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Generalized Correntropy Filter-Based Fault Diagnosis and Tolerant Control for Non-Gaussian Stochastic Systems Subject to Sensor Faults

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ABSTRACT In this paper, a generalized correntropy filter-based fault diagnosis (FD) and fault tolerant control (FTC) strategy is proposed for stochastic systems with heavy-tailed distributed noises. In order to deal with the non-Gaussian noises involved in the stochastic systems, a generalized correntropy criterion (GCC) is reviewed first. Then, based on this criterion, an output feedback controller is designed for the healthy stochastic system to make the system output track the set-point as closely as possible. Considering the sensor fault, a GCC filter-based FD method is established, where residuals are used to detect and isolate the sensor fault. Moreover, when the sensor fault is diagnosed, normal signals are used to reconstruct the system so that the system can maintain run normally. Finally, the wind energy conversion system with three types of sensor faults is used to verify the feasibility and efficiency of the proposed FD and FTC method.

INDEX TERMS Fault diagnosis and tolerant control, generalized correntropy criterion (GCC), sensor fault, non-Gaussian systems.

I. INTRODUCTION

Modern technologies and industrial systems demand for safety and reliability during their applications. Once a fault occurs in sensors and/or actuators, which may not be dealt with by the conventional control systems, the system behavior performance will deteriorate drastically. Hence, an increasing attention has been paid to the design of fault tolerant control (FTC) schemes, which have been widely considered and implemented in various areas [1]. For instance, a FTC design method was proposed for four-wheel independently driven electric vehicles in [2]. And another FTC approach was utilized to track a reference input for a spacecraft under faulty conditions in [3].

The existed FTC methodologies can be classified into two kinds: passive FTC and active FTC. These two approaches use different design methodologies for the same control objective. The passive FTC may degrade the system performance. And when the system subjects a large set of faults, the design of a passive FTC is generally difficult because many constraints must be satisfied [4]. Comparatively, the active FTC approach is more flexible to deal with different types of faults [5]. It needs the fault detection and diagnosis (FDD) scheme to provide timely and accurate fault information. Observer/filter-based FDD schemes have been shown to be effective methods [6]–[8]. In [6], sensor fault detection and isolation method for wind turbines was proposed based on subspace identification and Kalman filter techniques. For nonlinear dynamic systems, adaptive observer method was used to isolate and identify sensor faults in [7]. In [8], a fuzzy detective observer-based fault-tolerant control scheme is proposed for a class of multiple input fuzzy bilinear systems with unmeasurable states. Those methods show their effectiveness to diagnose sensors and/or actuator faults based on the assumption that the random variables considered in the systems are Gaussian ones.

However, the noises in most practical systems are not necessarily Gaussian, and moreover, the nonlinearity of the systems may lead to non-Gaussian randomness even if the noises obey Gaussian distribution. In this case, the mean and variance cannot sufficiently characterize the statistical property of the stochastic processes. And the above FTC strategies may not have their advantages. As well all known that, the behavior of a stochastic process can be completely characterized in many cases by the shape of its statistical distribution which is represented by the probability density functions (PDF). Therefore, by using a multi-layer perceptron (MLP) neural network approximating the output PDFs, an optimal FTC scheme using PDFs was studied for the general stochastic continuous time systems in [9]. In [10], an FDD algorithm design was to use the measured output PDFs and the input of the system to construct a stable filter-based residual generator such that the fault can be detected and diagnosed. Based on a minimum entropy filter, the fault isolation (FI) problem was investigated in [11] for nonlinear non-Gaussian systems with multiple faults (or abrupt changes of system parameters) in the presence of noises.

There are two main problems about the above results: 1) the target PDF may be unavailable; 2) the model used for FTC design did not have a direct physical meaning and the size of the NN can be very large if the output PDF shape is complicated in terms of having a large number of peaks. Subsequently, filters based on minimum entropy criterion were established for FDD and FTC respectively in [12] and [13]. Based on a minimum entropy filter, sensor fault detection and isolation problems were solved in [12] for variable-speed WECSs subject to non-Gaussian disturbances. However, it didn't give the control strategy to tolerant the occurred sensor fault. Different from general stochastic distribution control (SDC) systems, [13] extended the FD algorithm of the non-Gaussian SDC system to the non-Gaussian singular SDC system by a state equivalent transformation. And the adaptive observer based minimum entropy FTC method was proposed.

There are two types of non-Gaussian distributions: light-tailed and heavy-tailed distributions. It is approved that the correntropy is insensitive to outliers especially with a small kernel bandwidth, therefore, the maximum correntropy criterion (MCC) has been successfully used in robust adaptive filtering in impulsive (heavy-tailed) noise environments [14]–[18]. Different form the Gaussian kernel as the kernel function adopted in correntropy, generalized Gaussian density (GGD) function was used to formulate a more flexible definition of correntropy called generalized correntropy [19]. And based on the generalized maximum correntropy criterion (GCC), a novel adaptive filtering design method was proposed. Combining the advantages of kernel methods and generalized correntropy, [20] proposed a new kernel adaptive filtering algorithm.

In this work, a novel GCC filter is presented to generate residuals and then the sensor faults can be detected and isolated according to the residuals. After diagnosing the sensor fault, normal signals are used to reconstruct the system so that the system can maintain run normally. The contributions can be shown as follows: 1) The influence of heavy-tailed noises on the filter design for multivariate systems without sensor fault is analyzed. 2) Considering heavy-tailed non-Gaussian noises, GCC is used to design the filter, which is insensitive to outliers especially with a small kernel bandwidth. 3) A set of GCC filter-based fault diagnosis and reconstruction framework is formulated for non-Gaussian stochastic systems subject to sensor faults. 4) The proposed correntropy-based FD and FTC method is applied to the wind energy conversion systems (WECSs) with heavy-tailed noises and sensor fault.

The remainder of this paper is organized as follows: a brief review of generalized correntropy are presented in Section II. System model is described in Section III. Based on generalized correntropy criterion, FDI algorithm and FTC algorithms are proposed in Section IV. In Section V, the proposed method is applied to wind energy conversion systems to illustrate its feasibility and efficiency. Finally, conclusions are drawn in Section VI.

II. REVIEW OF THE GENERALIZED CORRENTROPY CRITERION

Correntropy is a local similarity measure directly related to the probability of how similar two random variables are in a neighborhood of the joint space controlled by the kernel bandwidth [19]. Given two m-dimensional random vectors $X = [X_1, X_2 \cdots X_m]^T$ and $Y = [Y_1, Y_2 \cdots Y_m]^T$, the correntropy is defined as:

$$V_{\sum_\sigma}(X, Y) = E[K_{\sum_\sigma}(X - Y)] \tag{1}$$

where E denotes the expectation operator. $K_{\sum_\sigma}(X, Y)$ is a multi-dimensional Gaussian kernel function, which can be obtained by the single-dimensional Gaussian kernels $\kappa_\sigma(\cdot)$ [19]:

$$K_{\sum_\sigma}(X, Y) = \prod_{i=1}^{m} \kappa_\sigma(X_i - Y_i) \tag{2}$$

where

$$\kappa_\sigma(X_i, Y_i) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-(X_i - Y_i)^2}{2\sigma^2}\right) \tag{3}$$

A well-known generalization of Gaussian density function, called the generalized Gaussian density (GGD) function, is given by

$$\begin{aligned} G_{\alpha,\beta}(X_i, Y_i) &= \frac{\alpha}{2\beta\Gamma(1/\alpha)} \exp\left(-\left|\frac{X_i - Y_i}{\beta}\right|^\alpha\right) \\ &= \gamma_{\alpha,\beta}\exp(-\lambda|X_i - Y_i|^\alpha) \end{aligned} \tag{4}$$

where Γ denotes the gamma function, $\alpha > 0$ is the shape parameter, $\beta > 0$ is the scale (bandwidth) parameter, $\lambda = \frac{1}{\beta^\alpha}$ is the kernel parameter, and $\gamma_{\alpha,\beta} = \frac{\alpha}{(2\beta\Gamma(1/\alpha))}$ is the normalization constant. The purpose of adding this constant is to convert the function into a probability density function.

Therefore, a generalized correntropy can be obtained by using the generalized Gaussian kernel function (4):

$$V_{\sum_{\alpha,\beta}}(X, Y) = E\left[\prod_{i=1}^{m} G_{\alpha,\beta}(X_i, Y_i)\right] \tag{5}$$

In practice, the joint distribution of X and Y is usually unknown, and only a finite number of samples

$\{(X_1^i, X_2^i, \cdots X_m^i)\}_{i=1}^N$ and $\{(Y_1^i, Y_2^i, \cdots Y_m^i)\}_{i=1}^N$ are available. In this case, the sample mean estimator of the generalized correntropy is:

$$\hat{V}_{\sum_{\alpha,\beta}}(X, Y) = \frac{1}{N}\sum_{j=1}^{N}\left[\prod_{i=1}^{m} G_{\alpha,\beta}\left(X_i^j, Y_i^j\right)\right] \tag{6}$$

Since the generalized correntropy $V_{\sum_{\alpha,\beta}}(X, Y)$ is positive and bounded [19], $0 < V_{\sum_{\alpha,\beta}}(X, Y) \leq [G_{\alpha,\beta}(0)]^m = (\gamma_{\alpha,\beta})^m$, the generalized correntropy cost function between X and Y can be defined as:

$$J_{GC}(X, Y) = (\gamma_{\alpha,\beta})^m - E\left[\prod_{i=1}^{m} G_{\alpha,\beta}(X_i, Y_i)\right] \tag{7}$$

III. SYSTEM MODEL

Consider the following linear stochastic model with heavy-tailed noises and sensor faults:

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + Wv_k \\ y_k = Cx_k + f_s y_k^F + \zeta_k \end{cases} \tag{8}$$

where $x_k \in \mathbb{R}^n$ is the state vector, $u_k \in \mathbb{R}^p$ is the control input, $y_k \in \mathbb{R}^m$ is the system output, $v_k \in \mathbb{R}^n$ and $\zeta_k \in \mathbb{R}^m$ are the heavy-tailed distributed noises. A, B, C and W are constant matrices with proper dimensions. $f_s \in \mathbb{R}^m$ is a sensor fault event vector and y_k^F is a scalar function which represents the evolution of the sensor fault.

Firstly, the closed-loop system is designed without the existence of sensor faults. Denote the set-point as r_k, the control algorithm should be designed to make the system output y_k track r_k as closely as possible, i.e. $e_k = r_k - y_k$ almost approaches to zero. The controller structure is selected as the form of output feedback:

$$u_k = Ky_k \tag{9}$$

where $K \in \mathbb{R}^{p\times m}$ is the gain of feedback to be determined.

Since noises involved in the system (8) obey heavy-tailed distribution, the GCC proposed in Section 2 is used to obtain the gain K, which can be expressed as:

$$\begin{aligned} K^* &= \arg\min_K (J_{GC}(e_k)) \\ &= \arg\min_K \left\{(\gamma_{\alpha,\beta})^m - E\left[\prod_{i=1}^{m} G_{\alpha,\beta}(e_i)\right]\right\} \end{aligned} \tag{10}$$

By using the stochastic gradient method, we can get K iteratively:

$$K_k = K_{k-1} - \eta_1 \left.\frac{\partial J_{GC}(e_k)}{\partial K_k}\right|_{k=k-1} \quad (k = 1, 2, \cdots), \tag{11}$$

where $\eta_1 > 0$ is the learning rate factor.

According to the above presentation, the optimal gain can be computed and a summary of the steps is listed as follows:

Step 1: Set the initial value of gain K_0 and denote $k := 1$.

Step 2: Estimate $J_{GC}(e_k)$ according to (6) in Section 2.

Step 3: Solve the optimal gain by (11) and the input (9).

Step 4: Implement the input on the process and collect the process outputs to recursively update the generalized correntropy of the output tracking error. Then repeat the procedure from Step 2 to Step 4 for the next time step, $k = k + 1$.

IV. FAULT TOLERANT CONTROL STRATEGY

Measured outputs obtained from sensors are used to design the system controller. When sensor fault occurred, wrong calculation of the controller will lead to worse performance. In this section, a novel GCC filter-based sensor fault tolerant control method is proposed for the non-Gaussian system.

A. GCC FILTER

The filter dynamics can be formulated as follows:

$$\begin{cases} \hat{x}_{k+1} = A\hat{x}_k + Bu_k + L_k(y_k - \hat{y}_k) \\ \hat{y}_k = C\hat{x}_k \\ u_k = Ky_k \end{cases} \tag{12}$$

where $L_k \in \mathbb{R}^{n\times m}$ is the filter gain matrix to be determined.

According to the dynamic system model, the state estimation error and output error can be respectively formulated as:

$$\begin{aligned} e_{k+1}^x &= x_{k+1} - \hat{x}_{k+1} \\ &= (Ax_k + Bu_k + Wv_k) - \left(A\hat{x}_k + Bu_k + L_k\left(y_k - \hat{y}_k\right)\right) \end{aligned} \tag{13}$$

$$\begin{aligned} &= (A - L_k C)\, e_k^x + Wv_k - L_k f_s y_k^F - L_k\zeta_k \\ e_k^y &= y_k - \hat{y}_k = Ce_k^x + f_s y_k^F - L_k\zeta_k \end{aligned} \tag{14}$$

The purpose of the filter design is to determine the filter gain such that the state estimation error is approaching to zero with small randomness. Due to non-Gaussian noises imposed on the estimation error dynamics (13) and (14), the filter gain L_k will be designed based on the GCC. Therefore, the performance index is formulated as:

$$J_k = R_1 \cdot J_{GC}(e_k^x) + \frac{1}{2}R_2 l_k^T l_k \tag{15}$$

where $J_{GC}(e_k^x)$ is the generalized correntropy of the state estimation error e_k^x, the second term of (15) is the energy constrain of the filter gain. $l_k = [L_{1k}^T L_{2k}^T \cdots L_{mk}^T]^T$, L_{ik} is the i^{th} colum of L_k, i.e. $L_k = [L_{1k}L_{2k}\cdots L_{mk}]$. R_1 and R_2 are weights that correspond to correntropy and the filter gain.

The filter gain L_k can be obtained by restructuring elements of l_k, which can be formulated recursively:

$$l_k = l_{k-1} + \Delta l_k \tag{16}$$

Both sides of the above equation are left multiplied by their transposes at the same time:

$$l_k^T l_k = l_{k-1}^T l_{k-1} + 2l_{k-1}^T \Delta l_k + \Delta l_k^T \Delta l_k \tag{17}$$

According to the performance index J_k, we denote $P_k = R_1 \cdot J_{GC}(e_k)$, and then the Taylor expansion of P_k is described as:

$$P_k \approx \bar{P}_0 + \bar{P}_1^T \Delta l_k + \frac{1}{2}\Delta l_k^T \bar{P}_2 \Delta l_k \tag{18}$$

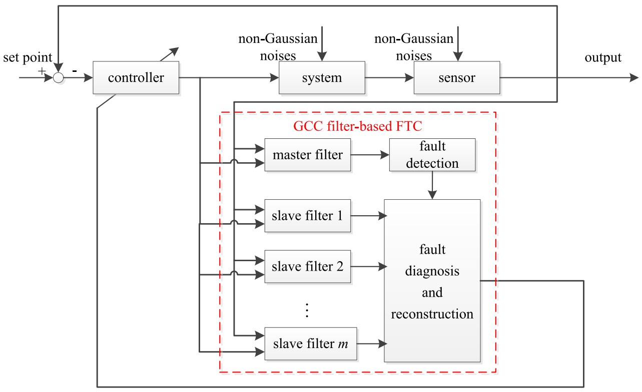

FIGURE 1. GCC filter-based FTC strategy.

where $\bar{P}_0 = P_k|_{l_k=l_{k-1}}, \bar{P}_1 = \left.\frac{\partial P_k}{\partial l_k}\right|_{l_k=l_{k-1}}, \bar{P}_2 \left.\frac{\partial^2 P_k}{(\partial l_k)^T(\partial l_k)}\right|_{l_k=l_{k-1}}$.

Therefore, the performance index J_k can be estimated as

$$J_k \approx \bar{P}_0 + \bar{P}_1^T \Delta l_k + \frac{1}{2}\Delta l_k^T \bar{P}_2 \Delta l_k + \frac{1}{2}R_2\left(l_{k-1}^T l_{k-1} + 2l_{k-1}^T \Delta l_k + \Delta l_k^T \Delta l_k\right) \quad (19)$$

Then, the optimal filter gain can be obtained by solving $\frac{\partial J_k}{\partial \Delta l_k} = 0$:

$$\Delta l_k = -(\bar{P}_2 + R_2 I_n)^{-1}\left(\bar{P}_1 + R_2 l_{k-1}\right) \quad (20)$$

According to (16)-(20), l_k can be obtained, and the filter gain L_k can also be eventually formulated.

B. FAULT DETECTION AND ISOLATION

From the established GCC filter, we know that when there is no fault, the estimation error will be approaching to zero. And once one sensor has fault, the estimation state will deviate from the correct value, there will be residuals. Therefore, the residual can be used to detect and isolate the sensor fault. To address this, a set of GCC filter-based fault diagnosis and reconstruction framework shown in Fig.1 for system (8) is proposed.

The master filter in Fig. 1 is used to detect whether the sensor has fault. Given a proper threshold $\varepsilon > 0$, the sensor fault can be detected according to the following criterion:

$$\begin{cases} \left\|E\left(e_k^x\right)\right\| < \varepsilon, & \text{no fault occurs} \\ \left\|E\left(e_k^x\right)\right\| \geq \varepsilon, & \text{fault has occured} \end{cases} \quad (21)$$

where $\left\|E\left(e_k^x\right)\right\| = \sqrt{\sum_{i=1}^{n}\left[E\left(e_{ik}^x\right)\right]^2}, e_k^x = \left[e_{1k}^x, e_{2k}^x, \cdots e_{nk}^x\right]^T$.

When one fault has been detected, m slave filters in Fig.1 are adopted to locate the fault. It should be noted that n state variables are measured by different sensors, and each measuring value and control input are separately used to design the m filters, composing filters set, so each state of system can be estimated by each filter respectively. Firstly, the residuals between every two state estimations are obtained:

$$\begin{cases} \Psi_1 = \left|\hat{x}_{i1} - \hat{x}_{i2}\right| \\ \Psi_2 = \left|\hat{x}_{i2} - \hat{x}_{i3}\right| \\ \vdots \\ \Psi_{m-1} = \left|\hat{x}_{i,m-1} - \hat{x}_{i,m}\right| \\ \Psi_m = \left|\hat{x}_{i,m} - \hat{x}_{i1}\right| \end{cases} \quad (22)$$

where $\hat{x}_{ij}$ $(i = 1, 2, \cdots, n; j = 1, 2, \cdots, m)$ represents the estimation of the i^{th} state variable from the j^{th} sensor. Then, a group of fault isolation index is established based on (22) and expressed as below:

$$\begin{cases} \Upsilon_1 = \Psi_1 \Psi_m \\ \Upsilon_2 = \Psi_1 \Psi_2 \\ \vdots \\ \Upsilon_m = \Psi_{m-1} \Psi_m \end{cases} \quad (23)$$

The fault isolation feature is displayed in Table 1, which helps to explain the specific fault isolation strategy. If no fault occurred in sensor, the state variable estimations of different filters are in good agreement, and residuals are extremely small. Hence, the fault isolation indexes are all fluctuating around zero value. When fault occurred in sensor i, the corresponding state variable estimation achieved from filter i will change, while other filters' output remains unchanged. Hence, some elements of the fault detection index will no longer be zero. Therefore, faulty sensor isolation for system (8) can be realized by comparing fault isolation index with the threshold H.

TABLE 1. Signature for fault isolation.

Fault isolation index	Υ_1	Υ_2	$\cdots$	Υ_m
Normal	0	0	$\cdots$	0
Fault in sensor 1	1	0	$\cdots$	0
Fault in sensor 2	0	1	$\cdots$	0
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
Fault in sensor m	0	0	$\cdots$	1

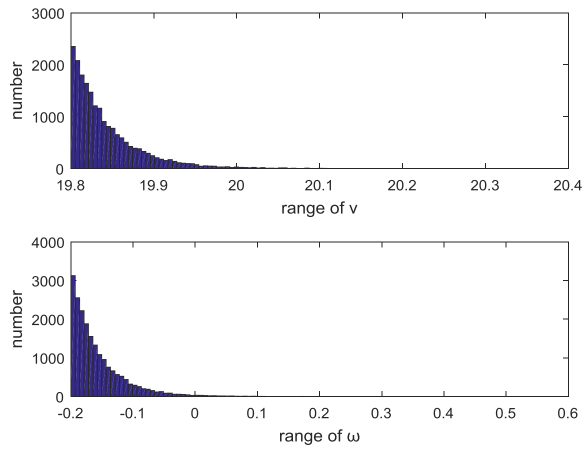

FIGURE 2. Noises involved in the WECS.

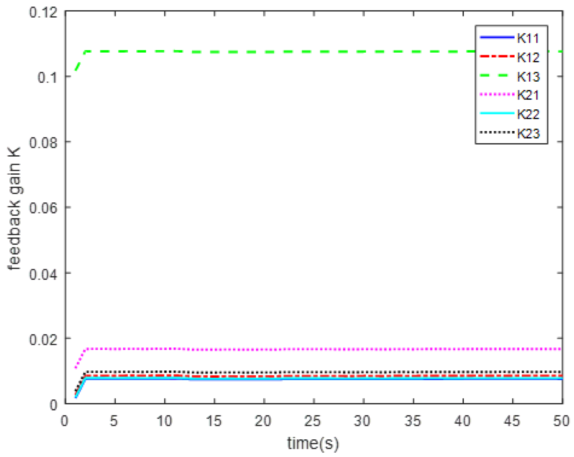

FIGURE 3. Gain elements of the optimal controller.

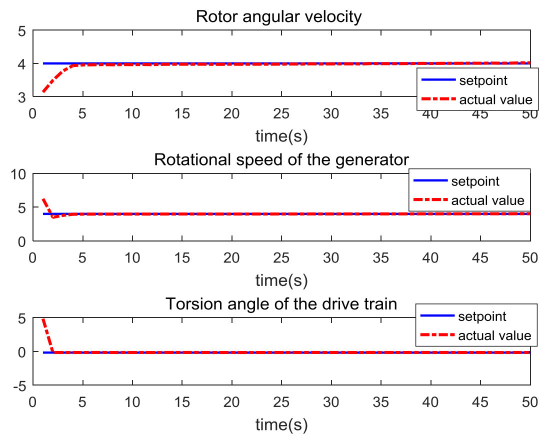

FIGURE 4. Output response.

C. SYSTEMS RECONSTRUCTION

Once the faulty sensor i is located, the feedback information from this sensor will be cut off. At the same time, the weighted sum of outputs from other normal sensors $\hat{y}_i = \frac{1}{m-1}\sum_{j=1, j\neq i}^{m} w_j \hat{y}_j, \left(\sum_{j=1, j\neq i}^{m} w_j = 1\right)$ is used as the output of the faulty sensor and back to the closed-loop system. And then, the controller could be designed according to the algorithm in Section 3. Therefore, the online reconstruction is established.

V. APPLICATION TO WIND ENERGY CONVERSION SYSTEMS (WECSs)

In this section, the wind energy conversion systems (WECSs) in [12] is used to verify the feasibility and efficiency of the proposed sensor fault tolerant control method. Noises in the WECSs are supposed to obey the heavy-tailed distribution, which can be shown in Fig.2.

A. CONTROLLER DESIGN IN NORMAL CASE

When there is no fault in WECSs, the optimal controller can be designed by using the method proposed in Section 3.

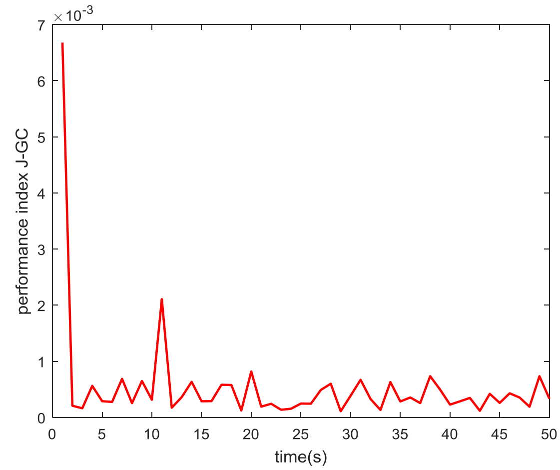

FIGURE 5. Performance index $J_{GC}(e_k)$.

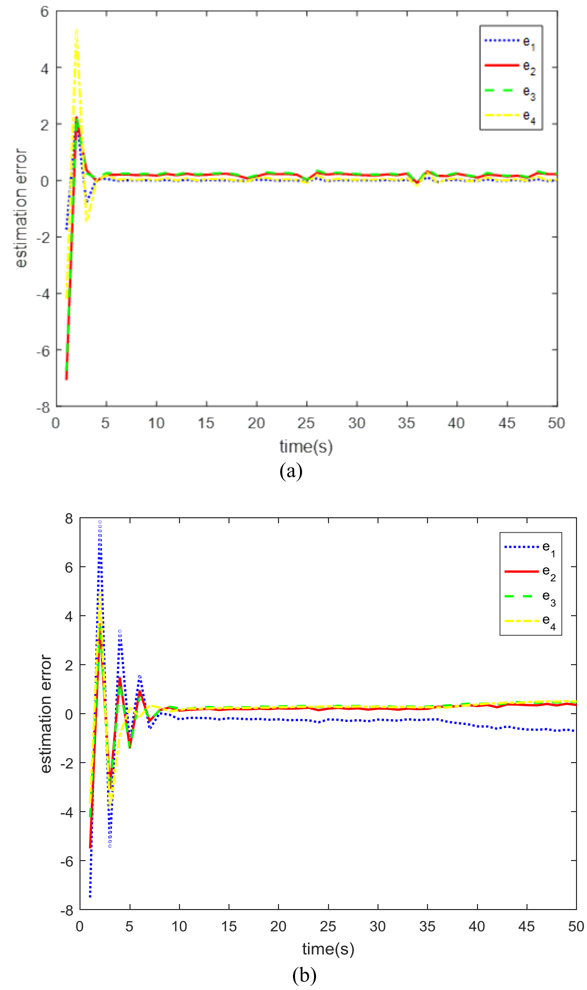

FIGURE 6. State estimation error ((a) GCC filter; (b) MEE filters).

Let the output set-point be $r_k = \begin{bmatrix} 4 & 4 & 0.17 \end{bmatrix}^T$, then, the variations of feedback gain elements are shown in Fig.3. Fig.4 shows the actual outputs of the WECSs can track the set-point very well under the optimal controller. And the cor-

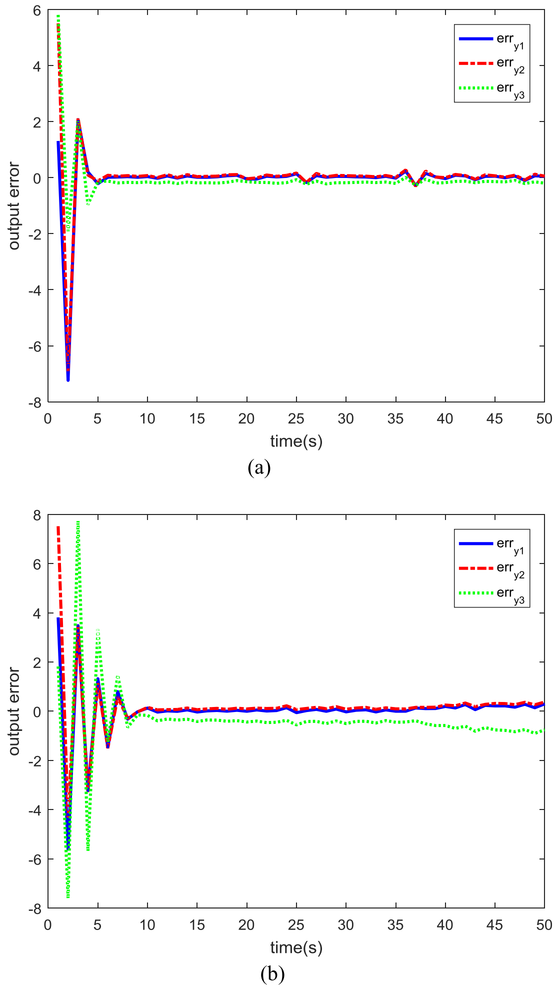

FIGURE 7. Output estimation error ((a) GCC filter; (b) MEE filters).

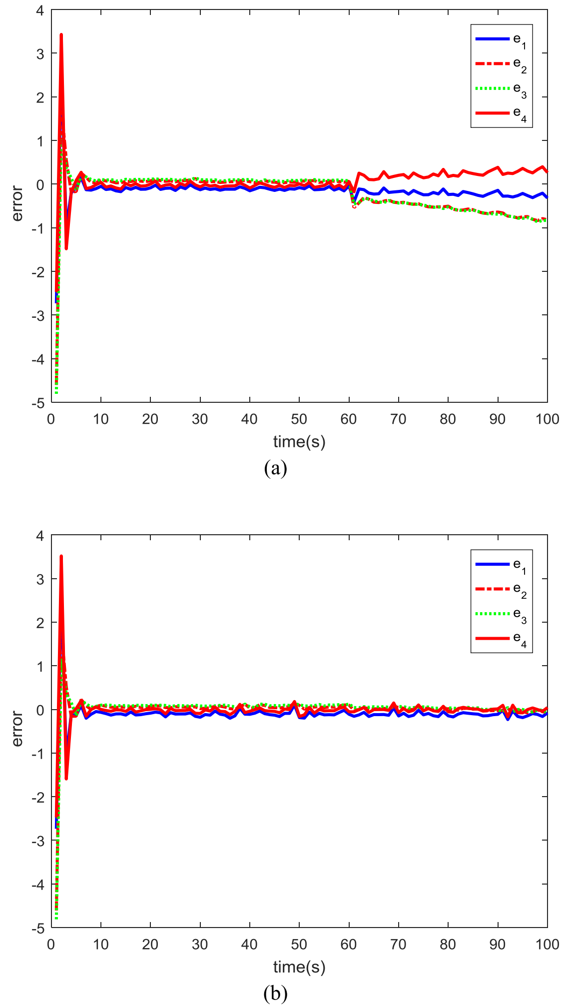

FIGURE 8. Estimation error based on two different filters ((a) GCC filter; (b) MEE filters).

responding performance index, shown in Fig.5, is decreasing with time, approaching to zero.

B. GCC FILTERS DESIGN IN NORMAL CASE

Comparative simulation results between MEE filter and the proposed GCC filter for the WECS in normal case are shown in Figs. 6 and 7. From these figures, it can be seen that both the MEE and GCC filter can make the state estimation error and output error approach to zero. Compared with the results of MEE filter in Fig. 6 (b) and Fig. 7 (b), the estimation errors of GCC filter in Fig.6 (a) and Fig. 7 (a) are closer to zero with smaller randomness. The mean value and variance of the state estimation error of GCC filter and MEE filter are shown respectively in Table 2, from which we can see the advantages of the proposed GCC filter.

C. FAULT DIAGNOSIS AND TOLERANT CONTROL

Here, three possible faults (failure fault, constant gain fault and constant bias fault), are chosen to analyze the performance of algorithms.

TABLE 2. Mean value and variance of the state estimation error.

		GCC filter	MEE filter
Mean	$E(e_1)$	-0.0034	-0.3289
	$E(e_2)$	0.0830	0.1236
	$E(e_3)$	0.1192	0.2104
	$E(e_4)$	0.0254	0.2022
Variance	$V(e_1)$	0.1754	3.4005
	$V(e_2)$	1.1544	1.2208
	$V(e_3)$	1.0741	1.0823
	$V(e_4)$	1.0094	1.1661

Case 1 (Constant Gain Fault): Under Heavy-tailed noises, a constant gain fault is imposed on the torsion angle sensor at 60 s:

$$y_{3k}^{F} = \begin{cases} 0, & k \leq 60s \\ -0.98 y_{3k}^{healthy}, & k > 60s \end{cases} \quad (24)$$

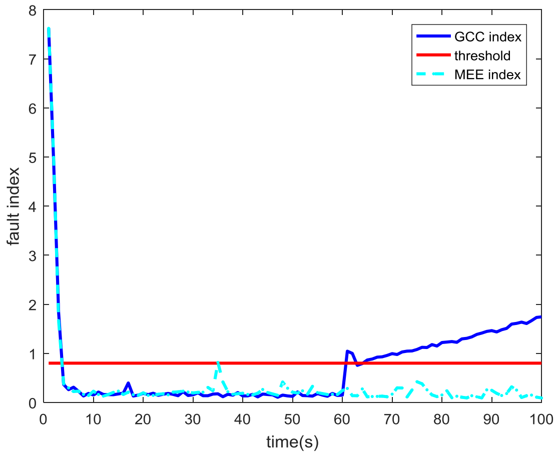

FIGURE 9. Fault detection index.

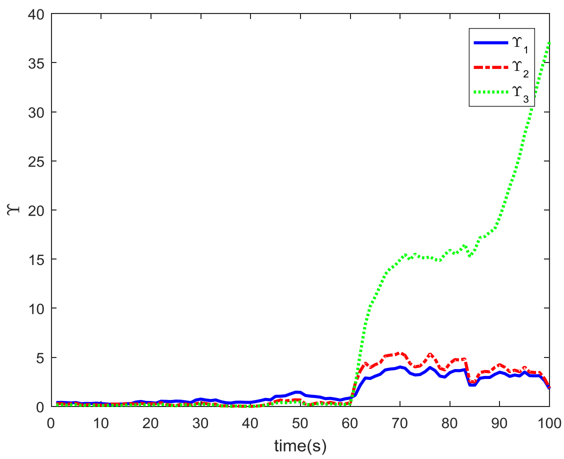

FIGURE 10. Fault isolation index.

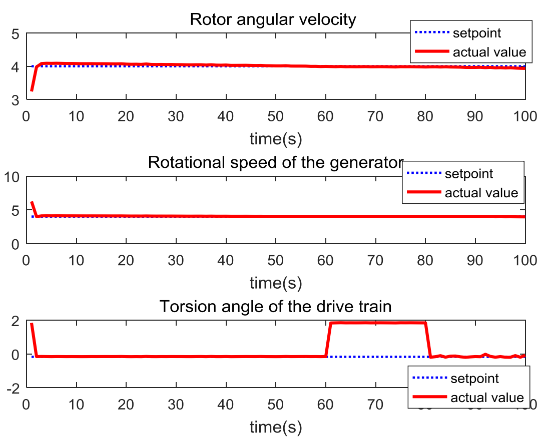

FIGURE 11. Output responses before and after fault tolerant control.

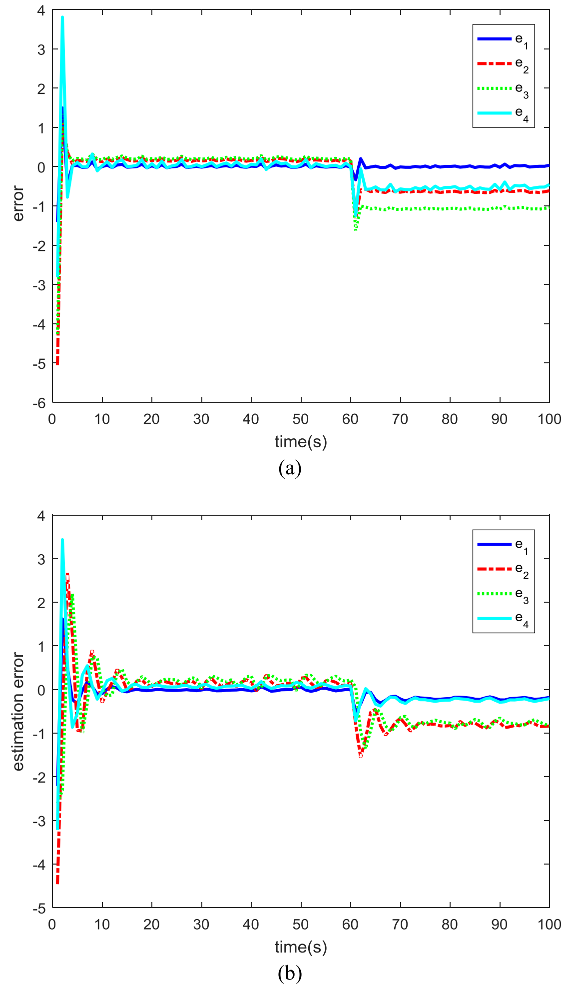

FIGURE 12. Estimation error based on two different filters ((a) GCC filter; (b) MEE filters).

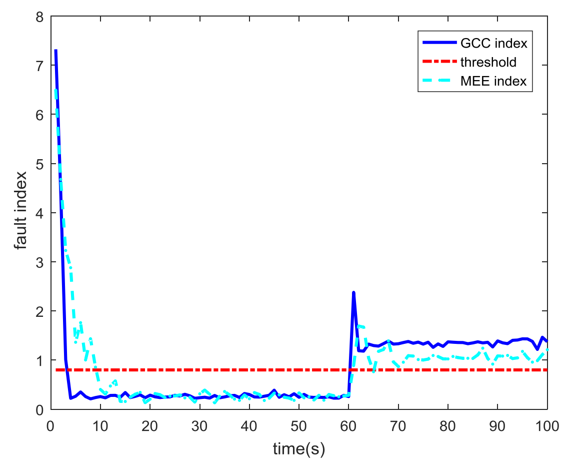

FIGURE 13. Fault detection index.

where $y_{3k}^{healthy}$ is measured by the third corresponding healthy sensors. State estimation errors based on GCC filter and MEE filter are respectively shown in Figs. 8(a) and 8(b). It can be seen from Fig. 8(a) that the state errors based on GCC deviate from zero and the generated residuals become larger after the constant gain sensor fault occurring, while errors based on MEE in Fig. 8(b) are always approaching to zero whether the fault occurs or not. According to Fig. 9, before fault occurs, the real-time values of the fault detection indexes

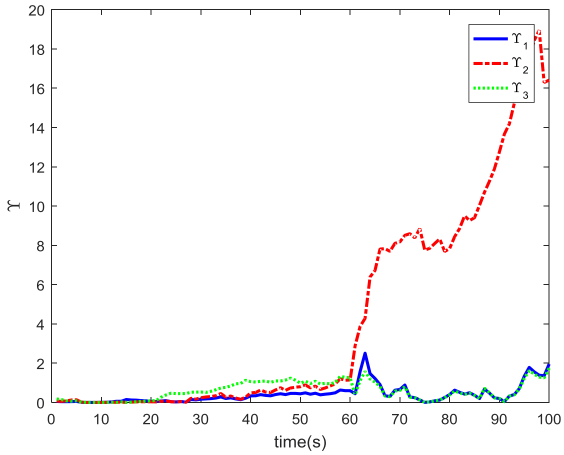

FIGURE 14. Fault isolation index.

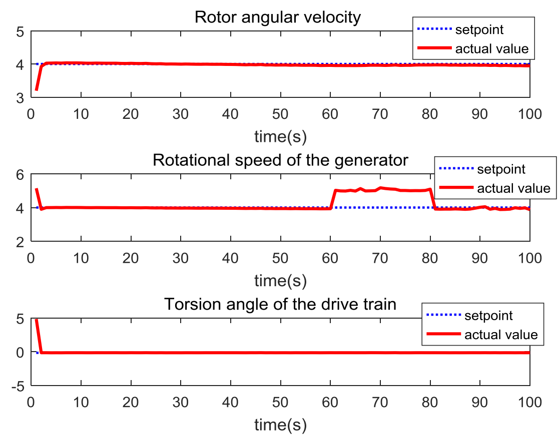

FIGURE 15. Output responses before and after fault tolerant control.

under GCC and MEE filters are both less than the threshold $\varepsilon = 0.8$. When fault occurs in the third sensor at 60 s, the fault detection index under GCC filter rises and exceed the threshold after a short delay, which means the fault can be detected. However, the fault detection index under MEE remains less than the threshold, which means it cannot detect the sensor fault. It can be observed from Fig. 10 that the value of Υ_3 becomes much larger than both Υ_2 and Υ_1 after 60s. Therefore, the fault in sensor 3 can be isolated according to the fault decision functions (23).

Case 2 (Constant Bias Fault): A constant bias fault is imposed on the generator speed sensor at 60s:

$$y_{2k}^F = \begin{cases} 0, & k \leq 60s \\ 3, & k > 60s \end{cases} \tag{25}$$

From Fig.12, it can be seen that the constant bias fault signal leads to the increasing residuals generated by both proposed filter and MEE filter. Fault detection indexes under GCC filter and MEE filter shown in Fig. 13 both rises and exceed the threshold, but variance of the former index is more significant. According to Fig.14, we can find that sensor 2 has fault. And then, the fault tolerant control is added at. Fig.15 shows the effectiveness of the proposed system reconstruction strategy.

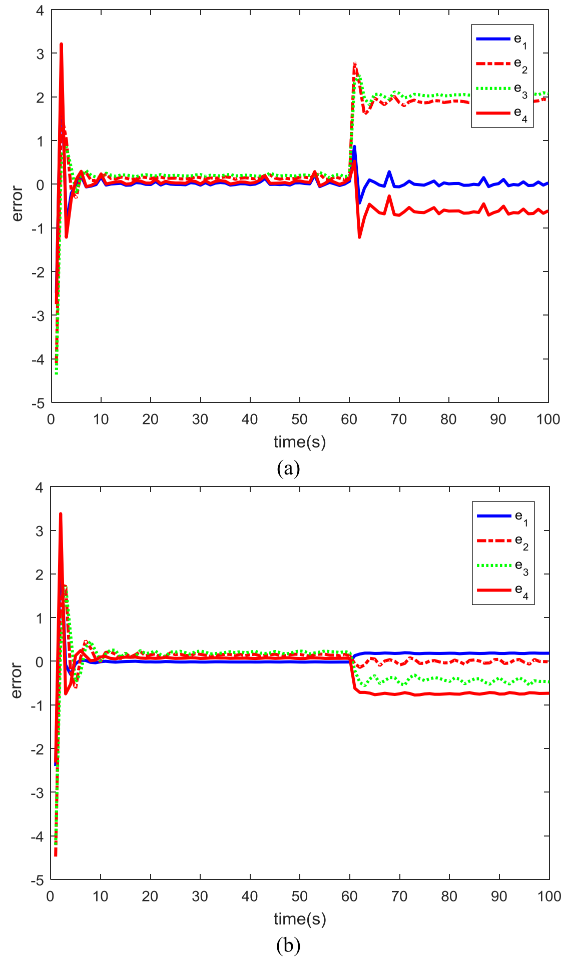

FIGURE 16. Estimation error based on two different filters ((a) GCC filter; (b) MEE filters).

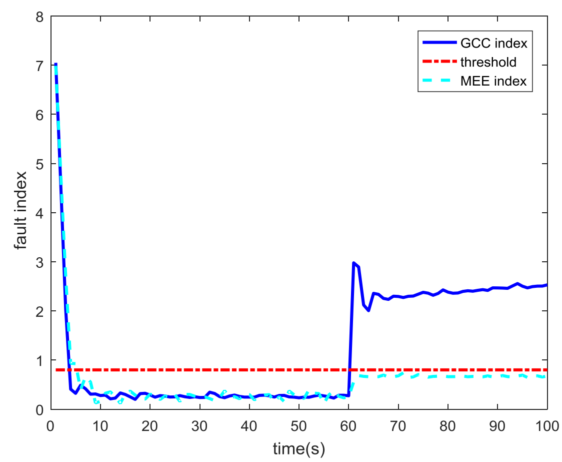

FIGURE 17. Fault isolation index.

Case 3 (Frozen Fault): A frozen fault is imposed on the rotor angular velocity sensor at 60s:

$$y_{1k}^F = \begin{cases} 0, & k \leq 60s \\ 2 - y_{1k}^{healthy}, & k > 60s \end{cases} \tag{26}$$

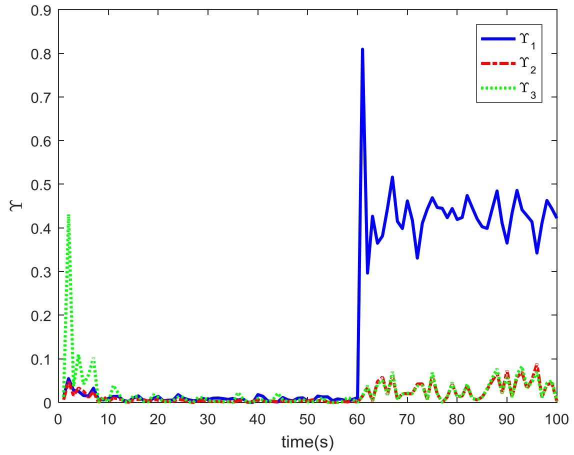

FIGURE 18. Fault isolation index.

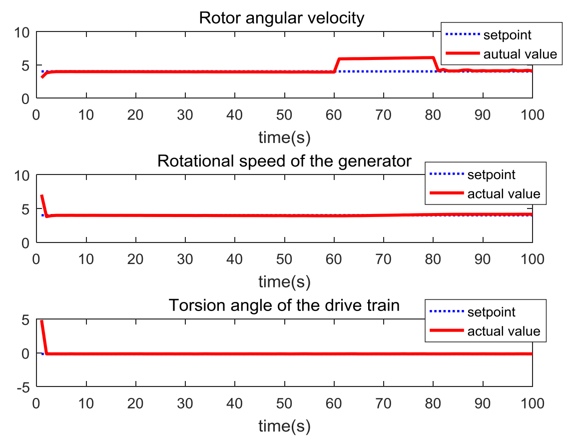

FIGURE 19. Output responses before and after fault tolerant control.

where $y_{1k}^{healthy}$ is measured by the first corresponding healthy sensors. Compared with the state estimation errors generated by MEE filter shown in Fig. 16(a), state errors in Fig. 16(b) generated by GCC filter significantly deviates from zero after 60s and finally approaches to a certain value with small fluctuation. According to the fault detection index shown in Fig. 17, we know that there is a fault in WECSs. Furthermore, from Fig. 18 it can be seen that the first sensor fault is located using the fault isolation law (23). Then, based on the proposed fault tolerant control method, the fault influence can be eliminated and the system output tracking errors return to zero.

VI. CONCLUSIONS

A new generalized correntropy filter based fault diagnosis and tolerant control strategy has been proposed for non-Gaussian systems with sensor fault in this work. The filter and controller are derived by using the minimum generalized correntropy criterion (GCC) as the optimality criterion, instead of using the minimum error entropy (MEE) criterion. MCC has the advantage that it is a local criterion of similarity and it should be very useful for cases when the measurement noise is nonzero mean, non-Gaussian, with large outliers. In order to diagnose the sensor fault, a bank of GCC filters are formulated, including one master filter and a set of slave filters. Residuals generated from these two kinds of filters are used to detect and isolate the sensor fault, respectively. After locating the faulty sensor, the feedback information from this sensor will be cut off, and right signals will be constructed using normal sensors. The proposed method is applied to the WECS, and simulation results illustrate that our method can effectively achieve the sensor fault diagnosis and tolerant control task.

At present, we only consider the single sensor fault case. If more than one sensor fails simultaneously, filters inputs will contain fault data so that fault indication signals may exceed threshold of fault diagnosis, high false alarm rate and missed detection rate will be occurred by using the proposed FD method. Therefore, the extension to multiple sensor and actuator faults occurring simultaneously will be investigated in the future work.

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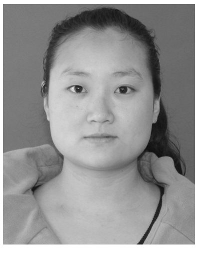

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