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A new current sensor incipient fault diagnosis method for converters in wind energy conversion systems

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Dear editor,

The efficient and clean characteristics of wind energy have led to the development of wind power generation as one of the most sophisticated ways of power generation [1]. To guarantee the reliability and safety of the energy conversion process, current sensors have played a significant role in the wind energy conversion systems (WECSs). However, to the best of the author's knowledge, the literature concerning current sensor fault diagnosis is limited.

Currently, the most frequently used methods for current sensor fault diagnosis are the observer-based approaches that depend on the preciseness of the established mathematical models [2]. Unfortunately, as the wind power generation systems are always complex and equipped with nonlinear dynamic characteristics, it is challenging to establish precise mathematical models or estimate unknown system parameters.

Furthermore, because of the influence of noise and disturbances in WECSs, it is extremely challenging to detect current sensor incipient faults having small fault characteristics. To diagnose the incipient faults and by considering the problem of complex system modeling or system parameter estimation, a signal-based approach is proposed herein to deal with the current sensor incipient faults of the grid-side converter in WECSs. First, the grid-side three-phase currents are processed using the Hilbert transform (HT) for instantaneous amplitude estimation. Principle component analysis (PCA) and the Kullback-Leibler (KL) divergence are then applied for fault feature extraction. Finally, a theoretical model is established for estimating the small gain fault amplitude. The block diagram of the proposed novel current sensor incipient fault diagnosis method is shown in Figure 1.

Fault model and data matrix. For the grid-side current sensors in WECSs, if the output current of phase u suffers from a small gain fault, the three-phase current outputs will be

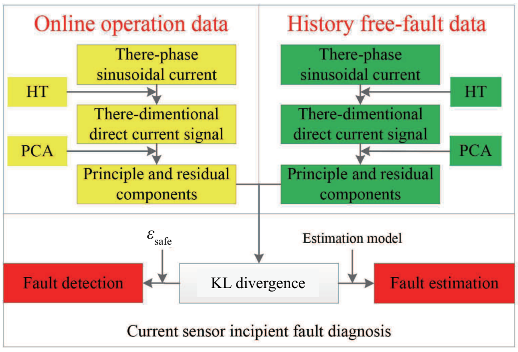

Figure 1 (Color online) The block diagram of the proposed method.

$$
\begin{aligned}
I_u^f &= (1-a)I_u^*,\\
I_v^f &= \left(1+\frac{1}{2}a\right)I_v^*,\\
I_w^f &= \left(1+\frac{1}{2}a\right)I_w^*,
\end{aligned}
\tag{1}
$$

where the variables I_u^*, I_v^*, I_w^* and I_u^f, I_v^f, I_w^f represent the estimated instantaneous amplitudes of fault-free and fault outputs, respectively. Variable a represents the amplitude of the small gain fault. Thus the data matrix with small gain fault a can be constructed as

$$\boldsymbol{X} = [I_u^f, I_v^f, I_w^f]. \tag{2}$$

Then the corresponding covariance matrix is

$$S = \frac{1}{L-1}\bar{\boldsymbol{X}}^{\mathrm{T}}\bar{\boldsymbol{X}}, \tag{3}$$

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where $\bar{\boldsymbol{X}}$ denotes the centered data matrix using free-fault data I_u^*, I_v^* and I_w^*.

Incipient fault detection. To decrease the dimension of the measured data matrix, we introduce the PCA algorithm and analyze the principal and residual components for small abnormal monitoring or incipient fault detection. Compared with the square prediction error (SPE) statistic and Hotelling's T^2 statistic, the KL divergence is more sensitive to small changes in stochastic processes. Thus, the KL divergence is used to quantitatively represent the difference between the probability density distributions of score vectors with faults and that without faults [3, 4].

Considering the influence of measurement noise or an unknown disturbance, a low nonzero divergence for real-world data exists. Therefore, a threshold $\varepsilon_{\text{safe}}$ must be set to decide whether a fault or an abnormal event has occurred because the KL divergence could be nonzero even in a healthy case. Additionally, the detection threshold $\varepsilon_{\text{safe}}$ can be determined through enormous history fault-free operating data. When the online computed KL divergence is larger than the default threshold $\varepsilon_{\text{safe}}$, it means that the process or system is affected by a fault or an abnormal event.

Incipient fault estimation. First, the first-order and second-order derivatives of the covariance matrix S are computed. Based on the Taylor expansion, the change of the kth eigenvalue of S, which is caused by small gain fault a, can be computed as

$$\Delta\lambda_k = (\boldsymbol{p}_k^*)^{\mathrm{T}}\frac{\partial S}{\partial a}(\boldsymbol{p}_k^*)a + \frac{1}{2!}(\boldsymbol{p}_k^*)^{\mathrm{T}}\frac{\partial^2 S}{\partial a^2}(\boldsymbol{p}_k^*)a^2, \qquad (4)$$

where $\boldsymbol{p}_k^*$ denotes the loading vector concerning λ_k.

Because of the central processing of $\boldsymbol{X}$, the kth eigenvalue λ_k is equal to the variance of the corresponding score vector t_k. Besides, under the assumption of Gaussian distribution, the KL divergence of the two probability density functions f_k and f_k^* can be computed using the mean and variance of the score vectors t_k and t_k^*. Then, the KL divergence of operation data between the fault-free and fault cases is computed as follows:

$$\mathrm{KL}(f_k^*, f_k) = \frac{(\Xi_1 a + 3/2\Xi_2 a^2)^2}{2\lambda_k^*(\lambda_k^* + \Xi_1 a + 3/2\Xi_2 a^2)}. \qquad (5)$$

In (4), variables Ξ_1 and Ξ_2 equal $\frac{1}{L-1}(\boldsymbol{p}_k^*)^{\mathrm{T}}\delta(\boldsymbol{p}_k^*)$ and $\frac{1}{L-1}(\boldsymbol{p}_k^*)^{\mathrm{T}}\tau(\boldsymbol{p}_k^*)$, respectively, where δ and τ denote the constant matrices computed in (4).

Assuming that the number of selected principal components is equal to d, the value of fault amplitude can be estimated theoretically using

$$\hat{a} = \frac{-\Xi_1 + \sqrt{(\Xi_1)^2 + 6\Xi_2\lambda_d^*(\mathrm{KL} + \sqrt{\mathrm{KL}^2 + 2\mathrm{KL}})}}{3\Xi_2}. \qquad (6)$$

Conclusion. This study presented a signal processing-based incipient fault diagnosis approach to realize the fault detection and estimation of current sensors in WECSs. Three-phase currents are converted into a three-dimensional direct current signal using the Hilbert transform, enabling multivariate statistical analysis. Besides, combined with the KL divergence that is sensitive to small changes, a theoretical model is established to estimate the incipient fault amplitude of current sensors.

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