Black-box system identification approach for damage detection in a small-scale wind turbine blade

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Abstract. System identification techniques play an important role in structural health monitoring of engineering components. In this study, we used a set of measurements of vibration-based experiments of a small-scale wind turbine (WT) blade to assess its structural condition under healthy and damaged scenarios. Firstly, a black-box system identification with ordinary least squares was implemented, considering a linear autoregressive exogenous (ARX) model to represent the dynamics of the WT blade. This method required a high-order ARX model. Nonlinear ARX (NARX) modeling was also performed, however, it did not demonstrate advantages over the linear one in terms of reducing model complexity or prediction errors. In addition, a recursive least squares algorithm was implemented to identify changes in the structural dynamics induced by the presence of crack-like defects. The procedure was carried out under various defect severity scenarios and showed satisfactory performance in monitoring the health condition changes. The applied system identification strategy performs well and is a reliable monitoring tool for diagnosing damage in the WT blade.

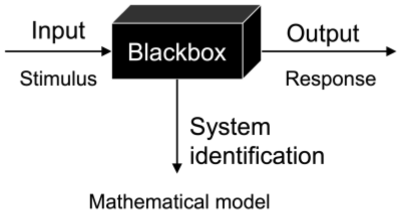
1. Introduction

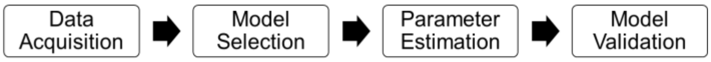
Wind turbines (WT) are essential for sustainable and renewable energy production, and the blades are key components to convert wind power into electricity. However, their operating environments with complex natural conditions can lead to damage and failures. It is not easy to detect damage due to their remote installations and structural complexity, whereas severe damage will result in significant economic loss [1][1]. For this reason, WT blades are worthy of special attention among various application fields of structural health monitoring (SHM) for ensuring structural integrity and better decision-making about maintenance strategies.

Damage detection of WT blades is divided into local measurement and global measurement. The first employs non-destructive testing (NDT) techniques on a localized area; and the second one utilizes vibration-based method to monitor overall conditions of the blade [2]. From vibration-based signal responses, system identification tools can be used to extract features of the blade to track dynamic variations induced by damage or loading conditions.

2. System identification

Black-box system identification is a modeling approach utilized when the physical governing laws of a system are not explicitly known or too complex to be modeled. This technique is based on analyzing the system's input and output data to obtain a mathematical model which represents the physical system, as depicted in Figure 1(a). The framework of model developing and improving consists basically of four steps: acquiring input-output data, selecting a model structure, estimating model parameters, and validating the model's adherence by comparing predictions with measurements, as shown in Figure 1(b).





(a) (b)

Figure 1. (a) Black box system identification; (b) Basic steps of system identification

2.1. Model selection

A commonly used model in linear black-box system identification is ARX (Auto regressive with exogenous input) model, which seeks to represent the current output as a linear combination of current input and past outputs and exogenous inputs. The architecture of ARX model is shown in Eq. (1).

$$\underbrace{y(t)}_{\substack{\text{current}\\ \text{output}}} = \underbrace{a_1 y(t-1) + a_2 y(t-2) + \cdots + a_{na} y(t-na)}_{\text{past outputs}} + \underbrace{b_1 u(t)}_{\substack{\text{current}\\ \text{input}}} + \underbrace{b_2 u(t-1) + \cdots + b_{nb} u(t-nb+1)}_{\text{past inputs}} + \underbrace{e(t)}_{\text{noise}} \qquad \text{Eq. (1)}$$

where, na and nb are called number of delays of output and input, respectively. They determine the number of past outputs and inputs that affect the current response. The higher their values, the more complex the system dynamics.

NARX (Nonlinear auto regressive with exogenous input) model is a nonlinear generalization of ARX. It assumes a nonlinear relationship between past outputs and exogenous inputs. Its architecture is shown in Eq. (2).

$$y(t) = F[y(t-1),\ \ldots,\ y(t-na),\ u(t),\ u(t-1), \ldots, u(t-nb+1)] + e(t) \qquad \text{Eq. (2)}$$

where, $F[.]$ is a nonlinear function.

2.2. Parameter estimation

Computational algorithms are employed to find the best-fit model parameters. A frequently used method is Least squares (LS). It minimizes the sum of squared errors between predicted data and measured data of the entire dataset, assuming the parameters are unchanged for all available data.

Recursive least squares (RLS) is an adaptive algorithm utilized for online or real-time parameter estimation. It allows us to track and monitor time-varying system dynamics by updating estimates every time that new measured data becomes available. This way, real-time predictions can be made considering the current patterns of the system’s behavior without requiring extensive computational memory. To make this possible, the covariance matrix, which reflects the uncertainty associated with parameter estimates, is updated recursively with each data acquisition.

3. Case study: Wind turbine blade with crack-like damages

In this work we used an open-database benchmark implemented by Ou, *et al* [3-4], which was obtained in vibration-based experiments of a small-scale WT blade with a length of 1.75 m under several damage scenarios and temperatures.

Initially, the blade was tested in healthy state. Three cracks were introduced at 17%, 30%, and 50% along the entire length of the blade, as depicted in Figure 2. The size of each crack had been progressively increased to 5, 10 and 15cm. All the damage scenarios with different positions and intensities are listed in Table 1.

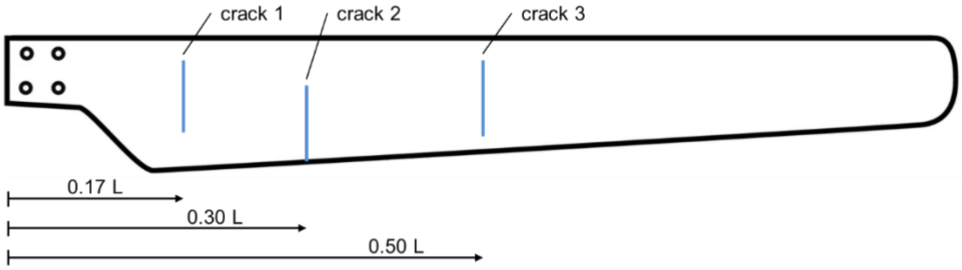


Figure 2. Cracks located at 17%, 30% and 50% of total length of the test specimen, adapted from [3]

Table 1. Experimental cases at healthy state and damaged states

Case label	Description			Temperature
R	Healthy state			-15 to 40 ℃
E	Crack 1: 5 cm	Crack 2: 5 cm		-15 to 40 ℃
F	Crack 1: 5 cm	Crack 2: 5 cm	Crack 3: 5 cm	-15 to 40 ℃
G	Crack 1: 10 cm	Crack 2: 5 cm	Crack 3: 5 cm	-15 to 40 ℃
H	Crack 1: 10 cm	Crack 2: 10 cm	Crack 3: 5 cm	-15 to 40 ℃
I	Crack 1: 10 cm	Crack 2: 10 cm	Crack 3: 10 cm	-15 to 40 ℃
J	Crack 1: 15 cm	Crack 2: 10 cm	Crack 3: 10 cm	-15 to 40 ℃
K	Crack 1: 15 cm	Crack 2: 15 cm	Crack 3: 10 cm	-15 to 40 ℃
L	Crack 1: 15 cm	Crack 2: 15 cm	Crack 3: 15 cm	-15 to 40 ℃

For vibration tests, the force and acceleration were measured as input and output of the WT blade, respectively. Sine sweep and white noise excitation signals were used in experiments. The sampling frequency was 1,666 Hz and the duration of each test was 120 seconds. Figure 3 shows the force and acceleration signals at healthy state under 0 ℃ in time domain and Figure 4 shows those in frequency domain. The white noise forcing signal contains excitation frequencies reaching approximately 600 Hz, whereas the sine sweep forcing signal includes frequencies only up to 300 Hz.

This preliminary investigation indicates that the dataset of experiments with the former signal is better suited for building models for this WT blade, when compared to using those with the latter signal. Thus, the system identification hereafter will be performed based on datasets from white noise forcing experiments.

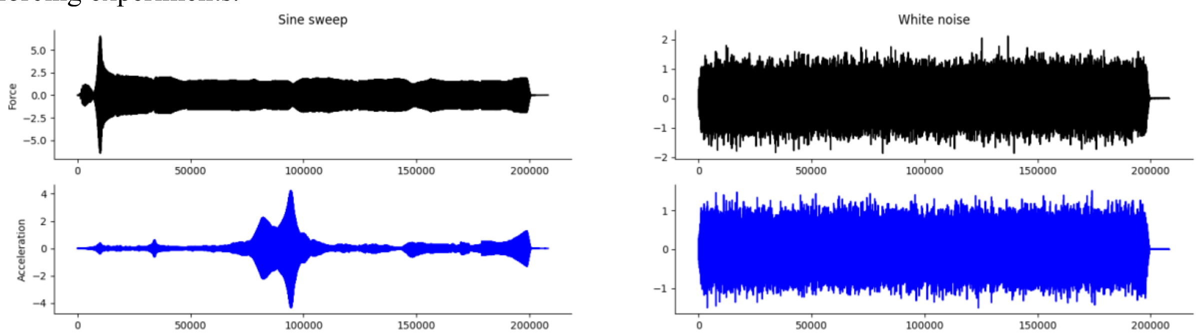


Figure 3. Sine sweep and white noise forcing signals and acceleration output signals in the time domain

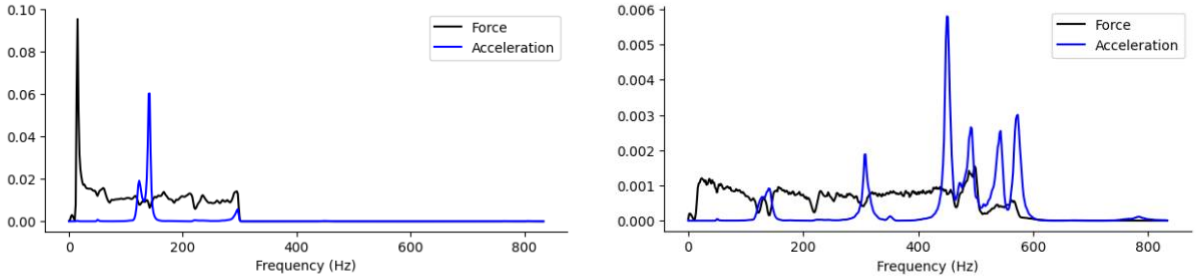


Figure 4. Sine sweep and white noise forcing signals and acceleration output signals in the frequency domain

4. Results
In this study, we compared different black-box system identification models to represent the WT blade and two parameter estimation methods were used. The data from vibration tests at 0°C were analyzed and the results are presented in this section.

4.1. Model selection
To assess the presence of nonlinearity in the system's dynamics, a comparative analysis was conducted between performances of ARX and NARX models while describing the WT blade in the healthy state, i.e., case R, at 0 °C. The validation results are presented in Table 1, where the coefficient of determination was used to evaluate the model's adherence to the actual system response.

The results indicate that the ARX model is appropriate for modeling the system, while the NARX model doesn't present a better predictive capacity despite its increased complexity. In addition, a large number of past outputs and exogenous inputs have effects on the current response, which means that the dynamics of the system are complex. Thus, the ARX model with $na = nb = 18$ was selected for system identification analysis hereafter.

Table 2. R^2 of predictions using different model structures for the healthy state

n=na=nb	**ARX**	**2nd order NARX**
5	0.160	0.160
10	0.442	0.442
15	0.722	0.722
18	0.800	0.800
20	0.778	0.777
23	0.857	-
26	0.947	-

4.2. Least squares parameter estimation
Using the LS algorithm we implemented in *Matlab* and considering the previously selected model structure, we obtained mathematical models individually for the WT blade in the healthy state and all damage scenarios of Table 1. The parameter estimates for all cases are plotted sequentially in Figure 5, and the coefficients of determination of one-step-ahead and free-run predictions are shown in Table 3.

Figure 5 evidently shows that the WT blade model parameters vary significantly from one damage scenario to the subsequent worse one, while remaining unchanged characterizing a unique dynamic behavior in each single scenario, as assumed in the LS method.

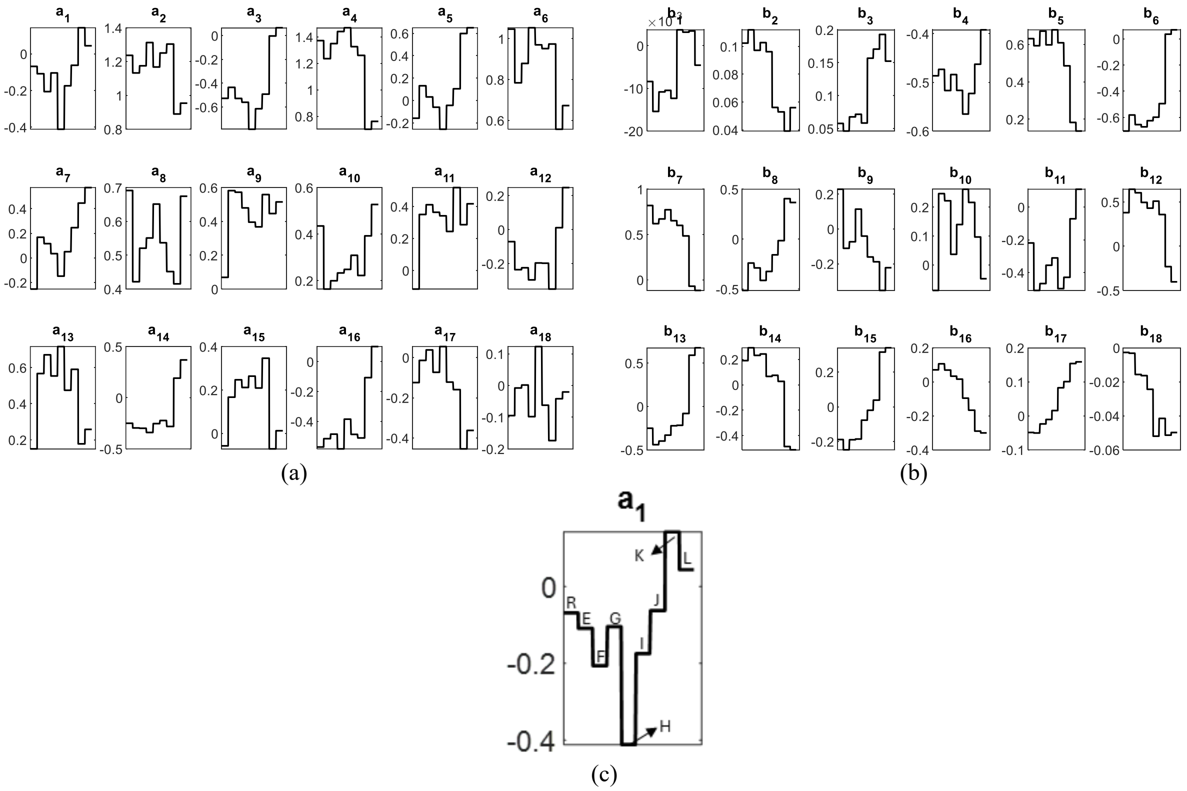


Figure 5. Parameter estimation: (a) past outputs, (b) current and past inputs, and (c) parameters remain unchanged in each scenario and change from one scenario to another

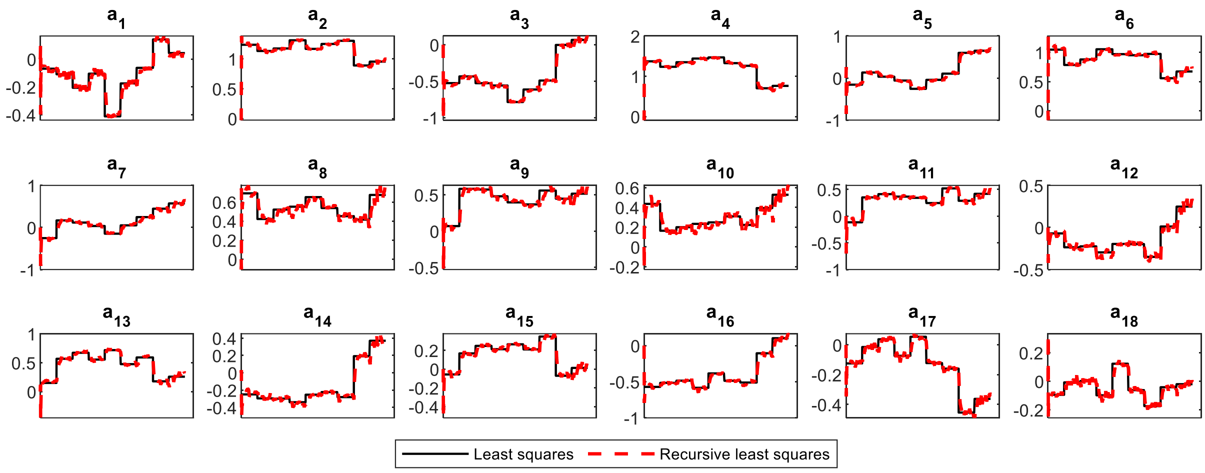
Table 3. R^2 of predictions using least squares parameter estimation for all cases

Case label	R^2 (One-step-ahead prediction)	R^2 (Free run prediction)
R	0.9926	0.9272
E	0.9905	0.9161
F	0.9903	0.8999
G	0.9908	0.8671
H	0.9926	0.9310
I	0.9915	0.9044
J	0.9892	0.8566
K	0.9879	0.9160
L	0.9844	0.9142

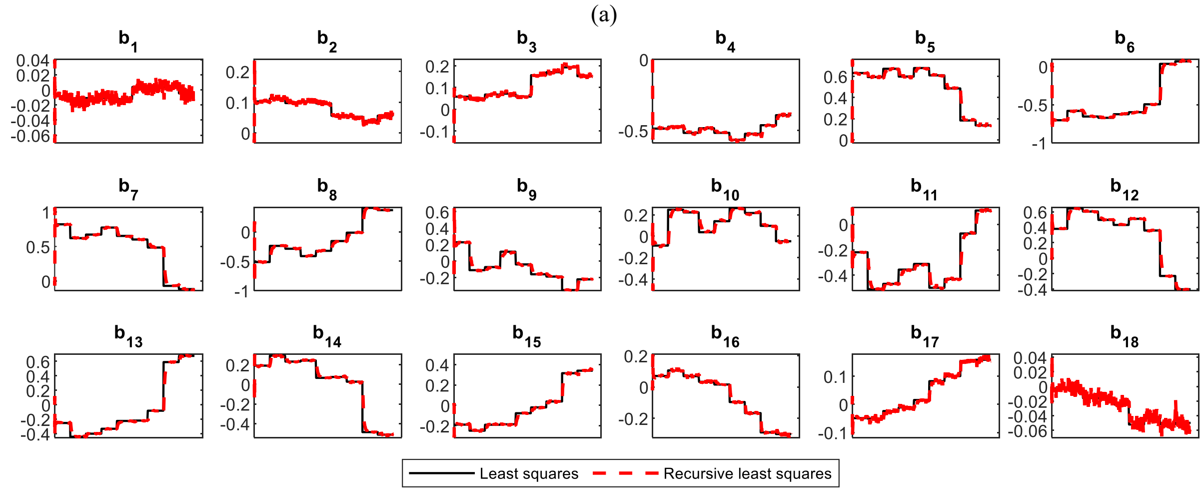
4.3. Recursive LS parameter estimation

A RLS algorithm was also implemented in *Matlab*, which continuously updates the covariance matrix and adapts parameter estimates with each data acquisition, over approximately 1,800,000 acquisition points, corresponding to a total of the concatenation of 9 cases with about 200,000 data points each case. The real-time parameter estimates are presented in Figure 6, where the results obtained through the LS method are also plotted for comparison.

The results of RLS method effectively captured time-varying dynamics in the WT blade even within each damage scenario, in contrast to the stationary dynamics assumed by LS method, which may not reflect the reality of damage development in field applications. In practice, damage and consequent system deterioration occurs progressively, instead of forming well-defined scenarios as considered in this study. To accurately map time-varying behaviors, such adaptive modeling is required.



(a)



(b)

Figure 6. Real-time parameters estimation using recursive algorithm with covariance resetting: (a) past outputs, and (b) current and past inputs

It is worth noting that, despite the extensive dataset, the RLS algorithm demonstrated remarkable computational efficiency by executing the adaptive parameter estimation for the entire dataset in a short time. This effectiveness and adaptability are advantageous in most online or real-time tracking and monitoring applications.

5. Conclusion

In this study, we modeled a small-scale wind turbine blade through black-box system identification techniques, based on an extensive dataset from vibration tests performed under varying structural integrity conditions.

The model selection procedure indicated that, despite the absence of significant nonlinearity within the blade's dynamics, its inherent complexity required an ARX model with high orders of input and output delays.

The LS and RLS methods were employed to estimate parameters in building the model. The RLS algorithm stands out for its adaptability and efficacy in tracking time-varying dynamic changes on the blade from healthy state to various damage scenarios.

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