LPV modelling and fault diagnosis in wind turbine benchmark system

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***Abstract*—In this paper, we present a fault detection approach of a linear parameter varying (LPV) system using residuals generator based on the use of the predictor based LPV subspace identification approach (LPV PBSID). To address this problem of fault detection in the pitch subsystem considered in the wind turbine benchmark introduced in IFAC SAFEPROCESS 2009, the failure events are caused by jumps in the damping ratio and natural frequency values of the model. The damping ratio is increased and the natural frequency is decreased with the hydraulic pressure variation. Satisfactory results have been obtained of the proposed approach using the proposed fault scenarios.**

I. Introduction

The fault diagnosis and prediction of many industrial processes has become of importance because of its great influence on the operational continuation of process. Correct diagnosis and early detection of incipient faults avoids harmful, sometimes devastating consequences. The task consists of the detection of faults in the processes, actuators and sensors. In wind turbine benchmark a set of pre-defined faults with different locations and types are proposed [1],[2] in this paper the dynamic change in pitch system is treated.

This procedure of fault detection is based either on the knowledge about the system or on the model of the system [3]. Model based fault detection is often necessary to obtain a good diagnosis of faults [4], the methods used in model based diagnosis are state observer based scheme, parity equations based scheme and parameter estimation.

Fault diagnosis consists of comparing the behavior of the real system with that of its model. In an ideal case, the system and the model behave exactly the same and when a fault is detected the behaviors are different, this difference is termed as residual, this difference between real system and model behaviors, can be used to diagnose and isolate the malfunction [5].

For linear time invariant systems (LTI), this task is largely solved by powerful tools. However, physical system generally has a non linear behavior and using LTI models in many real applications, this type of models is not sufficient for high performance designs. In order to achieve good performance and still using linear techniques, the Linear Parameter Varying systems are recently received considerable attention [6].

Recently, a number of applications of such systems were published like compressors, wind turbines, aerospace application, biomedical applications. Which are systems depending on a known scheduling vector. In this work the pitch subsystem of wind turbine system will be used which is modeled as an LPV model with hydraulic pressure as scheduling variable. On the hypothesis that damping ratio and natural frequency have an affine variation with hydraulic pressure, this affine LPV model is used in subspace estimation algorithm.

The contribution of this paper is that this estimation method is used to fault detection in pitch system by residual generation in LPV model case. This work is organized as follows: In Section 2, a predictor based LPV subspace identification approach method is detailed. In section 3, the modeling of pitch system as an LPV model is presented. Section 4 deals with simulation experiments whose illustrate the implementation of the proposed approach of fault diagnosis of LPV pitch system. Finally, section 5 gives some concluding remarks.

II. LPV Prediction Based Subspace Identification

There are two methods for LPV Prediction Based Subspace Identification: global LPV estimation and an interpolation of local model [7] that can lead to unstable representations of the LPV structure while the original system is stable [8]. That is why in this paper we present a subspace identification algorithm to identify LPV systems which does not require interpolation or identification of local models.

A. LPV PBSID

1) Problem formulation: In the model used in identification the system input and the observer matrices depend linearly on the time varying scheduling vector [9]. For the derivation of the algorithm we consider the following LPV equations (1) and (2),

$$x_{k+1} = \sum_{i=1}^{m} \mu_k^{(i)} (A^{(i)} x_k + B^{(i)} u_k + K^{(i)} e_k) \tag{1}$$

$$y_k = C x_k + D u_k + e_k \tag{2}$$

with $x_k \in R^n, u_k \in R^r, y_k \in R^l$ are the state, input and output vectors and e_k denotes the zeros mean white innovation process and m is the number of local model or scheduling parameters:

$$\mu_k = \left[1, \mu_k^{(2)} \ , ..., \ \mu_k^{m}\right]^T$$

(1) and (2) can be written in the predictor form (3),

$$x_{k+1} = \sum_{i=1}^{m} \mu_k^{(i)} (\tilde{A}^{(i)} x_k + \tilde{B}^{(i)} u_k + K^{(i)} y_k) \tag{3}$$

with

$$\tilde{A}^{(i)} = A^{(i)} - K^{(i)} C$$
$$\tilde{B}^{(i)} = B^{(i)} - K^{(i)} D$$

2) Assumptions and notation: $z_k = \left[u_k^T \ , \ y_k^T\right]^T$
We define a past window denoted by p

$$\bar{z}_k^p = \begin{bmatrix} z_k \\ z_{k+1} \\ . \\ . \\ . \\ z_{k+p-1} \end{bmatrix}$$

we define the matrix

$$P_{p/k} = \mu_{k+p-1} \otimes .... \otimes \mu_k \otimes I_{r+l}$$

then we can define

$$N_k^p = \begin{bmatrix} p_{p/k} & . & . \ . & 0 \\ . & p_{p-1/k+1} & & \\ . & & . & \\ . & & \ \ . & \\ 0 & & & p_{1/k+p-1} \end{bmatrix}$$

Now we define the matrices U, Y and Z given in (4),(5) and (6).

$$U = [u_{p+1} \ , ..., \ u_N] \tag{4}$$

$$Y = [y_{p+1} \ , ..., \ y_N] \tag{5}$$

$$Z = \left[N_1^p \bar{z}_1^p \ , ..., \ N_{N-p+1}^p \bar{z}_{N-p+1}^p\right] \tag{6}$$

Then we define the controllability matrix:

$$\kappa^p = [l_p \ , ..., \ l_1]$$

with

$$l_1 = \left[\bar{B}^{(1)} \ , ..., \ \bar{B}^{(m)}\right]$$

and

$$l_j = \left[\tilde{A}^{(1)} l_{j-1} \ , ..., \ \tilde{A}^{(m)} l_{j-1}\right]$$

If the matrix $\left[Z^T \ , U^T\right]$ has full row rank, the matrix $C\kappa^p$ and D can be estimated by solving the following linear regressor problem (7) [10],

$$\min_{C\kappa^p, D} \|Y - C\kappa^p Z - DU\|_F^2 \tag{7}$$

where $\|.\|_F$ represents the Frobenius norm and it can be solved by using traditional least squares like in LTI identification for time varying systems also an observability matrix for the first model:

$$\Gamma^p = \begin{bmatrix} C \\ C\tilde{A}^{(1)} \\ . \\ . \\ . \\ C(\tilde{A}^{(1)})^{p-1} \end{bmatrix}$$

with

$$\bar{\kappa}_p^k = [\varphi_{p-1,k+1} \breve{B}_k, ..., \varphi_{1,k+p-1} \breve{B}_{k+p-2}, \breve{B}_{k+p-1}]$$

and

$$\breve{B}_k = [\tilde{B}, K_k]$$

(3) can be transformed into:

$$x_{k+p} = \varphi_{p,k} x_k + \bar{\kappa}_p^k \bar{z}_k^p$$
$$x_{k+p} = \varphi_{p,k} x_k + \kappa^p N_k^p \bar{z}_k^p$$

where

$$\varphi_{p,k} = \tilde{A}_{K+p-1} ... \tilde{A}_{k+1} \tilde{A}_k$$

If the system (3) is uniformly exponentially stable the approximation error can be made arbitrarily small then:

$$x_{k+p} \approx \kappa^p N_k^p \bar{z}_k^p$$

To calculate the observability matrix Γ times the state X , calculating the matrix:

$$\Gamma\kappa^p = \begin{bmatrix} Cl_p & Cl_{p-1} & . \ \ . & Cl_1 \\ 0 & CA^{(1)} l_{p-1} & . \ \ . & C\tilde{A}^{(1)} l_1 \\ . & & . & \\ . & & \ \ . & \\ 0 & & & C(\tilde{A}^{(1)})^{p-1} l_1 \end{bmatrix}$$

We use the following SVD:

$$\widehat{\Gamma^p \kappa^p Z} = \begin{bmatrix} \upsilon & \upsilon_{\sigma\perp} \end{bmatrix} \begin{bmatrix} \sum_n & 0 \\ 0 & \sum \end{bmatrix} \begin{bmatrix} V \\ V_\perp \end{bmatrix}$$

Then the state is estimated by:

$$\widehat{X} = \sum_n V$$

Finally C and D matrix are estimated using output equation and A and B are estimated using the state equation (1).

The algorithm (LPV-PBSID) can be summarized as follows [9]:

- Create the matrices U, Y and Z using (4),(5) and (6),
- Solve the linear problems given in (7),
- Construct Γ times the state X,
- Estimate the state sequence,
- With the estimated state use the linear relations to obtain the system matrices.

In the case of a really small p that is more worthwhile we have a biased estimate, when the bias is too large it is be a problem that is why a large p would be chosen but this method suffers from the curse of dimensionality [11], the number of rows of Z grows exponentially with the size of the past window, the number of rows is given by:

$$\rho_Z = (r+\ell)\sum_{j=1}^{p} m^j$$

To overcome this drawback the kernel method will be introduced in the next subsection [12].

B. KERNEL METHOD

The equation (7) has a unique solution if the matrix has full row rank and is given by:

$$\begin{bmatrix} \widehat{C\kappa^p} & \widehat{D} \end{bmatrix} = Y \begin{bmatrix} Z^T & U^T \end{bmatrix} \left(\begin{bmatrix} Z \\ U \end{bmatrix} \begin{bmatrix} Z^T & U^T \end{bmatrix} \right)^{-1}$$

When it isn't the case the solution is computed by using the SVD of the matrix:

$$\begin{bmatrix} Z \\ U \end{bmatrix} = \begin{bmatrix} \upsilon & \upsilon_\perp \end{bmatrix} \begin{bmatrix} \sum_m & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V^T \\ V_\perp^T \end{bmatrix}$$

Then the solution is given by:

$$\begin{bmatrix} \widehat{C\kappa^p} & \widehat{D} \end{bmatrix} = YV\sum_m^{-1} \upsilon^T$$

$$\begin{aligned} (Z^{i,j})^T Z^{1,j} &= (\prod_{v=0}^{p-j} \mu^T_{\tilde{N}+v+j-i}\mu_{\tilde{N}+v+j-1})(z^T_{\tilde{N}+j-i} z_{\tilde{N}+j-1}) \\ Z^T Z &= \sum_{j=1}^{p} (Z^{1,j}) Z^{1,j} \end{aligned} \tag{8}$$

$$\min_{\alpha} \|\alpha\|_F^2 \tag{9}$$

with

$$Y - \alpha\left[Z^T Z + U^T U\right] = 0$$

The matrix can be can be constructed as follows (10).

$$\Gamma\kappa^p Z = \begin{bmatrix} \alpha \sum_{j=1}^{p} (Z^{1,j})^T Z^{1,j} \\ \alpha \sum_{j=2}^{p} (Z^{2,j})^T Z^{1,j} \\ \vdots \\ \alpha \sum_{j=p}^{p} (Z^{p,j})^T Z^{1,j} \end{bmatrix} \tag{10}$$

The LPV-PBSID (kernel) can be summarized as follows [9]:

- Create the matrices $U^T U$ using (4) and $Z^T Z$ and $(Z^{i,j})^T (Z^{i,j})$ using (8),
- Solve the linear problem given in (9),
- Construct Γ times the state X using (10),
- Estimate the state sequence,
- With the estimated state, use the linear relation to obtain the system matrices.

III. CASE STUDY :WIND TURBINE BENCHMARK SYSTEM

In this work a specific variable speed turbine is considered. It is a three blade horizontal axis turbine with a full converter. The energy conversion from wind energy to mechanical energy can be controlled by changing the aerodynamics of the turbine by pitching the blades or by controlling the rotational speed of the turbine relative to the wind speed. The mechanical energy is converted to electrical energy by a generator fully coupled to a converter. Between the rotor and the generator a drive train is used to increase the rotational speed from the rotor to the generator [13]. This model can be decomposed into submodels: Aerodynamic, Pitch, Drive train and Generator [14], [15]. In this paper we detect a fault in the pitch subsystem explained in the following subsection.

A. Pitch system model

In the wind turbine benchmark model, the hydraulic pitch is piston servo mechanism which can be modeled by a second order transfer function (11) [16],[17].

$$\frac{\beta(s)}{\beta_r(s)} = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{11}$$

Notice that β_r refers to reference values of pitch angles and $\zeta = 0.6\ rad/s$ and $\omega_n = 11.11\ rad/s$.
The pitch model can be written in the following space state (12),

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -2\xi w_n x_2 - {w_n}^2 x_1 + {w_n}^2 u \end{cases} \tag{12}$$

with $x_1 = \beta$, $x_2 = \dot{\beta}$, and $u = \beta_r$.

Which can be discretized using an Euler approximation then the following system (13) is obtained,

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) \end{cases} \tag{13}$$

with

$$A = \begin{bmatrix} 1 & Te \\ -Te \times w_n^2 & -2Te \times \xi \times w_n + 1 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 \\ Te \times w_n^2 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

B. LPV Pitch system model

These parameters w_n and ξ are variable with hydraulic pressure [17] , [18], then the pitch model can be written as the next LPV model (14) [19],

$$\begin{cases} x(k+1) = A(P)x(k) + B(P)u(k) \\ y(k) = Cx(k) \end{cases} \quad (14)$$

with

$$A(P) = \begin{bmatrix} 1 & Te \\ -Te \times w_n^2(P) & -2Te \times \xi(P) \times w_n(P) + 1 \end{bmatrix}$$

$$B(P) = \begin{bmatrix} 0 \\ Te \times w_n^2(P) \end{bmatrix}$$

$$y(k) = x_1(k) = \beta(k)$$

IV. Results

The pitch system, which in this case are hydraulic, have a possibility of faults on all three blades. The considered faults in the hydraulic system can result in changed dynamics due to dropped main line pressure.This dynamic change is the variation of damping ratio between nominal value 0.6 rad/s and 0.9 rad/s and natural frequency between 3.42 rad/s and nominal value 11.11 rad/s [19].

In this work, a fault detection subspace estimator is designed to determine the presence of a fault and a residual generation is used for decision of fault detection.

To illustrate the performance of this fault detection a pressure sequence with normal value and parameters have the nominal value before time $t = 15000s$ and variable at interval time $t = 15000s$ to $t = 25000s$, that parameters varies between nominal and faulty value: damping ratio varied between 0.6 rad/s and 0.63 rad/s and natural frequency between 10.34 rad/s and 11.11 rad/s. This pressure sequence is given in figure (1).

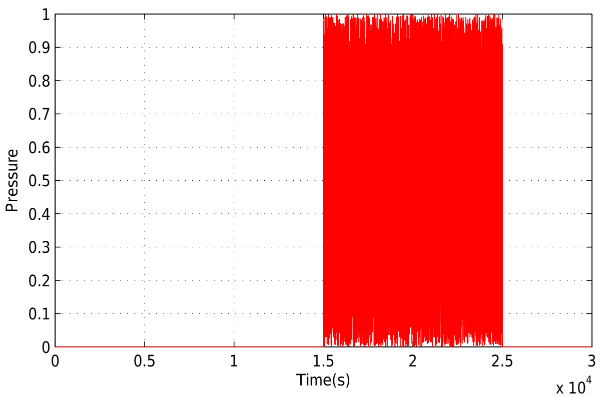

Fig. 1. Pressure sequence

To achieve the subspace estimator described in section 2, we use $m = 3$: Number of scheduling parameters, $N = 30000$, p : past window =5 and

$A \in R^{n \times n}$
$B \in R^{n \times r}$
$C \in R^{l \times n}$

Then $n = 2$; $r = 1$; $l = 1$. The estimated pitch angle obtained is illustrated in figure (2).

The convergence for the estimation method is evaluated by looking at the value of the variance-accounted-for (VAF) on a data set different from the one used for identification.

The VAF value is defined as:

$$VAF(y_k, \widehat{y_k}) = \max\left\{1 - \frac{\text{var}(y_k - \widehat{y_k})}{\text{var}(y_k)}, 0\right\} \times 100\%$$

The VAF value obtained with this identification method applied to angle pitch estimation is 97% with noise and 100% without.

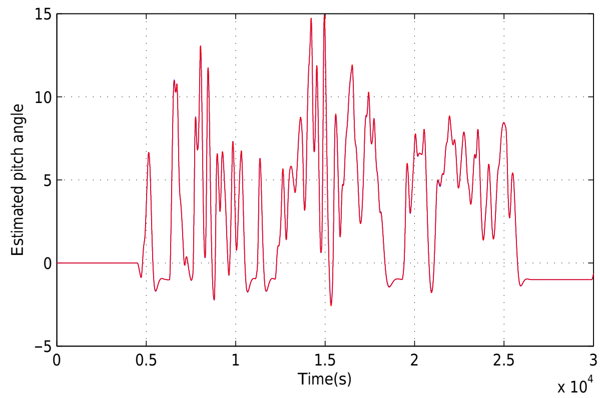

Fig. 2. Estimated pitch angle

The difference between the reference and the estimated value of the same variable at each time instant (the sample time is 0.01 second) is representing in the figure (3), which is called residue which is used to decide about the faults. In the case of this figure, the residue signal is non null between time $t = 15000s$ and $t = 25000s$, it shows that a fault occurs in this interval time and the system is in nominal case outside.

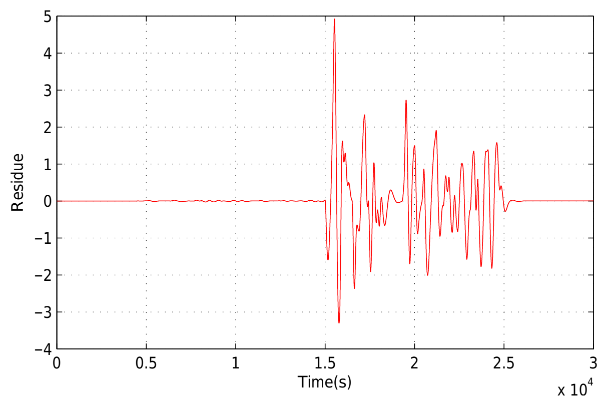

Fig. 3. Residue signal

V. Conclusion

This paper addresses the design of fault detection in pitch subsystem of wind turbine benchmark. This diagnosis approach with model is based on an LPV estimation then a residue is generated that is the comparison between the real and the nominal behavior of this system, this residue is non zero when a fault occurs. Simulations show satisfactory fault diagnosis system performance. An extension of the work presented here could be applying this fault detection algorithm to other wind turbine subsystems and to find a robust fault detection approach to take into account the uncertainty of model and to avoid the false alarm.

References

[1] J. Blesa, D. Rotondo, V. Puig, and F. Nejjari, "Fdi and ftc of wind turbines using the interval observer approach and virtual actuators/sensors," *Control Engineering Practice*, vol. 24, pp. 138–155, 2014.

[2] S. Tornil-Sin, C. Ocampo-Martinez, V. Puig, and T. Escobet, "Robust fault diagnosis of nonlinear systems using interval constraint satisfaction and analytical redundancy relations," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 44, no. 1, pp. 18–29, 2014.

[3] M. A. V. P. H. Chouiref, B. Boussaid and C. Aubrun, "Lpv model validation of wind turbine," in *International Conference on Control, Engineering and Information Technology (CEIT'14)*, 2014.

[4] J. Blesa, V. Puig, and J. Saludes, "Identification for passive robust fault detection using zonotope-based set-membership approaches," *International Journal of Adaptive Control and Signal Processing*, vol. 25, no. 9, pp. 788–812, 2011.

[5] H. Chouiref, B. Boussaid, M. N. Abdelkrim, and C. Aubrun, "Nonlinear fault tolerant control based parameter estimation diagnosis: Application to induction motors," in *10th International Multi-Conference on Systems, Signals & Devices (SSD), 2013*, pp. 1–6, IEEE, 2013.

[6] G. Mercere, M. Lovera, and E. Laroche, "Identification of a flexible robot manipulator using a linear parameter-varying descriptor state-space structure," in *50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC), 2011*, pp. 818–823, IEEE, 2011.

[7] H. Tanaka, Y. Ohta, and Y. Okimura, "A local approach to lpv-identification of a twin rotor mimo system," in *The 18th IFAC World Congress*, vol. 18, pp. 7749–7754, 2011.

[8] R. Toth, F. Felici, P. S. Heuberger, and P. M. Van den Hof, "Discrete time lpv i/o and state space representations, differences of behavior and pitfalls of interpolation," in *European Control Conference (ECC), 2007*, pp. 5418–5425, IEEE, 2007.

[9] J.-W. van Wingerden and M. Verhaegen, "Subspace identification of bilinear and lpv systems for open-and closed-loop data," *Automatica*, vol. 45, no. 2, pp. 372–381, 2009.

[10] P. Gebraad, J. Van Wingerden, G. Van der Veen, and M. Verhaegen, "Lpv subspace identification using a novel nuclear norm regularization method," in *American Control Conference (ACC), 2011*, pp. 165–170, 2011.

[11] J.-W. Van Wingerden, *Control of wind turbines with'Smart'rotors: proof of concept & LPV subspace identification.* TU Delft, Delft University of Technology, 2008.

[12] V. Verdult and M. Verhaegen, "Kernel methods for subspace identification of multivariable lpv and bilinear systems," *Automatica*, vol. 41, no. 9, pp. 1557–1565, 2005.

[13] B. Boussaid, C. Aubrun, and N. Abdelkrim, "Set-point reconfiguration approach for the ftc of wind turbines," in *18th IFAC World Congress, IFAC WC'2011*, pp. 12395–12400, 2011.

[14] B. Boussaid, C. Aubrun, and M. Abdelkrim, "Two-level active fault tolerant control approach," in *8th International Multi-Conference on Systems, Signals and Devices (SSD), 2011*, pp. 1–6, IEEE, 2011.

[15] B. Boussaid, C. Aubrun, and N. Abdelkrim, "Active fault tolerant approach for wind turbines," in *International Conference on Communications, Computing and Control Applications (CCCA), 2011*, pp. 1–6, IEEE, 2011.

[16] P. F. Odgaard, J. Stoustrup, and M. Kinnaert, "Fault-tolerant control of wind turbines: A benchmark model," *IEEE Transactions on Control Systems Technology*, vol. 21, no. 4, pp. 1168–1182, 2013.

[17] J. S. P. Odegaard and M. Kinnaert, "Fault tolerant control of wind turbines-a benchmark model," in *7th IFAC symposium on fault detection, supervision and safety of technical processes,Barcelona,spain*, 2009.

[18] P. F. Odgaard and J. Stoustrup, "Results of a wind turbine fdi competition," in *8th IFAC symposium on fault detection, supervision and safety of technical processes*, pp. 102–107, 2012.

[19] C. Sloth, T. Esbensen, and J. Stoustrup, "Robust and fault-tolerant linear parameter-varying control of wind turbines," *Mechatronics*, vol. 21, no. 4, pp. 645–659, 2011.