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# Identification of Sensor Fault Characteristics Based on Adaptive Kernel Principal Component Analysis

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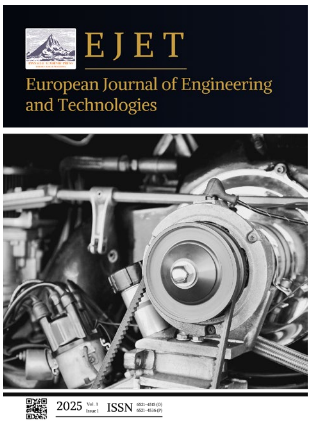


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**Abstract:** With the ongoing advancement of industrial automation towards higher levels of intelligence, such as increased use of machine learning and artificial intelligence for process optimization, multidimensional monitoring and real-time fault diagnosis of complex industrial processes have emerged as critical challenges for ensuring the reliable operation of production systems and the consistent quality of products. Among multivariate statistical process monitoring approaches, conventional Principal Component Analysis (PCA) is inherently constrained by its linear projection mechanism, leading to significant performance degradation when addressing process data exhibiting nonlinear characteristics. To overcome this limitation, this study proposes an Adaptive Kernel Principal Component Analysis (AKPCA) method based on kernel space mapping. By utilizing Mercer kernel functions, the original process data is nonlinearly mapped into a Reproducing Kernel Hilbert Space (RKHS), thereby enhancing the separability of nonlinear features. Furthermore, a two-tier fault diagnosis framework is established: the first tier employs an adaptive KPCA model integrated with a sliding window mechanism for fault detection, while the second tier utilizes a Contribution Analysis (CA) algorithm for fault source identification. To validate the robustness of the proposed method, we simulate four representative types of faults — bias faults, complete failures, offset faults, and precision degradation. Experimental results substantiate that the adaptive KPCA approach not only accurately detects faults but also effectively localizes fault sources through contribution analysis.

**Keywords:** Kernel Principal Component Analysis (KPCA); fault detection; contribution analysis; sensor fault diagnosis

## 1. Introduction

The increasing demand for quality monitoring and safe operation of industrial processes over the past decades has continuously driven the advancement of fault detection and diagnosis (FDD) methodologies. As a representative of data-driven techniques, multivariate statistical methods have been widely applied in this domain, including Principal Component Analysis (PCA), Partial Least Squares (PLS), and the emerging Independent Component Analysis (ICA), among others [1-8]. Among these, PCA has become the most mainstream solution in process monitoring due to its ability to project high-dimensional noisy data onto a low-dimensional subspace that retains the major variance.

However, there exists an inherent contradiction between the linear nature of conventional PCA and the nonlinear characteristics of industrial systems, prompting researchers to explore nonlinear extensions such as kernel methods. Kernel Principal Component Analysis (KPCA) achieves this by mapping data into a high-dimensional feature space via nonlinear kernel functions and performing PCA in that space, thus addressing a wide range of nonlinear scenarios through an eigenvalue decomposition. Although KPCA has demonstrated great potential in monitoring applications, it still suffers from two critical limitations:

1) model construction requires storing a symmetric kernel matrix whose size depends on the number of reference samples, resulting in increased computational complexity as the sample size grows.
2) static models are unable to adapt to system dynamics, potentially leading to false alarms.

Specifically, a KPCA model with fixed parameters may incur significant monitoring errors due to gradual process parameter drifts.

To overcome these shortcomings, such as the limitations of static models in adapting to process dynamics, adaptive methodologies have garnered increasing attention in recent years. The adaptive KPCA approach proposed in achieves fault diagnosis by dynamically updating monitoring statistics [9]. Existing adaptive frameworks can be broadly categorized into two types: real-time updating mechanisms for the kernel matrix and adaptive control chart strategies (such as adaptive Hotelling's $T^2$ statistics), both of which have demonstrated superior statistical performance compared to traditional static methods.

This research introduces an innovative fault detection and isolation approach for nonlinear and time-varying systems, extending the adaptive control chart concept through the use of kernel principal component analysis (KPCA). The method distinguishes itself by embedding multivariate exponentially weighted moving average (MEWMA) techniques to capture shifts in the process mean, and by merging this predicted drift information with KPCA-derived principal components to formulate monitoring statistics that better adapt to dynamic system behavior.

## 2. Adaptive KPCA-Based Process Monitoring Method

Kernel Principal Component Analysis (KPCA), as a nonlinear extension of Principal Component Analysis (PCA), fundamentally aims to project the original data into a high-dimensional feature space $H$ via a nonlinear mapping $\emptyset$ , followed by performing linear PCA in this transformed space.

Let us denote a dataset consisting of samples $x_j \in R^{1\times n}$, where $j = 1,\dots,M$ with $M$ indicating the number of total observations. The associated covariance matrix $C \in R^{M\times M}$ within the feature space is given by:

$$C = \frac{1}{M}\sum_{j=1}^{M} \emptyset(x_j)\emptyset^{\mathrm{T}}(x_j) \tag{1.1}$$

Here, $x_j$ represents the *j*-th data point in the feature space, where the data has been standardized to have a mean of zero and a variance of one. The eigenvalues and eigenvectors corresponding to the covariance matrix C in this space can be obtained by solving the following eigenvalue decomposition problem:

$$\lambda_k v_k = C v_k \tag{1.2}$$

Where $\lambda_k \in R$and $v_k \in R^{M\times 1}$ represent the *k*-th eigenvalue and its associated eigenvector. A collection of real-valued coefficients $\alpha_k^i \in R$, with $i = 1,\dots,M$, such that:

$$v_k = \sum_{i=1}^{M} \alpha_k^i \emptyset^{\mathrm{T}}(x_j) \tag{1.3}$$

Since directly accessing $\emptyset(x)$ is typically infeasible, the eigenvalue decomposition of the covariance matrix $C$ is instead reformulated through the use of the Gram kernel matrix $K \in R^{M\times M}$, which is defined as:

$$[K]_{ij} =< \emptyset(x_i), \emptyset(x_j) >= k(x_i, x_j) \to i, j = 1,\dots,M \tag{1.4}$$

Due to this fundamental property, the inner product in the feature space can be evaluated indirectly via a suitable kernel function $k(x,y) = \langle(\emptyset(x_i), \emptyset(x_j))\rangle$ defined in the input domain. Commonly adopted kernel functions include the polynomial kernel, sigmoid kernel, and radial basis function ($RBF$) kernel, each of which adheres to Mercer's theorem.

Prior to performing Kernel PCA (KPCA), it is necessary to center the data in the feature space. This can be accomplished by substituting the kernel matrix $K$ with:

$$\widetilde{K} = K - 1_M K - K 1_M + 1_M K 1_M \tag{1.5}$$

Where:

$$1_M = \frac{1}{M}\begin{bmatrix} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \end{bmatrix} \in R^{M \times M} \tag{1.6}$$

The ultimate step in the KPCA approach involves solving the following eigenvalue problem:

$$M\lambda\alpha = \widetilde{K}\alpha \tag{1.7}$$

For the standard orthogonal eigenvectors $\alpha_1, \alpha_2, \ldots, \alpha_M$ and the corresponding eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_M$, dimensionality reduction is performed by preserving the top d eigenvectors. The selection of the number of principal components to retain is guided by the following criterion:

$$\frac{\sum_{k=1}^{d} \lambda_k}{\sum_{j=1}^{M} \lambda_i} \times 100 \geq thc, d < M \tag{1.8}$$

In the equation, $thc$ represents a threshold specified by the user, typically given as a percentage.

For each $k = 1, \ldots, d$, the $j$-th principal component score of a new sample $x \in R^{1 \times n}$ is computed by projecting $t_k(x)$ onto the corresponding eigenvector $v_k$ within the feature space $F$, as shown below:

$$t_k(x) = \langle v_k, \emptyset(x) \rangle = \sum_{i=1}^{M} \alpha_k^i \langle \emptyset(x_i), \emptyset(x) \rangle \tag{1.9}$$

In the equation, $\alpha_i^k$ represents the *i*-th component of the eigenvector $\alpha_k$.

To monitor system health, Hotelling's $T^2$ is commonly used to monitor the system portion of the dataset, defined as:

$$T^2(x) = [t_1(x), \ldots, t_d(x)] \Lambda^{-1} [t_1(x), \ldots, t_d(x)]^T \tag{1.10}$$

In the equation, $\Lambda = diag(\lambda_1, \ldots, \lambda_d)$, the $100(1-\beta)\%$ confidence level of $T^2$ can be determined by the $F$-distribution.

$$T_{lim}^2 = \frac{d(M-1)}{M-d} F_{d,M-d,\beta} \tag{1.11}$$

Where $F_{d,M-d,\beta}$ denotes the critical value from the F-distribution at a confidence level $\beta$, with degrees of freedom $(d, M-d)$, respectively.

Hotelling's $T^2$ statistic, as a classical multivariate process monitoring indicator, has been widely applied in the field of industrial fault detection and diagnosis. This statistic effectively identifies abnormal changes in the system's operational state by analyzing the covariance structure between process variables. In practical implementation, when the $T^2$ statistic obtained from online monitoring exceeds the preset control limits, the system can determine that a fault condition exists. The determination of control limits requires a balance between the false alarm rate (Type I error) and the missed detection rate (Type II error), and is typically optimized based on the statistical distribution characteristics of normal operating condition data, combined with hypothesis testing theory.

Equation (1.10) shows that the traditional KPCA monitoring statistic is based solely on the sum of squared score vectors of the current sample (i.e., the $T^2$ statistic) for process monitoring, without fully considering the directional information of potential mean shifts in dynamic industrial processes. This inherent flaw leads to the traditional method being sensitive only to significant process shifts, while having limited ability to detect gradual, small faults. To overcome this limitation, this paper proposes a novel adaptive KPCA monitoring statistic, which is innovative in three main aspects: first, by constructing an augmented data matrix to effectively represent the dynamic characteristics of the process; second, by using whitening transformation to process kernel principal components, so that the transformed covariance matrix has the properties of a unit matrix; and third, by utilizing a multivariate exponentially weighted moving average (MEWMA) technique that incorporates dynamic weights to reflect temporal process changes, thereby facilitating the development of an adaptive aggregated monitoring statistic.

To analyze the temporal behavior of the process, the initial step involves extending each observation vector by concatenating it with the preceding $l$ observations, so that:

$$x_k^l = [x_k, x_{k-1}, \ldots, x_{k-l}] \in R^{1 \times m(l+1)} \tag{1.12}$$

Where $x_k$ is within the range of sample $k(k = 1,\dots,M)$. Then, the augmented data matrix is generated as:

$$X^l = \begin{bmatrix} x_{l+1}^l \\ x_{l+2}^l \\ \vdots \\ x_M^l \end{bmatrix} = \begin{bmatrix} x_{l+1} & x_l & \cdots & x_1 \\ x_{l+2} & x_{l+1} & \cdots & x_2 \\ \vdots & \vdots & \ddots & \vdots \\ x_M & x_{M-1} & \cdots & x_{M-1} \end{bmatrix} \quad (1.13)$$

The dataset should be standardized to have a mean of zero and a variance of one. Notably, an automatic method for selecting the parameter $l$ has been introduced in prior work, where it has been shown that setting $l = 1 \ or \ 2$ is generally adequate to capture the changing dynamics of the majority of processes [10].

The radial basis kernel transformation matrix $X^l$ undergoes eigenvalue decomposition, and the centered kernel matrix $\widetilde{K} \in R^{(M-l)\times(M-l)}$ can subsequently be calculated using the following equation (1.5). The largest $d$ eigenvalues (denoted as $\Lambda = diag(\lambda_1,\dots,\lambda_d) \in R^{d\times d}$) and the corresponding eigenvectors (denoted as $H = [\alpha_1,...,\alpha_d] \in R^{(M-1)\times d}$) can be retained, which are obtained using the empirical criterion from equation (1.8).

The radial basis kernel transformation matrix $X^l$ undergoes eigenvalue decomposition, after which the mean-adjusted kernel matrix $\widetilde{K} \in R^{(M-l)\times(M-l)}$ is calculated according to equation (1.5). The top ddd eigenvalues, arranged in the diagonal matrix $\Lambda = diag(\lambda_1,\dots,\lambda_d) \in R^{d\times d}$ ), along with their associated eigenvectors $H = [\alpha_1,...,\alpha_d] \in R^{(M-1)\times d}$, are selected based on the empirical rule given in equation (1.8).

Furthermore, to transform the data toward a Gaussian distribution, the high-dimensional data must first be whitened and subsequently mapped onto the unit sphere through normalization. The whitened KPCA score vector $z_k$ for a given test sample $x$ can be computed using the following expression:

$$z_k(x) = \sqrt{M}\Lambda^{-1}H^T\left[\tilde{k}(x_1,x),\dots,\tilde{k}(x_M,x)\right]^T \quad (1.14)$$

This ensures that $z_k(x) \in R^d$ satisfies $E\{z_k(x)z_k^T(x)\} = I$, where its covariance matrix is the identity matrix.

As theoretical analysis shows, traditional KPCA monitoring methods construct monitoring statistics based solely on the instantaneous sample amplitude information (i.e., $T^2$ statistic), without effectively integrating the directional features of process mean shifts. In the case of missing prior information in multivariate process monitoring (especially when the direction of process shifts is unknown), based on multivariate statistical process control (MSPC) theory, it is recommended to use the following standard form of the Hotelling's $T^2$ control chart:

$$T^2(x) = z_k^T(x)z(x) > c \quad (1.15)$$

Here, $c$ represents the control threshold. When the statistic $T^2$ surpasses this threshold, it indicates the presence of a fault within the system.

If the direction of the process mean shift is identified, the multivariate control chart is adaptable to various types of shift patterns. Assuming the process mean changes from the initial value $\mu_0 = 0$ to a targeted shift $\mu_1 = m$, the associated statistical hypothesis test can be formulated as follows:

$$\begin{cases} H_0: \mu = 0 \\ H_1: \mu = m \end{cases} \quad (1.16)$$

Here, $\mu$ denotes the process mean, while $m$ indicates the anticipated shift. To evaluate the hypothesis, a likelihood ratio test is employed, with the likelihood function $f(z_k|\mu)$ defined as follows:

$$\Gamma_k = \frac{f(z_k|H_1)}{f(z_k|H_0)} = exp\left(m^T z_k(x) - \frac{1}{2}m^T m\right) \quad (1.17)$$

Where $f(.|.)$ represents the pmf, which is specified at $z_k(x)$ for the actual observations of $\mu$. By taking the natural logarithm of (17), the following expression can be derived:

$$L_k = \ln\left(\frac{f(z_k|H_1)}{f(z_k|H_0)}\right) = m^T z_k(x) - \frac{1}{2}m^T m \quad (1.18)$$

Using the likelihood ratio above, the following statistic is derived:

$$T^2(x) = m^T z_k(x) - \frac{1}{2}m^T m > c \quad (1.19)$$

Since $m$ is a constant value, it can be rewritten as:

$$T^2(x) = m^T z_k(x) > c' \quad (1.20)$$

Where:

$$c' = c + \frac{1}{2} m^T m \quad (1.21)$$

The obtained $T^2$ chart is designed for scenarios where the process shift remains constant. That is, after a change occurs, both its size and direction are assumed to be fixed and known. In practical industrial settings, however, such shifts are typically unknown and may vary over time. Consequently, investigating the effectiveness of the $T^2$ chart when drift information is unavailable is highly important.

By modeling the shift as an offset occurring at sample $k$, the control chart evaluates the process condition at each sample point through testing the following hypothesis:

$$\begin{cases} H_0: \mu = 0 \\ H_1: \mu = m_k \end{cases} \quad (1.22)$$

Similar to the constant shift, a new statistical chart can be obtained as follows:

$$AT^2(x) = m^T z_k(x) - \frac{1}{2} m^T m > c \quad (1.23)$$

Continuous updating and repeated application of the control chart to the multivariate process leads to improved expected performance. Because the true mean shift evolves over time, the estimated mean shift is recursively updated with incoming data, thereby rendering the process adaptive.

The SPE is defined as follows:

$$SPE = \left\| \emptyset(x) - \emptyset_p(x) \right\|^2 \quad (1.24)$$

In the equation, $\emptyset(x)$ is the sum of the products of the score vectors and corresponding eigenvectors for all non-zero eigenvalues, which simplifies to:

$$SPE = \sum_{j=1}^{n} t_j^2 - \sum_{j=1}^{p} t_j^2 \quad (1.25)$$

In the equation, $n$ represents the number of non-zero eigenvalues, and $p$ is the number of principal components. The confidence limit of the SPE can be calculated based on its approximate distribution:

$$\mathrm{SPE}_\alpha \sim g\chi_h^2 \quad (1.26)$$

In the equation, $\alpha$ represents the significance level, and $g$ and $h$ denote the weight parameter and degrees of freedom of the $SPE$, respectively. Assuming $a$ and $b$ are the estimated mean and variance of the $SPE$, $g$ and $h$ can be approximated as $g = b/2a$ and $h = 2a^2/b$. Similar to the PCA method, the $SPE$, which is frequently used in sensor fault diagnosis, is selected as the monitoring index here.

Since the positioning accuracy of the angle sensors has a significant impact on system performance, this study employs a dynamic balance model based on Kernel Principal Component Analysis (KPCA) for fault diagnosis of four angle sensor variables. In terms of model parameter selection, the Gaussian kernel function width parameter is optimized and determined as $\sigma = 10$ using cross-validation [11]. For experimental data collection, 330 sets of measurement values from the thruster tilt angle sensor were selected as sample data. To comprehensively assess the model's performance, the study conducted a systematic simulation of four typical fault modes of the sensor, including bias fault, complete failure, drift fault, and accuracy degradation fault. The Square Prediction Error (SPE) monitoring results for each fault mode are shown in the Figure 1.

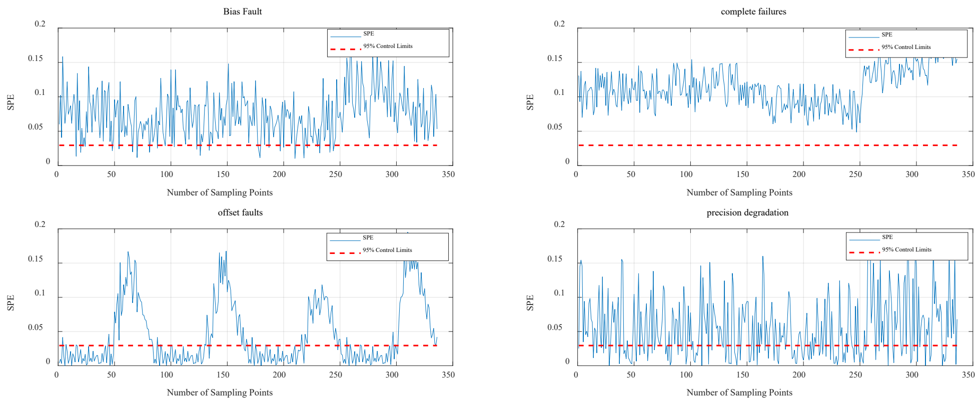


**Figure 1.** The Squared Prediction Error (SPE) for each fault mode.

From Figure 1, it can be observed that all four common faults of the sensor can be effectively monitored using the SPE indicator of KPCA. However, the type and location of the fault still require further diagnosis.

### 3. T² Contribution-Based Fault Diagnosis

When the SPE (Squared Prediction Error) monitoring index detects an abnormality in the system, it is necessary to further identify the faulty variables and analyze the root causes of the fault to complete the full fault diagnosis process. However, the adaptive KPCA method has two inherent limitations in nonlinear feature extraction: firstly, the method does not rely on an explicit nonlinear transformation function; secondly, the kernel function mapping results in a loss of correspondence between the original measurement space and the feature space variables. To address this issue, this study proposes using contribution plot analysis for fault tracing: firstly, the contribution of each original measurement variable to the fault is calculated, and then, by comparing the relative change rate of each variable's contribution before and after the fault, accurate separation and localization of the fault variables are achieved, providing a reliable basis for subsequent fault mechanism analysis. The contribution of the $j$-th original measurement variable to the $T^2$ statistic is defined as:

$$cont_{j,i} = \sum_{i=1}^{p} \left| t_i^T x_j \,/\, \lambda_i \right| \tag{1.27}$$

The percentage change in its contribution is:

$$\begin{cases} \Delta cper_j = cper_{tf,j} - cper_{tn,j} \\ cper_{tf}/_{tn,j} = \dfrac{cntr_{j,i}}{\sum_{j=1}^{s_n} cntr_{j,i}} \end{cases} \tag{1.28}$$

In the formula, $p$ represents the number of principal components, $t_i$ and $x_j$ (standardized) represent the $i$-th nonlinear principal component and the $j$-th sensor measurement variable, $\lambda_i$ is the $i$-th eigenvalue, $t_f$ and $t_n$ represent the moments when the sensor has and has not failed, and $s_n$ is the number of sensors.

Based on the adaptive KPCA fault diagnosis model established earlier, after detecting a system fault using the SPE statistic, further identification of the fault source is required. To this end, this paper employs a contribution analysis method, which calculates the percentage change in the contribution of each sensor variable before and after the fault occurrence using equation (1.28) (as shown in the Figure 2). This method quantifies the relative contribution change of each variable under fault conditions, enabling the effective separation and localization of the fault variables.

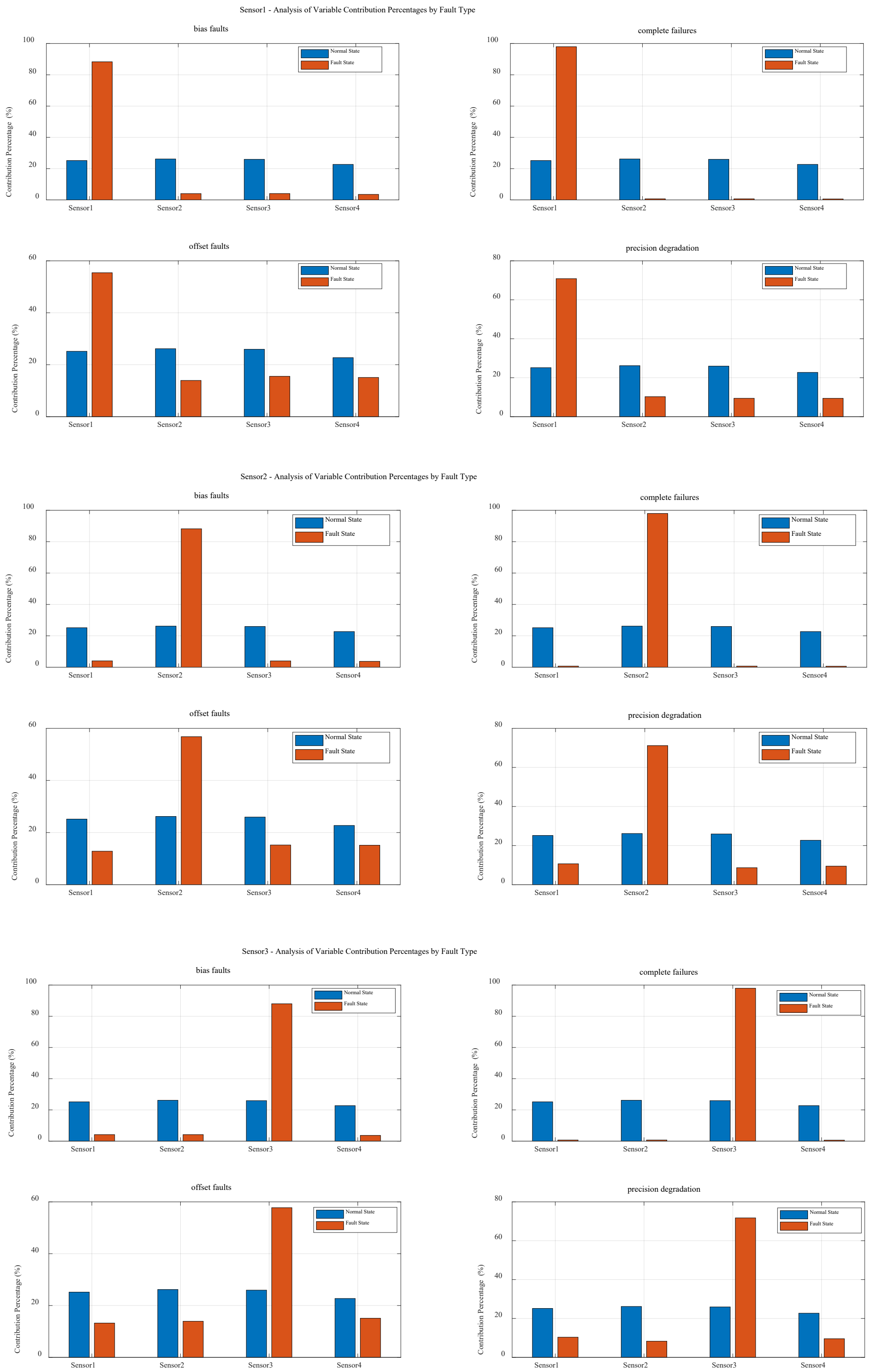


**Figure 2.** Fault Variable Contribution Percentage Change Chart.

As shown in the figure, by comparing the contribution percentage changes of each sensor under the four fault modes, it can be observed that after the fault occurs, the contribution of a particular variable shows a significant spike. It is worth noting that the corresponding angle sensor is exactly the fault injection point set in the experiment. This result validates the effectiveness of the fault separation method based on contribution analysis. The experimental data indicate that the adaptive KPCA diagnostic model developed in this study can reliably detect typical sensor faults such as bias faults, complete failure, offset faults, and accuracy degradation, and accurately locate the faulty sensor.

## 4. Diagnostic Examples

When analyzing the multi-angle sensor dataset using the adaptive KPCA diagnostic model, it was observed that the Squared Prediction Error (SPE) statistic continuously exceeded the control limits, indicating the presence of abnormal sensor conditions.

As shown in the Figure 3, by analyzing the time series data of 320 sampling points before and after the fault occurrence, it can be seen that when the system enters a fault state, the SPE statistic surpasses the preset monitoring threshold. This pattern aligns with the typical evolution characteristics of sensor faults, validating the effectiveness of the proposed adaptive KPCA model.

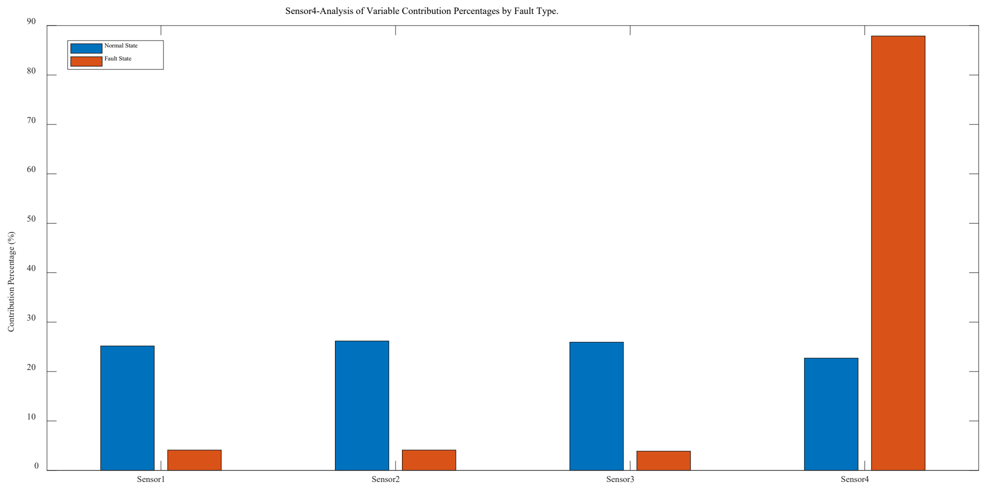


**Figure 3.** Sensor4-Analysis of Variable Contribution Percentages by Fault Type.

Subsequently, the variable contribution percentages of each sensor before and after the fault occurrence were calculated to quantify the fault characteristics. The results show that when the system experiences a deviation fault, the contribution percentage of the 4th sensor's variable significantly increases. This characteristic can serve as an important basis for diagnosing faults in this sensor (see Figure 4).

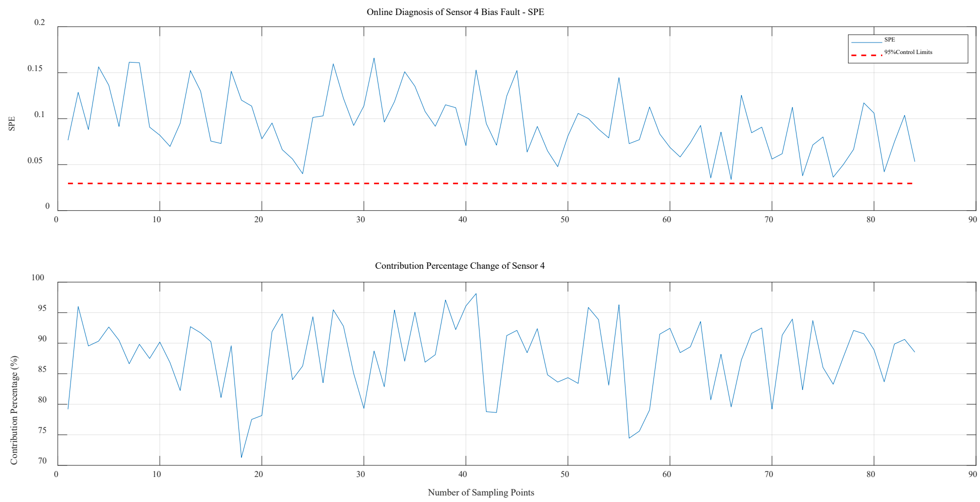


**Figure 4.** Fault Variable Contribution Percentage Change Chart.

## 5. Conclusion

Compared to traditional PCA methods, the adaptive KPCA method demonstrates significant advantages in dimensionality reduction in nonlinear feature spaces. This method not only offers a wider range of principal component selection but also effectively handles nonlinear problems, achieving accurate classification of different types of faults. In sensor fault diagnosis for complex control systems with strong nonlinear characteristics, adaptive KPCA exhibits excellent performance by mapping fault data to a high-dimensional feature space for feature extraction. Simulation results show that, based on tests of four typical fault types, the adaptive KPCA method combined with the SPE statistic effectively enables sensor fault monitoring. Further analysis indicates that by monitoring the percentage changes in each sensor's variable contribution, it is possible to not only accurately identify faulty variables but also precisely locate the fault source and analyze its causes. Notably, this method demonstrates exceptional diagnostic stability for faults involving the degradation of sensor accuracy. Experimental data confirm that the fault diagnosis performance of the adaptive KPCA method is significantly superior to traditional linear PCA methods.

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