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A NOVEL BI-COMPONENT STRUCTURAL HEALTH MONITORING STRATEGY FOR DERIVING GLOBAL MODELS OF OPERATIONAL WIND TURBINES

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Abstract

The short and long-term variability characterizing operational Wind Turbine (WT) structures limits applicability of existing Structural Health Monitoring (SHM) strategies for diagnostics and condition assessment. In this paper, a novel modeling approach is proposed delivering global models able to account for a wide range of operational conditions of a WT System. The approach relies on the merging of environmental and operational variables into the modeling of monitored vibration response via a two-step methodology: a) implementation of a Smoothness Priors Time Varying Autoregressive Moving Average (SP-TARMA) method for modeling the non-stationary response, and b) implementation of a Polynomial Chaos Expansion (PCE) probabilistic model for modeling the response uncertainty. The bi-component tool is applied on long-term data, collected as part of a continuous monitoring campaign on a real operating WT structure located in Dortmund, Germany. The delivered statistical model of the structure yields a robust representation of the underlying structural dynamics, distinguishing actual structural damage from performance shifts attributed to environmental and operational agents.

1 INTRODUCTION

The most significant challenge in developing SHM strategies for civil infrastructure lies in the uniqueness of each structure, which effectively dismisses the possibility of generalizing baseline data obtained from type-testing or pre-established standardization procedures [1]. In this context, it becomes imperative to introduce and validate the applicability of various damage detection schemes [2, 3], which are so far limited to simulation and laboratory studies within a controlled testing environment, into the field, i.e., on actual operational civil structures. To a certain extent, this is so far achieved within the framework of Operational Modal Analysis (OMA) techniques, which have proved quite attractive for practical SHM applications, especially for large civil infrastructure [4]. The OMA set of methods is oriented towards Linear Time Invariant (LTI) systems, while more refined schemes pertaining to systems that deviate from the traditional linear elastic regime, e.g. non-stationary systems, are less frequently applied onto civil systems [5, 6].

WT structures interestingly hold a symbolic role in system identification since as early as the 1990s, when in pioneering research the well-known NExT framework was proposed and applied for the first time on WTs [7]. This later laid down the foundation of what OMA represents today, albeit subsequently research focus shifted to other civil structures (e.g. bridges, towers, stadiums). However, with Europe's current strategic planning focusing on renewable energy management, WTs are resurging as a focal point for both the industrial, and the research communities [8]. In that context, the growing demands for higher productivity and reduced downtime of modern WT structures, calls for improved and automated SHM strategies, ensuring early-stage damage detection and structural diagnostics, reliability in power supply, as well as optimal operation and maintenance ([9] to [12]).

The recent emergence of relevant technologies on one side, and the complexity of WT structures on the other side, renders the implementation of existing SHM regimes and solutions into practice a rather challenging task. Indeed, the difficulty in developing appropriate maintenance strategies may be attributed amongst others sources to: limited knowledge of the loading conditions (presence of considerable aeroelastic effects and altering rotational components in the excitation forces), the complexity of the multiparty WT system, varying operational regimes and environmental factors, as well as the typical uncertainties related to incomplete and imperfect sensor data, modeling errors, complex and unique to the location soil-structure interaction effects [13].

However, the major challenge for an efficient performance-based structural framework lies in the time varying nature of WT structures, linked to the changing operational regimes and varying environmental agents, and the misinterpretation of this variability [14]. The latter may result in false alarms hindering effective operation of associated damage detection and intervention control systems.

One possible approach to address the aforementioned challenge is implementation of strategies which may describe the structure in its complete operational spectrum, incorporating the uncertainties related to various sources in suitable prediction models. Research studies in this field are mainly based on two general approaches, namely methods based on filtering out the influence of environmental factors from estimated performance indices [15], and methods based on merging the measured environmental variables into models of measured vibration response (extracted performance indicators, e.g. modal parameters) [16] to [18]. It is worth noting that a thorough investigation of the environmental and operational effects on the modal parameters of the tower of an operational 5 MW prototype wind turbine is presented in the recent work of Hu et al. [15]. Following the first approach, in the same study, the authors extract a structural health index of the operating WT by removing temperature effects from selected natural frequency estimates based on a principal component analysis method.

The research study presented herein will follow the second approach via implementation of a bi-component SHM framework on an operating WT structure located in Dortmund, Germany [19]. The two step methodology is based on the idea of modeling the relationship between measured output-only vibration response data and measured operational variables by employing: i) a system identification model for the adequate description of structural dynamics, and ii) a PCE model for the projection of these estimates on the probability space of the measured environmental and operational conditions. The described framework was introduced and successfully applied for the purpose of damage detection of the benchmark SHM project of the Z24-bridge in Switzerland by Spiridonakos & Chatzi in [16], [17]. Spiridonakos et al. in a recent study [18] implemented this approach together with the time varying autoregressive modeling of the short term dynamics for tracking of the performance of an actual operating WT tower located in Lübbenau, Germany.

The results of the presented study herein demonstrate the effectiveness and high potential of the proposed method for automated condition assessment of large real world structures, operating in a wide range of conditions.

2 THE BI-COMPONENT FRAMEWORK

The fundamental concept of the proposed strategy evolves around two separate time-window scales: i) a short-term time framework, and ii) a long-term time framework, both governed by the specifics of the actual operating structure.

The complexity related to the interacting subsystems of the structure (namely the rotating blades, moving yaw mechanism, and pitch angle changes) and the alternating aerodynamics loads affecting the type of operational regime, result in a complex vibrating system necessitating adoption of efficient time-tracking estimation methods. In this context, the proposed short-term framework aims at accurately modeling this temporal variability charactering the system, while observing the structure as an isolated system (a structure on its own). In contrast to the short-term framework, the “zoomed out” long-term framework is focused on the tracking of the evolution of the variability in a longer time horizon. This is herein accomplished by a bi-component tool, which combines the parametric SP-TARMA method, for identifying structural performance indicators (short-term framework), with a PCE probabilistic model, for quantifying the uncertainty in the identified structural performance indicators (long-term framework). This enables the tracking of uncertainty evolution in structural response due to the randomness of environmental and operational parameters. The proposed framework aims at delivering a stochastic model that represents a “symbiotic relationship” between output-only vibration response data and measured operational variables (Fig. 1).

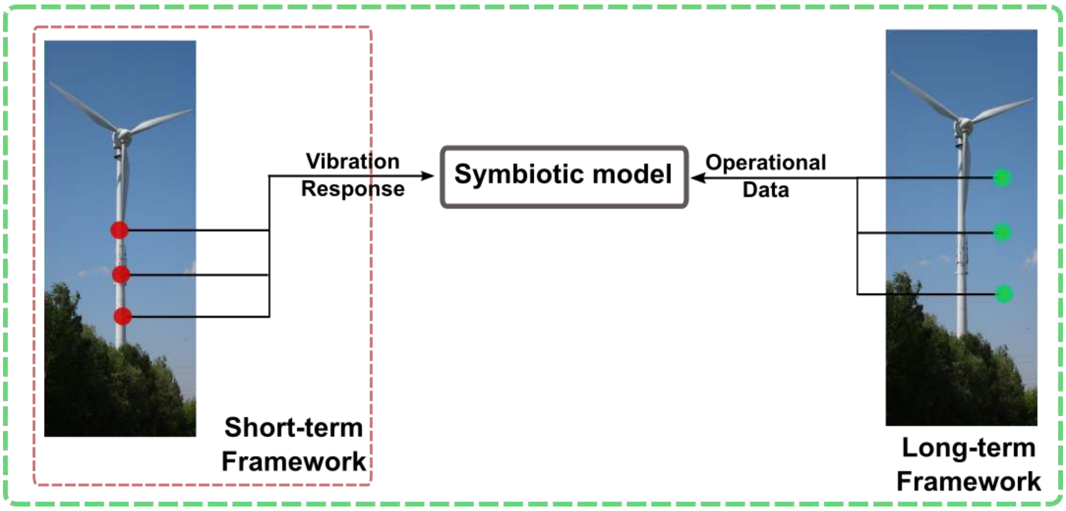


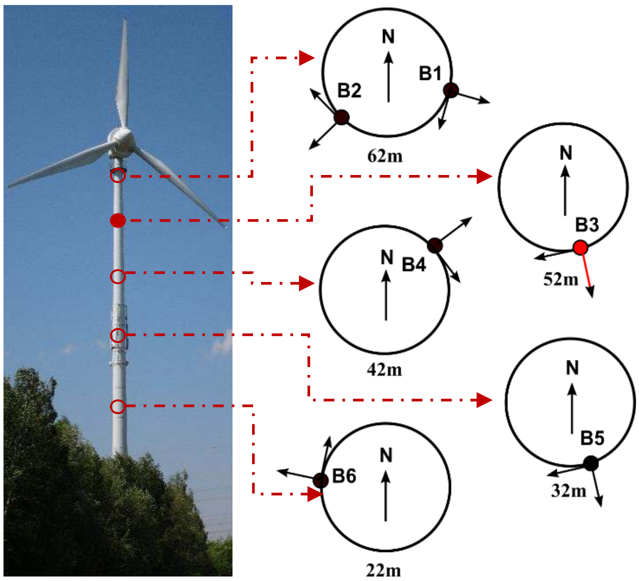
Figure 1. A conceptual overview of the proposed bi-component framework

3 THEORY BACKGROUND AND APPLICATION CASE STUDY

The SHM bi-component framework introduced in the previous section is presently applied on a WT structure located in the vicinity of Dortmund, Germany. The monitored structure under study is a 63m high real WT under operation (Fig.2), approaching its 20 year design lifespan. It therefore represents a valuable research specimen for investigating applicability of the developed tools in an actual scale.

An extensive monitoring system has been installed to continuously record structural response (ambient vibration acceleration and displacement), environmental (wind velocity and direction, ambient and structural temperature) and operational data of the WT structure for a period of four years, from October 2010 to October 2013. A more detailed overview of the complete acquisition system can be found in [19].

For the purpose of developing a time-sensitive tool capable of tracking long-term variability in the WT dynamics, the measured ambient vibration accelerations along the WT tower are utilized herein, along with environmental and operational data. The output-only vibration is monitored at five different positions along the WT shaft (Fig. 2) by means of triaxial accelerometers (PCB-3713D1FD3G MEMS sensors). All aforementioned parameters are recorded at a sampling frequency of 100 Hz in hour-long data sets, during the complete monitoring period.



Power	500 kW
Tower height	63 m
Height of the rotor center	65 m
Number of blades	3
Length of blade	19.13 m
Rotor speed	variable, 18-36 rpm
Blade material	GRP
Tower material	steel
Construction year	1997

Figure 2. Schematic overview of acceleration sensors (left), WT structure characteristics (right)

3.1 WT under parked conditions

When employing output-only vibration data, corresponding to parked conditions of the WT structure, the modal properties of the system may be inferred via implementation of common OMA techniques, based on the key assumption of time invariance.

The present case study utilizes the stationary ARMA method (prediction error method) for estimating the dynamic properties of the structure for selected data records corresponding to parked conditions during an emergency stop test event of the structure (Sensor B3, Fig. 2). In Fig.3 the ARMA based stabilization plot is presented, together with results of a stochastic subspace identification method, based on a canonical variate algorithm (appended in the background). Furthermore, the plotted spectrogram (Short Time Fourier Transform; Hamming data window; NFFT = 512; overlap 98%), which is provided on the right subplot of the same figure, clearly demonstrates the stationarity of natural frequencies within the explored time frame.

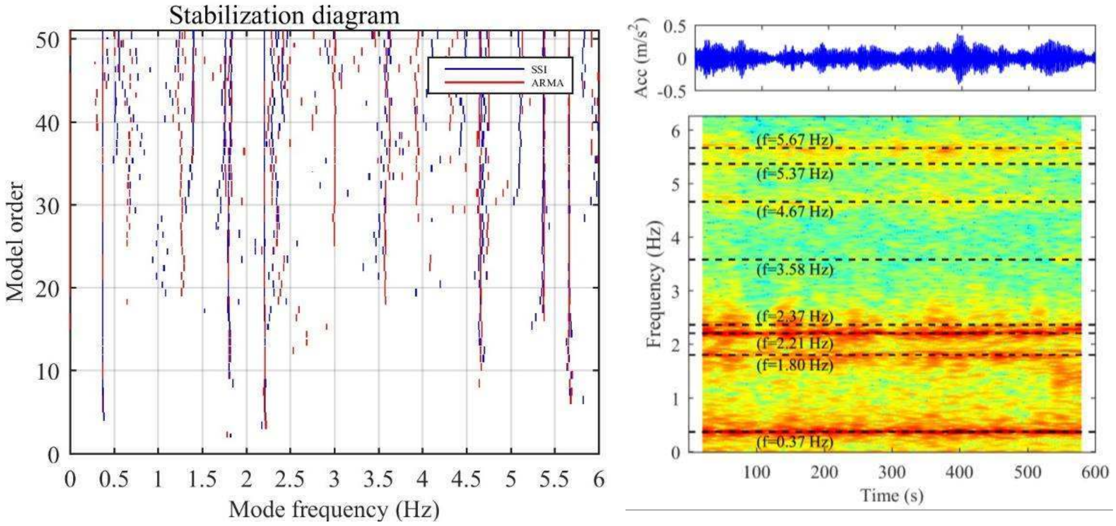


Figure 3. Dynamics of the parked WT. Left: Stabilization plot for the stationary ARMA and SSI methods (model orders from 2 to 50). Right: Spectrogram and ARMA(18,18) estimates

3.2 Short-term framework

In contrast to the stationary response of a parked WT structure, a spectrogram of an operating WT reveals nonstationary dynamics, varying even within the range of few minutes (Fig 4).

The compact parametric formulation provided by the Smoothness-Priors Time-varying AutoRegressive Moving Average (SP-TARMA) models has proven a suitable tool for tracking the changing structural dynamics [5]. Within the specific subclass of the Smoothness Priors models, the unknown AR and MA parameters of a general TARMA model are constrained by stochastic difference equations, which govern the evolution of the time varying $a_i[t]$ and $c_i[t]$ parameters. Therefore, the full SP-TARMA model may be completely described by i) a model for the system response y[t] (Eq. 1) and ii) a model which “controls” the time evolution of the AR and MA parameters of the first model (Eqs. 2 and 3):

$$y[t] + \sum_{i=1}^{n_a} a_i[t] \cdot y[t-i] = e[t] + \sum_{i=1}^{n_c} c_i[t] \cdot e[t-i], \quad e[t] \sim NID(0, \sigma_e^2[t]) \tag{1}$$

$$(1-\mathrm{B})^{\kappa} \mathrm{a_i}[\mathrm{t}] = \mathrm{w_{a_i}}[\mathrm{t}], \qquad \mathrm{w_{a_i}}[\mathrm{t}] \sim \mathrm{NID}(0, \sigma^2_{\mathrm{w_a}}[\mathrm{t}]) \tag{2}$$

$$(1-\mathrm{B})^{\kappa} \mathrm{c_i}[\mathrm{t}] = \mathrm{w_{c_i}}[\mathrm{t}], \qquad \mathrm{w_{c_i}}[\mathrm{t}] \sim \mathrm{NID}(0, \sigma^2_{\mathrm{w_c}}[\mathrm{t}]) \tag{3}$$

where t designates discrete time (with $i = 1,2, \dots, N$) of the observed nonstationary signal $y[t]$, $e[t]$ is the residual sequence (i.e., the unmodeled part of the signal, assumed to be normally identically distributed with zero mean and time-varying variance $e[t]{\sim}NID(0, \sigma_e^2[t])$) and $a_i[t]$, $c_i[t]$ the time-varying AR and MA parameters, respectively, for AR/MA order equal to n. B is the backshift operator ($B^k x[t] = x[t-k]$), κ designates the difference equation order, and $w_i[t]$ zero-mean, Gaussian sequences with time-dependent variance, uncorrelated, mutually uncorrelated and also uncrosscorrelated with $e[t]$.

The user-defined parameters, i.e., the AR/MA order n, the ratio of the residual variances $\nu = \sigma_w^2[t]/\sigma_e^2[t]$, and the order of the stochastic difference equations κ, should provide the best fitting model for the actual structure. Statistical based "penalty" approaches provide a selection tool for the range of values, which ensures adequate modeling precision without overfitting the modeled signal [5]. Thus, for given orders n, k and residual variance ratio v, the SP-TARMA model parameters from [Eqs. (1) to (3)] are obtained via the Kalman Filter scheme. The latter is combined with an Extended Least Squares-like algorithm to alleviate the nonlinear state estimation problem, which is typical for the full SP-TARMA case [18].

The previously described short-term framework is herein applied to recorded signals [sensor B3 (Fig.2)] corresponding to normal operating conditions of the monitored WT structure. For the purposes of the SP-TARMA simulation, the one-hour acceleration time histories were low-pass filtered and down-sampled to 12.5 Hz (cutoff frequency at 6 Hz) and observed as 10-min long data sets. The selected complete one-month period (June 2013) resulted in 4242 10-min long datasets, which after a preliminary tuning phase was utilized in an automated fashion within the short-term framework. When compared to the spectrogram (Short Time Fourier Transform; Hamming data window; NFFT = 512; overlap 98%), which is plotted in the background, Fig. 4 clearly indicates the capability of the fitted SP-TARMA (n_a=18, n_c=18, κ=1, ν=0.0001) model in tracking the evolution of the estimated frequencies of the monitored structure. The stationary ARMA approach on the contrary simply reports the averages of the nonstationary frequencies. In the same figure, a zoomed view of the Bayesian statistical criteria for the selected range of user-defined parameters is presented (right plot).

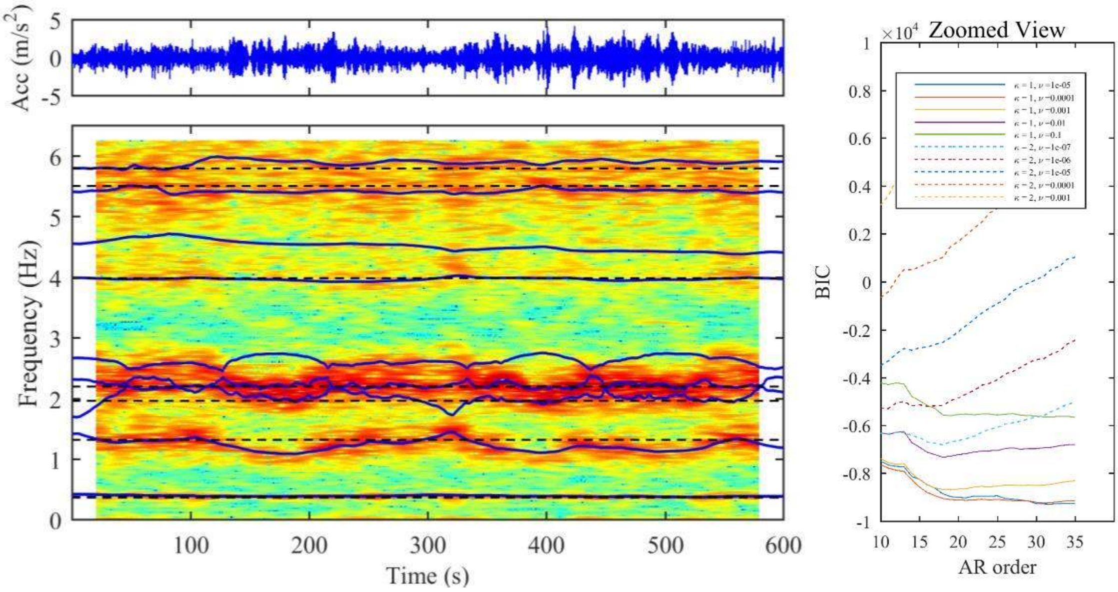


Figure 4. Left: ARMA(18,18) versus SP-TARMA(18,18) model estimates (spectrogram in the background). Right: Zoomed view of Bayesian Criterion plot for model order selection (10 to 35)

3.3 Long-term framework

In casting this problem in the probability domain, various uncertainty quantification methods may be employed for delivering the relationship between outputs (structural response estimates) and inputs (environmental and operational loads) to the system.

Let us assume a system S, comprising M random input parameters represented by independent random variables, e.g. measured wind velocities or temperature values, gathered in a random vector Ξ of prescribed joint Probability Density Function (PDF) $p_{\Xi}(\xi)$. A PCE model may be employed to generate a mathematical expansion of the model's random output variable $Y = S(\Xi)$ on multivariate polynomial chaos basis functions $\varphi_d(\Xi)$, constructed through tensor products of the corresponding univariate functions and appropriately related to the model's random input data vector Ξ. Namely, the univariate polynomials may be chosen in accordance to the PDF of the random input variables $p_{\Xi}(\xi)$, and thus straightforwardly associated to a well-known family of orthogonal polynomials [18]. Then, for an output variable of finite variance, the PCE model assumes the form [20]:

$$\mathrm{Y} = \mathrm{S}\left(\mathit{\Xi}\right) = \sum_{\mathbf{d} \in \mathrm{N}^{\mathrm{M}}} \theta_{\mathbf{d}} \varphi_{\mathbf{d}}\left(\mathit{\Xi}\right) \tag{4}$$

where θ_d are unknown deterministic coefficients of projection, and d is the vector of multi-indices of the multivariate polynomial basis with total maximum degree $\left|\mathbf{d}_{\mathrm{j}}\right| = \sum_{\mathrm{m}=1}^{\mathrm{M}} \mathrm{d}_{\mathrm{j,m}} \leq \mathrm{P}$ for every single index j. In this case, the number of terms in Eq. (4) is equal to:

$$\mathrm{p} = \frac{\left(\mathrm{M}+\mathrm{P}\right)!}{\mathrm{M}!\mathrm{P}!} \tag{5}$$

where M designates the number of random variables and P denotes maximum basis degree. The truncated PCE model to the first p terms yields a finite parameter vector θ_d which may be estimated by solving Eq. (4) in a least squares sense.

For the current case study, as a preliminary step before utilizing the PCE model, the selected input parameters are transformed to independent and uniform variables. In Fig. 5 (right plot) the 10 minute averages of the selected SCADA parameters, corresponding to the 4242 acceleration measurements, are plotted. In the same figure the correlation plots for each pair of chosen output variables is presented (left plot). Several pairs (marked red) are correlated with correlation larger than 0.5 (the largest correlation is 0.86). In order to transform the input data to independent variables, thus satisfying the PCE method requirement, the Independent Component Analysis (ICA) method is applied. The ICA tool extracts independent unobservable (latent) variables by exploiting higher order statistics (maximizing non-Gaussianity of the unobserved sources). Furthermore, ICA provides the possibility for reducing data inputs. A concise overview of the method, as well as a comprehensive flowchart of the ICA algorithm is presented in [16].

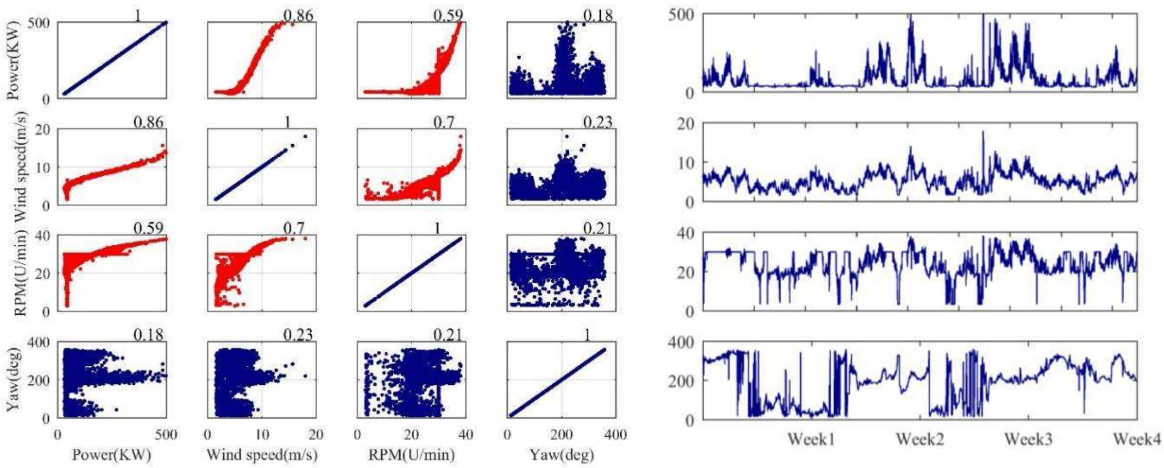


Figure 5. Left: Scatter plots of selected PCE input variables and estimated correlation values.
Right: Time history plots of selected PCE input variables for 4242 datasets.

Inspection of the eigenvalues of the covariance matrices of the four SCADA variables Fig. 5 (left plot), reveals three independent components. The corresponding ICA-based latent variables are presented in Fig. 6. For the purpose of constructing the random vector Ξ of prescribed joint PDFs $p_{\Xi}(\xi)$, the ICA estimates are further transformed into uniformly distributed variables via use of the non-parametrically estimated cumulative distribution functions.

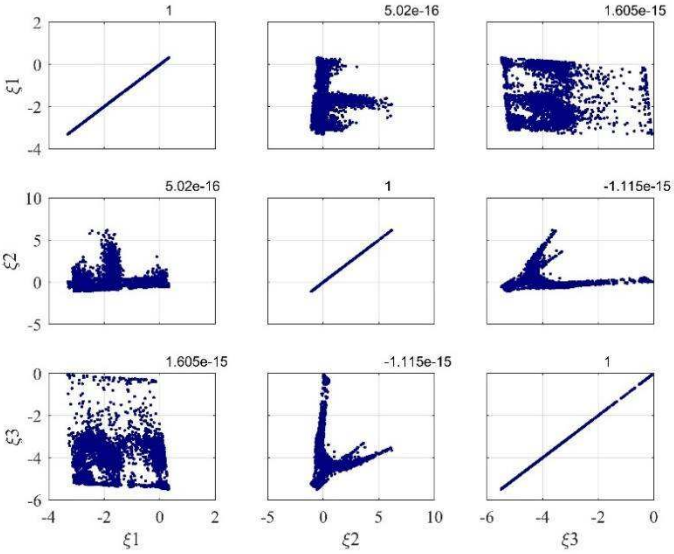


Figure 6. Scatter plots of ICA-based input variables and estimated correlation values

As a last step, the SP-TARMA model output variables and the PDFs of the measured operational input data are fed into the PCE (long-term) framework (Fig. 7). The standard deviation (std) of the SP-TARMA (18,18) residuals for the 10 minute intervals are selected as the PCE output parameter. In accordance with the uniform PDFs of the input data, the Legendre polynomials are selected as the PC functional basis [18]. The maximum polynomial order is selected equal to five, as further increasing the maximum order does not significantly improve the accuracy of the expansion.

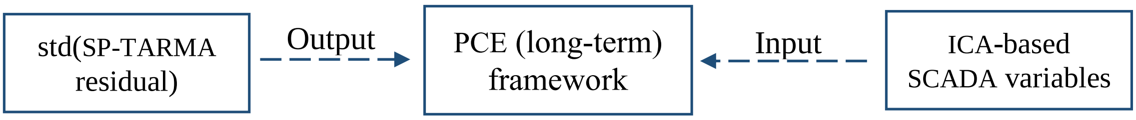


Figure 7. Schematic overview of the last step: input/output data fed into the long-term framework

The std of the residuals for each dataset and the PCE model estimates are plotted in Fig. 8. A total of 4242 data sets, which correspond to four weeks of measurements, are divided into a three-week estimation period and a one-week validation period. The PCE errors are plotted in the lower part of the figure, along with the corresponding 95% confidence intervals calculated for the fitted Gaussian distribution of the estimation set errors. It may be observed that the PCE model is capable of simulating the std(e) output variable with very good accuracy, and the model residual falls within the 95% confidence intervals for both sets. For the actual structure under study no damages were observed, with results verifying the applicability of the proposed framework for the continuous monitoring period of one month.

The assessment capabilities of the method will be further tested over a more extended time frame and a broader set of input/output parameters during the continuous 4 year monitoring campaign. This will further allow us to link typical operating regimes to specific structural behavioral patterns of the WT system. The end goal is to furnish an autonomous diagnostic tool, capable of tracking and diagnosing structural condition during the WT life-cycle.

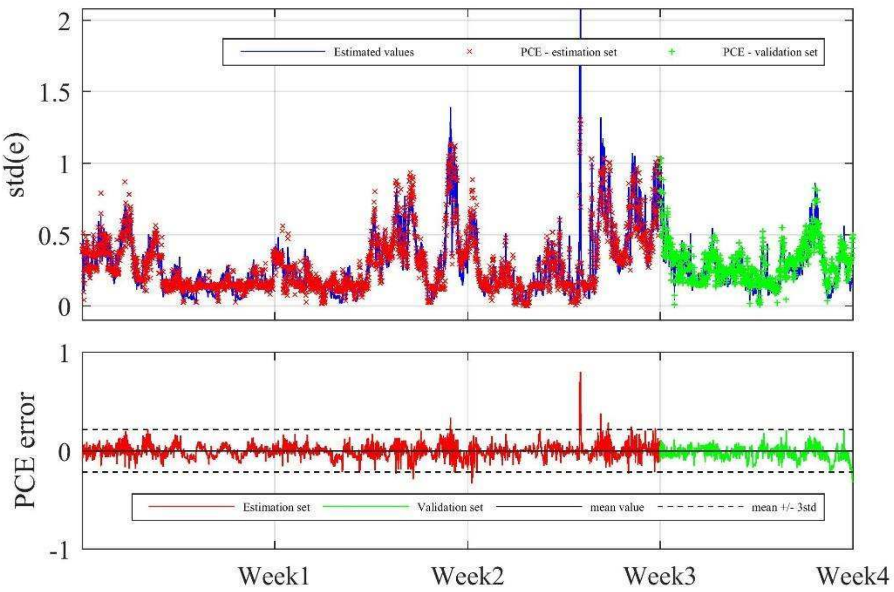


Figure 8. Std of SP-TARMA(18,18) model residual (up) and PCE errors with 95% confidence intervals (bottom)

4 CONCLUSIONS

In order to identify a comprehensive dynamic model of WT systems two aspects need to be addressed: the non-stationarity present in collected response data and the temporal variability of the identified model parameters. By merging environmental and operational variables into the modeling of vibration response, the proposed framework serves as the first step towards automated condition assessment. Successful implementation of the devised strategy on an operating WT structure in Dortmund (Germany) verifies the robustness of the approach. The outcomes of this study demonstrate the potential of the proposed bi-component tool for incorporation within a holistic SHM damage detection framework, further extended via statistical hypothesis testing (to be explored next).

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