Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2025 SCPE. Volume 26, Issues 3, pp. 1317–1325, DOI 10.12694/scpe.v26i3.4212

ONLINE EVALUATION OF ERROR STATE OF CURRENT TRANSFORMER BASED ON DATA ANALYSIS

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Abstract. In order to solve the problem of measurement errors being easily affected by various factors and poor stability of all fiber current transformers, the author proposes an online evaluation of the error status of current transformers based on data analysis. The author proposes a method for evaluating the error status of all fiber current transformers based on correlation analysis: collecting measurement data of three all fiber current transformers at the same measurement point in the converter station, under the constraint of electrical physical correlation, principal component fractal is applied to the measurement data of all fiber current transformers, and error evaluation is mapped to the analysis of changes in Q-statistics. The experimental results indicate that: The method proposed by the author can achieve real-time evaluation of measurement errors in all fiber current transformers, with an evaluation accuracy of up to 0.2 levels. This method greatly improves the evaluation efficiency of measurement errors in all fiber current transformers, reduces the effective power outage time of the power grid, and provides data support for the reliable operation, state prediction, and related technology improvement of all fiber current transformers.

Key words: All fiber current transformer, Measurement error, Standard transformer, Principal Component Analysis

1. Introduction. The online monitoring technology of power equipment is a method of monitoring the insulation status of high-voltage electrical equipment using operating conditions. The important feature is the use of high sensitivity sensors to collect information on the deterioration of electrical equipment insulation during operation, which can accurately monitor the insulation status of operating equipment and provide reliable guarantees for the safe operation of the power system. The secondary output signal of an all fiber current transformer includes the true state information of the primary current and its own measurement error information [1]. Using statistical analysis methods to perform correlation analysis on the secondary output signals of three all fiber current transformers at the same measurement point. Based on the changes in correlation, online evaluation of the error status of all fiber current transformers can be achieved. According to the different analysis objects and application scenarios, correlation analysis methods include binary variable correlation analysis, regression analysis, correlation analysis, and cluster analysis [2].

The ultra-high voltage direct current transmission system has the characteristics of high voltage and large load. The accurate acquisition of primary voltage and current signals is the basis for ensuring the safety, stability, and economic operation of the ultra-high voltage direct current transmission system. The high voltage and high load operation requirements also put forward higher requirements for the reliability and stability of DC measurement equipment. At present, DC measurement equipment mainly includes all fiber current transformers, zero flux current transformers, and DC voltage dividers. Among them, all fiber current transformers have the highest configuration proportion in ultra-high voltage DC transmission systems, exceeding 90%. The current method used for error evaluation and detection of measurement equipment in substations, such as transformers, is the comparison and calibration of standard equipment [3,4]. Because standard equipment has high requirements for operating environment, the method of comparing and calibrating with standard equipment needs to be carried out regularly under power outage conditions in substations. The impact of measurement error changes in all fiber optic current transformers on other equipment in the converter station,

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especially energy metering is a long-term cumulative process. However, the essence of regular testing is to conduct a time-domain sampling evaluation of the error status of all fiber current transformers. The testing results have a high degree of randomness. When the measurement error of all fiber current transformers changes during maintenance, this method cannot detect it in a timely manner, and there is a lag in the error detection of all fiber current transformers. On the other hand, all fiber current transformers are mainly used in ultra-high voltage converter stations, with high voltage levels and high primary currents, which also require higher standards. The method of comparing and testing with standards requires a lot of financial and material resources, and has poor economic efficiency. Therefore, it is necessary to conduct online evaluation of the error status of all fiber current transformers without standard equipment, in order to timely detect the deterioration trend of equipment error status [5,6].

2. Literature Review. As a key equipment for current signal sensing in DC transmission systems, accurate measurement of the primary signal is the most critical parameter indicator for measuring the status of all fiber optic current transformers. The accuracy of secondary measurement data from all fiber optic current transformers can be compromised or fail due to performance degradation or failure in any component of the equipment[7]. For instance, Chakraborty, S. S. et al. introduced an enhanced approach that integrates inductance and capacitance within the LVDC bus. This innovative filter diminishes the root mean square (RMS) value of the high-frequency (HF) link current by 29% under conditions of unity power factor operation[8]. Zhao, J. et al. proposed a frequency domain simulation method that does not require circuit synthesis. By combining fast and slow pulse tests, the transmission characteristics of three types of windings in 1000kV GIS CT were cleverly measured. Through disturbance simulation of ultra-high voltage substations, it was found that the radiation loss of the casing has a suppressive effect on high-frequency response, but the influence of frequency related ground impedance can be ignored. Therefore, it is recommended to use a fast damping oscillation wave immunity test not lower than IEC standard level 4 to test the anti-interference performance of secondary equipment in ultra-high voltage substations [9]. Chen et al. presented the harmonic specifications for power system transformers along with the fundamentals of Rogowski coil electronic current transformers. They outlined a straightforward and effective technique for measuring harmonics using Rogowski coil electronic current transformers, and evaluated their performance using high-precision harmonic sources, standard current transformers, and transformer calibrators. The findings demonstrate that this approach offers robust applicability, ease of use, and significantly broadens the spectrum of available harmonic measurement methodologies[10].

In essence, due to the unpredictable nature of power system node conditions within intricate operational settings, existing methodologies fall short in accurately assessing measurement errors across all fiber optic current transformers. To address this challenge, the author suggests an error state assessment approach for all fiber current transformers utilizing correlation analysis. By scrutinizing error patterns in the output signals of all fiber current transformers and leveraging the redundant structural setup characteristic of such transformers in ultra-high voltage converter stations. Data is collected simultaneously from three transformers at identical measurement points within the station. Adhering to electrical-physical correlation constraints, principal component fractal analysis is conducted on the transformer data, with error evaluation mapped to changes analyzed through Q-statistics. Data analysis shows that the method proposed by the author can achieve real-time evaluation of measurement errors in all fiber current transformers, with an evaluation accuracy of up to 0.2 levels. The author's research findings can be extended to the state diagnosis and online evaluation of measurement errors in other DC measurement equipment, and can promote the development of error detection mode in DC measurement equipment from regular passive detection to real-time active self detection [11].

3. Research Methods.

3.1. Error Evaluation Model. Under normal operation, there is a certain deviation between the secondary measurement data of the full fiber current transformer and the true information of the observed primary current signal. This deviation value will be compared and calibrated with standard equipment before the full fiber current transformer is put into operation. It is usually small and stable, and can meet the requirement of 0.2 level measurement accuracy at most. Its mathematical expression can be expressed as follows:

$$x_{ft} = kI_{ft} + v_{ft} + s_{fx} \tag{3.1}$$

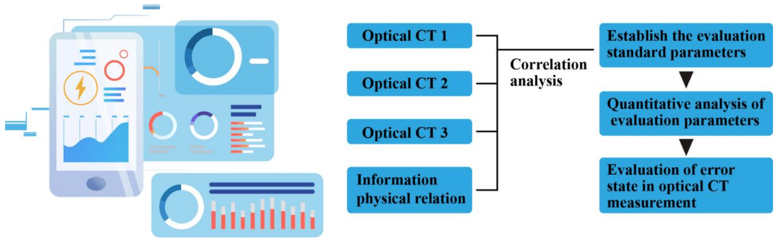

Fig. 3.1: Error evaluation model for all fiber optic current transformers

In equation 3.1, x_{ft} represents the secondary measurement information of the all fiber current transformer; I_{ft} is the observed primary current signal; k is the transmission coefficient of the all fiber current transformer; v_{ft} and s_{fx} are the random errors and systematic errors of all fiber current transformers, respectively. Among them, the random error v_t belongs to a type of free noise, usually satisfying a Gaussian distribution, while the system error s_x is determined by the performance structure of the all fiber current transformer.

$$\begin{cases} x_{1ft} = k_1 I_{ft} + v_{f1t} + s_{f1x} \\ x_{2ft} = k_1 I_{ft} + v_{f2t} + s_{f2x} \\ x_{3ft} = k_3 I_{ft} + v_{f3t} + s_{f3x} \end{cases} \tag{3.2}$$

When three all fiber current transformers operate normally at the same measurement point, the fluctuation of the secondary output signal is mainly due to the normal fluctuation of the next current signal under the influence of the load, that is, the secondary output signal of the three all fiber current transformers is linearly correlated. Therefore, the linear correlation between the secondary output signals of three all fiber current transformers during the initial calibration and operation can be used as the evaluation benchmark. By conducting correlation analysis on the secondary output signals of three all fiber current transformers at the same measurement point, the normal fluctuation of the primary current signal can be separated from the signal deviation caused by the error changes of the all fiber current transformers. By using numerical analysis methods to statistically analyze the error information after peeling, online evaluation of the error status of three sets of all fiber current transformers can be achieved [12]. The error state evaluation model for all fiber current transformers based on correlation analysis is shown in Figure 3.1.

3.2. Basic Principles of Principal Component Analysis. The calculation process of principal component analysis is to collect $X \in \Phi^{n\times 3}$ operating data samples from three all fiber current transformers at the same measurement point, where n is the number of measurement data samples. Decompose the data matrix X

$$X = \hat{X} + E = TP^T + T_e P_e^T \tag{3.3}$$

In equation 3.3, $\hat{X} = TP^T$ represents the principal subspace of the data, which includes the fluctuation information of the primary current under the influence of load; $E = T_e P_e^T$ is the residual subspace of the data, which contains the fluctuation information of measurement errors of all fiber current transformers.

The matrices P and Pe can be obtained by performing singular value decomposition on the covariance matrix R of the running data

$$R = X^T X/(n-1) = [P_1 P_2 P_3] \bigwedge [P_1 P_2 P_3]^T \tag{3.4}$$

In equation 3.4 $\bigwedge = diag(\lambda_1, \lambda_2, \lambda_3)$ and $\lambda_1 \geqslant \lambda_2 \geqslant \lambda_3$ are the eigenvalues of the covariance matrix R; $[P_1 P_2 P_3]$ is the corresponding feature vector. The larger the eigenvalue, the stronger the correlation between the data.

For the online evaluation requirements of the error status of three all fiber current transformers under the same measurement point studied by the author, the secondary measurement data of all fiber current transformers mainly includes: fluctuation information of primary current under load influence and fluctuation

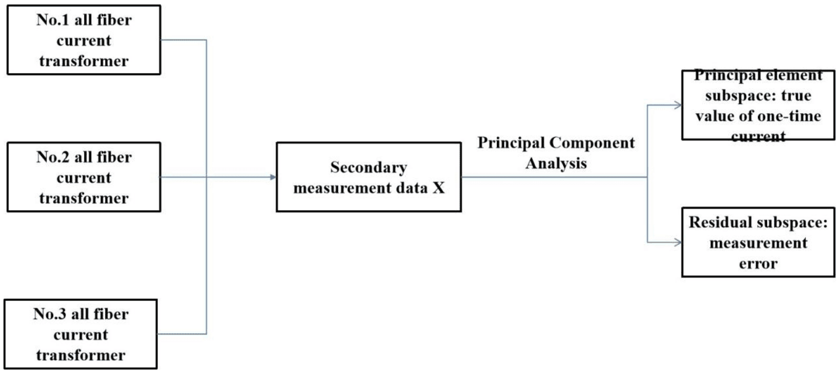

Fig. 3.2: Error detection of all fiber optic current transformers based on principal component analysis

information of measurement error of all fiber current transformers under multiple factors influence. When all components of the fiber optic current transformer are operating normally, the change in measurement error is much smaller than the fluctuation information of the next current affected by the load. By employing principal component analysis (PCA) to break down the measurement data gathered from three all fiber current transformers stationed at identical measurement points, the resulting principal component subspace embodies the genuine essence of the primary current signal. Meanwhile, the residual subspace encapsulates the error-related details stemming from the all fiber current transformers. Figure 3.2 illustrates the error detection process of these transformers facilitated by principal component analysis. For the all fiber current transformer studied by the author, the residual subspace is $P_e = [P_2 P_3]$.

3.3. Calculation of evaluation threshold. According to the above analysis, it can be concluded that using principal component analysis to analyze the measurement data of three sets of all fiber current transformers, the relevant information of measurement errors will be projected into the residual subspace. The degree of deviation in the measurement error of the full fiber current transformer can be determined by calculating the Q-statistic of the operating data in the residual subspace. The calculation method for Q-statistic is

$$Q = (XP_eP_e^T)(XP_eP_e^T)^T = XP_eP_e^TX^T \leqslant Q_c \tag{3.5}$$

In equation 3.5, Q_c is the statistical threshold with a significance level of α. When the Q statistic is greater than this value, it indicates that there is abnormal fluctuation in the measurement error of the all fiber current transformer, which can be calculated according to equation 3.6

$$Q_c = \theta_1 \left[\frac{C_\alpha \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1} \right]^{\frac{1}{h_0}} \tag{3.6}$$

In equation 3.6: $\theta_i = \sum_{j=\alpha+1}^{3} \lambda_j^i (i = 1, 2, 3)$;$h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2^2}$; C_α is the critical value of a normal distribution at a detection level of α.

When there is no fluctuation in the measurement error of all fiber optic power transformers, the expected value of the Q-statistic for the measurement data of three sets of all fiber optic current transformers is

$$E(Q) = trE\{I_iP_eP_e^T[I_iP_e]^T\} \tag{3.7}$$

When the error fluctuation of a certain all fiber current transformer is f_i, the mathematical model of the process operation data is

$$X_{fti} = kU_iI_{ti} + U_if_i \tag{3.8}$$

In equation 3.8, U_i is the column vector corresponding to the identity matrix. When the error of an all fiber current transformer at the same measurement point experiences abnormal fluctuations, the expected value of the Q-statistic in the residual subspace of the operating data changes as follows:

$$\Delta E(Q) = E(f_i^2)||P_{ei}||^2 \tag{3.9}$$

According to equation 3.9, when the measurement error of the all fiber current transformer undergoes abnormal changes, the Q-statistic of the measurement data of three all fiber current transformers at the same measurement point will increase, which is positively correlated with the square of the expected error value. Therefore, the state evaluation of measurement errors can be achieved by calculating the Q-statistic of the measurement data of three all fiber current transformers at the same measurement point.

3.4. Anomaly identification methods. When the Q-statistic of the process operation data of an all fiber current transformer exceeds its statistical control threshold Q_α, it indicates that the measurement error of a certain all fiber current transformer has experienced abnormal fluctuations. At this point, it is necessary to further determine which all fiber current transformer has experienced abnormal fluctuations. The contribution plot method is usually used for judgment [13,14].

When the Q-statistic exceeds its threshold, the contribution rate of the measurement data X_o^i of the i-th all fiber current transformer to the Q-statistic is

$$Q_i = e_i^2 = (X_i - \hat{X}_i)^2 \tag{3.10}$$

In equation 3.10, Xi is the column vector corresponding to the measurement data matrix; The column vector corresponding to the main element subspace data matrix of $\hat{X}_i$.

3.5. Error Evaluation Process. Based on the above content, the evaluation process of the error status of three all fiber current transformers at the same measurement point in the converter station using principal component analysis is shown in Figure 3.3. The specific steps are as follows:

1. Collect secondary measurement data of three all fiber current transformers at the same measurement point after calibration and operation, and obtain the process operation data matrix X;
2. Perform singular value decomposition on the data matrix and calculate its eigenvalues $\lambda_1, \lambda_2, \lambda_3$ and its corresponding eigenvectors $[PP_e]$;
3. Selection test confidence α (generally selectable) α= 0.99), calculate the statistical threshold Qc of the Q-statistic according to formula 3.6.
4. Collect secondary measurement data of three all fiber current transformers at the same measurement point during operation, and calculate the Q-statistic of process information according to equation 3.5. If it is less than the statistical threshold Q_c, it indicates that the three all fiber current transformers at the same measurement point to be evaluated are in normal operation; If it is greater than the statistical threshold Q_c, it indicates that there is an abnormal fluctuation in the error state of the all fiber current transformer at this time [15].
5. When the Q-statistic of three all fiber current transformers under the same measurement point to be evaluated exceeds the statistical threshold Q_c, calculate the contribution rates according to equation 3.10, identify the all fiber current transformers with abnormal error fluctuations, and guide relevant personnel in operation, maintenance, and repair work.

3.6. Simulation analysis. Considering that all fiber current transformers are currently mainly used in ultra-high voltage direct current transmission systems with large capacity and high voltage levels, the economic feasibility of conducting error experiments on all fiber current transformers in the laboratory is poor. The author mainly uses numerical simulation methods to analyze and verify the proposed method. At present, the all fiber current transformers in ultra-high voltage converter stations mainly adopt a digital closed-loop technology route, which mainly includes two parts: optical path and detection circuit. The structural schematic diagram of the all fiber current transformer is shown in Figure 3.4. The primary current I(t) forms interference based on the Faraday effect. After photoelectric conversion, signal conditioning, digital to analog conversion, and value

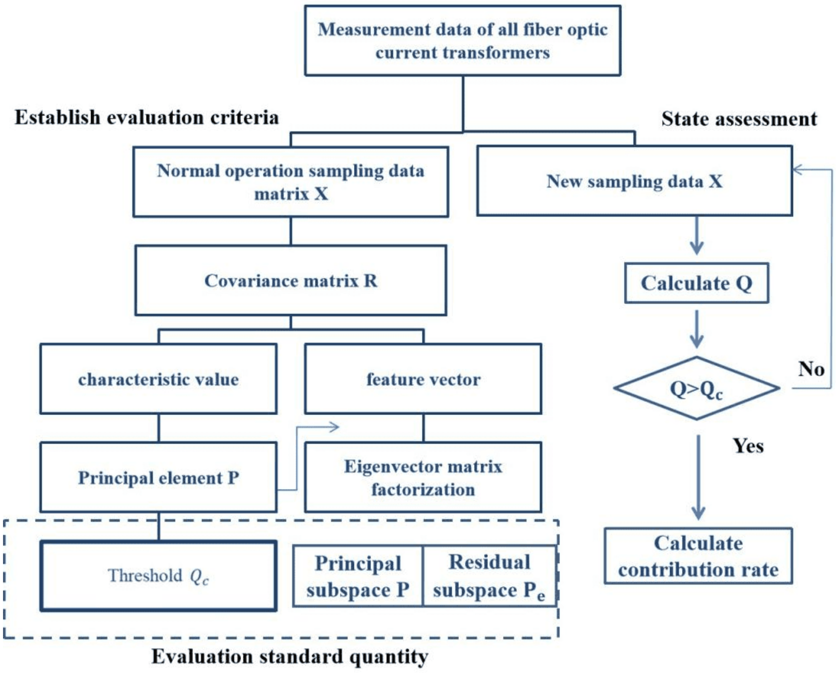

Fig. 3.3: Evaluation process for measurement error of all fiber optic current transformers

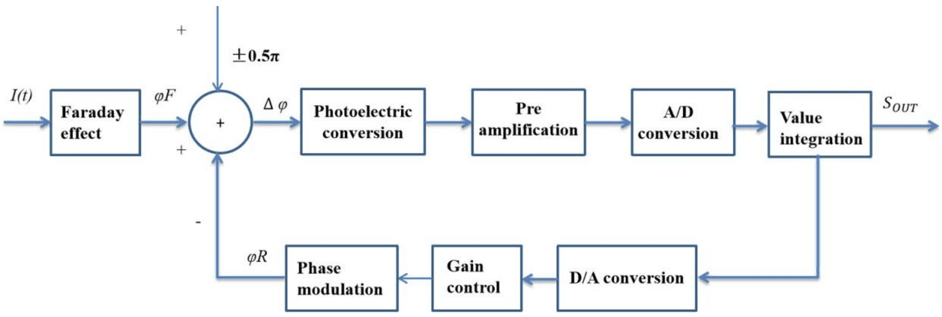

Fig. 3.4: Structural schematic diagram of an all fiber current transformer

integration, a closed-loop feedback signal is formed to compensate for the electro-optic phase feedback, in order to output accurate primary current information [16].

The signal transmission process diagram of the all fiber current transformer is shown in Figure 3.5. Among them, the Faraday magneto optic effect of a single current can generate a phase angle difference process, which can be represented by a proportional coefficient K_f=4NV (N is the number of turns of the sensing fiber, V is the Verdet constant of the sensing fiber). The photoelectric conversion process can be equivalent to a proportional link, with a proportional coefficient of K_1 and a proportional coefficient of K_2 for the preamplifier circuit, the proportional coefficient of the A/D conversion circuit is $K_{AD} = 2^n/U_{ref}$ (n represents the conversion bits of AD, Uref is the reference voltage of the A/D converter), the z-transformation of the value integration is 1/(1-z^{-1}), the proportional coefficient of the D/A converter is K_4, the post gain coefficient is K_5, and the phase modulation is a differential process, its transmission process can be equivalent to $K_m(1 - z^{-1})$. The simplified process flowchart is shown in Figure 3.6.

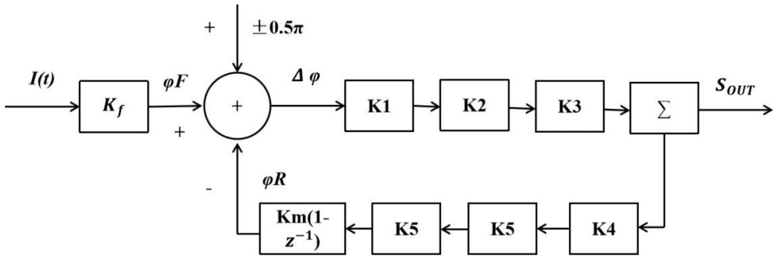

Fig. 3.5: Signal transmission process diagram of full fiber current transformer

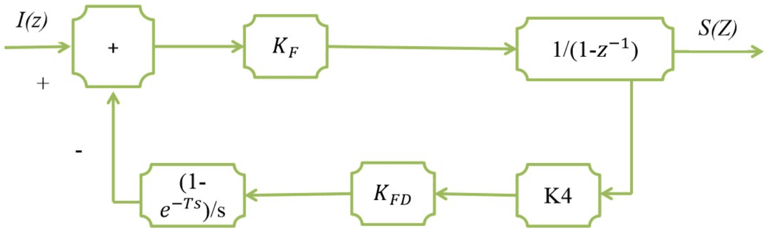

Fig. 3.6: Simplified signal transmission flowchart

In Figure 3.6:

$$K_F = K_f \cdot K_1 \cdot K_2 \cdot K_3 \tag{3.11}$$

The closed-loop transfer function of the all fiber current transformer can be obtained from Figure 3.6 as

$$\frac{S(z)}{I(z)} = \frac{K_F z}{(1 + K_{FD} K_F) z - 1} \tag{3.12}$$

By adjusting the conversion coefficients of various components in the signal transmission system of the all fiber current transformer, various error degradation states of the all fiber current transformer can be simulated [17,18]. The key factor affecting the accuracy of error evaluation for all fiber current transformers under the condition of no standard transformer is the non-stationary time-varying characteristics of the primary current at the node. It is necessary to analyze and verify the method proposed by the author based on the measured data during the operation of all fiber current transformers. The author selected the actual measurement data of a newly calibrated and put into operation all fiber current transformer at a certain converter station (this series of all fiber current transformers has 5 fiber optic sensing turns, 16 A/D conversion bits, and 16 D/A converter bits, resulting in K_F=0.178 and K_{FD}=1.021) for analysis. Simultaneously collect process operation data of three all fiber current transformers at the same measurement point of the converter station. The sampling frequency of this series of all fiber current transformers is 10kHz. The amplitude information of the measurement data is calculated every second, and the average amplitude information of the measurement data during this time period is calculated every 10 minutes. As a sampling point, a total of 7300 sampling points are obtained.

4. Results and Discussion.

4.1. Analysis of Normal Operation Status. According to equation 3.13, calculate three sets of measurement data for simulating all fiber current transformers, and use the first 1000 sets of process operation data as training data to establish an error evaluation model for all fiber current transformers. Use PCA for data analysis, and the model parameters can be obtained as shown in Table 4.1.

Table 4.1: Principal Component Model Parameters

Confidence level	Principal element number	Main component proportion/%	Statistical control threshold	Expected value of statistics
0.99	1	98.8037	0.1402	0.0406

An error state evaluation was conducted on the secondary output data of the three simulated all fiber current transformers mentioned above. The process monitoring of the Q-statistic resulted in abnormal amplitude data accounting for 5.04%, respectively. When considering the Q-statistic and its threshold calculation, the concept of confidence was introduced, and the proportion of abnormal data was randomly distributed. It can be considered that the measurement error of the all fiber current transformer did not fluctuate, which is consistent with the actual situation of the newly calibrated and put into operation of the all fiber current transformer [19].

4.2. Error Analysis. By adjusting the proportion coefficient of the preamplifier circuit of the first all fiber current transformer, a fixed deviation of 0.2% is achieved in its output. Referring to equation 3.13, the measurement data of three sets of simulated all fiber current transformers are calculated accordingly. The error in the secondary measurement data of these transformers is then evaluated, with the process of Q-statistics monitoring. It's observed that the Q-statistic of all three all fiber current transformers surpasses their statistical control limit, indicating an abnormal alteration in their measurement error. Utilizing equation 3.10, the contribution rate of the secondary measurement data from the three transformers to the Q-statistic is computed. Notably, the first all fiber current transformer exhibits the highest contribution to the Q-statistic, suggesting a change in its measurement error, aligning with the real scenario. This method proposed by the author enables accurate evaluation of the measurement error of all fiber current transformers without the reliance on standard devices. The highest evaluation accuracy can meet the evaluation requirements for measurement errors of 0.2 level all fiber current transformers [20].

5. Conclusion. The author proposes an online evaluation of current transformer error status based on data analysis (online monitoring of measuring current transformers). Drawing from an examination of the error traits of all fiber optic current transformers and their deployment specifics within ultra-high voltage converter stations, a novel long-term online monitoring approach for measuring their errors is suggested, grounded in correlation analysis. Initially, the method employs principal component analysis to conduct correlation analysis on the measurement data from three all fiber current transformers stationed at identical measurement points within the converter station. The error fluctuation information of the transformers themselves and the primary current fluctuation information caused by the load are separated, and standard statistics are constructed using normal measurement data for real-time monitoring of all fiber current transformers. Collect actual measurement data of all fiber optic current transformers at the converter station and conduct error simulation analysis. The results show that, this method can quickly evaluate the deterioration status of measurement errors in all fiber current transformers, with a recognition accuracy of up to 0.2 levels. This method greatly improves the evaluation efficiency of measurement errors in all fiber current transformers, reduces the effective power outage time of the power grid, and provides data support for the reliable operation, state prediction, and related technology improvement of all fiber current transformers.

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Edited by: Bradha Madhavan
Special issue on: High-performance Computing Algorithms for Material Sciences
Received: Jun 28, 2024
Accepted: Aug 7, 2024