Fault Diagnosis of Pitch Sensor Bias for Wind Turbine Based on Multi-Innovation Kalman Filter algorithm

Dinghui WU, Yiyang LI, Zhicheng JI

Abstract

This paper presents a fault diagnosis method for detecting pitch sensor offset fault according to the mechanical structure char-acteristics of wind turbine. The method establishes ~~correspondences~~ between the change of pitch angle and the minute displacement which produced by the force acting on tower of wind turbine. It is based on the change of displacement to diagnosis ~~whether~~ the fault occurs. With regard to the large noise of sensors, we adopt multi-innovation ~~k~~alman filter to enhance the estimation accuracy and convergence speed. The simulation results show that the multi-innovation kalman filter based method can diagnosis the fault effectively and it is better than common kalman filter.

1 Introduction

Wind energy is playing a more and more important role in world power production [1]. Since most wind farms are located in desert or sea areas where the natural environment is harsh [2], it is common for wind turbines to have faults. Modern wind turbines often adopt fault tolerant control method to maintain normal operation, and fault diagnosis is the premise and necessary ~~condition~~ [3]. Variable pitch system is an important substructure of wind turbines, the pitch fault will affect the power generated when wind velocity is above the rated one.

There have been many fault diagnosis methods for wind turbines. In [4], Watson has studied the rotor fault based on wavelet analysis, which involves monitoring the power output and processing the data to obtain the magnitude of par-ticular frequency components. This method can extract the characteristics of fault, however, wavelet analysis must be calculated off-line, which limits the widespread application. In [5], Guo has studied the current feedback sensor fault, speed sensor fault and constant gain output fault of wind turbine control system. Guo ~~trains~~ the neural networks to analyze fault condition by selecting the appropriate eigenvalue and training samples. But, neural networks algorithm relies on a large amount of training samples, which may not be available in remote areas. Some kind faults of wind turbines do not change system structure, and may affect the system parameters, we can set up the linear model of the turbines, and fault information can be reflected on the parameters' change. ~~So~~, the system identification technology can be adopted to fault detection and diagnosis [6].

When the wind velocity is above the rated one, the control objective is to maintain constant generated power [7], which is realized by adjusting the angle of three pitches. The pitch angle sensor is an important part of the closed-loop pitch system, if offset fault happens to pitch angle sensor, the whole pitch system will

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Key laboratory of Advanced Process Control for Light Industry, Ministry of Education, Jiangnan University, Wuxi, China
Corresponding author:
Dinghui Wu, Key laboratory of Advanced Process Control for Light Industry, Ministry of Education, Jiangnan University, Wuxi 214133, China
Email: wh033098@163.com
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become unstable. Under the effective wind velocity, there will be a thrust acting on the rotor, which makes the tower sway back and forth [8], and results in a tiny displacement. The value of thrust is dependent on thrust coefficient, and the thrust coefficient is rely on pitch angle and tip-speed ratio, therefore, the pitch angle will influence the thrust. A corresponding relationship can be formed between the pitch angle and the tiny displacement, but the pitch sensor fault will break the relationship. As a consequence, the fault can be detected by monitoring the relationship.

The above method involves a large number of data processing, the ~~k~~alman filter based on multi-innovation is utilized to filter the value obtained from the pitch angle sensor and tower displacement sensor. The multi-innovation algorithm extends the scalar value [9–11], and the proposed approaches use not only the current data but also the past data, which significantly improve the precision of the estimate and the convergence speed [12]. The tower displacement calculated from pitch angle and the displacement from sensor should be equal when the pitch angle sensor is normal. ~~When~~ there is a deviation between two displacements, ~~we can detect a fault~~.

The rest of the paper is organized as follows. Section 2 gives wind turbine model for simulation, and presents the fault model for analysis. In Section 3, the fault diagnosis and data processing procedure using multi-innovation kalman filter is given. Section 4 contains a simulation result and followed by the conclusion in Section 5.

2 Wind Turbine Model

2.1 Aerodynamic Model

The wind energy captured from the three blades is transformed to rotational motion of the rotor, the rotor speed is $\omega_r(t)$. The captured wind energy is dependent on effective wind speed $v_r(t)$, air density ρ and the rotor swept area A and power coefficient $C_p(\lambda(t), \beta(t))$. The power coefficient is rely on tip-speed ratio $\lambda(t)$ and pitch angle $\beta(t)$. The aerodynamic torque $T_a(t)$ applied to rotor by blade can be obtained from tip-speed ratio $\lambda(t)$ and blade radius r [13]:

$$\lambda(t) = \frac{r\omega_r(t)}{v_r(t)} \tag{1}$$

$$T_a(t) = \frac{1}{2\omega_r(t)}\rho A v_r^3 C_p(\lambda(t), \beta(t)) \tag{2}$$

2.2 Tower Model

The wind acting on the rotor of each blade also results in a thrust on the rotor, it can be calculated ~~like~~ [14]:

$$F_t(t) = \frac{1}{2}\rho A v_r^2(t) C_t(\lambda(t), \beta(t)) \tag{3}$$

The thrust coefficient $C_t(\lambda(t), \beta(t))$ is also dependent on $\lambda(t)$ and $\beta(t)$.

The resulting tower force $F_{th}(t)$ on the tower at hub height~~,~~ h , depends on the azimuth angle of rotor, which is the synthesis of three thrust [8] :

$$F_{th}(t) = \sum^{3} i = 1 F_{th,i}(t) \tag{4}$$

$$F_{th,i}(t) = F_{t,i}(t)(1 + \frac{r_t}{h} cos(\Psi_i(t))) \tag{5}$$

Where, $F_{t,i}$ is the thrust from blade i, r_i is the distance from the hub to where the thrust acts on the blade. The relationship between $\Psi_1(t)$, $\Psi_2(t)$, $\Psi_3(t)$ and the location of the blades are illustrated in ~~Fig.~~ 1.

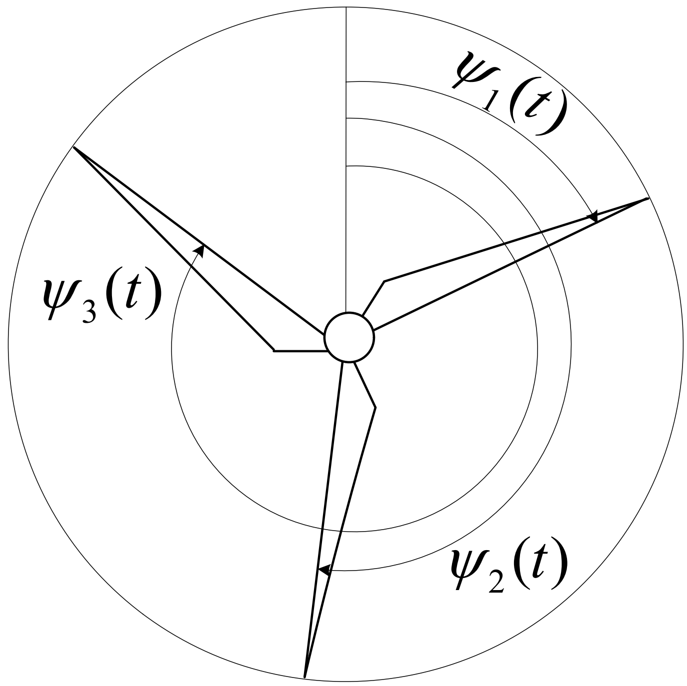

Figure 1: Position of blades

As the equation shows, the location of the blades affects the tower force components. This is different from the aerodynamic torque, which is independent of the location of the blades.

When under the tower force, the tower will produce a tiny displacement $x_t(t)$, as it is the only measured variable in the tower model, the movement of the tower can be described by a linear displacement of the nacelle. As Fig. 2 shows, the tower model is given as a spring-damper:

$$M_t \ddot{x}_t(t) = F_{th}(t) - B_t \dot{x}_t(t) - K_t x_t(t) \tag{6}$$

Where, M_t is the top mass of the tower, B_t is the tower damping coefficient, K_t is the tower torsion coefficient.

2.3 Pitch Model

The pitch actuator is modeled as a second order system [15] :

$$\frac{\beta(s)}{\beta_{ref}(s)} = \frac{\omega_n^2}{s^2 + 2\varsigma\omega_n s + \omega_n^2} \tag{7}$$

$$\ddot{\beta}(t) = 2\varsigma\omega_n \dot{\beta}(t) - \omega_n^2 \beta(t) + \omega_n^2 \beta_{ref}(t) \tag{8}$$

$$\beta_m(t) = \beta(t) + v_\beta(t) \tag{9}$$

Where, $\beta_{ref}(t)$ is the reference to the pitch angle, ω_n is the natural frequency of the pitch actuator model, ς is the damping ratio of the pitch actuator model, $\beta_m(t)$ is the value returned from the pitch angle sensor and v_β is the measurement noise.

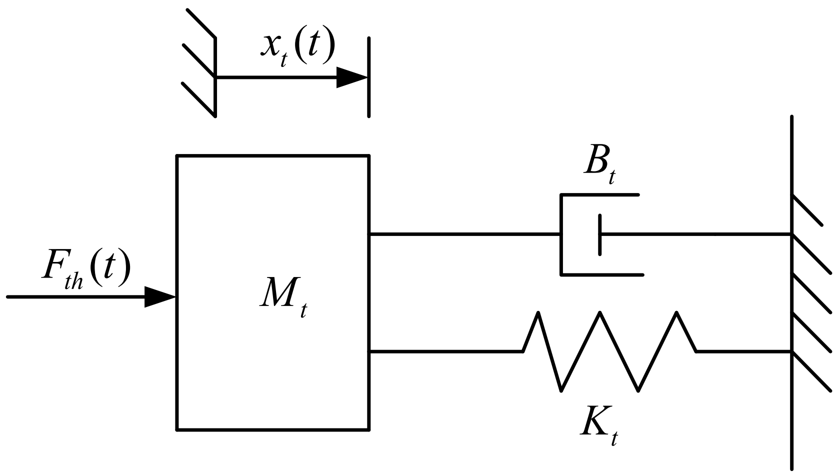

Figure 2: Tower model

When a offset pitch angle fault happens, the model of the actuator is changed to:

$$\ddot{\beta}(t) = -2\varsigma\omega_n\dot{\beta}(t) - \omega_n^2(\beta(t) + \beta_{bias}(t)) + \omega_n^2\beta_{ref}(t) \tag{10}$$

$$\beta_m(t) = \beta(t) + \beta_{bias}(t) + v_\beta(t) \tag{11}$$

Where, $\beta_{bias}(t)$ is the offset added to the pitch angle sensor output.

3 Algorithm of Fault Diagnosis

3.1 Structure of Diagnosis System

A fault diagnosis structure is designed for pitch system, which is illustrated in Fig. 3.

From the thrust equation shown in Eq. 3, the thrust $F_t(t)$ on blade is related to the thrust coefficient C_t , and the coefficient C_t is related to $\lambda(t)$ and $\beta(t)$. The tower force $F_{th}(t)$ can be deduced from Eq. 4 and Eq. 5. By applying Eq. 6, we can obtain the tiny displacement $x_t(t)$ from the tower force $F_{th}(t)$. A small offset in pitch angle will result in a small change in thrust coefficient, and the tower force will change correspondingly which makes the displacement vary synchronously. As a result, by monitoring the variation of displacement, the fault can be detected.

To maintain constant wind power output, the closed-loop pitch system work continuously to obtain the pitch angle objective β_0. If there is a constant offset output $-\theta$ adding to the pitch angle sensor, the sensor output will become $\beta_m = \beta_0 - \theta$. For pitch control system, the value from measurement does not match the control objective, so under the action of pitch actuator, the pitch is adjusted to force the sensor output back to objective, that is $\beta'_m = \beta_m + \theta = \beta_0$. Due to the offset in the sensor output, the real pitch angle is $\beta = \beta'_m + \theta = \beta_0 + \theta$. Therefore, we draw the conclusion that the measured displacement x_{tm} is different from the calculated one which is obtained from β_0. The fault severity can be concluded by comparing the measured and calculated displacement.

As the wind turbines work in a harsh condition, the value returned from the sensor is polluted by a lot of noise and the displacement caused by the sensor offset fault is rather small, it possible for the displacement information be submerged by the noise. It is necessary to filter the sensor output, the kalman filter based

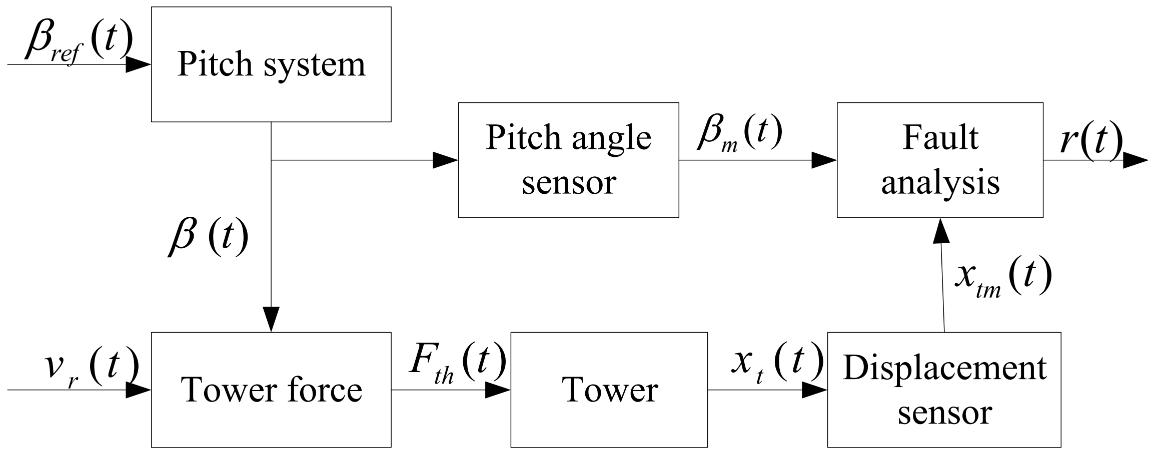

Figure 3: Structure of diagnosis sytem

on multi-innovation technology is an efficient way to obtain the optimal state estimation, and realize the accurate judgement of the sensor offset fault.

3.2 Kalman Filter Based on Multi-Innovation

Kalman filter is a kind of recursion method which estimate the optimal system state [16]. The kalman filter consists of two steps: a prediction step and an update step. In the prediction step, an estimate of the state at the current timestep is produced from the previous timestep. The predicted step combines the a priori prediction with the current observation information to refine the state estimate.

Innovation is defined as useful information which can improve parameter's or state's estimation accuracy [17]. For the linear discrete system of the wind turbine, the conventional kalman filter can be written as the following five equations:

$$\hat{x}_{k|k-1} = A_{k-1}\hat{x}_{k-1} \tag{12}$$

$$P_{k|k-1} = A_{k-1}P_{k-1}A_{k-1}^T + \Gamma_{k-1}Q_{k-1}\Gamma_{k-1}^T \tag{13}$$

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k[z_k - C_k\hat{x}_{k|k-1}] \tag{14}$$

$$P_k = [I - K_kC_k]P_{k|k-1} \tag{15}$$

$$K_k = P_{k|k-1}C_k^T[C_kP_{k|k-1}C_k^T + R_k]^{-1} \tag{16}$$

~~W~~here, $x_{k|k-1}$ is posteriori state estimate at time k given observations up to and including at time k, $P_{k|k-1}$ is the posteriori error covariance matrix, A_{k-1} is the state transition model which is applied to the previous state $\hat{x}_{k-1}$, K_k is the optimal kalman gain, $\hat{x}_k$ is the updated state estimate, P_k is the updated estimate covariance, C_k and Q_k is the noise covariance.

The single innovation for the conventional kalman filter is defined as:

$$c(k) = z_k - C_k\hat{x}_{k|k-1} \tag{17}$$

Then we extend the single innovation to multi-innovation, which means that

$$\begin{aligned} E(p,k) &= \begin{bmatrix} e(k) \\ e(k-1) \\ \vdots \\ e(k-p+1) \end{bmatrix} \\ &= \begin{bmatrix} z_k - C_k \hat{x}_{k|k-1} \\ z_{k-1} - C_{k-1}\hat{x}_{k-1|k-2} \\ \vdots \\ z_{k-p+1} - C_{k-p+1}\hat{x}_{k-p+1|k-p} \end{bmatrix} \end{aligned} \tag{18}$$

Where p is the innovation length. Then the updated state estimate is changed to

$$\begin{aligned} \hat{x}_k &= A_{k-1}\hat{x}_{k-1} + [K_k, K_{k-1}, K_{k-2}, ..., K_{k-p}]E(p,k) \\ &= A_{k-1}\hat{x}_{k-1} + \sum_{i=1}^{p} K_i(k)e(k-i+1) \end{aligned} \tag{19}$$

~~Here we choose~~ $K_i(k) = K(k-i+1)$.

3.3 Design of State and Observation Equation

The measurement of displacement $x_{tm}(k)$ is processed by multi-innovation kalman filter to obtain the optimal state estimate , which is polluted by noise. Under the random tower force, the wind turbine is not moving uniformly from the equilibrium position. In order to get the discretization expression of the displacement and its derivative, the sampling period $T_0 = 0.01s$ is taken, it is assumed that within a sampling period of displacement generated by the wind turbine tower, it moves uniformly. $x_{tm}(k)$ is the displacement measured at time kT_0, by applying the kinematics formulas, the motion of tower can be obtained:

$$x_{tm}(k+1) = x_{tm}(k) + \dot{x}_{tm}(k)T_0 \tag{20}$$

$$\dot{x}_{tm}(k+1) = \dot{x}_{tm}(k) \tag{21}$$

The displacement and velocity of tower is chosen as the state parameter, then the system state at time kT_0 is:

$$x(k) = \begin{bmatrix} x_{tm}(k) \\ \dot{x}_{tm}(k) \end{bmatrix} \tag{22}$$

Then the state space model is:

$$\begin{bmatrix} x_{tm}(k+1) \\ \dot{x}_{tm}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T_0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{tm}(k) \\ \dot{x}_{tm}(k) \end{bmatrix} + w(k) \tag{23}$$

The observation equation is:

$$z(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_{tm}(k) \\ \dot{x}_{tm}(k) \end{bmatrix} + v(k) \tag{24}$$

The pitch sensor output β_m is also polluted by noise, the method utilized to process displacement can also be applied here. The pitch angle changed in a single period is uniform motion, and the similar state equation can be established:

$$\begin{bmatrix} x_{tm}(k+1) \\ \dot{x}_{tm}(k+1) \\ \beta_m(k+1) \\ \dot{\beta}_m(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T_0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T_0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{tm}(k) \\ \dot{x}_{tm}(k) \\ \beta_m(k) \\ \dot{\beta}_m(k) \end{bmatrix} + w(k) \tag{25}$$

$$z(k) = \begin{bmatrix} x_{tm}(t) \\ \beta_m(t) \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_{tm}(k) \\ \dot{x}_{tm}(k) \\ \beta_m(k) \\ \dot{\beta}_m(k) \end{bmatrix} + v(k) \tag{26}$$

The state space model is:

$$x(k+1) = Ax(k) + w(k) \tag{27}$$

$$z(k) = Cx(k) + v(k) \tag{28}$$

~~W~~here, the parameter matrixes are $A = \begin{bmatrix} 1 & T_0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T_0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$, $C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$.

The procedure for multi-innovation kalman filter is described as following: the optimal state estimate $\hat{x}(k)$ and state covariance $P(k)$ is known at timestep k, first compute the optimal kalman gain $K(k)$, innovation $e(k)$, then choose the appropriate innovation length p, the innovation is extended to innovation matrix $E(p,k)$ and the optimal state estimate $\hat{x}(k+1)$ at timestep $k+1$ can be calculated. After the state covariance at timestep $k+1$ is updated to $P(k+1)$, the recursive algorithm can move to the next cycle, to achieve he optimal estimation of the next timestep.

4 Simulation

In this section, the fault diagnosis for pitch angle sensor offset fault is simulated. ~~Fig.~~ 4 is the original observation of tower displacement~~.~~ Fig. 5 is the displacement curve of kalman filter, and Fig. 6 is the displacement curve of multi-innovation kalman filter. It is shown from comparison that, both conventional and multi-innovation kalman filter can remove the influence of noise, and multi-innovation is more precise.

The innovation length p ~~introduced by~~ multi-innovation kalman filter not only can improve the accuracy of estimation, but also can improve the convergence speed. ~~But~~ large innovation length p involves a lot of matrix computation, which may be out of the processor's ability. As ~~the~~ Fig. 7 ~~illustrates~~, the innovation length $p = 8$ is a appropriate one.

This algorithm can also be used to detect the severity of the fault. The tested wind velocity is $25m/s$, in $40s - 100s$, the fault happens, a offset $-3°$ is added to the pitch angle sensor output. It is shown in Fig. 8 that, the displacement of tower changes significantly.

In Fig. 9, the offset changes to $-5°$, in $20s - 140s$, the wind velocity accelerates every ten seconds. As the fig depicted, the tower displacement is also related to the wind velocity. In Fig. 10, the wind velocity is $25m/s$, the offset added to pitch angle output increases every ten seconds. The result shows that the displacement changes corresponding to offset.

The relationship between wind velocity, pitch angle sensor offset and tower displacement is shown in Fig. 11

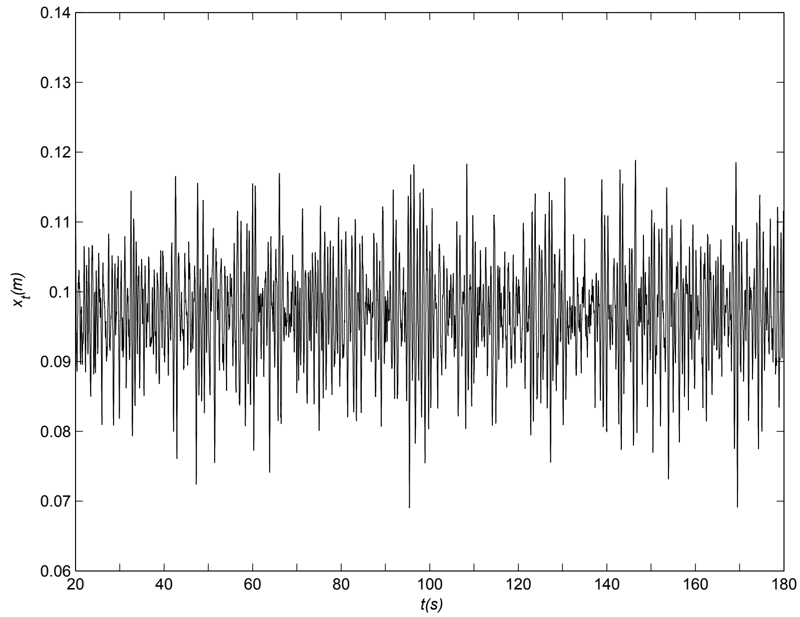

Figure 4: Observation of displacement

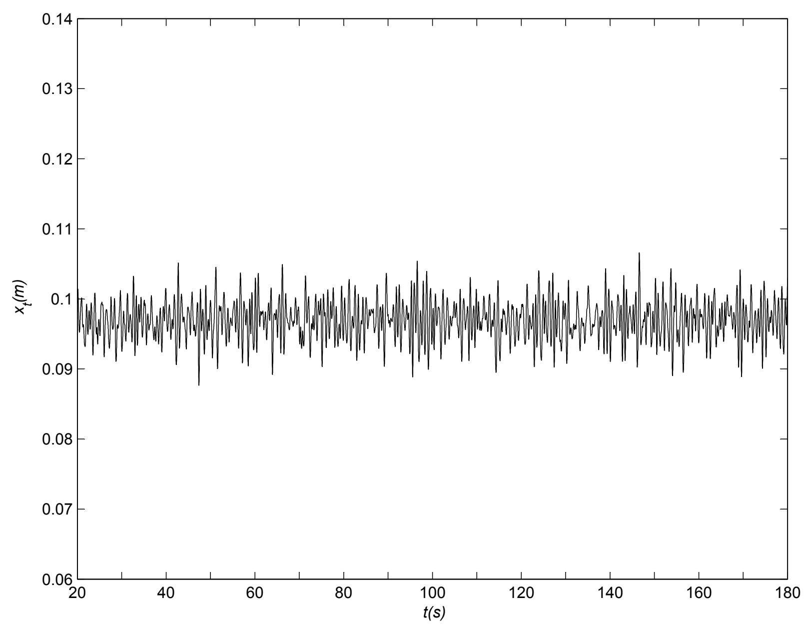

Figure 5: Displacement curve of kalman filter

5 Conclusion

In this paper, the pitch angle sensor offset fault is considered, and a relationship between sensor offset and the tiny displacement of tower is established for fault diagnosis. To obtain more precise displacement state,

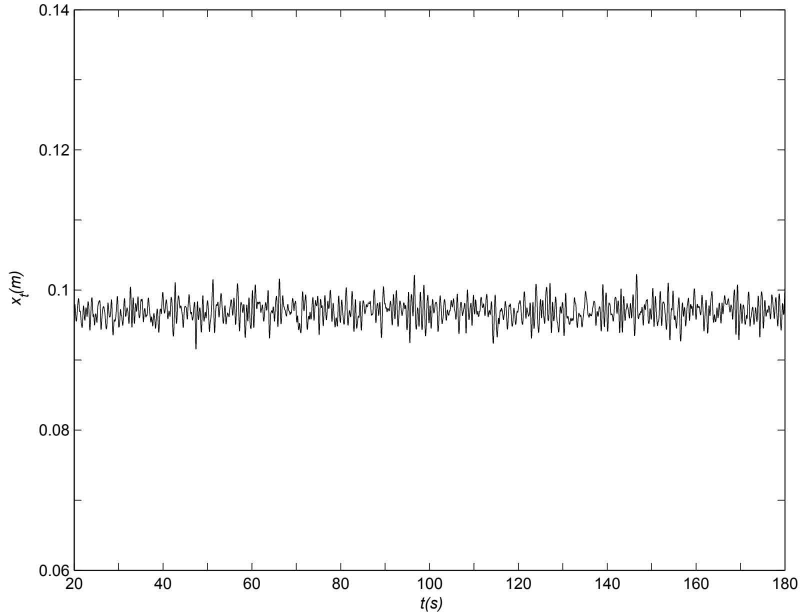

Figure 6: Displacement curve of multi-innovation kalman filter

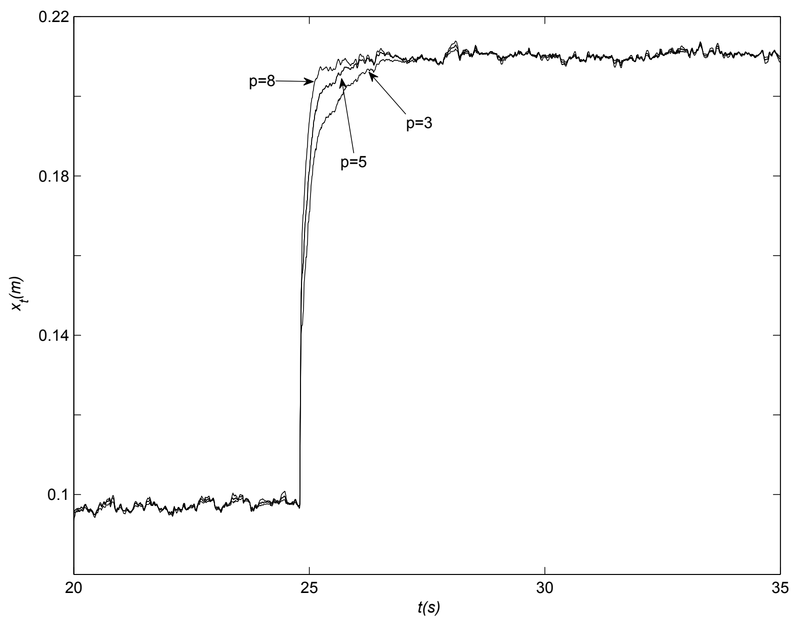

Figure 7: Displacement of different innovation length

the conventional kalman filter is extended to multi-innovation kalman filter. The multi-innovation algorithm also shows more faster convergence speed. By querying the figure given in the paper, the sensor offset value can be estimated from the wind velocity and the displacement deviation.

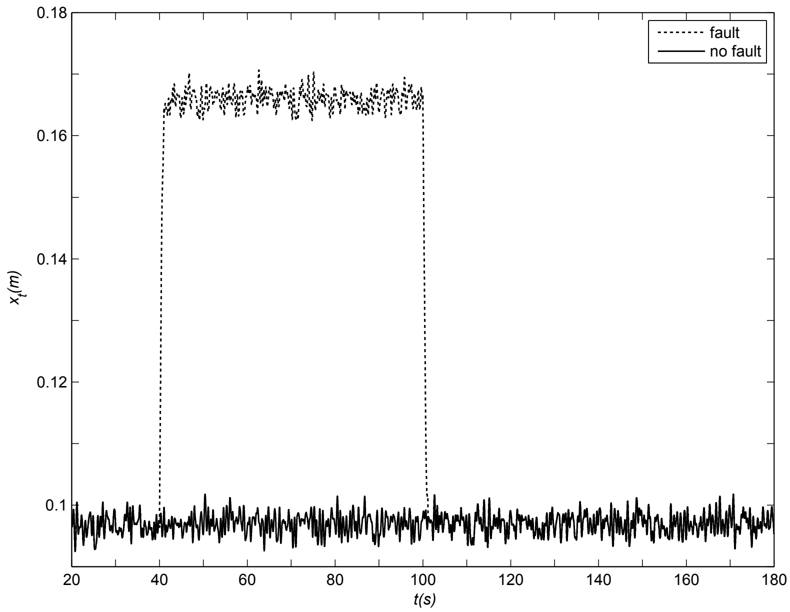

Figure 8: Displacement of fault and fault-free

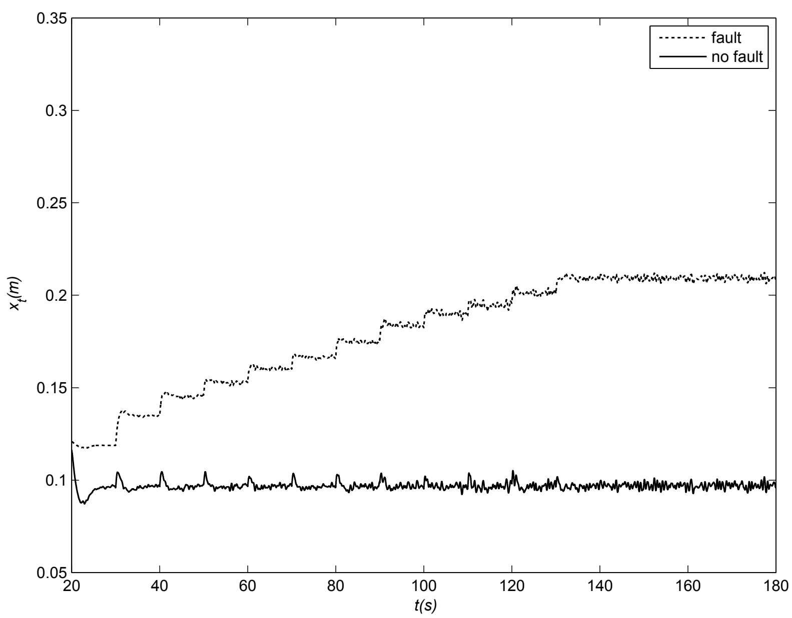

Figure 9: Displacement of different wind velocity

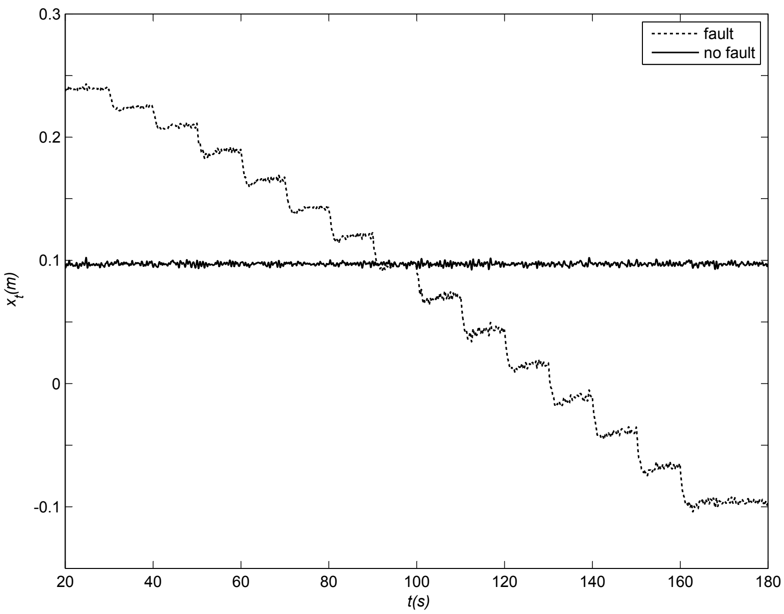

Figure 10: Displacement of different pitch angle

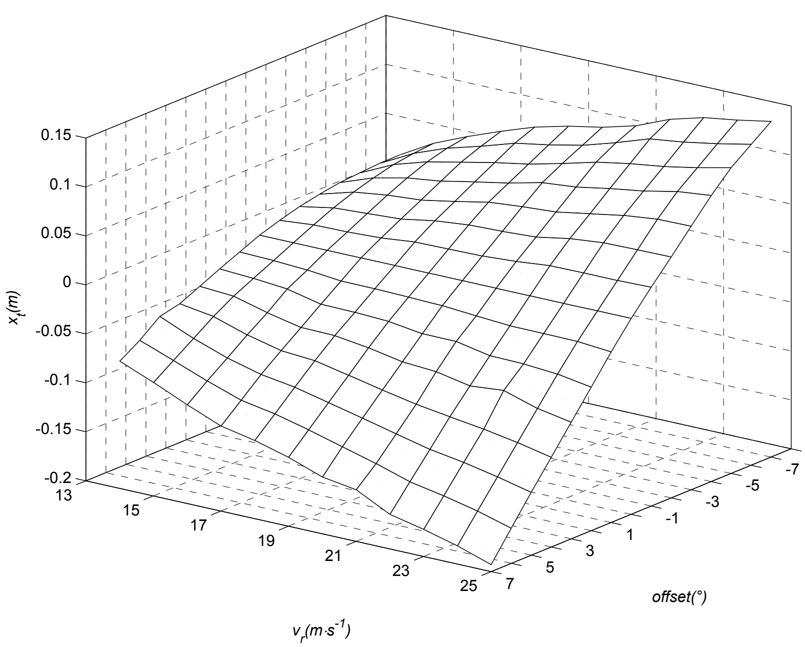

Figure 11: Wind velocity-pitch angle-displacement

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