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DATA-DRIVEN TOOL FOR STRUCTURAL HEALTH MONITORING OF OPERATING WIND TURBINES

The growing number of existing infrastructure with decreased or indeterminate reliability, and on the other hand, constant design of lighter, albeit more productive structures facilitate the adoption of automated Structural Health Monitoring (SHM) identification tools capable of unprejudiced diagnosis of in-service structures. In comparison with customarily exploited simulation-based approaches, data-based schemes or hybrid analysis (data/finite element model) can often introduce a more objective perspective on the behavior of operating structures, and as a result can enable long-term, automated and even online assessment.

Recent trends for energy conservation have placed the focus on Wind Turbine (WT) structures, which represent systems characterized with complex dynamics and alternating operating nature. We propose a diagnostic framework able to describe the variability of such monitored systems. The novel approach combines the Smoothness Priors Time Varying Autoregressive Moving Average (SP-TARMA) method for modeling the non-stationary structural response, and a Polynomial Chaos Expansion (PCE) probabilistic model for modeling the propagation of response uncertainty.

The computational tool is applied on long-term data, collected from an active sensing system installed for four years on a real operating WT structure located in Dortmund, Germany. The long-term tracking of the obtained PCE-SPTARMA Diagnostic Indicator (DI) is further assessed by means of a statistical analysis. The results demonstrate that the proposed treatment yields a DI sensitive to unfamiliar fluctuations in measured Environmental and Operational Parameters (EOP).

Keywords: data-driven SHM, operating wind turbine, structural variability, environmental variability

1. INTRODUCTION AND CONCEPT

Data-driven SHM tools hold the potential to reduce the multiple sources of uncertainty and variability typical for real systems, and thus become particularly valuable for infrastructures that bear critical importance in society. In this context, as result of today's rising trends of energy management, wind turbines reached the forefront of significant infrastructures that demand instantaneous implementation.

However, EOP-born variations in measured structural responses, known to mimic real damage states of the structure, underline the necessity of utilization of SHM strategies which rely on elimination or integration of environmental factors from/with obtained structural performance indicators [1-4, 6]. On the other hand, structures characterized with time-varying dynamics are resilient to traditionally applied Operational Modal Analysis (OMA)-based methods limited to implementation with time invariant systems [7].

The proposed diagnostic tool represents a multicomponent algorithm with a "binocular" visualization of the problem since it is adept in providing a link between output-only vibration response data and measured EOPs, Figure 1.

More precisely, the fluctuations that are typical for the inherent (short-term) system dynamics are modeled by means of a parametric SP-TARMA method (Step 1). In a second step identified structural performance indicators, corresponding to short-term modeled responses, are integrated into a PCE tool. The PCE probabilistic modeling approach connects the variability of the structural response to the randomness of measured EOPs.

Finally, the statistical model (Step 3) enables the long-term tracking of a selected PCE-SPTARMA descriptive indicator and facilitates timely reaction to any identified changes in patterns or distributions of the selected output indicator.

2. THEORY AND APPLICATION

The described SHM strategy is applied on a 0.5MW WT erected in 1997, located in the vicinity of Dortmund, Germany. The continuous measurement of acceleration data is recorded by triaxial accelerometers installed at five different height positions of the WT structure. The vibration data is supported with SCADA data records, both sampled with the frequency of 100 Hz, Figure 2.

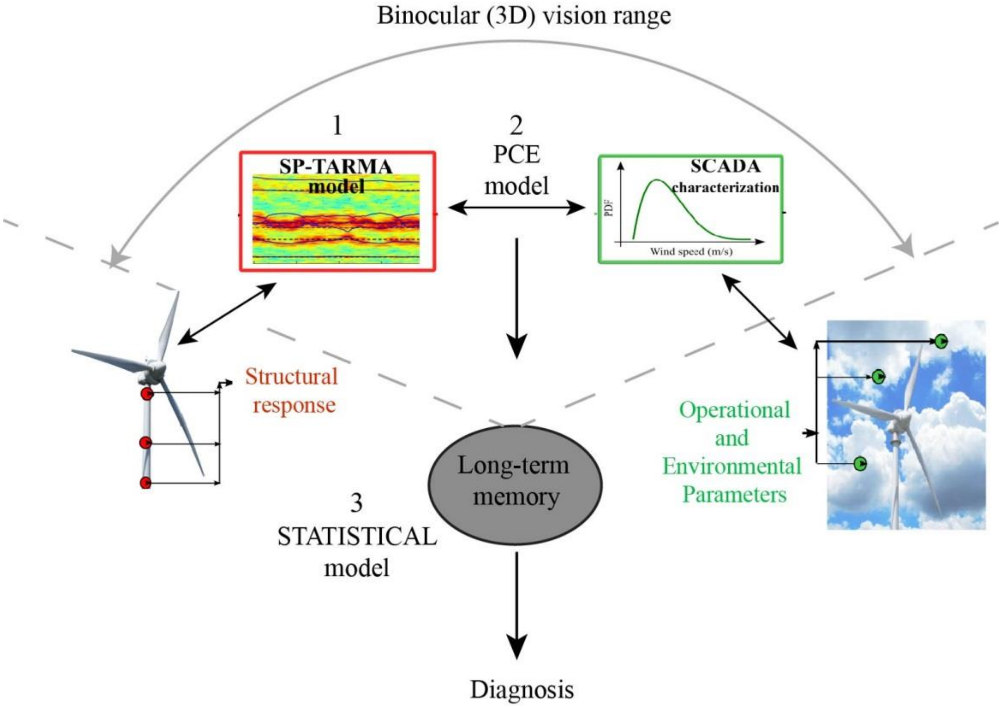

Figure 1. Conceptual model of the SHM strategy and applied methods.

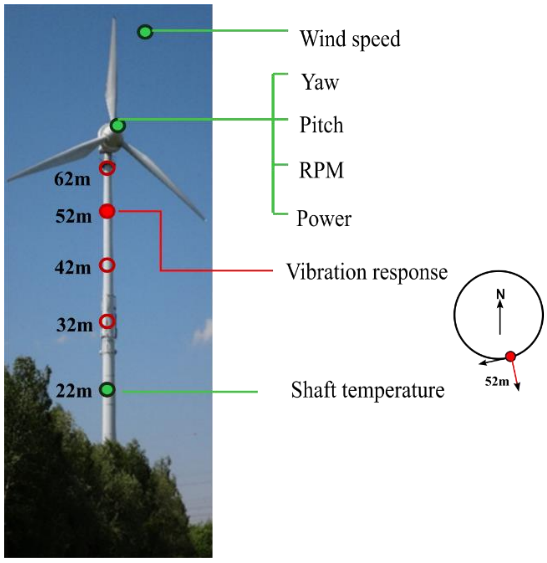

Figure 2. Photo of the actual structure and schematic overview of utilized data.

The nonstationary dynamics typical for an operating WT structure can be successfully tracked via the compact parametric formulation provided by the SP-TARMA models [2]. A full SP-TARMA model is described by an assemblage of three equations, one representing the modeled signal (system response), and two stochastic difference equations governing the time evolution of the unknown AR and MA parameters of the model. Thus, an adequate modelling of a measured nonstationary signal is ensured by proper selection of three user-defined parameters, i.e. the AR/MA order n, the ratio of the residual variances *v*, and the order of the stochastic difference equations *κ*, Figure 3.

The PCE tool is an uncertainty quantification method, which enables the relationship between outputs (structural response performance indicators) and inputs (environmental and operational loads) to the system. A PCE model can be described by a mathematical expansion of a random system output variable on multivariate polynomial chaos basis functions [2]. Spectral representations, such as the PCE method, rely on several regularity requirements, namely finite variance of the outputs, orthonormality of the polynomial basis, and statistical independence of the input variables [5].

The statistical modelling is based on Control chart analysis on the obtained PCE-SPTARMA residual (DI), Figure 4. The results from a univariate outlier analysis of SCADA records verify the sensitivity of the obtained PCE-SPTARMA model to novel fluctuations in measured EOPs. For a two-month training period, the validation set of the estimated DI illustrates that index values exceeding the ± 3std thresholds (99.7% confidence intervals calculated for the fitted Gaussian distribution of the estimation set) can be linked to novel data ranges of the measured influencing agents, more precisely temperature and RPM values between months March and November 2012, as well as April and September in year 2013.

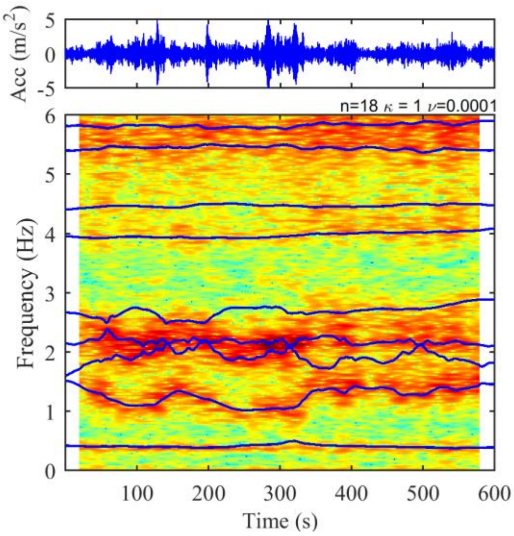

Figure 3. SP-TARMA frequency estimates for fitted model *M*(n=18, v=0.0001, κ=1) (spectrogram in the background).

3. CONCLUSIONS

The proposed data-based strategy delivered a sensitive PCE-SPTARMA diagnostic indicator able to capture the non-stationary response and the long-term response variability of the actual operating WT structure for a monitoring period of twenty one months. The obtained data-driven model verifies the future prospective of the strategy for development of an automated SHM diagnostic tool capable of separating benign EOP fluctuations from pattern alterations due to actual structural damage. The sensitivity of the diagnostic indicator to scheduled changes in operating regimes and system fluctuations of the WT structure will be sought in a following step.

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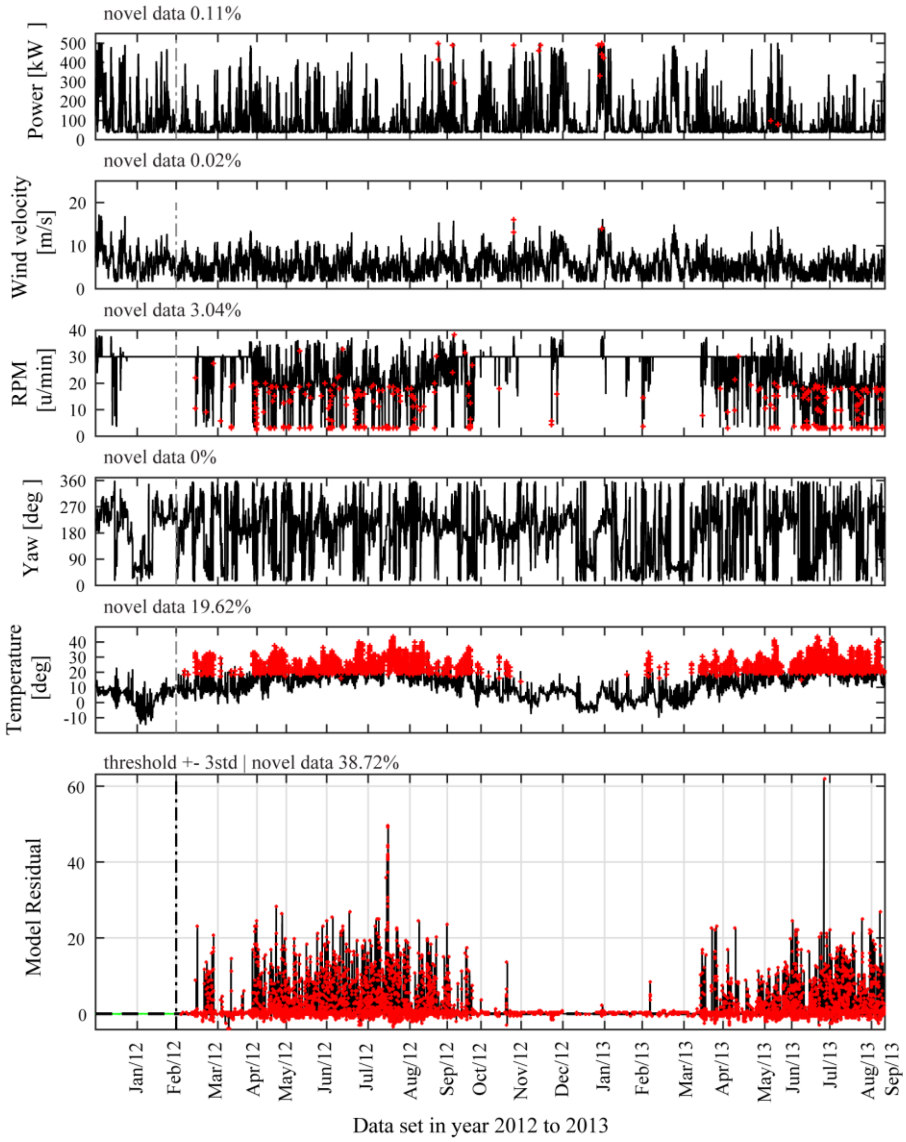

Figure 4. Two-month training set: Identified novel data (red points) within time history of 10-min mean values of measured SCADA and Control chart of the PCE-SPTARMA residual.

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