ДГКМ
ДРУШТВО НА ГРАДЕЖНИТЕ КОНСТРУКТОРИ НА МАКЕДОНИЈА

Партизански одреди 24,
П.Фах 560, 1001 Скопје
Северна Македонија

MASE
MACEDONIAN ASSOCIATION OF STRUCTURAL ENGINEERS

Partizanski odredi 24,
P. Box 560, 1001 Skopje
North Macedonia

subj.-no.

mase@gf.ukim.edu.mk
http://mase.gf.ukim.edu.mk

DATA-DRIVEN STRUCTURAL HEALTH MONITORING AND DIAGNOSIS OF OPERATING WIND TURBINES

Simona BOGOEVSKA[1], Eleni CHATZI[2], Elena Dumova-Jovanoska[3], Rüdiger Höffer[4]

ABSTRACT

The necessity for real-time condition assessment of operational full-scale systems is nowadays progressively accentuated with the decreased or indeterminate reliability of existing infrastructure, as well as the continuous utilization of new materials for design of lighter, albeit more productive structures. Structural Health Monitoring (SHM)-based diagnosis holds considerable potential for tackling the uncertainties associated to the customarily exploited simulation-based approaches, and as a result, can facilitate long-term, automated and even online assessment of in-service structures.

The growing needs and rising trends for energy savings and recycling have placed Wind Turbines (WTs) among those infrastructures that bear critical importance. Unlike conventional structures, WTs are characterized by temporal variability. We propose a diagnostic framework able to describe the variability of the monitored WT system, in this way reaching beyond the applicability margins of the traditionally utilized operational modal analysis. 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. The obtained data-driven model verifies the future prospective of the strategy for development of an automated SHM diagnostic tool capable of separating benign Environmental and Operational Parameters (EOP) fluctuations from pattern alterations due to actual structural damage.

Keywords: *Data-driven diagnostics; Operating wind turbine; Structural variability; Uncertainty propagation*

---

[1] Assistant MSc, Faculty of Civil Engineering, University Ss. Cyril and Methodius, Skopje, Republic of North Macedonia, simona.bogoevska@gf.ukim.edu.mk

[2] Prof. PhD, Department of Civil, Environmental and Geomatic Engineering, ETH, Zurich, Switzerland, chatzi@ibk.baug.ethz.ch

[3] Prof. PhD, Faculty of Civil Engineering, University Ss. Cyril and Methodius, Skopje, Republic of North Macedonia, dumova@gf.ukim.edu.mk

[4] Prof. PhD, Faculty of Civil and Environmental Engineering, Ruhr University Bochum, Bochum, Germany, Ruediger.Hoeffer@rub.de

1. INTRODUCTION

The latest technological progress has created solid grounds for widespread application of various sensing techniques and acquisition systems on actual full-scale structures, which in turn accentuated the favorable outcomes of data-aided assessment of operational engineering structures. Continuous monitoring strategies facilitate the utilization of data-based tools, often characterized with a more objective and flexible approach in dealing with the omnipresent sources of uncertainty and variability characterizing real systems and environment.

Data-based schemes or hybrid analysis approaches (data/finite element model) become particularly valuable for infrastructures that bear critical importance in society. In this context, recent trends for energy conservation have placed the focus on WTs. Although historically linked to the very first conundrums of full-scale SHM attempts, as structures characterized with complex dynamics and alternating operating nature WTs persist to challenge experts in the field. Namely, as a result of their time-varying dynamic behavior WTs are resilient to traditionally applied Operational Modal Analysis (OMA)-based methods which are limited to implementation with time invariant systems [1]-[2], i.e. parked or idling condition of the structure, mode-by-mode or case-by-case investigation [3]. On the other hand, the identified EOP-born variations in structural responses, known to mimic real damage states of the structure, triggered the emergence of strategies which rely on elimination, pattern identification, or integration of environmental factors [8]-[11] from/with obtained structural performance indicators.

The workings of the PCE-SPTARMA data-driven tool, previously tested by the authoring team on two operating WT structures [11], are herein further explored by expanding the validation periods of monitored data. Whereas the twenty one-month long implementation on a real operating WT structure confirms the robustness of the strategy, fusion of the proposed strategy with a novelty detection algorithm and probability distribution divergence measure demonstrates the high potential for further automated structural health assessment.

2. CONCEPT AND THEORY BACKGROUND

In an operating mode WTs experience intense loading, non-stationary response and a significant dependence on their working conditions (wind, waves, temperature), eventually suffering signs of fatigue and deterioration. In this context, the fundamental concept of the proposed strategy revolves around two separate time-window scales: i) short-term time framework and ii) long-term time framework. The uniqueness of the approach lies exactly in this “binocular” visualization of the problem, which eventually enables addressing both behavioral signatures associated to collected WT response data, i.e., (short-term) non-stationarity and long-term temporal variability, Fig. 1.

The proposed PCE-SPTARMA tool is a multicomponent algorithm adept in capturing the short and long-term variability of the observed system. Through tracking of measured structural responses the tool provides a link between output-only vibration response data and measured EOPs. 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). Identified structural performance indicators, corresponding to short-term modeled responses, are then integrated into a PCE tool. The PCE probabilistic modeling approach connects the variability of the structural response to the randomness of measured EOPs (Step 2). 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 indicators. Comprehensive overviews of commonly applied statistical concepts in SHM can be found in [12]-[14].

The separate computational methods are further summarized and presented with a concise theoretical overview. The reader is guided to further appropriate references for more detailed information on the theoretical background.

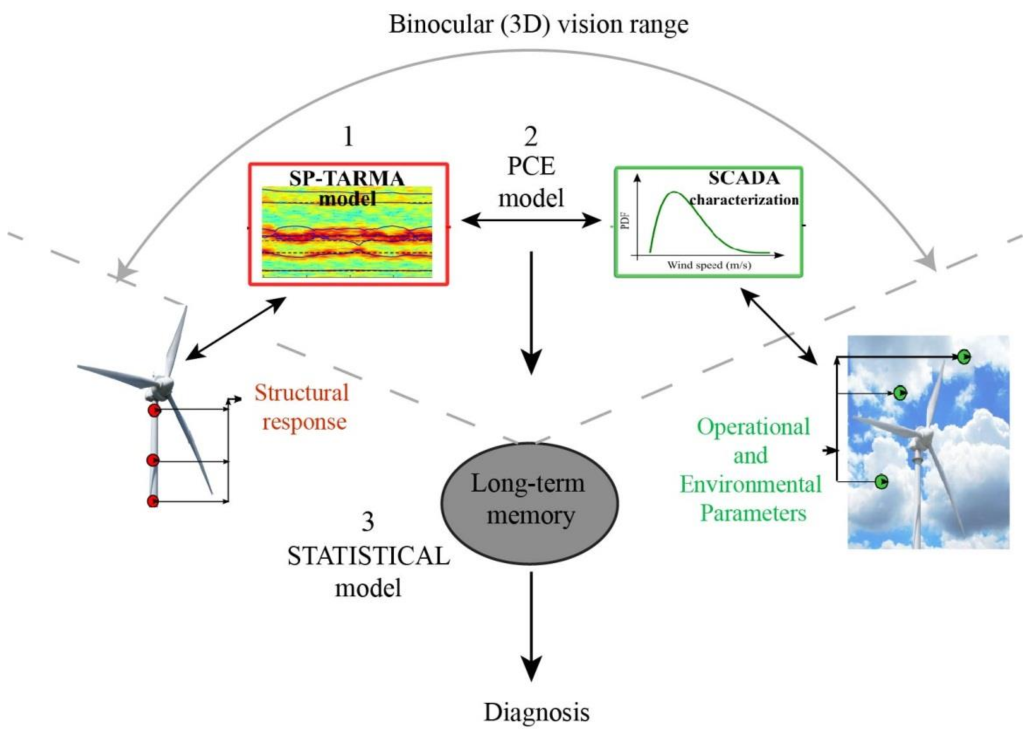


Fig. 1. Conceptual model of the SHM strategy and applied methods

2.1. Modeling non-stationarity (Step 1)

The nonstationary dynamics typical for an operating WT structure can be successfully tracked via the compact parametric formulation provided by the SP-TARMA models [15]. A full SP-TARMA model is completely 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 [16]. Statistical approaches such as minimization of the AIC (Akaike information criterion) or the BIC (Bayesian information criterion) improve the optimal selection of these values without overfitting the modeled signal. Finally, for a selected model $M(n, v, \kappa)$ the SP-TARMA model parameters are obtained via the Kalman Filter scheme combined with an Extended Least Squares-like algorithm [15].

2.2. Modelling uncertainty (Step 2)

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 [11]. 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 [17]. Hence, the polynomial chaos basis functions orthonormal with respect to the probability space of the system's random inputs have to be properly selected to ensure the necessary orthogonality relationship. Furthermore, the statistical independence of input data needs to be properly verified and possibly addressed via computational approaches capable of extracting independent (latent) variables from observed data, such as the Independent Component Analysis (ICA) tool [18]. Then for a selected family of polynomial functions and maximum polynomial order P, the solution of the deterministic unknown parameters of a truncated PCE model are estimated via the least squares approach based on minimization of the sum of the squared residuals between true (observed) and modeled (predicted) system outputs [17].

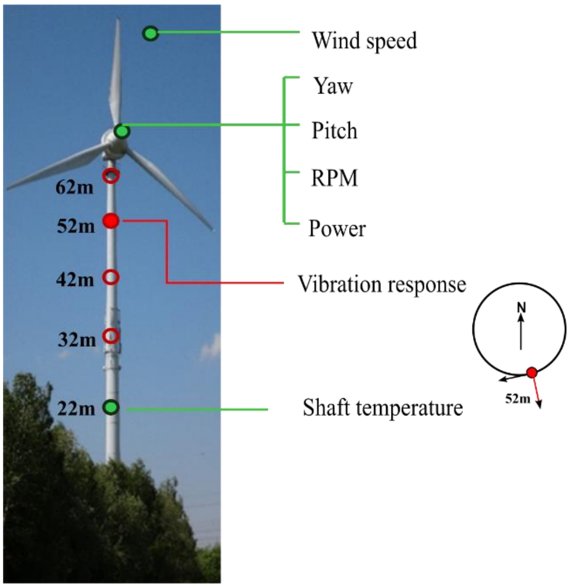
2.3. Statistical modelling (Step 3)

The statistical modeling within the proposed data-driven framework verifies the sensitivity of the obtained PCE-SPTARMA model to novel fluctuations in measured EOPs. The utilized algorithm is based on Control chart analysis and the Kullback–Leibler divergence metric applied on the obtained PCE-SPTARMA residual (DI). The latter measures the difference between a reference (training set) probability distribution of the obtained DI, and distribution that corresponds to new estimates of the DI (validation set).

3. APPLICATION CASE STUDY

The practical utilization of the described SHM strategy is presented with a case study of a 0.5MW WT erected in 1997, located in the vicinity of Dortmund, Germany, Fig. 2. The continuous measurement of acceleration data is recorded by triaxial accelerometers (PCB-3713D1FD3G MEMS sensors) 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. The presented results correspond to almost two complete years of continuously monitored data (January 2012 to September 2013). The last three months of year 2013 are disregarded from the assessment as a result of missing temperature data from various sensor malfunctions.



Power	500 kW
Height of the rotor center	65 m
Length of blade (3 total)	19.13 m
Rotor speed	18-36 rpm
Blade material	GRP
Tower material	steel
Construction year	1997

Fig. 2. Schematic overview of measured data (left), WT structure characteristics (right)

In order to illustrate the time variable dynamics of the presented WT case study, first the stationary ARMA method (prediction error method) is utilized 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. In Fig. 3 the ARMA based Stabilization plot is presented, together with results of a stochastic subspace identification method, 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.

3.1. Short-term framework

Acceleration records from a selected sensor location (marked at Fig. 2), corresponding to the working conditions of the structure, were low-pass filtered and down-sampled to 12.5 Hz, with a cut-off frequency at 6 Hz. Subsequently, 10-min long preprocessed data sets were implemented within the short-term framework. The tuning of an appropriate SP-TARMA model to actual 10-min long signals is a crucial point of the short-term modeling phase. Towards this end, plots of the AIC and BIC for model order selection are significant indicative tools that facilitate the fitting process of the user-defined parameters of the SP-TARMA model (i.e. the model order n, the smoothness constraint order κ and the residual variance ratio ν). A detailed inspection of a selection of response data sets in conjunction with their estimated statistical criterion plots revealed an optimal fitting with the parameter values equal to n=18, κ=1, ν =0.0001. For a graphic comparison, Fig. 3 presents a fitted and an over fitted 10-min long data set signal with ν =0.0001 and ν =0.001, respectively. Further discussion and graphical outputs on the SP-TARMA tuning process for the actual WT structure can be found in [11].

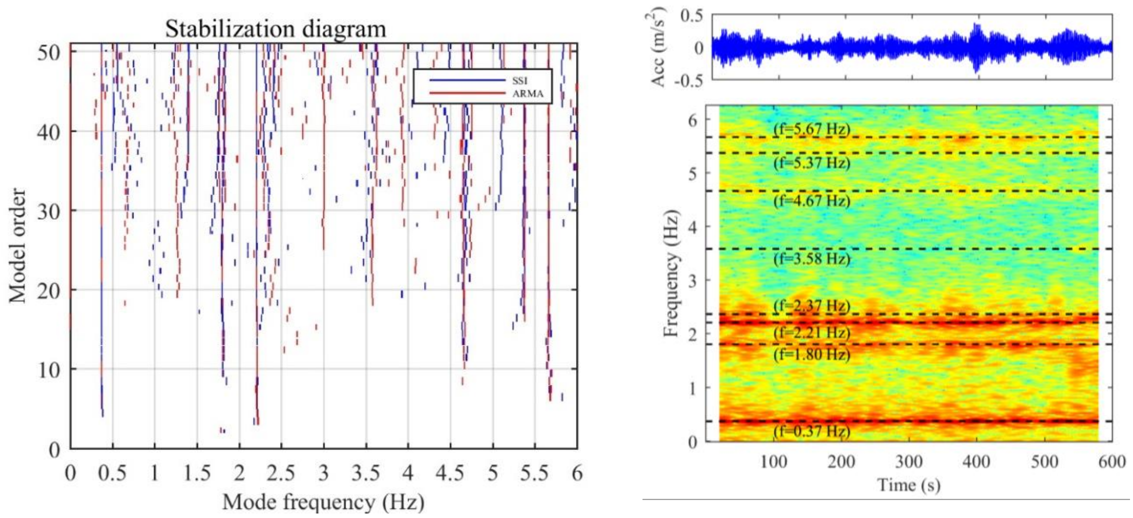


Fig. 3. Dynamics of the parked WT. Left: Stabilization plot for the stationary ARMA and SSI methods (model orders from 2 to 50). Right: Spectrogram and ARMA(18,18) estimates

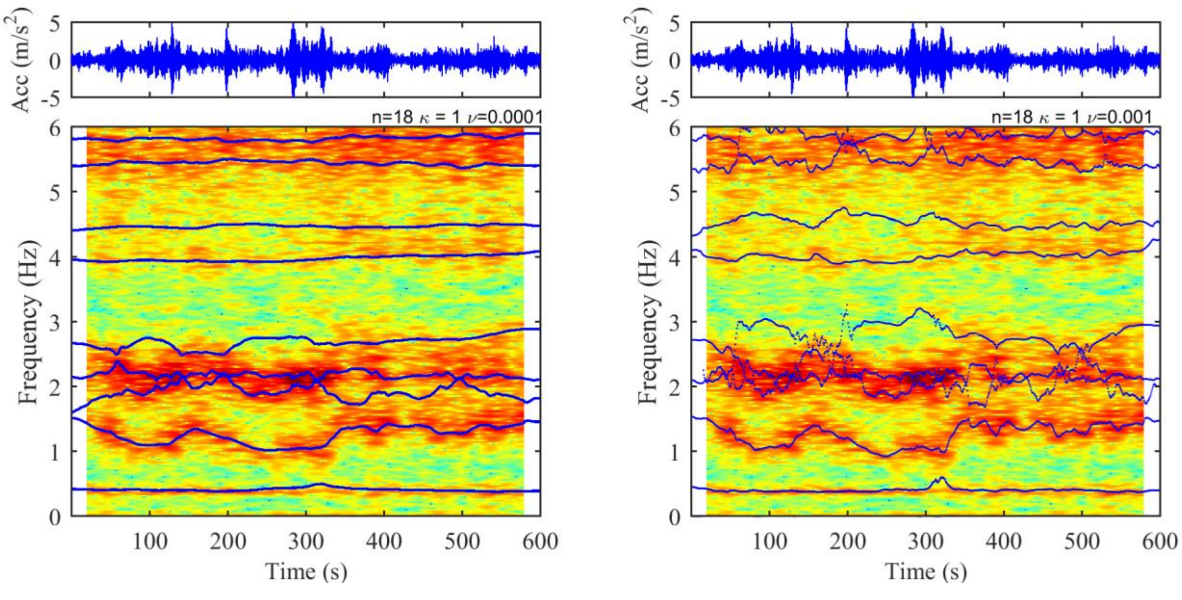


Fig. 4. SP-TARMA estimates (spectrogram in the background): fitted (left) and overfitted (right)

3.2. Long-term framework

Measured data corresponding to operational and environmental parameters was organized as 10-min averages and further processed to be utilized as input variables into the long-term framework. More precisely, five SCADA parameters (wind velocity, RPM of the rotor, power production, yaw angle, and shaft temperature) were transformed to independent variables via the ICA algorithm. In order to preserve all the existing information the number of ICA latent variables was kept same as the maximum number of available EOP. For the purpose of satisfying the second PCE prerequisite, the ICA estimates are further transformed into uniformly distributed variables via use of the non-parametrically estimated cumulative distribution functions. Hence, in accordance with the uniform PDFs of the input data, the Legendre polynomials are selected as the PC functional basis. The standard deviation (std) of the SP-TARMA residuals for the 10 minute intervals, analysed as part of the short-term framework, is selected as the PCE output parameter.

The final step is statistical analysis of a selected DI. In this case the residual of the obtained PCE model is selected as a DI. The results from the Kullback–Leibler divergence, applied daily on the obtained DI, are presented in Fig. 5. The sensitivity of the DI values to unfamiliar EOPs fluctuations is tested for two, four and twelve-month training periods. The red dots, marked at the plot are the first alarming values delivered by the tested statistical model. The second test is performed with Control chart analysis on the selected DI. Figs. 6 to 8 illustrate the performance of the charts for the three different training lengths.

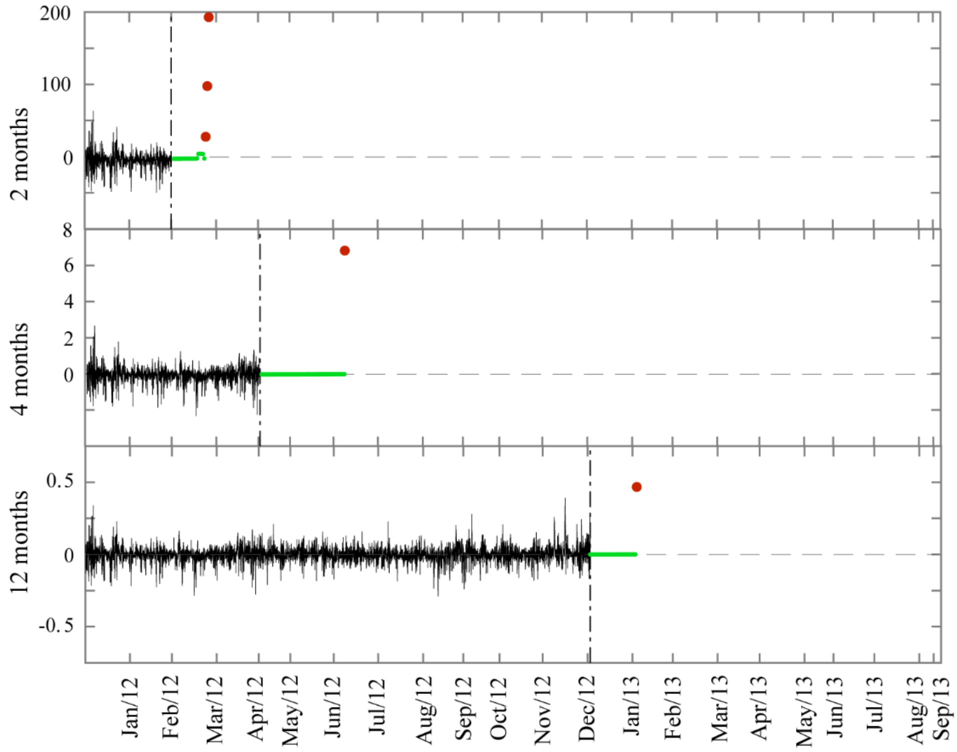


Fig. 5. Kullback–Leibler divergence applied on the obtained DI with cumulative assessment of one DI value per day, and tested for 2, 4, 12 months of training.

For further verification of the performance of the applied statistical metrics (Control charts and Kullback–Leibler divergence) , the input data time histories are analyzed by means of outlier analysis via the commonly utilized univariate discordancy measure given in [19]. The method identifies samples from a testing set which have values beyond a predefined limit. These are interpreted as novelties. In this context, the definition of thresholds is vital part of the process. An adaptive method that takes into account the actual empirical chi-square distribution function of the estimated distances (instead of a fixed quantile) is herein applied [20].

In Fig. 6, for a two-month training period, the validation set of the estimated DI and statistical outlier analysis of the input data time histories illustrate that index values exceeding the ± 3std thresholds (99.7% confidence intervals calculated for the fitted Gaussian distribution of the estimation set of PCE residuals) can be linked to novel data ranges of the measured influencing agents, more precisely temperature and RPM values between months March and November year 2012, as well as April and September in year 2013.

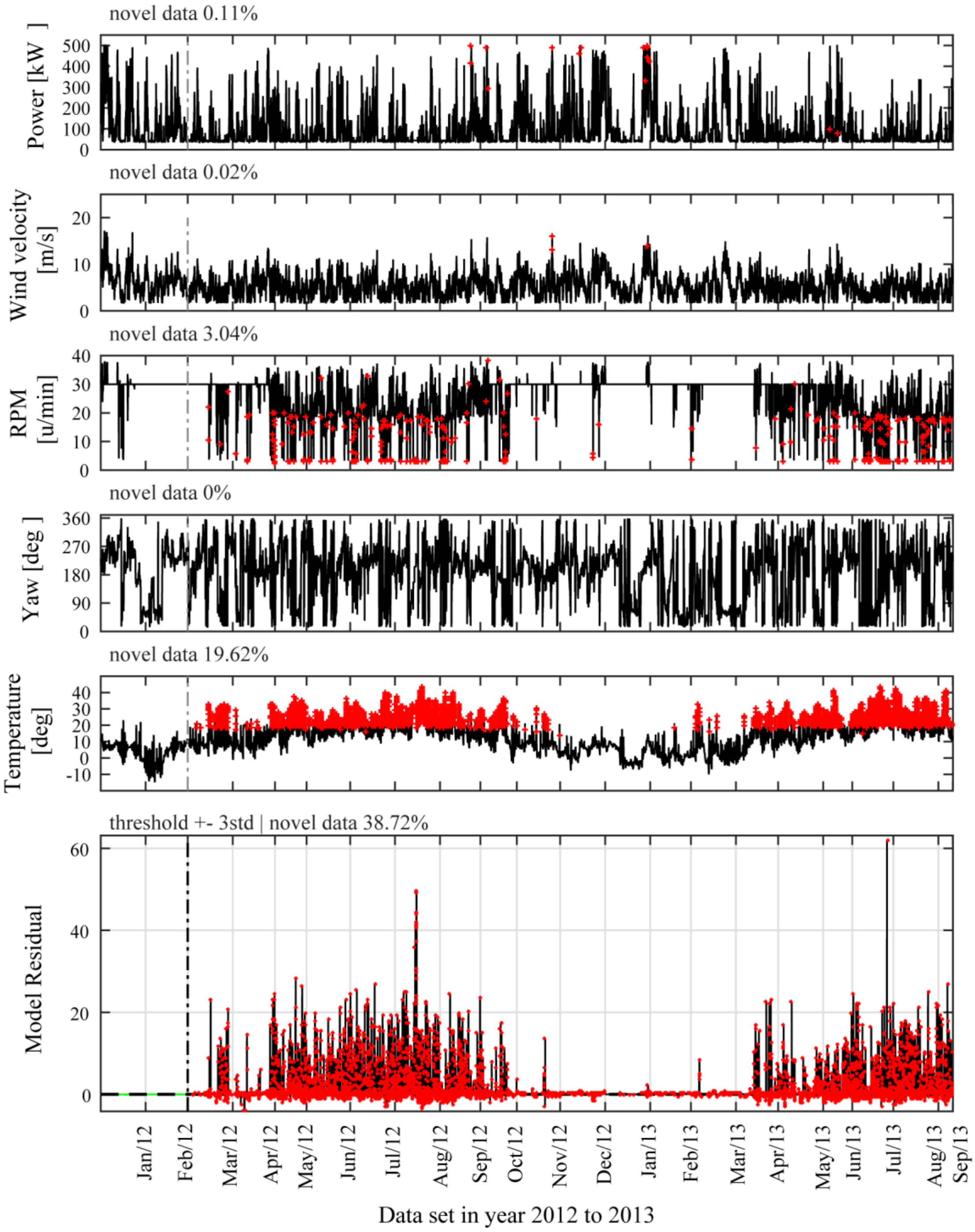


Fig. 6. Two-month training set. Identified novel data (red points) within time history of 10-min mean values of measured SCADA and Control chart of the Model residual.

Further increase of the training period (Figs. 7 to 8) results in decrease in the outlier percentages (SCADA variables with zero percent are not included in the plots) and correspondingly the DI values become significantly reduced. In the case of the twelve-month period of training, the outlier percentages drop below 0.2% and the DI distribution pattern of the testing set is evidently improved, with substantially less points above the threshold values. Furthermore, it is clearly demonstrated that the sensitivity of the applied Kullback–Leibler divergence to new data ranges of measured EOPs agrees well with the detected outliers within SCADA variables (Figs. 6-8).

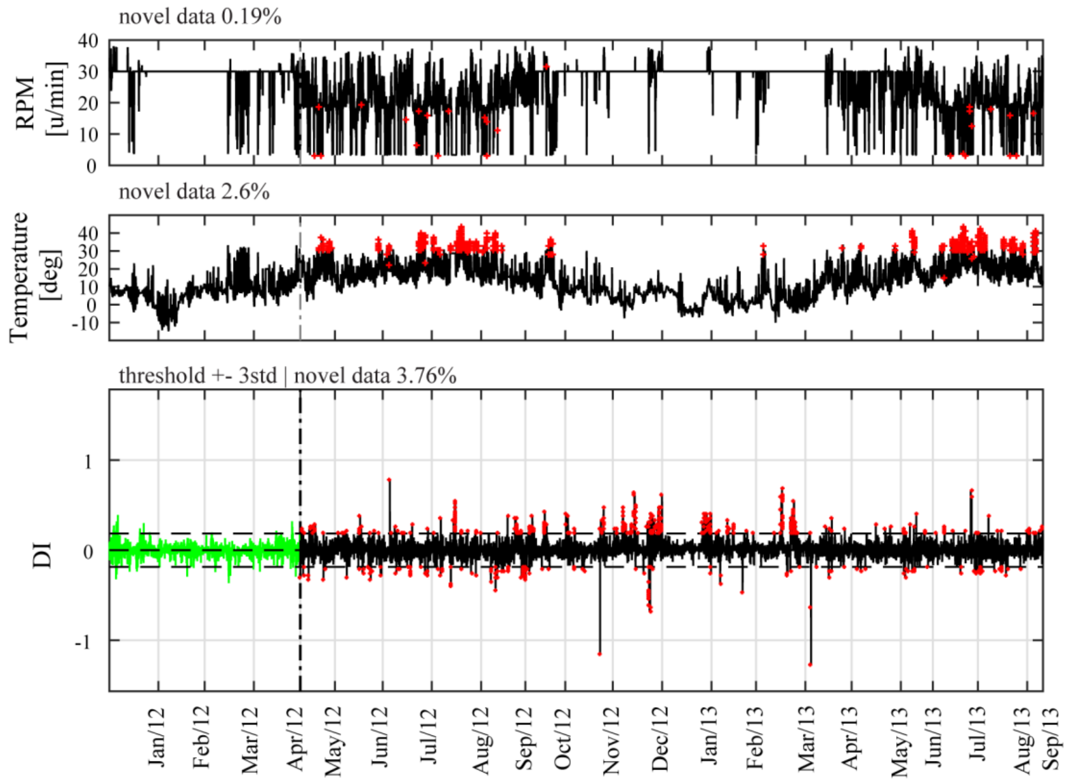


Fig. 7. Four-month training set. Identified novel data (red points) within time history of 10-min mean values of measured SCADA and Control chart of the DI.

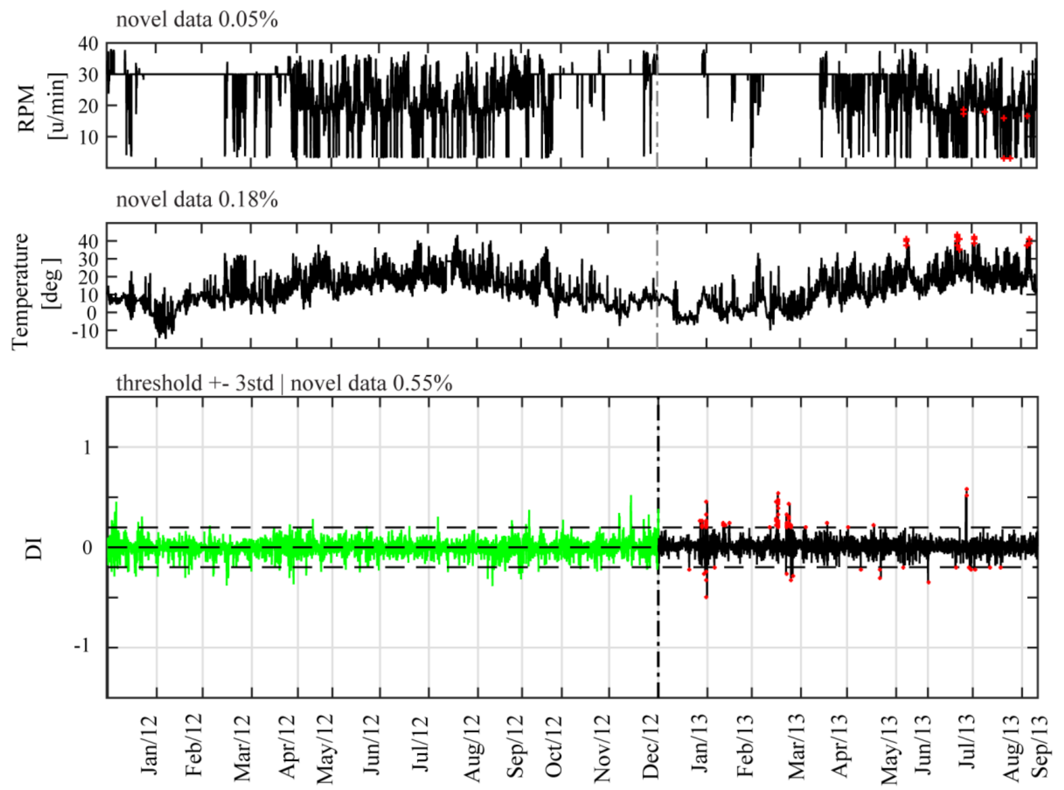


Fig. 8. Twelve-month training set. Identified novel data (red points) within time history of 10-min mean values of measured SCADA and Control chart of the DI.

4. CONCLUSIONS

The adoption of automated SHM identification tools capable of unprejudiced diagnosis of in-service structures gradually becomes a necessity. 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.

Measured ambient vibration accelerations of an actual operating WT tower in Dortmund (Germany) along with environmental and operational data were exploited within a multicomponent data-driven SHM framework. 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 potential for further enhancements of the tool, towards real-time computing platform able to guide operators in the management of WT structures, is verified by outlier analysis of recorded SCADA data, as well as utilization of Control chart analysis and Kullback–Leibler divergence measure on the obtained indicator, for various training lengths. 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.

REFERENCES

[1] Tcherniak, D., Chauhan, S. and Hansen, M. H., Applicability limits of operational modal analysis to operational wind turbines, Proceedings of 28th International Modal Analysis Conference, Jacksonville, Florida USA, 2010.

[2] Ozbek, M., Meng, F. and Rixen, D. J. (2013) Challenges in testing and monitoring the in-operation vibration characteristics of wind turbines, Mechanical Systems and Signal Processing 41, 649–666.

[3] Limongelli, M.P., Chatzi, E., Döhler, M., Lombaert, G. and Reynders, E., Towards extraction of vibration-based damage indicators, Proceedings of 8th European Workshop On Structural Health Monitoring, Bilbao, Spain, 2016.

[4] Weijtjens, W., Verbelen, T., De Sitter, G. and Devriendt, C. (2015) Foundation structural health monitoring of an offshore wind turbine- a full-scale case study, Structural Health Monitoring 15, 389-402.

[5] Oliveira, G., Vibration-based structural health monitoring of wind turbines, PhD Thesis, University of Porto, Portugal, 2016.

[6] Hu, W. H., Thöns, S., Rohrmann, R. G., Said, S. and Rücker, W. (2015) Vibration-based structural health monitoring of a wind turbine system Part II: Environmental/operational effects on dynamic properties, Engineering Structures 89, 273–290.

[7] Dervilis, N., Worden, K. and Cross, E. J. (2015) On robust regression analysis as a means of exploring environmental and operational conditions for SHM data, Journal of Sound and Vibration 347, 279–296.

[8] Spiridonakos, M. and Chatzi, E., Polynomial chaos expansion models for SHM under environmental variability, Proceedings of 9th International Conference on Structural Dynamics, Porto, Portugal, 2014.

[9] Spiridonakos, M., Chatzi, E. and Sudret, B. (2016) Polynomial chaos expansion models for the monitoring of structures under operational variability, ASCE- ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering 2.

[10] Avendaño-Valencia, L.D. and Chatzi, E., (2017) Sensitivity driven robust vibration-based damage diagnosis under uncertainty through hierarchical Bayes time-series representations, Procedia Engineering 199, 1852-1857.

[11] Bogoevska, S., Spiridonakos, M., Chatzi, E., Dumova-Jovanoska, E. and Höffer, R. (2017) A Data-Driven Diagnostic Framework for Wind Turbine Structures: A Holistic Approach, Sensors 17, 720.

[12] Worden, K., Baldacchino, T., Rowson J. and Cross E., Some recent developments in SHM based on nonstationary time series analysis, Proceedings of the IEEE 104, 1589-1603, 2016.

[13] Deraemaeker, A. and Worden, K. (2018) A comparison of linear approaches to filter out environmental effects in structural health monitoring, Mechanical Systems and Signal Processing 105, 1–15.

[14] Martinez-Luengo, M., Kolios, A. and Wang, L. (2016) Structural health monitoring of offshore wind turbines: A review through the statistical pattern recognition paradigm, Renewable and Sustainable Energy Reviews 64, 91–105.

[15] Spiridonakos, M. D., Poulimenos, A. G. and Fassois, S. D. (2009) Output-only identification and dynamic analysis of time-varying mechanical structures under random excitation: A comparative assessment of parametric methods, Journal of Sound and Vibration 329, 768-785.

[16] Akaike, H. and Kitagawa, G., Eds. (1999) The practice of time series analysis, Chapter 11, Springer-Verlag, New York.

[17] Le Maître, O. P. and Knio, O. M. (2010) Spectral Methods for Uncertainty Quantification, Springer, Netherlands.

[18] Hyvärinen, A. and Oja, E. (2000) Independent component analysis: algorithms and applications, Neural Networks 13, 411–430.

[19] Keith Worden, Graeme Manson, and David Allman. “Experimental validation of a structural health monitoring methodology: Part I. Novelty detection on a laboratory structure”. In: Journal of Sound and Vibration 259.2 (2003), pp. 323–343.

[20] Filzmoser, P., Garrett, R. G. and Reimann, C., Multivariate outlier detection in exploration geochemistry, Technical report TS 03-5, Department of Statistics, Vienna University of Technology, Austria, 2003.