A new fault diagnosis approach for the pitch system of wind turbines

Dinghui Wu and Wen Liu

Abstract
To diagnose the fault in the pitch actuator of wind turbines which causes the change in pitch angles, a fault diagnosis method is proposed in this study. The method combines the interval prediction algorithm with the recursive subspace identification based on the variable forgetting factor algorithm. First, the recursive subspace identification based on the variable forgetting factor algorithm is used to estimate the linear parameter-varying model of the wind turbine, which solves the model uncertainty. Second, considering the boundary problem described by model uncertainties, the interval prediction algorithm is introduced based on the basis of the identification results. Moreover, whether the fault occurs or not is determined by judging whether the pitch angle is in the range of the upper and lower bounds. Thus, the robustness of fault detection is improved. Finally, the proposed approach is validated by simulation experiments.

Keywords
Wind turbine, pitch system, fault diagnosis, linear parameter varying, interval prediction

Introduction
As a key component of the wind turbine system, the pitch actuator is mainly responsible for adjusting the pitch angle. When wind speed is higher than the rated values and is lower than the cut-out values, the control objective is to maintain the wind turbine power at a constant level, which can be achieved by regulating pitch angles of the wind turbine. With the occurrence of pitch actuator faults, the dynamic response of the pitch angle either slows down or the pitch angle cannot be adjusted, which results in that the system cannot be controlled. Therefore, timely diagnosis is critical.

For nonlinear systems, such as the wind turbine system, the use of the linear time-invariant model in practical application cannot meet the requirements of high-performance control. To obtain a good performance, the common method is to stabilize the system using a low-level controller and identify the local linear models in different operating points. Finally, a linear parameter-varying (LPV) representation can be obtained using the interpolation method in different local models. In other words, the linear variable parameter system is introduced to utilize the linear technology better. The work presented in Toth et al. revealed that the use of interpolation between local models leads to unstable representations of the LPV structure when the initial structure of the system remains stable. Considering this problem, the separable least squares method is proposed to identify the LPV model in state space in Borges et al. Based on the fault
diagnosis model in the literature, a residual vector is mostly used to describe the consistency between the monitoring system predictive and actual values. Ideally, residuals are only affected by residual faults. However, considering the actual effects of the noise disturbance and the residual deviation caused by modeling, the fault diagnosis algorithm must be robust. In Wingerden and Verhaegen, a method that combines the interval prediction with the LPV subspace identification is proposed, which is characterized by robustness. In the pitch system, \( \omega_n \) and \( \zeta \) are parameters that vary with hydraulic pressure \( P \). When faults occur in the hydraulic system, the system dynamics change because the main pressure drops, which alters the system parameters. The traditional subspace identification has the low convergence rate on time-varying parameters. Thus, the problem of biased identification may exist in traditional subspace identification owing to the time-varying characteristics of the wind turbine system parameters.

This study contributes a new fault diagnosis method for the wind turbine pitch system. This method combines the interval prediction algorithm with the recursive subspace identification based on the variable forgetting factor algorithm. Assuming that damping ratio and natural frequency have a variation with hydraulic pressure, the LPV model based on hydraulic pressure as a scheduling variable for the pitch system is estimated using the recursive subspace identification based on the variable forgetting factor algorithm. The input and output data matrices’ construction mechanism based on the variable forgetting factor is constructed, and the gradient-type algorithm is introduced into subspace tracking to estimate the generalized observable matrix, which avoids the biased approximation of the subspace. In addition, the interval prediction is introduced based on the identification of the LPV model. Then, the interval upper and lower bounds representing the fault-free conditions are obtained using the interval prediction method. The occurrence of the fault is determined by judging whether pitch angles are in the range of upper and lower bounds. Finally, the effectiveness of the algorithm is verified by the simulation experiment of the wind turbine pitch system.

The remainder of this article is structured as follows: section “Recursive subspace identification based on the variable forgetting factor algorithm” describes the recursive subspace identification based on the variable forgetting factor algorithm. Section “Interval prediction” introduces interval prediction. Section “Wind turbine model” provides the pitch model of wind turbines. Section “Simulation” verifies the effectiveness of the algorithm through simulations, and section “Conclusion” summarizes the article.

### Recursive subspace identification based on the variable forgetting factor algorithm

The recursive subspace identification algorithm can be summarized in the following three basic steps: the construction of the data Hankel matrix, the solution of the generalized observable matrix (orthogonal factorization (QR), and singular value decomposition (SVD)), and the recursive estimation of the system matrix by the generalized observable matrix. This study adopts the recursive subspace identification based on the variable forgetting factor algorithm to improve the performance in tracking time-varying parameters. The online recursive identification of the state space model can be expressed as follows

\[
x(t + 1) = Ax(t) + Bu(t) + w(t) \\
y(t) = Cx(t) + Du(t) + v(t)
\]

where \(x(t + 1)\) is the state vector, \(u(t)\) is the input vector, and \(y(t)\) is the output vector. \(w(t)\) and \(v(t)\) are the noise.

To ensure the identification of the system and to verify the need for convergence analysis, the system is assumed to satisfy the following conditions:

1. \((A, B)\) with controllability, \((A, C)\) can be observed, and the system achieves minimal realization.
2. External input \(u\) is not associated with noise \(w\) and \(v\) and meets the condition of full incentive.

### Construction and updating design of Hankel matrices

The variable forgetting factor is introduced to improve the speed in tracking time-varying parameters. Normally, the forgetting factor acts on the data in the following forms (take outputs \(u(0)\sim u(4)\) as an example): \(\beta_{4-1}u(0), \beta_{4-2}u(1), \ldots, u(4)\), where \(\beta\) is the forgetting factor, \(\beta_{4-i} = \beta_1\beta_2\beta_3\beta_4\), \(\beta_{1-i}(i > j)\), and so on. When the input data \(u(5)\) are newly added, the new input data sequence is \(\beta_5(\beta_{4-1}u(0), \beta_{4-2}u(1), \ldots, u(4))u(5)\). The construction and updating of the Hankel matrix under the effect of the variable forgetting factor is as follows

\[
\begin{bmatrix}
\beta_{4-1}u(0) & \beta_{4-2}u(1) & \beta_{4-3}u(2) \\
\beta_{4-2}u(1) & \beta_{4-3}u(2) & \beta_{4}u(3) \\
\beta_{4-3}u(2) & \beta_{4}u(3) & u(4)
\end{bmatrix}
\xrightarrow{\beta_5}
\begin{bmatrix}
\beta_{4-1}u(0) & \beta_{4-2}u(1) & \beta_{4-3}u(2) & \beta_{5}u(3) \\
\beta_{4-2}u(1) & \beta_{4-3}u(2) & \beta_{4}u(3) & u(4) \\
\beta_{4-3}u(2) & \beta_{4}u(3) & u(4) & u(5)
\end{bmatrix}
\]

In forming input and output sequence \(\{u(i), y(i)\}(i = 0, 1, 2, \ldots, f)\), an initial Hankel matrix is
constructed as follows\textsuperscript{14} (take the input Hankel matrix $U_{0,i,j}^{\beta_0}$ as an example)

\[
U_{0,i,j}^{\beta_0} = \begin{bmatrix}
\beta_0^{-1}u(0) & \cdots & \beta_0^{-1}u(j-i+1) \\
\vdots & \ddots & \vdots \\
\beta_0^{-1}u(i-1) & \cdots & u(j)
\end{bmatrix}
\]

(2)

The matrix $Y_{0,i,j}^{\beta_0}$ can be similarly defined, where $j$ is the number of the initial column vector of $u$ and $\beta_0 \in (0, 1)$ is the initial forgetting factor. The initial data Hankel matrix can be written as follows

\[
U_{0,i,j} = T_m(0)U_{0,i,j}^{T(0)}
\]

(3)

\[
y_{0,i,j}^{\beta_0} = T_p(0)y_{0,i,j}^{T(0)}
\]

(4)

where

\[
T_m(0) = \text{diag}\{\beta_0^{-1}I_m, \beta_0^{-2}I_m, \ldots, I_m\}
\]

\[
T_p(0) = \text{diag}\{\beta_0^{-1}I_p, \beta_0^{-2}I_p, \ldots, I_p\}
\]

\[
T(0) = \text{diag}\{\beta_0^{-1}, \beta_0^{-2}, \ldots, 1\}
\]

The state sequence $X_{t}^{\beta_i}$ is defined as follows at time $t$

\[
X_i^t = [\beta_t^{-i+1}, \ldots, 1, \ldots, 1, \ldots, \beta_t X_{t-i} X_{t-i+1}]
\]

(5)

According to the definition of the above-mentioned matrix, the equation between the input and the output of the system is expressed as follows

\[
y_{0,i,t}^{\beta_i} = \Gamma_i^t X_{0,i,t}^{\beta_i} + H_i U_{0,i,t}^{\beta_i} + X_{0,i,t}^{\beta_i}
\]

(6)

where

\[
\Gamma_i^t = \left[(\beta_t^{-1}C)T(\beta_t^{-2}CA)T \cdots (\beta_t^{-i}CA)T\right]T
\]

(7)

Other matrices can be similarly defined. Assuming that the new input–output sequence $(u(t+1), y(t+1))$ is known at time $t+1$, the following data vector is constructed as follows\textsuperscript{12}

\[
\phi_{n+1}^{\beta_i}(t+1) = \begin{bmatrix}
\beta_t^{-1}u^T(t-i+1) \\
\vdots \\
\beta_t^{-i}u^T(t-i+2) \\
u^T(t)
\end{bmatrix}
\]

(8)

\[
\phi_{n+1}^{\beta_i}(t+1) = T_m(t+1)u(t-i+1)
\]

$\phi_{n+1}^{\beta_i}(t+1)$ can be defined in a similar manner.

Where $u(t-i+1) = \begin{bmatrix} u_{t-i+1} \\ \vdots \\ u_t \end{bmatrix}$, $i = j + t + 1$, $t = 0, 1, 2, 3, \ldots$, $T_m(t+1) = \text{diag}\{\beta_t^{-1}I_m, \beta_t^{-2}I_m, \ldots, I_m\}$.

where $\beta_{i+1}^{(t)} = \beta_{i+1}^{(t-1)}$, $\beta_0 \beta_0 \beta_0 \ldots \beta_0$ represents the first $i-1$ products of the forgetting factor sequence, $\beta_{i+1}^{-2}$ represents the first $i - 2$ products, and so on. Then, the updated Hankel matrix becomes

\[
\begin{bmatrix}
U_{0,i,t}^{\beta_{i+1}} \\
y_{0,i,t}^{\beta_{i+1}}
\end{bmatrix} = \begin{bmatrix}
\beta_{i+1} U_{0,i,t-1}^{\beta_i} \\
\beta_{i+1} y_{0,i,t-1}^{\beta_i}
\end{bmatrix} + \begin{bmatrix}
\phi_{n+1}^{\beta_i}(t+1)
\phi_{n+1}^{\beta_i}(t+1)
\end{bmatrix}
\]

(9)

The construction of the matrix reveals that the data have different influences on varying identification time. For the system online updating model, the time-varying characteristic exists in the process for the data to track changes better in system information. The mechanism of the variable forgetting factor is introduced into the construction of the data matrix to improve the convergence rate of the recursive algorithm, and the self-adaptive updating design of forgetting factor can be seen from Huang et al.\textsuperscript{12}

The solution of the generalized observable matrix

This section uses the above-mentioned Hankel matrix with the variable forgetting factor to achieve the estimation of the generalized observable matrix $\Gamma_i^{\beta_i}$.\textsuperscript{15} The Hankel matrix is then subjected to QR decomposition at time $t$

\[
\begin{bmatrix}
U_{0,i,t}^{\beta_i} \\
y_{0,i,t}^{\beta_i}
\end{bmatrix} = \begin{bmatrix}
R_{11}(t) & 0 \\
R_{21}(t) & R_{22}(t)
\end{bmatrix} \begin{bmatrix}
Q_1(t) \\
Q_2(t)
\end{bmatrix}
\]

(10)

After obtaining the new data at time $t+1$, this decomposition can be updated as follows

\[
\begin{bmatrix}
U_{0,i,t+1}^{\beta_{i+1}} \\
y_{0,i,t+1}^{\beta_{i+1}}
\end{bmatrix} = \begin{bmatrix}
\beta_{i+1} R_{11}(t) & 0 \\
\beta_{i+1} R_{21}(t) & \beta_{i+1} R_{22}(t)
\end{bmatrix} \begin{bmatrix}
Q_1(t) \\
Q_2(t)
\end{bmatrix}
\]

(11)

To achieve the estimation of the generalized observable matrix $\Gamma_i^{\beta_i}$, the SVD\textsuperscript{16} of the $R_{22}(t)$ is expressed as follows

\[
R_{22}(t) = \begin{bmatrix}
U_1(t) & U_2(t)
\end{bmatrix} \begin{bmatrix}
\Sigma_1(t) & 0 \\
0 & 0
\end{bmatrix} \begin{bmatrix}
V_1^T(t) \\
V_2^T(t)
\end{bmatrix}
\]

(12)

\[
\hat{\Gamma}_i^{\beta_i} = U_1(t) \Sigma_i^{1/2}(t)
\]

(13)

The following unconstrained optimization problem\textsuperscript{17} is used to implement the recursive updating of $\Gamma_i^{\beta_i}$. 

\[ J(W(t)) = \sum_{k=1}^{t} \beta_k \| x(k) - W(t)W^T(t)x(k) \|^2 \]
\[ = tr(G(t)) - 2tr(W(t)G(t)W(t)) + tr(W^T(t)G(t)W(t) \cdot W^T(t)W(t)) \]  
(14)

where \( G(t) = \sum_{k=1}^{t} \beta_k x(k) x^T(k) \), and \( x \) represents the matrix \( \mathbf{R}_2(t) \).

Subspace update formulas are expressed as follows
\[ y(t) = W^T(t - 1)x(t) \]  
(15a)
\[ C_i(t) = \beta_i C_i(t - 1) + y(t)y^T(t) \]  
(15b)
\[ W(i) = W(t - 1) - C_i(k)W(t - 1)y(t) - x(t)y^T(t) \]  
(15c)

A recursive updating of the signal subspace is achieved by solving the unconstrained optimization problem, that is, the recursive estimation of the generalized observable matrix \( \Gamma_i^Y \).

**Recursive implementation of system matrices**

The input and output matrices based on the variable forgetting factor cannot be directly described by the products of the factor and the data matrices. And the forgetting factor cannot be directly described by the literature, many approximations of the uncertain parameters are used.

\[
U_{\beta_i}(i) \approx T_m(t + 1)U(i)T(t + 1) \\
Y_{\beta_i}(i) \approx T_i(t + 1)Y(i)T(t + 1)
\]
(16)

Based on the recursive least square (RLS) algorithm, the recursive estimation of the system matrix is obtained after determining the estimated value of the generalized observable matrix \( \Gamma_i^Y \) of the system. Matrix \( C \) can be extracted directly from \( \Gamma_i^{Y^{(1)}} \) as follows
\[ C(t + 1) = \Gamma_i^{Y^{(1)}}(1 : p : 1 : n)/\beta_i^{(1)} \]  
(17)

Matrix \( A \) can be obtained by solving the following linear equation
\[
\hat{A}(t + 1) = \hat{A}(t - 1) + \gamma(t)\hat{P}(t)\hat{W}(t) \]
(18)

\[
\hat{A}(t) = \hat{A}(t - 1) + \gamma(t)\hat{P}(t)\hat{W}(t)
\]
(19)

To achieve matrices \( B \) and \( D \) from matrix \( H^\beta_i \), the term \( \Gamma_i^{B_i}x^\beta_i \) should be eliminated from formula (6). In formula (6), the term on the left is replaced with \( \Pi_{i-1}(t) \)

\( (\Pi_{i-1}(t) \) is the orthogonal complement of \( \hat{F}^\beta_i(t) \), whereas the term on the right is replaced with \( (U^\beta_{i+1})^2 \), that is, \( \Pi_{i+1}Y_{\beta_i}(U^\beta_{i+1})^2 = \Pi_{i+1}H^\beta_i + \Pi_{i+1}A_i^\beta_i(U^\beta_{i+1})^2 \).

At each moment, \( \Pi_{i+1}^Y \) is replaced by the most recent estimation. Then, the estimated values \( \hat{B} \) and \( \hat{D} \) of matrices \( B \) and \( D \) can be similar to the recursive solution shown in formula (19).

**Interval prediction**

The interval prediction method is introduced\(^\text{18}\) to improve the robustness of the recursive subspace identification based on the variable forgetting factor algorithm. Combining the interval prediction with the recursive subspace identification based on the variable forgetting factor algorithm improves the robustness of fault diagnosis while avoiding system instability. The interval prediction method is an extension of the classical system identification method, which is mainly used to provide parametric guarantees for nominal models and uncertain boundaries, including all the data collected in the model prediction interval within the fault-free situation. This method considers the additive and modeling uncertainties separately, in which the additive uncertainty is represented by the form \( e(k) \) of the additive fault, and modeling uncertainty is considered to be located in the parameters that expressed a nominal value plus some indeterminate set membership. In the literature, many approximations of the uncertain parameter set \( \Theta \) have been reported. In our example, the set \( \Theta \) is represented by a zonotope,\(^\text{19}\) as follows
\[
\Theta = \theta^0 + Hb^u = \{ \theta^0 + Hz : z \in B^u \}
\]
(20)

where \( \theta^0 \) is the nominal model obtained by the identification method, \( H \) is the matrix of uncertainty, \( B^u \) is the unified set of prediction vectors, and \( \oplus \) is the Minkowski sum. The parameter set \( \Theta \) is bounded by the interval box which centered on \( \theta^0 \),\(^\text{20}\) as follows
\[
\Theta = [\bar{\theta}_1, \hat{\theta}_1] \times \cdots [\bar{\theta}_p, \hat{\theta}_p] \]
(21)

where \( \bar{\theta}_i = \theta_i^0 - \lambda_i, \hat{\theta}_i = \theta_i^0 + \lambda_i, \lambda_i \geq 0, i = 1, \ldots, p \)
\[
\theta^0 = \left( \frac{\bar{\theta}_1 + \hat{\theta}_1}{2}, \frac{\bar{\theta}_2 + \hat{\theta}_2}{2}, \ldots, \frac{\bar{\theta}_p + \hat{\theta}_p}{2} \right)
\]
(22)
\[
H = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_p)
\]
(23)

A model can be converted into the following regression form
\[
\gamma(k) = \phi(k)\theta(k) + e(k)
\]
(24)

where \( \phi(k) \) is the regression vector that contains the input and output functions with the dimension \( 1 \times p \), \( \theta(k) \in \Theta \) is a parameter vector with the dimension...
\( p \times 1, \Theta \) is the set that bounds parameter values, \( e(k) \) is an additive fault defined by a constant value, and \( |e(k)| \leq \alpha \).

In the interval prediction method, the interval prediction output is as follows
\[
y(k) \in [\bar{y}(k) - \alpha, \bar{y}(k) + \alpha]
\]
(25)
where
\[
\bar{y}(k) = \hat{y}^0(k) - ||\phi(k)H||_1
\]
(26)
\[
\bar{y}(k) = \hat{y}^0(k) + ||\phi(k)H||_1
\]
(27)
\( \hat{y}^0(k) \) is the model output prediction with the nominal parameter matrix \( \theta^0 = [\theta_1, \theta_2, \ldots, \theta_p]^T \), which is identified via the recursive subspace identification based on the variable forgetting factor algorithm
\[
\hat{y}^0(k) = \varphi(k)\theta^0(k)
\]
(28)
Fault detection is performed based on whether the model prediction output satisfies formula (25). When the output is in the range of the upper and lower bounds, the system is in the fault-free cases; otherwise, the system is faulty.

**Wind turbine model**

The wind turbine system can convert wind into electrical energy output, and it is mainly composed of the following systems: aerodynamic, pitch, drive chain, and generator systems.\(^{21,22}\) From the control point of view, the wind turbine remains in two areas, namely, partial- and full-load regions.\(^{23}\) Therefore, the wind energy is converted into mechanical energy in two ways: when the wind turbine is running in a partial-load region and the pitch angle is maintained at an optimal value, the energy conversion is achieved by regulating the generator speed. When running in a full-load region, the wind speed is relatively high and the generator speed is normally maintained at a rated value. Thus, the energy is converted by regulating the pitch angle. The mechanical energy is converted into the electrical energy by a generator fully coupled to a converter, and the drive chain is located between the rotor and the generator to increase the rotational speed from the rotor to the generator.\(^{24}\) The pitch system model is only discussed here because the main purpose of this study is to diagnose the fault of the pitch system.

**LPV model of the pitch system**

In the wind turbine benchmark model, the pitch system is a hydraulic system, whose model can be regarded as a second-order dynamic system\(^{25}\) expressed as follows
\[
\begin{align*}
\frac{\beta(s)}{\beta_i(s)} &= \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \\
\end{align*}
\]
(29)
where \( \beta_i(s) \) is the reference of pitch angles, \( \omega_n \) is the natural frequency, and \( \zeta \) is the damping ratio of the pitch actuator. Then, the pitch system model can be written in the following form\(^{26}\)
\[
\begin{bmatrix}
\dot{x}_1(k) \\
\dot{x}_2(k)
\end{bmatrix} =
\begin{bmatrix}
0 & 1 \\
-\omega_n^2 - 2\zeta\omega_n & 0
\end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} +
\begin{bmatrix}
0 \\
\omega_n^2
\end{bmatrix} \beta_i
\]
(30)
Marking \( x_1 = \beta, x_2 = \dot{\beta}, u = \beta_r \), the expression is converted into
\[
\begin{bmatrix}
\dot{x}_1 \\
\dot{x}_2
\end{bmatrix} =
\begin{bmatrix}
0 & 1 \\
-\omega_n^2 - 2\zeta\omega_n & 0
\end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} +
\begin{bmatrix}
0 \\
\omega_n^2
\end{bmatrix} \beta_i
\]

The Euler formula can be used to describe the system, as follows
\[
\begin{bmatrix}
x(k+1) \\
y(k)
\end{bmatrix} =
\begin{bmatrix}
1 & T_e \\
0 & T_e \omega_n^2
\end{bmatrix} \begin{bmatrix} x(k) \\ y(k) \end{bmatrix} +
\begin{bmatrix}
0 \\
T_e \omega_n^2
\end{bmatrix} \beta_i
\]
(31)
where \( A = \begin{bmatrix} 1 & T_e \\ 0 & -T_e \omega_n^2 - 2T_e \zeta \omega_n + 1 \end{bmatrix} \), \( B = \begin{bmatrix} 0 \\ T_e \omega_n^2 \end{bmatrix} \), and \( T_e = 1 \).

In the pitch system, \( \omega_n \) and \( \zeta \) are the parameters that vary with hydraulic pressure \( P \).\(^{27}\) Then, the pitch system model may be expressed as the following LPV form, which uses hydraulic pressure \( P \) as the scheduling variable, according to Sloth et al.\(^{27}\)
\[
\begin{bmatrix}
x(k+1) \\
y(k)
\end{bmatrix} =
\begin{bmatrix}
1 & T_e \\
0 & T_e \omega_n^2
\end{bmatrix} \begin{bmatrix} x(k) \\ y(k) \end{bmatrix} +
\begin{bmatrix}
0 \\
T_e \omega_n^2
\end{bmatrix} \beta_i
\]
(32)
where \( A(\theta) = \begin{bmatrix} 1 & T_e \\ 0 & -T_e \omega_n^2 \end{bmatrix} \), \( B(\theta) = \begin{bmatrix} 0 \\ T_e \omega_n^2 \end{bmatrix} \), and \( y(k) = x_1(k) = \beta(k) \).

**Simulation**

The Simulink simulation is based on the 4.8-MW wind turbine benchmark model, and this benchmark model is based on a realistic generic three-blade horizontal variable turbine with a full converter coupling.\(^{28}\)

**Prediction interval based on the pitch system**

The pitch system model can be converted into the following regression form\(^{29}\)
\[
y(k) = \varphi(k)\theta(k)
\]
(33)
where \( 50 \text{ s} < t < 70 \text{ s} \), \( \theta = [\theta_1, \theta_2, \theta_3]^T \), \( t = 70 \text{ s} \), \( \theta_2 = -2\omega_n T_e + 2 \), and \( \theta_3 = T_e^2 \omega_n^2 \).

The overall structure of this study is shown in Figure 1. \( u \) is the function of inputs and \( y \) is the
function of outputs. The input and output data are obtained using the variable forgetting factor recursive subspace identification algorithm to estimate the wind turbine pitch system LPV model. Then, the interval prediction method is introduced to obtain a robust fault diagnosis of the wind turbine pitch system.

The pitch system is an LPV model which uses hydraulic pressure as the scheduling variable (see equation (32)) and the hydraulic pressure is affected in the event of faults. When faults occur in the hydraulic system, the system dynamics change because the main pressure drops, which alters the system parameters, as follows: the damping ratio changes in the range of 0.6–0.9 rad/s, and the natural frequency changes in the range of 3.42–11.11 rad/s according to the literature.\(^{27}\)

The interval upper and lower bounds shown in formulas (26) and (27), respectively, revealed that no faults occurred.

---

**Table 1. Fault setting.**

| Additive time-varying faults | High air content in oil |
|-----------------------------|------------------------|
| Additive time-varying faults of constant wind speed and variable wind speed: \(50 < t < 70\) s; the mode of the fault output is \(u_{out}(t) = u_{out.1}(t) + \cos(t)\). | High air content in oil of the actuator under constant wind speed and variable wind speed: \(t = 70\) s; high air content in oil is present in the actuator, and the fault lasts for 10 s. In 80 s, the system runs normally. |

---

**Fault setting**

Additive time variation and pitch actuator faults are observed in the two cases of the constant and variable wind speed. The constant wind speed chooses 22 m/s and the variable speed chooses \(v_{\text{min}} = 15\) m/s and \(v_{\text{max}} = 25\) m/s. The effectiveness of the algorithm is initially verified using a set of additive time-varying faults. Afterward, the pitch actuator fault is determined to verify the actual performance of the algorithm further (Table 1).

---

**Simulation analysis**

**Normal operation.** When the wind turbine is operating at a constant wind speed under normal operation, the fluctuation of the pitch angle is minimal. As shown in Figure 2, the pitch angle is stable, and the values are within the upper and lower bounds of the prediction interval. When the wind turbine is running under variable wind speed, the pitch angle must be adjusted accordingly with the change in the wind speed because the wind speed changes constantly and randomly, as shown in Figure 3. However, in cases when no faults occur, the pitch angle is always within the upper and lower bounds of the prediction interval, regardless of the change in the pitch angle.

---

**Additive time-varying fault.** In the period of 50–70 s, an additive time-varying fault, that is, the cosine fault, is
obtained under the conditions of the constant and variable wind speeds. Under the influence of the fault, the pitch actuator outputs superimpose a cosine signal, as shown in Figures 4 and 5. The figures show that from 0 to 50 s, the pitch angle is located within the upper and lower bounds of prediction interval, which indicates that the system operates normally. In the period of 50–70 s, the pitch actuator outputs superimpose the fault values so that the pitch angle exceeds the upper and lower bounds of the prediction interval, which demonstrates the system breakdown. After 70 s, the fault disappears and the pitch angle is back to the interval again, which indicates that the system operates normally.

**Pitch actuator fault.** In the period of 70–80 s, the high air content in oil is present in the actuator. The high air content in oil is a common fault, which changes the dynamics of the pitch system and causes a significant overshoot at the moment that the fault occurs and disappears resulting in system instability. The results of the fault diagnosis at the constant and variable wind speed are shown in Figures 6 and 7, respectively. The simulation results reveal that before 70 s, the pitch angle is located within the upper and lower bounds of the prediction interval, which shows the normal operations of the system. Between 70 and 80 s, the pitch actuator dynamic response slows down and the pitch angle cannot be adjusted in time, causing the pitch angle exceeding the upper and lower bounds of the prediction interval. After 80 s, the fault disappears and the pitch angle is back to the interval again, which indicates that the system is fault-free.

**Conclusion**

In this study, the proposed approach combining the interval prediction algorithm with the recursive subspace identification based on the variable forgetting factor algorithm is used to diagnose the fault in the pitch actuator of the wind turbine. The LPV model of the wind turbine is estimated using recursive subspace identification based on the variable forgetting factor algorithm, and the uncertainty of the model is solved in this manner. At the same time, the robustness of the fault detection is enhanced using the interval prediction method. When faults occur, the pitch angles’ curve goes
beyond the boundary which represents the no-fault condition. The method is verified by conducting simulation experiments of the additive time-varying fault and the high air content in oil in the wind turbine pitch system. The simulation results show that the algorithm can meet the performance of fault detection.

Declaration of conflicting interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the National Natural Science Foundation of China (nos 61572237 and 61672266).

References
1. Gsanger S and Pitteloud JD. World wind energy report 2011. Bonn: World Wind Energy Association, 2012.
2. Vidal Y, Tutiévin C, Rodellar J, et al. Fault diagnosis and fault-tolerant control of wind turbines via a discrete time controller with a disturbance compensator. Energies 2015; 8: 4300–4316.
3. Bianchi F, Mantz RJ and Christiansen CF. Gain scheduling control of variable-speed wind energy conversion systems using quasi-LPV models. Control Eng Pract 2005; 13: 247–255.
4. Wingerden JWV, Houtzager I, Felici F, et al. Closed-loop identification of the time-varying dynamics of variable-speed wind turbines. Int J Robust Nonlin 2009; 19: 4–21.
5. Groot Wassink M, Van De Wal M, Scherer CW, et al. LPV control for a wafer stage: beyond the theoretical solution. Control Eng Pract 2005; 13: 231–245.
6. Lovera M and Mercere G. Identification for gain-scheduling: balanced subspace approach. In: Proceedings of the American control conference, New York, 9–13 July 2007. New York: IEEE.
7. Mercere G, Lovera M and Laroch E. Identification of a flexible robot manipulator using a linear parameter-varying descriptor state-space structure. In: Proceedings of the IEEE conference on decision and control and European control conference, Orlando, FL, 12–15 December 2011, pp.818–823. New York: IEEE.
8. Toth R, Felici F, Heuberger PSC, et al. Discrete time LPV I/O and state space representations, differences of behavior and pitfalls of interpolation. In: Proceedings of the European control conference, Kos, Greece, 2–5 July 2007, pp.5418–5425. New York: IEEE.
9. Blesa J, Verdult V, Verhaegen M, et al. Subspace identification of bilinear and LPV systems for open- and closed-loop data. Automatica 2009; 45: 372–381.
10. Blesa J, Puig V, Romera J, et al. Fault diagnosis of wind turbines using a set-membership approach. IFAC Proc Vol 2011; 44: 8316–8321.
11. Huang JF, Zhang HX, Hu YT, et al. Subspace identification algorithm based on finite-memory variable forgetting factor. Control Theory Appl 2012; 29: 893–898.
12. Li DZ. Information fusion filtering theory with application. Harbin, China: Harbin Institute of Technology Press, 2007, pp.37–45.
13. Zhang C and Bitmead R. Subspace system identification for training-based MIMO channel estimation. Automatica 2005; 41: 1623–1632.
14. Yang H and Li SH. A novel recursive MOESP subspace identification algorithm based on forgetting factor. Control Theory Appl 2009; 26: 69–72.
15. Mercere G, Lecoeuche S and Lovera M. Recursive subspace identification based on instrumental variable unconstrained quadratic optimization. Int J Adapt Control 2004; 18: 771–797.
16. Yang B. Asymptotic convergence analysis of the projection approximation subspace tracking algorithms. Signal Process 1996; 50: 123–136.
17. Blesa J, Puig V and Saludes J. Identification for passive robust fault detection using zonotope based set membership approaches. Int J Adapt Control 2011; 25: 788–812.
18. Blesa J, Puig V, Romera J, et al. Fault diagnosis of wind turbines using a set-membership approach. In:
Proceedings of the 18th IFAC world congress, Milano, 28 August–2 September 2011.

20. Puig V, Quevedo J, Escobet T, et al. Passive robust fault detection of dynamic processes using interval models. IEEE T Contr Syst T 2008; 16: 1083–1089.

21. Boussaid B, Aubrun C and Abdelkrim MN. Two-level active fault tolerant control approach. In: Proceedings of the international multi-conference on systems, signals and devices, Sousse, Tunisia, 22–25 March 2011, pp.1–6. New York: IEEE.

22. Boussaid B, Aubrun C and Abdelkrim N. Active fault tolerant approach for wind turbines. In: Proceedings of the 2011 international conference on communications, computing and control applications (CCCA), Hammamet, Tunisia, 3–5 March 2011, pp.1–6. New York: IEEE.

23. Munteanu I, Bratcu AI, Cutululis NA, et al. Optimal control of wind energy systems: towards a global approach. London: Springer-Verlag, 2008.

24. Boussaid B. Set-point reconfiguration approach for the FTC of wind turbines. In: Proceedings of the 18th world congress: the international federation of automatic control, Milano, 28 August–2 September 2011, pp.12395–12400. Elsevier.

25. Odgaard PF and Stoustrup J. Results of a wind turbine FDI competition. In: Proceedings of the 8th IFAC symposium on fault detection, supervision and safety of technical processes (SAFEPROCESS), Mexico City, Mexico, 29–31 August 2012, pp.102–107. Elsevier.

26. Shi F and Patton R. An active fault tolerant control approach to an offshore wind turbine model. Renew Energ 2015; 75: 788–798.

27. Sloth C, Esbensen T and Stoustrup J. Robust and fault-tolerant linear parameter-varying control of wind turbines. Mechatronics 2011; 21: 645–659.

28. Odgaard PF, Stoustrup J and Kinnaert M. Fault-tolerant control of wind turbines: a benchmark model. IEEE T Contr Syst T 2013; 21: 1168–1182.

29. Chouiref H, Boussaid B, Abdelkrim MN, et al. LPV model-based fault detection: application to wind turbine benchmark. In: Proceedings of the 7th international conference on electrical sciences and technologies (CIS-TEM’14), Tunis, Tunisia, 3–6 November 2014. IEEE.