of the dynamics when compared to the spectrogram shown in the background. Figure 5 shows how the PCE method, coupled with the SP-TARMA model, enables the transition from short-term (structure on its own) to long-term (structure in interaction with its environment) stochasticity delivering performance indicators of the structure [12].




| Variables | |
|---|---|
| 1 | Wind direction [deg] |
| 2 | Min wind speed [m/s] |
| 3 | Average wind speed [m/s] |
| 4 | Max wind speed [m/s] |
| 5 | Min power [kW] |
| 6 | Average power [kW] |
| 7 | Max power [kW] |
| 8 | Nacelle direction [deg] |
| 9 | Nacelle temperature [°C] |
| 10 | Ambient temperature [°C] |

**Figure 2.** Example of long term 10-minute averaged SCADA data, and the list of available operational and environmental conditions through the SCADA system and the plot of the four selected input variables.

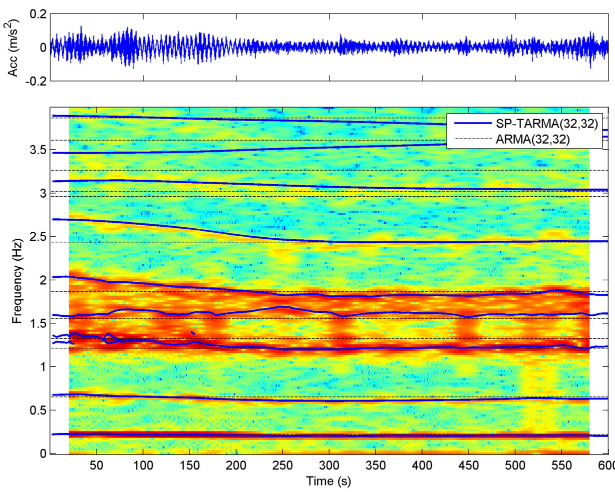



**Figure 3.** Dynamics of the WT under normal operation represented by a spectrogram of the accelerations time series. The non-stationary SP-TARMA model tracks with good accuracy the evolution of the dynamics when compared to the spectrogram shown in the background.

## CONCLUSIONS

We presented an Integrated Approach for Smart Monitoring, Inspection and Life-Cycle Assessment of Wind Turbines. The proposed approach fulfils a lack of integration of SHM for both short-term damage detection and long-term Life-Cycle Management, addresses the uncertainties in measurements, wind turbine operation and environmental conditions and finally integrates, seamlessly, “Near-real time” Aero-elastic and physics based simulations into an SHM framework.

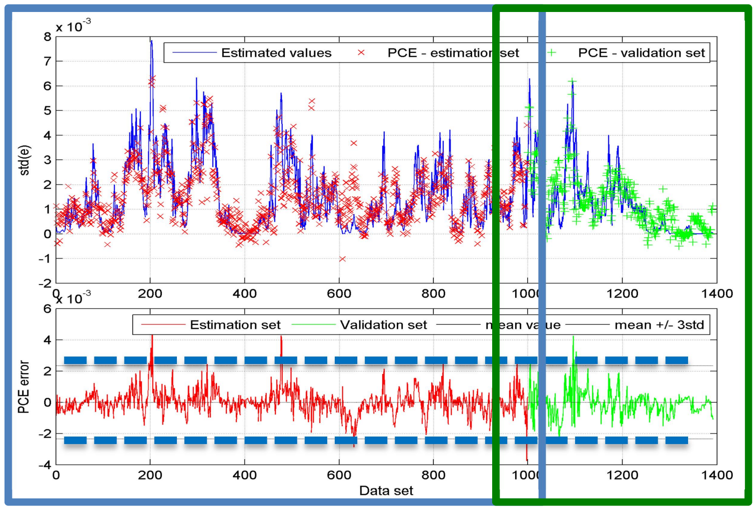



**Figure 4.** Long-term monitoring. SP-TARMA model residual *std* as obtained from the modelling of each vibration response dataset along with the PCE model expansion values. The PCE errors along with 95% confidence intervals (calculated from the estimation set) are also shown.

## ACKNOWLEDGEMENTS

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