Natural vibration response based damage detection for an operating wind turbine via Random Coefficient Linear Parameter Varying AR modelling

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Abstract. The problem of damage detection in an operating wind turbine under normal operating conditions is addressed. This is characterized by difficulties associated with the lack of measurable excitation(s), the vibration response non-stationary nature, and its dependence on various types of uncertainties. To overcome these difficulties a stochastic approach based on Random Coefficient (RC) Linear Parameter Varying (LPV) AutoRegressive (AR) models is postulated. These models may effectively represent the non-stationary random vibration response under healthy conditions and subsequently used for damage detection through hypothesis testing. The performance of the method for damage and fault detection in an operating wind turbine is subsequently assessed via Monte Carlo simulations using the FAST simulation package.

1. Introduction
Structural Health Monitoring (SHM) is of primary importance for wind turbine structures as damage may have catastrophic consequences. SHM systems are indeed appealing for reducing maintenance and repair costs and guaranteeing the safety of the infrastructure [1, 2]. Vibration based SHM is of particular interest, as it has the potential of global monitoring at minimal cost [3, 4]. Within this context, statistical time series methods are particularly attractive [5]. The effectiveness of such a method is strongly affected by the efficacy of the statistical time series model employed in representing the structural random vibration response. Thus, obtaining an accurate model is a main concern in the process of developing a vibration–based SHM system. In particular for operating wind turbines, the vibration response is random non-stationary, and also subject to various types of uncertainties [6, 7]. Thus achieving robust SHM is a challenging task [4]. Naturally, the proper handling of the vibration signal properties – including non-stationarity – is vital for effective SHM [8, 9]. In conventional methods, baseline time series models are identified from a single vibration signal under particular environmental and operational conditions, assuming that the dynamics observed in the vibration response would remain constant even under the effects of uncertainties [4, 5]. Yet, in order to effectively treat uncertainties it is necessary to monitor the behavior of the healthy structure during prolonged time periods in order to account for different operational and environmental conditions. More importantly, it is necessary to devise a methodology capable of combining the information conveyed in the baseline set, so as to yield a robust decision making mechanism.
In this sense, two different approaches are frequently used: a feature extraction/selection approach and a global model-based approach. In the feature extraction/selection approach, the characteristics that are least affected by uncertainties are extracted from the whole set of characteristics estimated through the models. Data transformation techniques, like principal component analysis, factor analysis, and others are often used in this context [10, 11]. The global model-based approach attempts to build a (normally parametric) stochastic model capable of explicitly taking into account the effects of environmental and operational conditions. For this purpose, it is possible to construct a model whose parameters are functions of one or more environmental/operational variables. Functionally Pooled AR/ARMA/ARX models [12], Linear Parameter Varying models [13], or Polynomial Chaos Basis AR models [14] are main examples. The identification of this type of models requires estimating the parameters and selecting a set of multivariate polynomial functions defined over a space spanned by the considered environmental and operational variables. The models may become complex, and computational complexity problems may arise.

As an alternative, Random Coefficient (RC) stochastic models may be used to describe the effects of uncertainties on the dynamics [15, 16]. Model identification in this case typically involves a Bayesian framework.

The present study addresses the problem of damage and fault detection in structures with non-stationary random vibration response subject to important environmental and operational variability through the use of Random Coefficient Linear Parameter Varying AutoRegressive (RC–LPV–AR) models. The work continues a previous study by the authors [17], in which Functional Series Time-dependent AutoRegressive (FS-TAR) models were used for representing the wind turbine's non–stationary random vibration response. The two key differences of the approach postulated in this study is the random nature of the model parameters, better accommodating operating and other uncertainties, as well as the Linear Parameter Varying nature (instead of the direct Time Varying) nature of the model that may lead to a better representation of the non–stationary dynamics itself. The obtained model parameters and corresponding modal quantities (frozen natural frequencies and damping ratios) are studied for healthy and damaged scenarios, while damage detection is performed via proper hypothesis testing.

2. The method
2.1. Non–stationary random vibration response representation via RC–LPV–AR

Let \( y[t] \) be a non-stationary signal defined over the normalized discrete time \( t \in \mathbb{Q} \), corresponding to a single realization of the RC–LPV–AR model:

\[
y[t] = -\sum_{i=1}^{n_a} a_i(\beta[t]) \cdot y[t-i] + w[t], \quad w[t] \sim \text{NID} (0, \sigma^2_w(\beta[t]))
\]  

\[
a_i(\beta[t]) = \sum_{k=1}^{p_a} a_{i,k} \cdot G_{b_a(k)}(\beta[t]), \quad a \sim \mathcal{N}(\bar{a}, \Sigma_a), \quad \sigma^2_w(\beta[t]) = \sum_{k=1}^{p_a} s_k \cdot G_{b_s(k)}(\beta[t])
\]  

where:

- \( a_i(\beta[t]), \sigma^2_w(\beta[t]) \) : AR parameters and innovations variance
- \( w[t] \) : Non-stationary innovations sequence
- \( \beta[t] \) : Scheduling variable
- \( G_{b_a(k)}(\beta[t]), G_{b_s(k)}(\beta[t]) \) : AR and innovations variance functional basis
2.2. Damage detection method using RC-LPV-AR models

Damage detection consists of determining whether a given test signal $y_{t}$ with corresponding parameter vector $\mathbf{a}_{\mathbf{t}}$ constitutes a realization of the model corresponding to the healthy state of the structure. In practice the parameter vector $\mathbf{a}_{\mathbf{t}}$ is not available, but its replaced by its corresponding estimate. Let $\mathcal{M}_{\mathcal{o}} = \{\mathcal{P}_{\mathcal{o}}, \mathcal{M}\}$ be the identified model of the vibration response of the structure at its baseline (healthy) state, with hyperparameters $\mathcal{P}_{\mathcal{o}} = \{\bar{\mathbf{a}}_{\mathcal{o}}, \Sigma_{\mathbf{a}_{\mathcal{o}}}, \mathbf{s}_{\mathcal{o}}\}$, and structure $\mathcal{M}$. Let $\mathbf{m}_{\mathbf{t}}$ designate the conventional LPV–AR model from the current state of the structure, then the damage detection problem consists on determining whether or not the event $\mathbf{m}_{\mathbf{t}} \in \mathcal{M}_{\mathcal{o}}$ is correct or not. With no extra information, the probability that the current model
is from the healthy state is equal to the prior probability of that event, but once a vibration response signal $y_u$ (and thus the corresponding parameter vector $a_u$) is available, one may use the Bayes theorem [21, Ch.4] as follows:

$$
P(m_u \in \tilde{M}_o | y_u, a_u) \propto p(y_u, a_u | \tilde{M}_o) \cdot P(m_u \in \tilde{M}_o)$$

(4)

where $p(y_u, a_u | \tilde{M}_o)$ is the joint probability from equation (2), and $P(m_u \in \tilde{M}_o)$ is the prior probability of the event $m_u \in \tilde{M}_o$. Under the Gaussianity assumption for the innovations and the coefficients of projection, the logarithm of $P(m_u \in \tilde{M}_o | y_u, a_u)$ may be expressed as:

$$
\ln P(m_u \in \tilde{M}_o | y_u, a_u) = \ln \mathcal{L}(a_u | y_u) - \frac{1}{2} d_M^2(a_u, \bar{a}_o) + C
$$

(5a)

$$
\ln \mathcal{L}(\theta_u | y_u) = -\frac{N}{2} \cdot \ln 2\pi - \frac{1}{2} \sum_{t=1}^{N} \left( \ln \sigma^2_u(\beta[t]) + \frac{y_u[t] + \sum_{i=1}^{n_u} a_i(\beta[t]) \cdot y_u[t-i]}{\sigma^2_u(\beta[t])} \right)
$$

(5b)

$$
d_M(a_u, \bar{a}_o) = \left( (a_u - \bar{a}_o)^T \cdot \Sigma_{a_o}^{-1} \cdot (a_u - \bar{a}_o) \right)^{1/2}
$$

(5c)

where $\ln \mathcal{L}(a_u | y_u)$ is the log-likelihood of the parameter vector $a_u$ given the current vibration signal $y_u$, $d_M(a_u, \bar{a}_o)$ is the Mahalanobis distance between the mean parameter vector $\bar{a}_o$ and the parameter vector $a_u$ corresponding to the current signal, and $C$ is a constant gathering the remainder constant terms. Then, for damage detection the following test may be performed:

$$
- \ln \mathcal{L}(a_u | y_u) + \frac{1}{2} d_M^2(a_u, \bar{a}) \leq l_{lim} \Rightarrow m_u \in \tilde{M}_o \quad (\text{healthy structure})
$$

$$
\text{otherwise} \Rightarrow m_u \notin \tilde{M}_o \quad (\text{damaged structure})
$$

(6a)

(6b)

where $l_{lim}$ is a detection threshold selected by the user. This threshold can also be optimized through a cross-validation approach [17], [21, Ch. 7].

3. Application example

3.1. Data description

The vibration signals used in this application example are obtained from a finite element model of a “NREL offshore 5-MW baseline wind turbine” simulated by means of the FAST wind turbine simulation code [22]. Four accelerometers are set on the structure: two at the tower top in the fore-aft and lateral directions; two around 25% of the blade chord of the third blade in the edgewise and flapwise directions. The rotor position is measured as well. The obtained vibration responses are 200 s long, sampled at 25 Hz. Further details can be found in [17].

3.2. Identification of the healthy state using RC-LPV-AR models

The obtained vibration response signals from the healthy state and from all the sensor locations are represented by means of RC-LPV-AR models. The RC-LPV-AR models use trigonometric basis for the expansion of the parameter evolutions, where the instant phase of the trigonometric basis is the instantaneous value of the rotor position. Specifically, the basis function is defined as follows

$$
G_0(\beta[t]) = 1, \quad G_{2k-1}(\beta[t]) = \sin(2\pi k \beta[t]), \quad G_{2k}(\beta[t]) = \cos(2\pi k \beta[t])
$$

where the scheduling variable $\beta[t] \in (0, 1)$ is the measured rotor position at time $t$. Notice that the use of this type of functional basis makes the parameters of the RC-LPV-AR model directly
dependent on the instant position of the rotor and thus any variation in the rotor speed is tracked by the model. This improves the tracking ability of the postulated RC-LPV-AR models in comparison to the FS-TAR models (as shown in [17]) in the representation of wind turbine vibration, since the rotor speed may have small variations as the control system of the wind turbine responds to the upcoming wind. The models are computed independently for each sensor to achieve simpler models and to compare the sensitivity of damage detection for different types of damage at each sensor location. The settings of the estimation methods and the identified model structures for each one of the sensor locations can be found in Table 1.

| ID step   | Description                                                                                                                                 |
|-----------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Estimation| Multi-stage method with WLS parameter estimation and instantaneous innovations variance estimate. Stopping criteria: parameter tolerance $10^{-9}$, objective fcn. tolerance $10^{-9}$, maximum No. of iterations 100. |
| Identification | Model order: Estimate LPV-AR($n$)[$p_a$, $p_s$] models with $n = 6, \ldots, 20$ and $p_a = p_s = 9$. Basis order: Estimate LPV-AR($n_a$)[$p$, $p$] models with best $n_a$ of previous step and $p_a = p_s = 1, 3, \ldots, 15$. Regularized covariance estimates. |
| Achieved structures | Tower top – fore-aft: LPV-AR($9$)[$7, 7$]; Tower top – lateral: LPV-AR($17$)[$7, 7$]; Blade 3 – flapwise: LPV-AR($6$)[$7, 7$]; Blade 3 – edgewise: LPV-AR($17$)[$7, 7$]. |

### 3.3. Simulated damage scenarios

Five types of damage are simulated with four increasing levels corresponding to typical damages or malfunctions in wind turbines [1, 2]. Each scenario is described in Table 2. For each scenario 100 realizations of the wind turbine response are simulated with different seeds for the generation of the turbulence time series. In comparison with the previous work [17], the present work evaluates two more damage scenarios (damages D and E), and utilizes larger number of realizations per structural state (50 realizations were used in the previous work).

| Type       | Description                                                                                                                                 |
|------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Damage A   | Increased mass on the last 10% of the length of the third blade. Four damage levels: 20%, 40%, 60% and 80% blade mass density increment.           |
| Damage B   | Stiffness reduction of the root of the third blade in the edgewise direction. Four damage levels: 15%, 30%, 45% and 60% blade edgewise stiffness decrement from the root up to 10% of the blade chord. |
| Damage C   | Stiffness reduction in the lateral direction at the base of the tower. Four damage levels: 5%, 10%, 15% and 20% tower stiffness decrement in the lateral direction, from the base up to 10% of the tower height. |
| Damage D   | Error in the yawing mechanism. Four damage levels: 2, 4, 6 and 8 degree errors from the upwind position in the yawing system.                  |
| Damage E   | Reduction of the damping coefficient of the slow speed shaft. Four damage levels: 15%, 30%, 45% and 60% damping coefficient decrement.          |

Figure 1 shows 90% confidence intervals of the RC-LPV-AR parameter trajectories derived from the vibration responses at the blade in the flapwise direction for all realizations at different
structural states (healthy and damages A to E). The most obvious difference from the healthy state is evidenced by damage D, where the parameter trajectories travel through almost totally different areas. In the remaining scenarios, the areas covered by parameter trajectories at the different structural states are largely overlapping.

Figure 1. 90% confidence intervals of the RC-LPV-AR parameter trajectories as a function of the rotor position $\beta$ on 100 realizations at different structural states. Results shown for sensor on the blade – flapwise direction with a RC-LPV-AR(6) model. Only highest damage levels are shown.

Figure 2 provides a comparison of the “frozen” modal quantities extracted from the mean parameter vectors $\bar{a}_s$ for the healthy and damage scenarios at their highest level of damage. Certain “frozen” natural frequencies and damping ratios are shown for a single period of rotation of the blades and are computed as explained in [18]. The trajectories followed at the healthy state are shown in black color, whereas the damages are shown in different colors. The trajectories of the modal quantities remain almost the same on the sensors at the tower top fore-aft direction and at the third blade in the edgewise direction. The changes are more obvious for the remaining sensors. Damage D induces the largest deviations in both frequency and damping ratio. In particular a large decrement of the damping ratio is evident in the first blade mode at the edgewise direction, and in the trajectories of the modal quantities on the flapwise direction. The changes are more discrete for the other types of damages.

3.4. Damage detection
Damage assessment is performed via the test described by Equation (6) based on the obtained RC-LPV-AR models for the healthy state. A cross-validation approach is used for the optimization of the detection threshold. Namely, the set of vibration response signals of each sensor is divided into 10 subsets, each one containing 10 vibration response signals from each reference state. Then, 90 signals from each structural state are used for training of the method (RC-LPV-AR model identification), while the remaining signals are used for evaluation.

Figure 3 shows the distribution of the damage detection statistic obtained for the vibration response at the blade on the flapwise direction for each type of damage and for each level of damage. The change in the distribution of the detection statistic is evident especially for damages A and D. Table 3 provides a summary of the performance of the damage detection method in terms of the Receiver Operating Characteristic (ROC) Area Under the Curve (AUC), measuring the discriminative ability of the detector [21, Ch. 9]. The results obtained with
Figure 2. Selected trajectories of the “frozen” natural frequencies and damping ratios derived from the average parameter vectors of the RC-LPV-AR models at different sensor locations and for different structural states. Highest damage levels considered for each damage type.

Figure 3. Distribution of the damage detection statistic obtained by the damage detection method based on RC-LPV-AR modeling for each one of the structural states and for each level of damage (indicated as L1,...,L4). Right plot shows the distribution of true negatives and true positives for increasing values of the threshold.

4. Conclusions
In this study the use of Random Coefficient Linear Parameter Varying AutoRegressive (RC-LPV-AR) models was postulated for the modeling and damage detection of structures with...
Table 3. Best detection performance per damage type of the proposed RC-LPV-AR model based damage detection method, and the single/multiple model based methods shown in [17].

| Method                          | Damage A | Damage B | Damage C | Damage D | Damage E |
|--------------------------------|----------|----------|----------|----------|----------|
| Single FS-TAR                  | 0.69     | 0.85     | 0.64     | 0.98     | 0.66     |
| Multiple FS-TAR - min rule     | 0.78     | 0.94     | 0.95     | 1.00     | 0.94     |
| Multiple FS-TAR - sum rule     | 0.79     | 0.95     | 0.92     | 1.00     | 0.89     |
| RC-LPV-AR model                | 0.90     | 0.75     | 0.94     | 1.00     | 0.94     |

Performance figures provided in terms of the mean of the ROC–AUC obtained after cross-validation. A ROC–AUC close to one indicates an excellent performance of the detector, whereas a ROC–AUC equal to 0.5 indicates that the detector has no discriminative ability [21, Ch. 9].

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