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RESEARCH ARTICLE

Online detection and diagnosis of sensor faults for a non-linear system

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Abstract

In systems, the fault is an internal occurrence. It becomes a failure if the defect is not detected and corrected. Sensors have been widely employed as a vital component of data collection systems, particularly in the industrial and agricultural sectors. Sensors are prone to failure due to their harsh operating environment. As a result, early detection of sensor faults is crucial for taking corrective action to reduce the impact. In this paper, faults in generator speed and wind turbine velocity have been investigated. The Extended Kalman Filter is utilized to identify the sensor faults in wind turbine model. The residual generation is used to detect the fault. The residual is the discrepancy between the real and estimated outputs. A Linear Quadratic Regulator controller is used for the stabilization of an unstable system.

Keywords: Fault, Sensor fault, Extended Kalman Filter, Wind turbine, Linear Quadratic Regulator.

Introduction

One of the most widely utilized renewable energy sources is wind energy. However, faults and unplanned wind turbine shutdowns are costly. Sensor measurements play a vital role in system health monitoring because sensor malfunctions result in inaccurate monitoring outputs, impacting the system's health. It requires fault detection techniques to identify faults at an early stage. Fault Detection and Isolation (FDI) is critical in various industries to ensure system safety and security (Kumar et al., 2021; Kumar et al., 2022) . To establish the kind, magnitude, place, and period of a failure, fault detection and isolation (FDI) methods are used. The robustness, velocity of liability detection and isolation distinguish fault detection and isolation techniques. This study compares anomaly detection systems based on Artificial Neural Architecture (ANN), Observer, Fuzzy, and Kalman filters. A set of residuals must be determined to achieve fault identification and isolation. Residuals provide information about the current state of the system as well as potential faults (Ghareveran and Yazdizadeh , 2019).

In fault detection research, fuzzy inference is mostly used. Because of the input and the partial dialectal terms and rules, it is difficult to detect and measure faults and early fault severities. A fuzzy logic technique is utilized to detect wind turbine faults depending on extended dialectal rules to solve this problem. A fuzzy interpretation system anomaly detection method is proposed to detect early wind turbine faults. Based on the defuzzied result, the fault factor is designed to measure fault severities. (Qu et al., 2019; Simani, Farsoni and Castaldi, 2015).

The fault detection structure has been implemented and calibrated to be more reactive to system faults while being least reactive to process noise and disturbances. A monitoring scheme based on the residual generation via a non-linear estimator is also developed. The presented technique detects and isolates single or multiple faults in wind turbine sensors (Hwas and Katebi, 2014).

Many types of anomalies in wind turbines, such as plant faults, actuator faults and sensor faults, can be identified accurately and conveniently by the estimator using the residual generated by the Extended Kalman Filter estimator. The residual is the difference between the true and estimated values of the Extended Kalman Filter. Examine the occurrence and non-occurrence of faults in wind turbines using the residual output. Many types of anomalies in wind turbines, such as plant faults, actuator faults and sensor faults, can be identified accurately and conveniently by the

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estimator using the residual generated by the extended Kalman filter estimator (Li et al., 2017; Ghareveran and Yazdizadeh, 2019).

In this work, wind turbine model is chosen for anomaly detection using the extended Kalman filter (Ribeiro, 2005; Trinh and Chafouk, 2011). The residual generation is used to detect the fault. The residual is the discrepancy between the output of the real system and the output of the estimated system. The state feedback controller is used to stabilize the unsteady system. This enhances the safety and security of the system.

System Modelling

The subsystems required to model the wind turbine are as follows

Wind velocity system

Wind velocity is a vital and attached part of the turbine. This is made up of two portions:

$$v = v_m + v_t(t) \tag{1}$$

Where v_m is the average wind velocity value and $v_t(t)$ is the turbulent portion of the wind velocity, respectively.

$$v_t(t) = \sum_{k=1}^{k} a_k cos w_k t + b_k sin w_k t \tag{2}$$

Where a_k and b_k are coefficients regularized with zero mean and variance (Idrissi, El bachtiri and Chafouk, 2017).

Aerodynamic system

Aerodynamic wind turbine blades convert kinetic energy of wind to rotational motion.
Produced torque is specified by:

$$T_{wt} = \frac{P_{wt}}{w_{wt}} \tag{3}$$

Where

$$P_{wt} = \frac{1}{2} \rho\pi R^2 v^3 C_p(\lambda.\beta) \tag{4}$$

$$C_p(\lambda.\beta) = (0.44\text{-}0.0167\beta)\sin\left(\frac{\pi(\lambda-2)}{13-0.3\beta}\right) - 0.00184(\lambda-2)\beta \tag{5}$$

$$\lambda = \frac{wR}{v} \tag{6}$$

Where "v - the velocity of wind, ρ- the density of air, R - the radius of rotor, C_p- the efficiency coefficient which depends on tip velocity ratio λ and blade pitch angle β. Each blade in the turbine contains a pitch actuator, which changes the blade's angle of attack". The following model expresses the connection between the blade pitch angle β and the pitch demand β_d.

$$\beta(s) = \frac{\beta_d(s)}{\tau_{pitch}s+1} \tag{8}$$

Where τ_{pitch} is a time constant that varies according to the actuator.

Mechanical Drive Train System

A shaft along with a gearbox make up this system. The gearbox increases the rotating velocity of the shaft, making it suitable for the electrical component. The mechanical drive train is based on a two-mass model. The model is described as:

$$T_{wt} = J_T\dot{w}_{wt} + K_s\theta_k + C_s w_{wt} - \frac{C_s}{n_g} w_g \tag{9}$$

$$T_e^c = -J_g\dot{w}_g + \frac{K_s}{n_g}\theta_k + \frac{C_s}{n_g} w_{wt} - \frac{C_s}{n_g^2} w_g \tag{10}$$

Where " T_e^c is the control torque, K_s is the torsional stiffness, C_s is the torsional damping, T_{wt} is the aerodynamic torque, J_T is the turbine inertia, J_g is the generator inertia, n_g is the gearbox ratio, w_{wt} is the rotor velocity and w_g is the generator velocity."

The difference between turbine rotor angle and generator rotor angle θ_k

$$\dot{\theta}_k = w_{wt} - \frac{w_g}{n_g} \tag{11}$$

Generator

Stator and rotor flux in d-q frame are

$$\Psi_{ds} = L_m|\vec{i}_{ms}| \tag{12}$$

$$\Psi_{qs} = L_s i_{qs} + L_m i_{qr} = 0 \tag{13}$$

$$\Psi_{dr} = L_m^2|\vec{i}_{ms}| + \sigma L_r i_{dr} \tag{14}$$

$$\Psi_{qr} = \sigma L_r i_{qr} \tag{15}$$

Where $|\vec{i}_{ms}| = |\vec{v}_s|/\omega_s L_m$, $\sigma = 1 - L_m^2/L_s L_r$ is used for the leakage coefficient

$$|\vec{v}_s| = \sqrt{3}V_s \tag{16}$$

Where V_s is the stator voltage

By considering some assumptions about generator for observability condition, the reduced order model written as

$$v_{ds} = R_s i_{ds} - \omega_s\Psi_{qs} + \frac{d\Psi_{ds}}{dt} = 0 \tag{17}$$

$$v_{qs} = R_s i_{qs} + \omega_s\Psi_{ds} + \frac{d\Psi_{qs}}{dt} \approx \omega_s\Psi_{ds} = |\vec{v}_s| \tag{18}$$

$$v_{dr} = \sigma L_r\frac{di_{dr}}{dt} + R_r i_{dr} - (\omega_s - \omega_m)\sigma L_r i_{qr} \tag{19}$$

$$v_{qs} = \sigma L_r\frac{di_{qr}}{dt} + R_r i_{qr} + (\omega_s - \omega_m)\left(\sigma L_r i_{dr} + \frac{\sqrt{3}L_m V_s}{\omega_s L_s}\right) \tag{20}$$

Where $\Psi_{ds}, \Psi_{qs}, \Psi_{dr}, \Psi_{qr}, i_{ds}, i_{qs}, i_{dr}, i_{qr}, v_{ds}, v_{qs}, v_{dr}, v_{qr}$ are Flux, current, and voltage in rotor and stator in the d-q frame. R_s, R_r, L_s and L_r are resistance and inductance of the rotor and stator. L_m is the mutual inductance then ω_s is the synchronous velocity.

The non-linear model of generator is written as

$$\begin{bmatrix}\frac{di_{dr}}{dt}\\ \frac{di_{qr}}{dt}\end{bmatrix} = \begin{bmatrix}\frac{1}{\sigma L_r}v_{dr} - \frac{R_r}{\sigma L_r}i_{dr} + (\omega_s - \omega_r)i_{qr}\\ \frac{1}{\sigma L_r}v_{qr} - \frac{R_r}{\sigma L_r}i_{qr} + (\omega_s - \omega_r)i_{dr} - \frac{\sqrt{3}V_s L_m}{\sigma L_r L_s} + \frac{\sqrt{3}V_s L_m}{\sigma L_r L_s \omega_s}\omega_m\end{bmatrix} \tag{21}$$

The output equation is

$$T_e = \frac{n_p\sqrt{3}L_m V_s i_{qr}}{L_s\omega_s} \tag{22}$$

By linearization of non-linear model, the generator model is described as

$$\begin{bmatrix}\frac{di_{dr}}{dt}\\ \frac{di_{qr}}{dt}\end{bmatrix} = \begin{bmatrix}\frac{1}{\sigma L_r}v_{dr} - \frac{R_r}{\sigma L_r}i_{dr} + (\omega_s - \bar{\omega}_m)i_{qr} - i_{qr0}\omega_m\\ \left(\frac{1}{\sigma L_r} - \bar{k}\right)v_{qr} - \frac{R_r}{\sigma L_r}i_{qr} + (\omega_s - \bar{\omega}_m)i_{dr} + \left(i_{dro} + \frac{\sqrt{3}V_s L_m}{\sigma L_r L_s \omega_s}\right)\omega_m\end{bmatrix}$$

Where $\bar{\omega}_m$, i_{qr0} and i_{dro} are generator velocity, rotor current in d-q frame at operating point.

$\bar{k}$ is defined as:

$$\bar{k} = \frac{\sqrt{3}L_m V_s}{\sigma L_s L_r v_{qr}^2} \tag{24}$$

The generalized form of linearized state space model is described as

$$\dot{x}(t) = Ax(t) + Bu(t)$$

$$y(t) = Cx(t) + Du(t) \tag{25}$$

The state space matrices can be represented as:

$$A = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 1 & \frac{-1}{n_g} & 0 & 0\\ 0 & \frac{-K_s}{J_T} & \frac{-C_s}{J_T} & \frac{C_s}{J_T n_g} & 0 & 0\\ 0 & \frac{K_s}{J_G n_g} & \frac{C_s}{J_G n_g} & \frac{-C_s}{J_G n_g^2} & 0 & 0\\ 0 & 0 & 0 & -i_{rq0} & \frac{-R_r}{\sigma L_r} & W_s - W_m\\ 0 & 0 & 0 & i_{dr0} + \frac{\sqrt{3}L_m V_s}{\sigma L_s L_r W_s} & -(W_s - W_m) & \frac{-R_r}{\sigma L_r} \end{bmatrix}$$

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0\\ 0 & \frac{1}{J_T} & 0 & 0 & 0\\ 0 & 0 & \frac{-1}{J_G} & 0 & 0\\ 0 & 0 & 0 & \frac{1}{\sigma L_r} & 0\\ 0 & 0 & 0 & 0 & \frac{1}{\sigma L_r} - k \end{bmatrix}$$

w

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

$$D = [0]$$

Where $E = \frac{-\sqrt{3}n_p L_m V_s K_c}{\sigma L_r L_s \omega_s}$

State variables, input variables and output variables of the wind turbine is given as

$$x = [\beta, \theta_k, \omega_{wt}, \omega_g, i_{dr}, i_{qr}]^T$$

$$u = [\beta_d, T_{wt}, T_e^c, v_{dr}, v_{qr}]^T$$

$$y = [\beta, \omega_{wt}, \omega_g, T_e]$$

For the wind turbine, the rated values of the system parameters are as follows (Table 1):

Faults in Wind Turbine

Some common types of wind turbine fault are generator faults, gearbox faults, pitch system faults and blade faults.

Generator Fault

When the generator fails in the wind turbine, no power is produced. Generator fault occurs often in wind turbines and mostly contain mechanical and cooling system faults. The mechanical fault is substantially rotor fault and bearing fault. Electrical fault are stator winding fault and rotor winding fault. The electrical fault in wind turbine is caused by short circuit. Refrigeration system failures occur on a longer duration of heat oil that leads to impairment to the alternators, and therefore the foremost details for these catastrophes are jams within oil mixing systems, leakage of oil, faulty pipelines and oil corrosion.

Gearbox Fault

Among the components of turbines, the gearbox takes the highest failure rate. The bearings cause the majority of turbine gearbox liability. Gearbox fault includes teeth surface pitting, teeth bonding, gear fracture, static indentation and bearing damage.

Pitch System Fault

Electric motor drive and hydraulic drive are two sorts of pitch systems that is employed in turbines. The electrical motor is the pitch system's most important component. The most common electrical motor pitch system faults are control structure catastrophes, mechanical scheme catastrophes, and battery structure catastrophes. Pitch angle liabilities, overheating motors, and communication failures are all examples of control system letdowns. Pitch

Table 1: System parameter

Variables	*Value*
Density of air, ρ	1.22 Kg/ m^3
Rotor radius, r	40 M
Rated power	2 Mw
Gearbox ratio, n_g	52.6
Inertia of turbine, $J_T J_T$	4.9*10^{-6} N m s^2
Inertia of generator, J_g	0.9*10^{-6} N m s^2
Torsional stiffness, K_s	3.5*10^5 N m^{-1}s
Torsional damping, C_s	114*10^6 N m^{-1}
Winding resistance of rotor, R_r	2.63 Mω
Magnetizing inductance, L_m	5.474 Mh
Winding inductance of rotor, L_r	5.606 Mh
Winding inductance of stator, L_s	5.643 Mh

gearbox problems is a frequent outcome in excessive current and heat increase of the running motor when it comes to mechanical system faults. When chargers fail and charging is unavailable, battery system problems are common. The turbine will run away since the battery-operated cannot deliver enough electrical power.

Blade Fault

Blade fissures and blade superficial cracks are the two types in blade failures. Blade damage will also occur during shipment and installation. Branches of trees scratch blade edges during transit to the wind farm, which will be a hidden problem in the future. Angle renovation and friction renovation will occur if the blade's center point is not aligned to the beam angle through the installation procedure, causing damage to the blade's front edge.

Fault Detection and Isolation Techniques

Fault Detection and Isolation (FDI) is critical for delivering safety and security action in many industries. A fault in any scheme causes the equipment to fail. Many FDI methods are used to control the fault's type, size, position, and time. The main goal of the fault detection and isolation technique is to raise the alarm due to a change in the system and to control the size, position, and time of the fault occurrence. Fault detection is used to determine whether or not faults exist. Fault isolation identifies the precise location of faults. FDI techniques are generally classified as

- Model-based method
- Data-driven method

Residual Generation For Wind Turbine

A set of residuals must be developed in order to achieve fault identification and isolation. The residual is the discrepancy among the real and estimated process output. Residual generation and evaluation operations are part of the liability detection algorithm. The residual generator produces a residual, which the Residual evaluator compares to a threshold to determine if a problem has occurred. If the value is beyond the threshold, a fault has occurred; otherwise, there is no fault present in the system (Figure 1).

To begin, a physical prototype of a turbine system is built, from which a system function for the EKF approach is specified. The projected outcomes from the EKF model and the yield of the turbine model are compared using identical inputs to determine fault diagnosis potential.

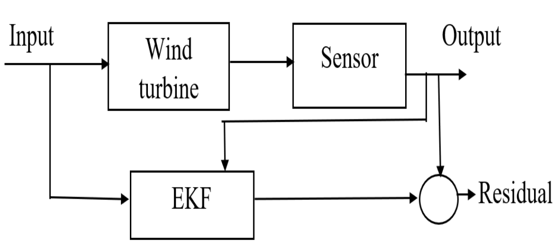

Figure 1: Residual generation for wind turbine

Extended kalman filter

The Extended Kalman Filter is a non-linear variant of the Kalman filter that linearizes a present mean and covariance estimate. It uses analytical methods like Taylor's series, Jacobian to linearize the non-linearity.

The extended Kalman filter is separated as two phases: forecast and update. The forecast phase applies the prior time step's state estimate to the present time step to get an estimate of the state. During the update phase, measurement data from the present time step is used to modify the forecast, resulting in a far more accurate state estimate for the same time step.

Non-linear System Dynamics:

$$X_K = f(X_{K-1}, U_{K-1}) + W_{K-1} \quad (26)$$

$$Z_K = h(X_K) + V_K \quad (27)$$

Where,

V_K and W_K are measurement noise and process noise, respectively.

X_K, U_K and Z_K are the system state, input and sensor measurement.

Time update equations

Predicted state:

$$\hat{X}_{K|K-1} = f(\hat{X}_{K-1}, U_{K-1}) \quad (28)$$

Predicted Covariance:

$$\hat{P}_{K|K-1} = F_K \hat{P}_{K-1} F_K^{T} + Q_K \quad (29)$$

Where the state transition matrices are defined to be the following Jacobians

$$F_K = \frac{\partial f}{\partial x}\Big|_{\hat{X}_{K-1}, U_{K-1}} \quad (30)$$

Measurement update equations

Innovation:

$$\tilde{Z}_K = Y_K - h(\hat{X}_{K|K-1}, 0) \quad (31)$$

Measurement covariance:

$$S_K = H_K \hat{P}_{K|K-1} H_K^{T} + R_K \quad (32)$$

Updated state:

$$\hat{X}_{K|K} = \hat{X}_{K|K-1} + K_K\left(Z_K - H_K \hat{X}_{K|K-1}\right) \quad (33)$$

Updated Covariance:

$$\hat{P}_{K|K} = (I - K_K H_K)\, \hat{P}_{K|K-1} \quad (34)$$

Kalman gain:

$$K_K = \hat{P}_{K|K-1} H_K^{T} S_K^{-1} \hat{P}_{K|K-1} H_K^{T} S_K^{-1} \quad (35)$$

Where the observation matrices are defined to be the following Jacobians:

$$H_K = \frac{\partial h}{\partial x}\Big|_{\hat{X}_{K-1}} \quad (36)$$

where F_K and H_K are Jacobian approximations

Result and Discussion

Under this section, a linear quadratic regulator (LQR) stabilizes the unstable system. Then an extended Kalman filter predicts the sensor faults in wind turbine system.

LQR Response

The simulation results of 2Mw wind turbine obtained from the LQR.

Figure 2 shows LQR response. Figure 3 displays controller input response. Based on the weights on the states and weights on the control input are controlled. LQR stabilizes the unstable system.

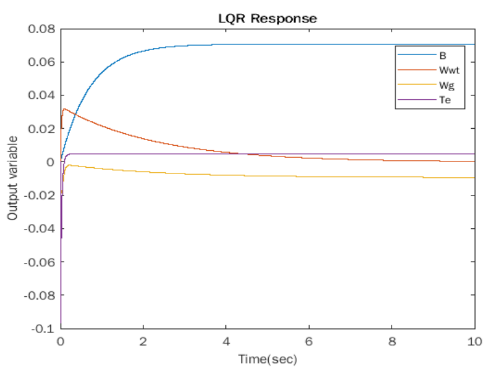

Figure 2: LQR response

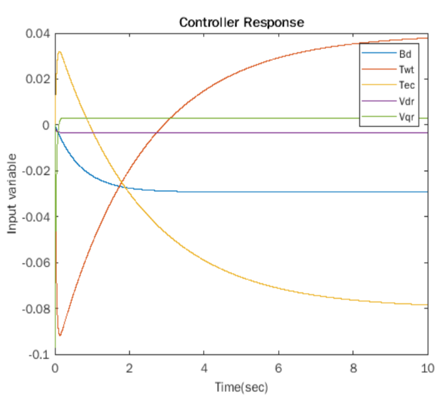

Figure 3: Controller input

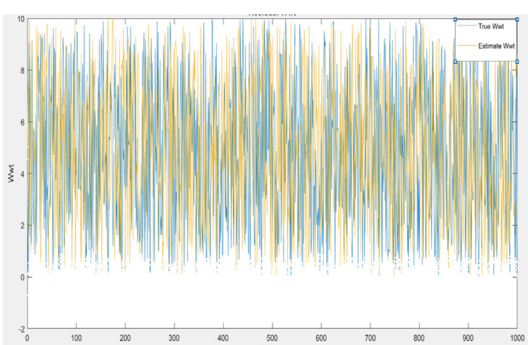

Figure 4: Measured and estimated state of wind turbine velocity

Estimated Output

Figure 4 and 5 displays that true and estimated state of velocity of wind turbine and generator. In Figure 4, the blue curve indicates the true value and yellow curve indicates the estimated velocity of wind turbine. In Figure 5, the red curve indicates the true value and green curve indicates the estimated velocity of wind turbine. Estimated state follows the true state.

Residual Response

Figure 6 and 7 displays the residual of wind turbine velocity and generator velocity. It shows the difference between the true and estimated wind turbine and generator velocity values. If they reach beyond the threshold value, the fault is present in wind turbine. In the velocity of the wind turbine, if it reaches beyond 1.8 the fault is present in wind turbine

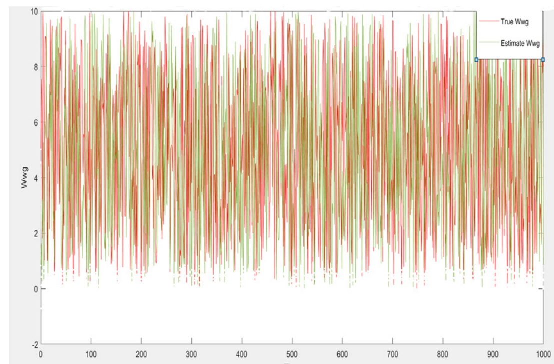

Figure 5: Factual and estimated state of generator velocity

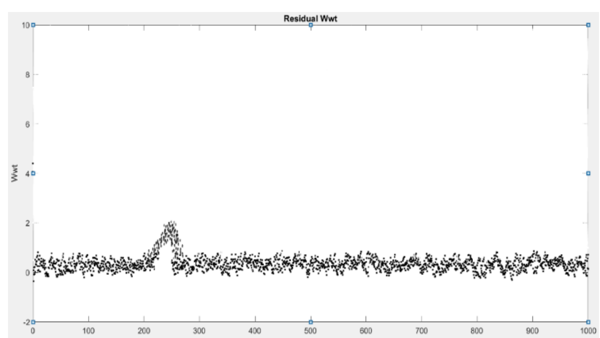

Figure 6: Residual of wind turbine velocity

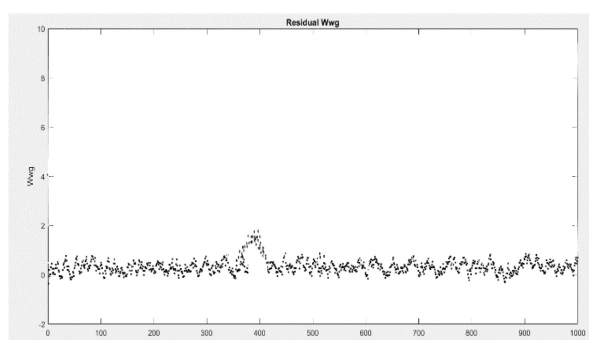

Figure 7: Residual of generator velocity

velocity. In the velocity of the generator, if it reaches beyond 1.2 the fault is present in generator velocity.

Conclusion and Future Work

Many studies have engrossed the FDI systems needed to operate wind farms properly. Wind turbine is unstable, so the state feedback controller stabilizes the system. Difficulties in fault detection and identification for a complicated wind turbine system. The ensemble Kalman filter is an effective predictor for estimating wind turbines' state. This approach is both non-linear and reliable. The estimator can detect a sensor fault accurately and easily, utilizing the residuals generated by the ensemble Kalman filter predictor.

In future work, the unscented Kalman filter and neural network can be utilized for anomaly detection and isolation need to enhance the efficiency (Kumar and Devakumar 2022).

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