Bearing Performance Degradation Assessment Based on Ensemble Empirical Mode Decomposition and Affinity Propagation Clustering

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ABSTRACT As key components in a rotating machinery system, bearings affect the safety of the entire mechanical system. Hence, early-stage monitor of bearing degradation is critical to avoid abrupt mechanical system failure. In this paper, a novel bearing performance assessment model is constructed based on ensemble empirical mode decomposition (EEMD) and affinity propagation (AP) clustering. Unlike most clustering methods, AP clustering, which automatically finds the center of all available clusters, can determine the bearing degradation status without an experience-based selection of the number of degradation states. The original bearing vibration signal is first decomposed by EEMD and its degradation fault features are extracted from the singular-value decomposition of intrinsic mode functions. Then, the degradation features are selected as the input of AP clustering to find the cluster centers of different bearing health statuses: "normal", "slight", and "severe". Last, a health evaluation indicator, referred to as the confidence value, which is obtained from the dissimilarity between actual samples and the various cluster centers, is used to evaluate the bearing health status. To prove the superiority of the approach, the proposed model is compared to various popular clustering methods, including, k-means, k-medoids, fuzzy c-means, Gustafson-Kessel, and Gath-Geva, and commonly used time-domain indicators such as root mean square and kurtosis. The experimental results show that the proposed method outperforms the above time-domain indicators and clustering methods in monitoring early-stage degradation, without presetting the number of clusters.

INDEX TERMS Affinity propagation clustering, bearings, ensemble empirical mode decomposition, performance degradation assessment.

I. INTRODUCTION

Rolling element bearings are widely used in mechanical machines to support rotating shafts. However, bearing failure is the main cause of mechanical failure. Therefore, early-stage detection of bearing degradation is vital [1]. Vibration signals are commonly used to monitor bearing health. This requires a signal processing model to process the original vibration signal.

The associate editor coordinating the review of this manuscript and approving it for publication was Mariela Cerrada.

Many signal-processing methods, including various time and frequency domain indices [2]–[5], wavelet transformation (WT) [6]–[9], empirical mode decomposition (EMD) [10]–[12], and ensemble empirical mode decomposition (EEMD) [13]–[15], have been proposed. Theodoros *et al.* used time-frequency indicators with a wavelet transform to assess the roller bearings' diagnostic performance [16]. Rodney *et al.* proposed a data-driven approach that relies on time-frequency domain features, including root mean square (RMS), to describe the evolution of bearing faults [17]. Shen *et al.* used various time-frequency
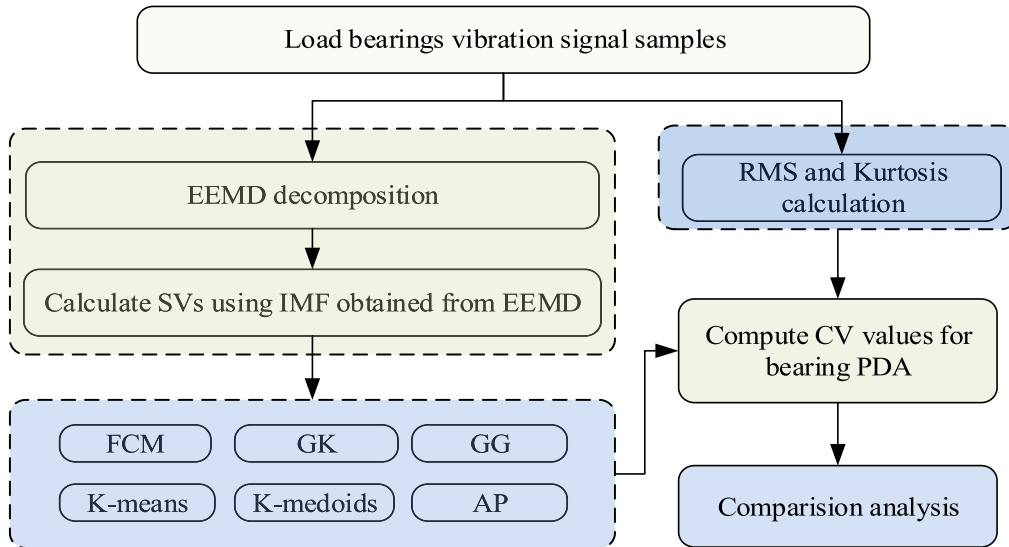
FIGURE 1. The flowchart of the proposed method.

metrics including RMS and WT to extract fault characteristics of rotating machinery. [18]. Tse and Wang proposed an RMS-based method that pre-processes vibration signals through pre-specified frequency bands to establish health indicators for performance degradation assessment (PDA) of bearings [19]. Lei *et al.* also used RMS to evaluate the degradation trend of bearings. Their experiments showed that the RMS can effectively describe the bearing degradation state [20]. Rai *et al.* used WT to enhance the pulse characteristics of the bearing signal to improve the quality of the fault feature extraction [21]. Qiu *et al.* [22] proposed a model based on WT and self-organizing maps to establish health indicators for robust bearing PDA. The eigen-vectors are combined with the RMS, kurtosis, and crest factor to measure the time-frequency domain. However, the WT method suffers from the need to select a wavelet function. The appropriate scale factor, shape factor, and center frequency must be selected in WT to ensure that the fault characteristics of the extracted bearings are accurate. WT is therefore unsuitable for adaptive decomposition of vibration signals. EMD is an adaptive method that overcomes the above disadvantages because the center frequency and bandwidth of the EMD filter can be adaptively decomposed into intrinsic mode functions (IMFs) according to the order of frequency from high to low [23]. However, several problems arise with EMD, especially mode mixing. To overcome this shortcoming, Wu *et al.* developed EEMD as an improvement over EMD [24]. The main idea of EEMD is to suppress the mode mixing problem by adding white noise. Both methods have been successfully applied to bearing PDA and fault diagnosis. Zhao *et al.* incorporated a consideration of approximate entropy (AE) into EMD to evaluate the bearing fault size [10]. Zhang *et al.* used EEMD to decompose the vibration signal of the rolling bearing into a series of IMFs, and then calculated the IMF entropy by
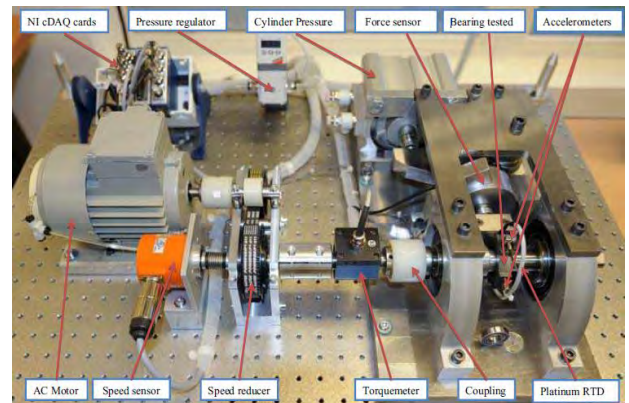

FIGURE 2. Overview of PRONOSTIA.

considering the energy entropy. Then, the extracted features were used as the input of a support vector machine (SVM) to diagnose the bearing faults [25]. A method for bearing fault diagnosis using EEMD, sample entropy, and SVM was used in [26]. Rai *et al.* proposed a method based on EEMD and k-medoids to implement bearing PDA and proved that the method is superior to RMS and kurtosis [27]. Given the above-mentioned successes of EEMD in a wide range of signal processing and fault diagnosis tasks, the method was chosen to process the original vibration signal in this study.

After the EEMD decomposition, the next step is to establish an evaluation model to build a health indicator for the bearing PDA that accurately identifies the input characteristics based on the bearing's health state. Clustering is one of the most commonly used methods for PDA construction and does not require manual data tags. Pan *et al.* proposed a method based on WT and fuzzy c-means (FCM) to implement bearing PDA. Although the constructed health
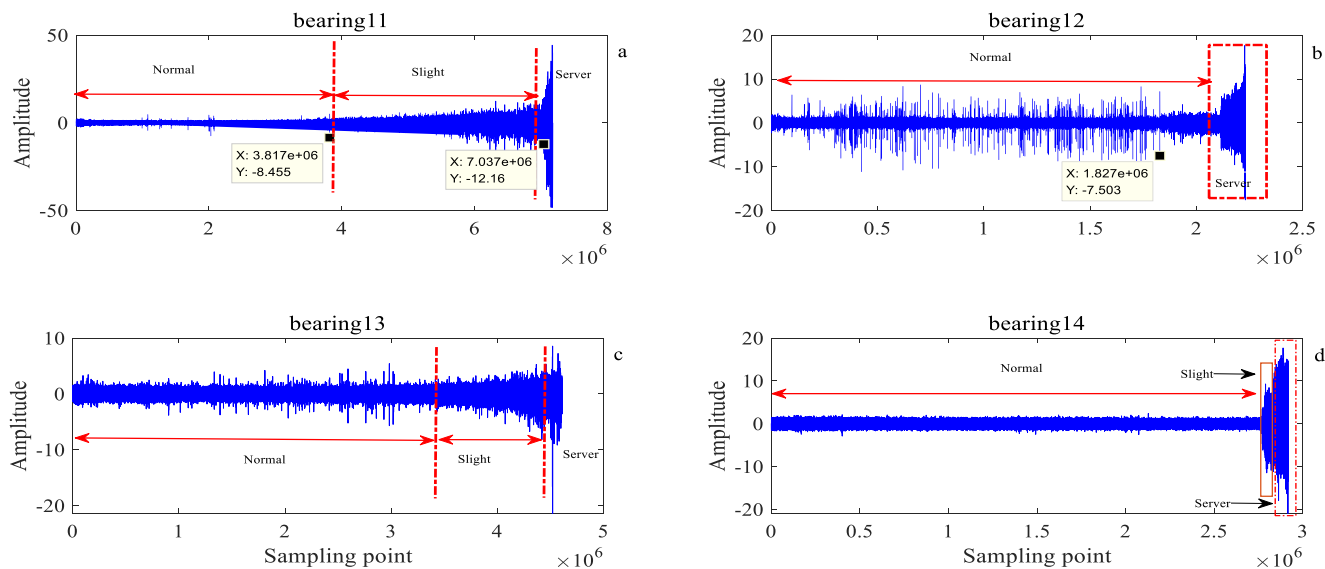
FIGURE 3. The time domain vibration waveform of (a): Bearing 11; (b): Bearing 12; (c): Bearing 13; (d): Bearing 14.

TABLE 1. Experimental data of the roller bearings under different conditions.

Bearing No.	Total samples	Speed (*rpm*)	Load (*N*)	Each sample length	Frequency (*kHz*)
bearing 11	2803	1800	4000	2560	25.6
bearing 12	871	1800	4000	2560	25.6
bearing 13	911	1800	4000	2560	25.6
bearing 14	1139	1800	4000	2560	25.6

indicators could effectively monitor bearing degradation at the end of bearing life, they could not effectively track the early stages of deterioration of the bearing [28]. Rai *et al.* used k-medoids clustering to construct a PDA model. They first used EEMD to decompose the original vibration signal, then used singular value decomposition (SVD) to find the singular value (SV) as the input of the k-medoids to locate three different state cluster center points, including "normal", "slight", and "severe". Finally, a health indicator named the confidence value (CV) was calculated from the distance between each sample and the cluster center point under the normal state, and was used to implement the bearing PDA [27]. However, FCM is only applicable to data sets with homogeneous structures because it uses Euclidean distance to calculate the similarity of any two samples. To overcome this shortcoming, Gustafson-Kessel (GK) clustering was developed as an FCM-based reinforcement method whose core idea is to use the adaptive distance norm and covariance matrix to calculate the distance between sample points [29]. FCM and GK are only applicable to data sets with spherical structures, while the data sets obtained from various engineering systems are non-spherical. Therefore, the Gath-Geva (GG) clustering method was developed to solve this problem, which uses fuzzy maximum likelihood estimation

to calculate the distance norm, making it applicable to data of various shapes [30].

Moreover, all of the above clustering methods require the user to preset the number of cluster center points, and these center points are often filtered by experts with practical experience. Due to the non-linearity and complexity of the vibration signal, it is difficult to obtain a suitable number of empirically determined clusters for a range of complex systems. Under normal circumstances, practical experience suggests that the wear state can be divided into three categories: normal, slight, and severe. However, if the bearing states transits abruptly between only two states, i.e. normal and severe, such reliance on practical experience may lead to misjudgment. Therefore, a knowledge-driven learning model is needed to automatically determine the optimal number of clusters.

The core feature of AP clustering is its sole use of responsibility and availability indicators to decide the probability of a point becoming a cluster center without prior knowledge [31]. AP clustering has previously been applied in fault feature selection and fault diagnosis. Ze *et al.* [32] proposed a method based on EEMD, WT, and AP clustering for adaptive feature selection. In their work, a number of fault features, such as time-frequency domain indicators, IMFs with time domain indicators, and wavelet decomposition energy, were filtered by a weight self-weight algorithm to obtain sensitive features at the first step. Then AP clustering was used to find suitable cluster centers, which were used to calculate the similarity matrix between each sensitive feature and the chosen cluster center points to obtain the optimized features. Finally, the optimized features were taken as the input of AP clustering for bearing fault diagnosis. However, the use of AP clustering method to establish health indicators of bearing status has so far been rare.
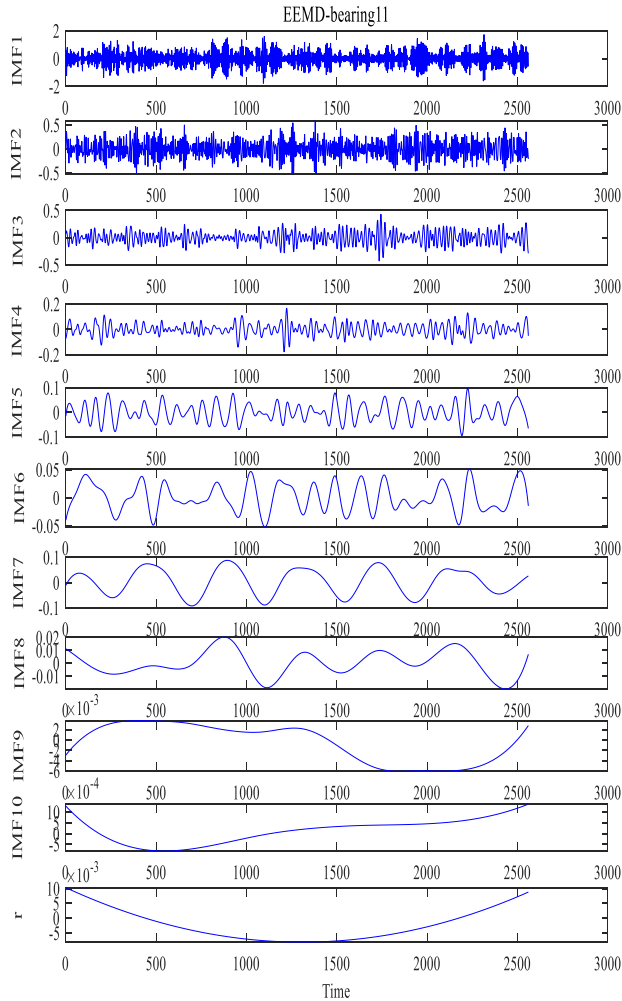
FIGURE 4. The results of EEMD decomposition for bearing 11.

In this work, an AP clustering method for bearing PDA assessment is proposed. The main contributions of this work are as follows:

(1) This paper first introduces the AP clustering to bearing PDA construction. Compared with other popular clustering methods, such as k-means and k-medoids, which require manual selection of cluster number in advance, the AP clustering automatically locates all the available cluster centers.

(2) Moreover, instead of calculating only one CV value, CV values corresponding to different cluster centers are evaluated to better determine the bearing status for each sample, especially when bearing encounters status transition.

(3) Finally, to demonstrate the performance of the proposed framework (EEMD-SVD-AP) in indicating bearing status, it is compared with other popular clustering methods, including FCM, GK, GG, k-means, k-medoids, and time domain indicators (RMS and kurtosis).

The rest of this paper is organized as follows. The basic theory of EEMD, SVD, and AP clustering is introduced in Section II. Section III describes the experimental platform and step-by-step introduction to the proposed method.
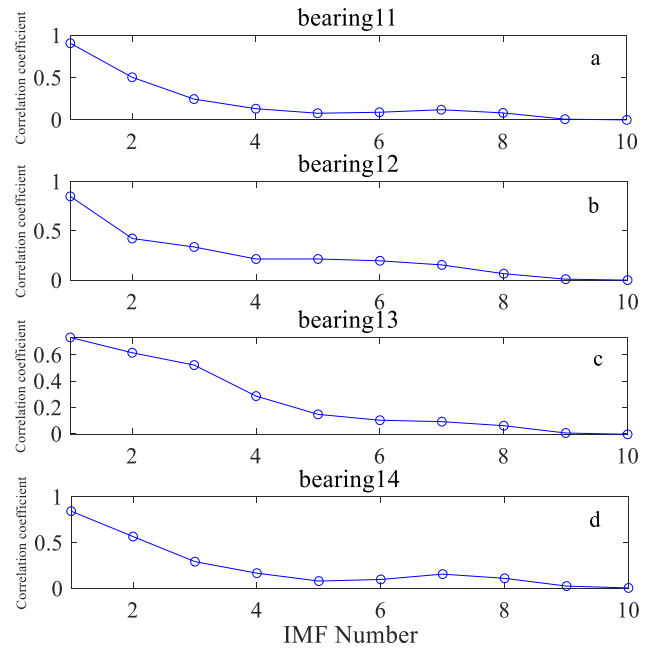

FIGURE 5. Correlation coefficients between the IMFs and original vibration signals.

Section IV shows the experimental validation and comparative analysis. The conclusion is presented in Section V.

II. BASIC THEORY OF EEMD AND AP

A. THEORETICAL FRAMEWORK OF EEMD

EEMD is proposed to overcome the mode mixing problem in EMD by Wu and Huang [24]. In this paper, the calculation procedure is as follows (basically following [33]):

Step 1: Given that $X(t)$ is the original vibration signal, add a random white noise signal $n_j(t)$ to $X(t)$

$$X_j(t) = X(t) + n_j(t) \qquad (1)$$

where $X_j(t)$ is the noise-added signal, $j = 1, 2, 3, \cdots, m$, and m is the number of trials.

Step 2: Decompose the original signals $X(t)$ into IMFs by using EMD as follows:

$$X_j(t) = \sum_{i=1}^{N_j} c_{ij} + u_{N_j} \qquad (2)$$

where c_{ij} indicates the ith IMF of the jth sample, u_{N_j} denotes the residue of the jth sample, and N is the number of arrangements of the jth sample.

Step 3: If $j < m$, then duplicate steps 1-2, adding random white noise at each cycle.

Step 4: After ensuring that $I = min(N_1, N_2, \cdots, N_m)$, compute the ensemble average of the IMFs of the decompositions as the final results according to (3).

$$c_i = \left(\sum_{j=1}^{M} c_{i,j} \right) / m \qquad (3)$$
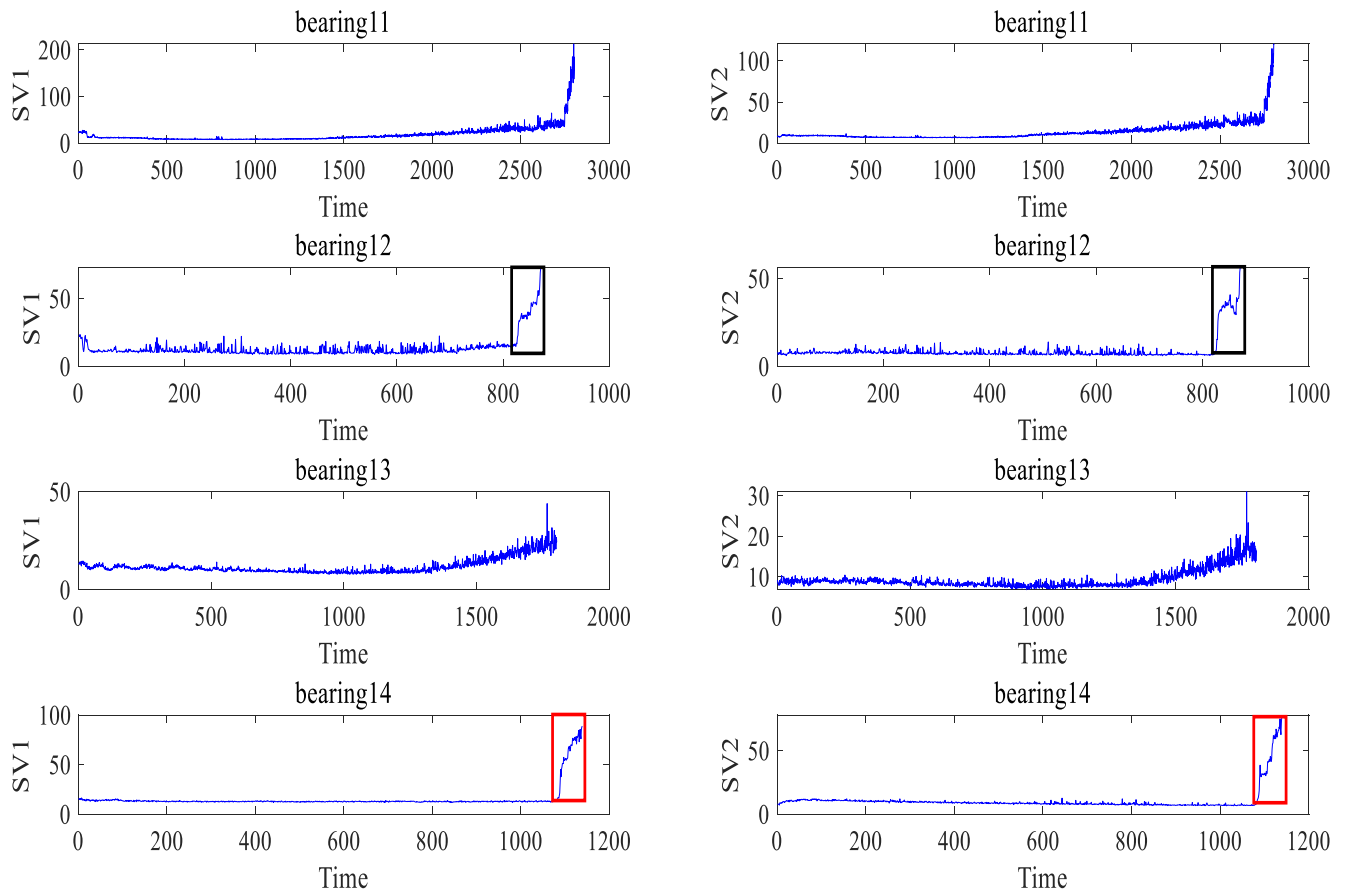
FIGURE 6. SV features extracted for bearing 11-14 from the first two IMFs using SVD.

Step 5: c_i $(i = 1, 2, 3, \cdots, I)$ denotes the ensemble average of each IMF of the decompositions.

B. THEORETICAL FRAMEWORK OF AP

The AP clustering algorithm proposed by Frey and Dueck [27] is based on neighbor information propagation. Unlike FCM, GK, and GG, which compute the mean value of the data points to obtain the centers of the clusters, AP clustering considers all samples as candidates for the cluster center points. The purpose of AP clustering is to produce a similarity clustering model between N samples, where in this paper the negative Euclidean distance squared is selected as the similarity measure function for any two samples,

$$S(i, j) = - \left\| x_i - x_j \right\|^2 \tag{4}$$

where $S(i, j)$ is the similarity between x_i and x_j.

The AP clustering algorithm uses the responsibility $R(i, k)$ and availability $A(i, k)$ to generate candidate cluster center points. Each iteration of the AP clustering algorithm is the process of alternately updating information between the two parameters $R(i, k)$ and $A(i, k)$. Here $R(i, k)$ is the likelihood of kth point x_k to be the cluster center of ith point x_i, $A(i, k)$ denotes the suitability of x_i, and x_k is its cluster center.

The detailed calculation steps of the AP clustering algorithm are as follows:

Step 1: Initialize the similarity matrix S by the similarity between any two samples. Set up the largest number of iterations t_{max}.

Step 2: Calculate $R(i, k)$ and $A(i, k)$ of each sample using (5-6).

$$R(i, k) = S(i, k) - \max_{j} \{A(i, j) + S(i, j)\}$$
$$j = 1, 2, \cdots N \text{ and } j \neq i, k \tag{5}$$

$$A(i, k) = \min \left\{ 0, R(k, k) + \sum_{j} \max(0, R(i, k)) \right\}$$
$$j = 1, 2, \cdots N \text{ and } j \neq i, k \tag{6}$$

$$R(k, k) = P(k) - \max_{j} \{A(k, j) + S(k, j)\}$$
$$j = 1, 2, \cdots N \text{ and } j \neq k \tag{7}$$

Step 3: Determine whether the kth point can be taken as the cluster center point according to (7).

$$R(k, k) + A(k, k) > 0 \tag{8}$$

Step 4: Update $R(i, k)$ and $A(i, k)$ of each sample.

$$R(i + 1, k) = (1 - lam) \cdot R(i, k) + lam \cdot R(i - 1, k) \tag{9}$$

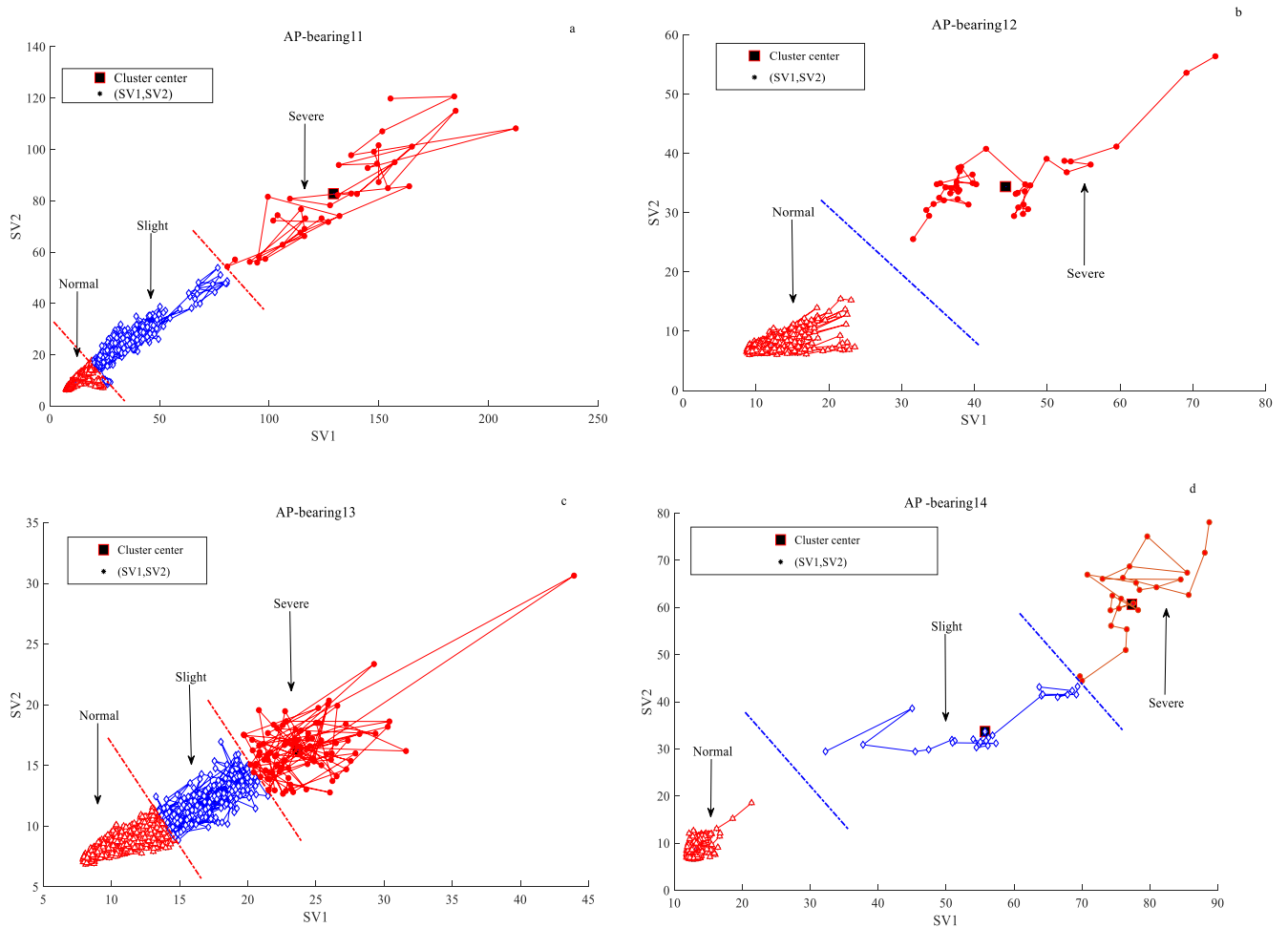$$A(i + 1, k) = (1 - lam) \cdot A(i, k) + lam \cdot A(i - 1, k) \tag{10}$$

FIGURE 7. Two-dimensional clusterings of bearings using AP clustering (a): Bearing 11 (b): Bearing 12 (c): Bearing 13 (d): Bearing 14.

Steps (3-4) are utilized to compute the $R(i,k)$ and $A(i,k)$ for each sample. Here *lam* in (9-10) denotes the damping factor. When updating the messages, it is important to avoid numerical oscillations in some cases.

Step 5: If t is greater than the maximum number of iterations t_{max} or the model reaches the termination condition, terminate the process. Otherwise, go back to step 2.

III. PROCEDURES FOR THE PROPOSED METHOD
This section presents the step-by-step introduction to the proposed method.

(1) The first step is feature extraction. First, all bearing samples are decomposed as sums of IMFs by EEMD. Then singular value decomposition is applied to obtain the first SV (SV1) and the second SV (SV2). The projected data samples are then served as the input of the proposed clustering method and other methods to be compared with.

(2) The second step is the building of the bearing PDA model. SV1 and SV2 are used to find the cluster center point among three states (normal, slight, and severe).

(3) The final step is status assessment. The sample dissimilarity is defined as the squared Euclidean distance

between them. The degeneration index (DI) to a cluster is calculated as the dissimilarity to the center of the cluster. Therefore, the larger DI, the less likely the sample belong to the cluster. The DI is further transformed into the confidence value (CV) using the following equation:

$$CV = exp(-DI/c) \tag{11}$$

where c is a proper scale factor. Unlike other clustering methods, where only one CV is calculated, our method obtains a CV vector corresponding to each clustering spotted, each CV value is interpreted as the likeliness of the sample been in the corresponding cluster.

Finally, the performance of PDA extraction using the proposed method is compared with other clustering methods. Additionally, the method presented is compared with the use of RMS and kurtosis. The above procedures are schematized in Fig. 1.

IV. EXPERIMENT AND COMPARISON
A. ORIGINAL VIBRATION SIGNAL
The rolling bearing experiment were conducted using the PRONOSTIA platform in the FEMTO Institute at the
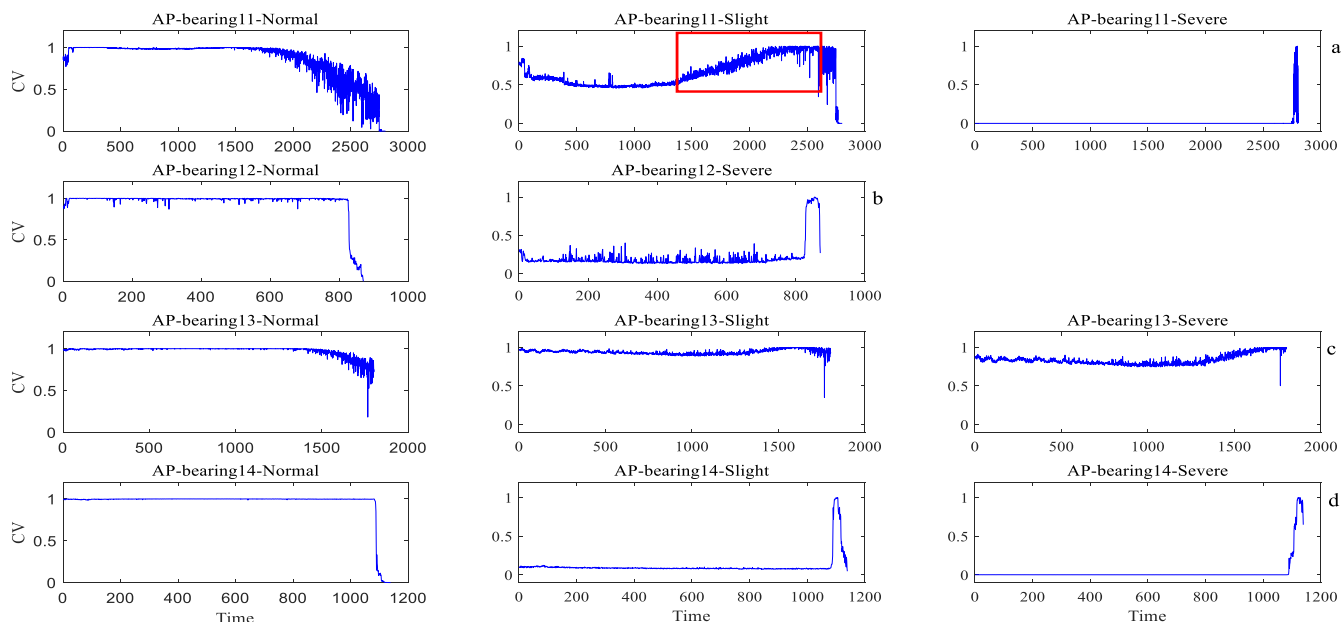
FIGURE 8. Calculated CVs when AP cluster center points are used in different conditions, including normal, slight, and severe (a): Bearing 11 (b): Bearing 12 (c): Bearing 13 (d): Bearing 14.

University of Franche-Comté, France [34]. An annotated photograph of the test platform is shown in Fig. 2.

Initially, the roller bearings have no defect. As the bearing speeds up and the radial load increases, the accelerated life test reproduces the entire degradation process of the bearing in a few hours. Therefore, the entire life cycle data of the rolling bearing can be quickly obtained and meanwhile various kinds of fault may be generated under different working conditions. The platform includes seven roller bearings in total. In this experiment, the roller bearing 11-14 were used. Table 1 summarizes the detail of the experiment setup.

Collected time domain waveforms for the original vibration signals of bearing 11, 12, 13, and 14 are shown in Fig. 3. Conventionally, a bearing is classified into one of the three degradation states including normal, slight, and severe.

Bearing 11 was sampled 2803 times with a length of 2560 for each sampling. As shown in Fig. 3(a), bearing 11's vibration signal increases gradually over time. During the normal state, the amplitude range of the vibration signal does not change substantially. Compared with the normal state, slight and severe have a significant increase in amplitude, especially for severe state. Bearing 13 is similar to bearing 11. In contrast, the vibration signal of bearing 12 contains noise in the normal state. The amplitude of the vibration is basically constant until it increases sharply to the highest value in the final stage. Therefore, bearing 12 has only two stages at first glance: normal and severe. It should be mentioned that the vibration signal of bearing 14 looks similar to that of bearing 12, but bearing 14 has the same three stages of degradation as bearing 11. From Fig. 3(d), the bearing 14 signal shows a gradual increase from normal to slight. Unlike bearing 12, the bearing 14 signal has two

phases of sharp increase in vibration amplitude, highlighted by a red rectangle (slight) and a red dotted rectangle (severe), while bearing 12 has only one such phase. Therefore, three degradation states, including normal, slight, and severe, are observed for bearing 14. The following experimental results will demonstrate that AP clustering can accurately distinguish the different degradation stages of these bearings without the need for a user with practical experience to select the center points of the assembly. In addition, a comparative analysis of AP clustering with other clustering methods (including k-means, k-medoids, FCM, GK, and GG) and time domain indicators (RMS and kurtosis) will be presented. bearing 14 signal has two phases of sharp increase in vibration amplitude, highlighted by a red rectangle (slight) and a red dotted rectangle (severe), while bearing 12 has only one such phase. Therefore, three degradation states, including normal, slight, and severe, are observed for bearing 14. The following experimental results will demonstrate that AP clustering can accurately distinguish the different degradation stages of these bearings without the need for a user with practical experience to select the center points of the assembly. In addition, a comparative analysis of AP clustering with other clustering methods (including k-means, k-medoids, FCM, GK, and GG) and time domain indicators (RMS and kurtosis) will be presented.

During the signal decomposition phase, the original vibration signal is decomposed by EEMD into a series of IMFs and arranged in frequency order. However, there are two key parameters in EEMD that need to be set, the ensemble number m and the amplitude of the added white noise $n_i(t)$ [13], [35]–[37]. In general, accurate results can be obtained if the ensemble number is set to a few hundred, and if the added
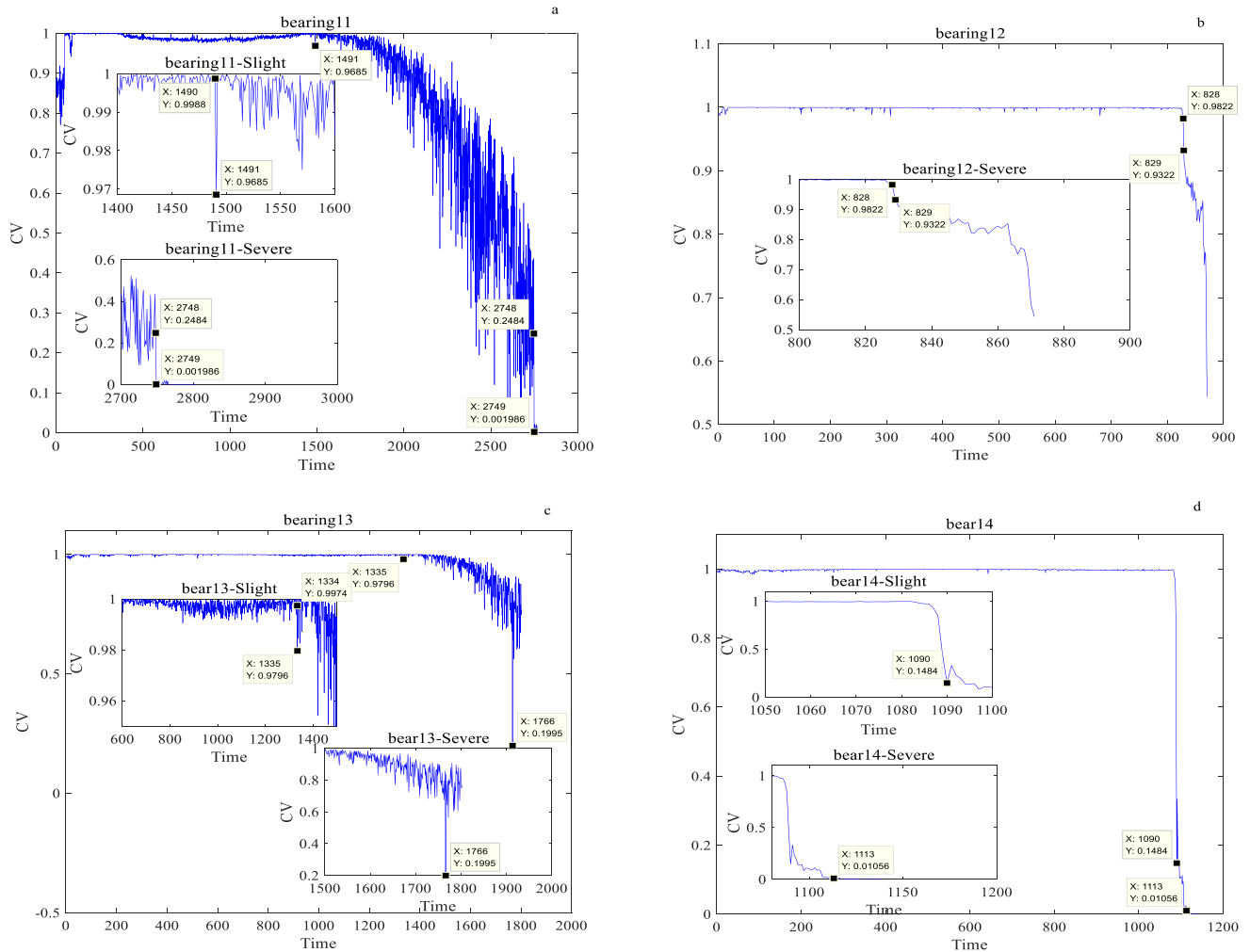
FIGURE 9. Calculated CVs when AP cluster center points on timescales extended through the entire lifetime are used in different conditions: normal, slight, and severe (a): Bearing 11 (b): Bearing 12 (c): Bearing 13 (d): Bearing 14.

white noise is a small fraction of the standard deviation. Then, an error of less than 1% is likely. In [11], the author suggests that the added white noise should be about 20% of the original signal standard deviation. In this paper, $m = 100$. Fig. 4 shows the result of the EEMD decomposition for bearing 11.

In Fig. 4, the first IMF of bearing 11 has the largest amplitude range of all IMF components, and the second IMF component has the second largest amplitude range. These results indicate that the first several IMFs contain the primary and most useful characteristic information of the original signal. To determine the degree of correlation between each IMF and the original signal, the correlation coefficient is calculated. The closer the correlation coefficient is to 1, the stronger the correlation and vice versa. The calculated correlation coefficients between the original signal and each IMF for all bearings are shown in Fig. 5.

As can be seen, the first two IMFs have the highest and the second highest correlation coefficient values. To facilitate

data visualization of the clustering results, the first two IMFs are selected and used to calculate the SV value. The first two SVs calculated for all bearings are shown in Fig. 6.

All of the SV curves accurately represent the trend in degradation of the respective bearings. The trend of degradation is a gradual increase for bearing 11 and 13, while bearing 12 and 14 appear to jump suddenly to the final wear stage. Compared with bearing 12, the degradation tendency of bearing 14, highlighted by the red rectangle, is more gradual, while the black rectangle shows that the jumping behavior of bearing 12 is obviously stepwise. Therefore, only two degradation states (normal and severe) are experienced during the life of bearing 12, while bearing 14 has both slight and severe degradation stages in addition to normal. These results indicate that EEMD combined with SVD has a good ability to extract the finer features of degradation. To identify the degradation state automatically, the next step is to use AP clustering to find the available cluster center points during the normal, slight, and severe degradation states.
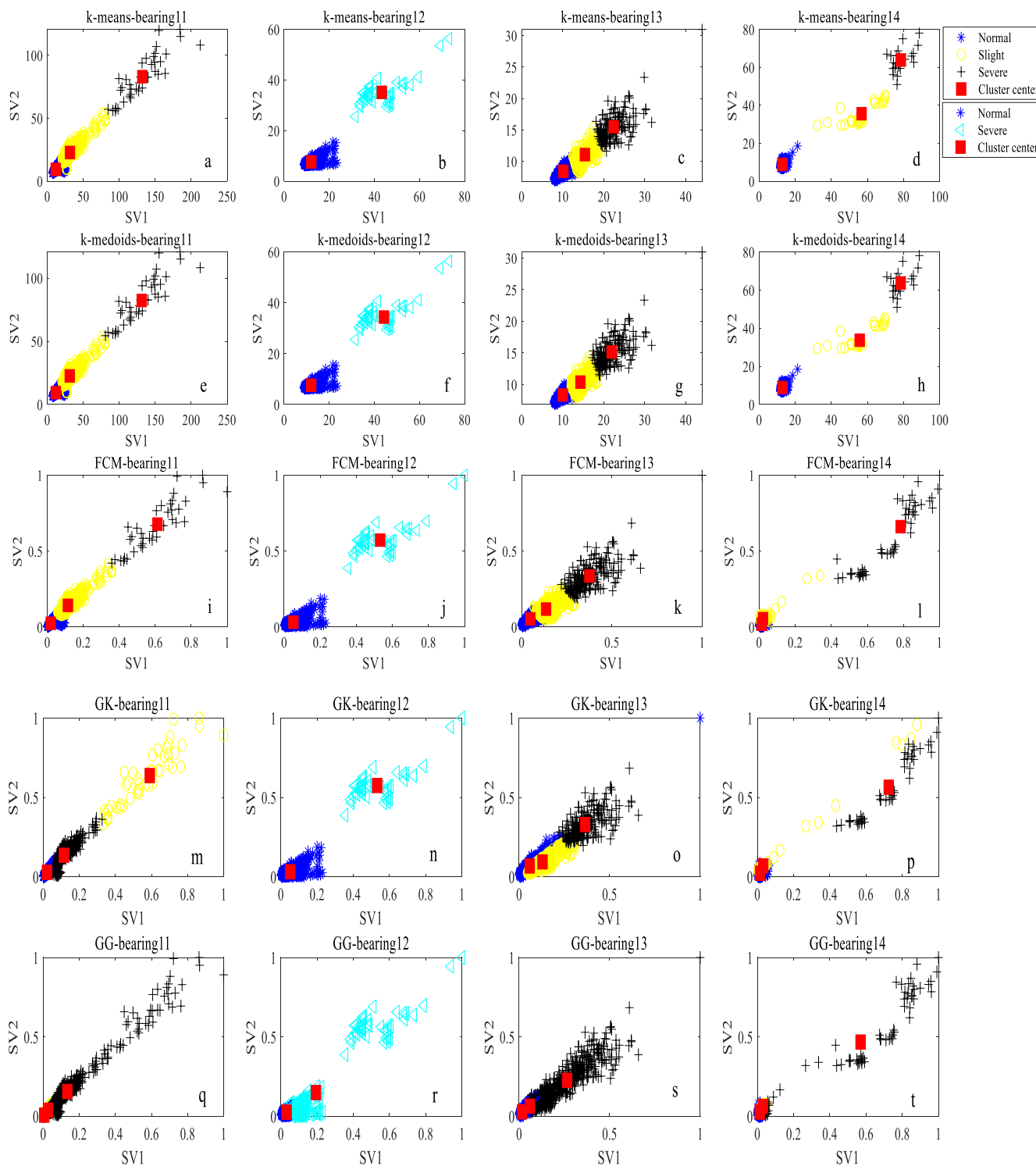
FIGURE 10. Two-dimensional clusterings of bearings using different clustering methods (a-d): k-means (e-h): k-medoids (i-l): FCM (m-p): GK (q-t): GG.

B. PARAMETER SETTING

In this section, FCM, GK, GG, k-means, k-medoids, and AP clustering methods are used to find the cluster center points at each degradation phase followed by a comparative analysis of these methods. For this purpose, some parameters must be pre-determined.

(1) FCM, GK, and GG: The number of cluster center points c for bearing 11, 13, and 14 is 3, while that for
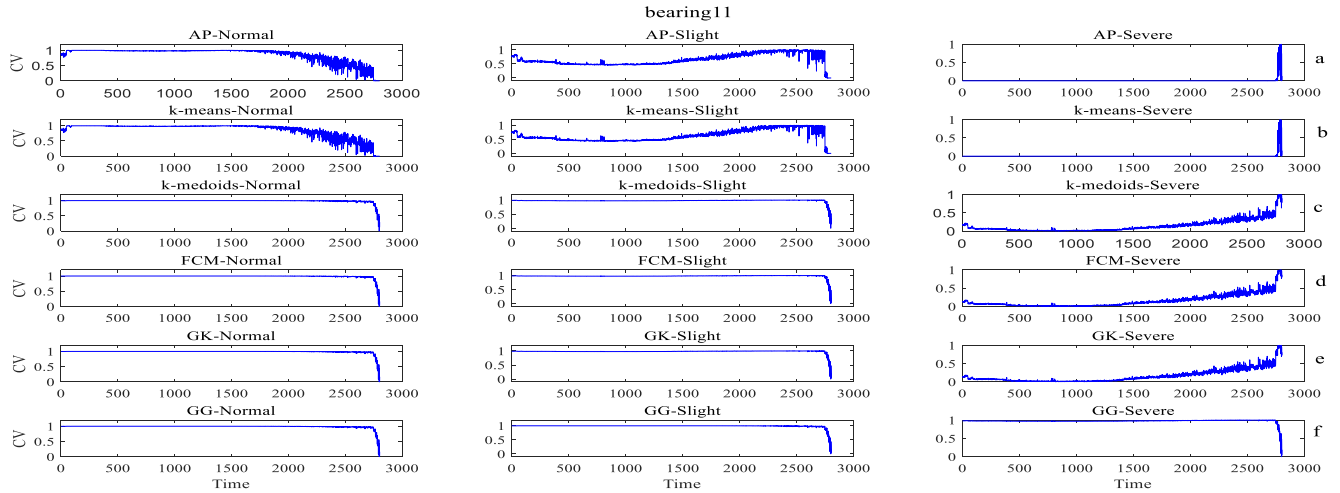
FIGURE 11. CV values calculated for bearing 11 by various clustering methods (a): AP, (b): k-means, (c): k-medoids, (d): FCM, (e): GK, (f): GG.

bearing 12 is 2. At the same time, the termination tolerance $\varepsilon = 1e - 6$. Euclidean distance is used as distance between any two samples.

(2) k-means, k-medoids: The setting of the number of cluster center points is the same as above. Again, the Euclidean distance is adopted.

(3) AP: the parameter p is usually fixed as the median value of the input similarities matrix. In (9-10), the parameter *lam* is often set within [0.6, 1] [29]. Here, we adopt $lam = 0.9$, and the largest iterative number $t_{max} = 100$.

C. RESULTS OF AP CLUSTERING

Clustering results using the AP method are shown in Fig. 7, where three clusters are identified for bearing 11, 13, and 14, while two clusters are identified for bearing 12, with the black squares on the figure representing the cluster center points. These clusters correspond to different degradation states including normal, slight, and severe. The determination of the cluster status is based on the SV value. As observed from Fig. 6, the SV value increases in general as the bearing degrades. Therefore, in Fig. 7, normal (red triangle), slight (blue diamond), and severe (red dot) clusters are identified for bearing 11, 13, and 14, while normal (red triangle) and severe (red dot) clusters are identified for bearing 12. The clustering results coincide with the observation in Fig. 3. Therefore, the AP method successfully identified all the available cluster center points for all four bearings.

Fig. 8 shows the CV values calculated for the clusters of the bearings. The consideration of all the CVs of different clusters help us better determine the wear state of the bearing. Take bearing 11 for example, three clusters are determined by the proposed algorithm, which is further identified as normal, slight and severe. Initially, the CV value corresponds to normal cluster is the maximum, indicating the bearing is functioning well. Around sample 1500, normal CV value starts to decrease, while slight CV value increases, indicating

the transition of the bearing state. Finally, at around sample 2850, the bearing state shifts abruptly to severe as the CV value of slight drops drastically and that of severe increases accordingly. Fig. 9 provides more details on the status transition areas. It's worth mentioning that the evolution of the CV matches the time domain observation of the bearing status as in Fig. 3. For bearing 12, 13 and 14, similar results can be obtained as of bearing 11.

In summary, the proposed AP method can properly address the number of bearing status, meanwhile the CV curve provides an intuitive way to precisely determine the bearing status for each sample.

D. COMPARISON WITH K-MEANS, K-MEDOIDS, FCM, GK, AND GG

In this section, the PDA performance of AP clustering is compared with the commonly used k-means, k-medoids, FCM, GK, and GG methods. The two-dimensional clustering results for all the bearings are shown in Fig. 10. The CVs for bearing 11, 12, 13, and 14 are illustrated in Fig. 11, 12, 13, and 14, respectively.

As in Fig. 10, the k-means and k-medoids successfully address all the clusters and present almost identical clustering results. While FCM and GK, both fail to distinguish the slight state from the normal state. The GG method presents the worst clustering results, which fails on bearing 11 and bearing 14. Nonetheless, it is still necessary to observe the CV curve from all clustering methods to further determine their effectiveness.

From Fig. 11 to Fig. 14, the performances of all the clustering methods are divided into three groups based on the likeliness of the resulting CV curves, a) AP and k-means; b) k-medoids, FCM and GK; c) GG.

For all four bearings, the resulting CV curves of the k-means method are verisimilar to those of the proposed AP clustering method. However, when the cluster number is unknown or incorrectly initialized, the k-means method
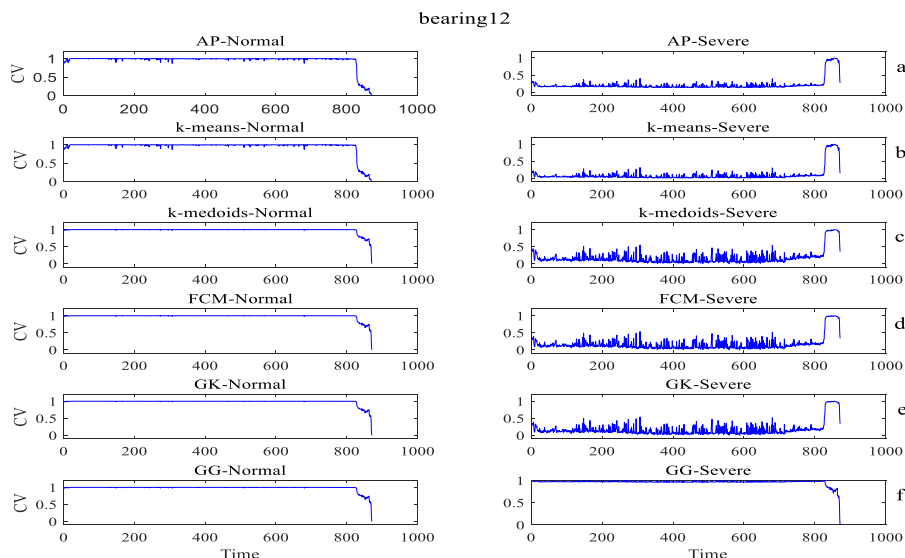
FIGURE 12. CV values calculated for bearing 12 by various clustering methods (a): AP, (b): k-means, (c): k-medoids, (d): FCM, (e): GK, (f): GG.
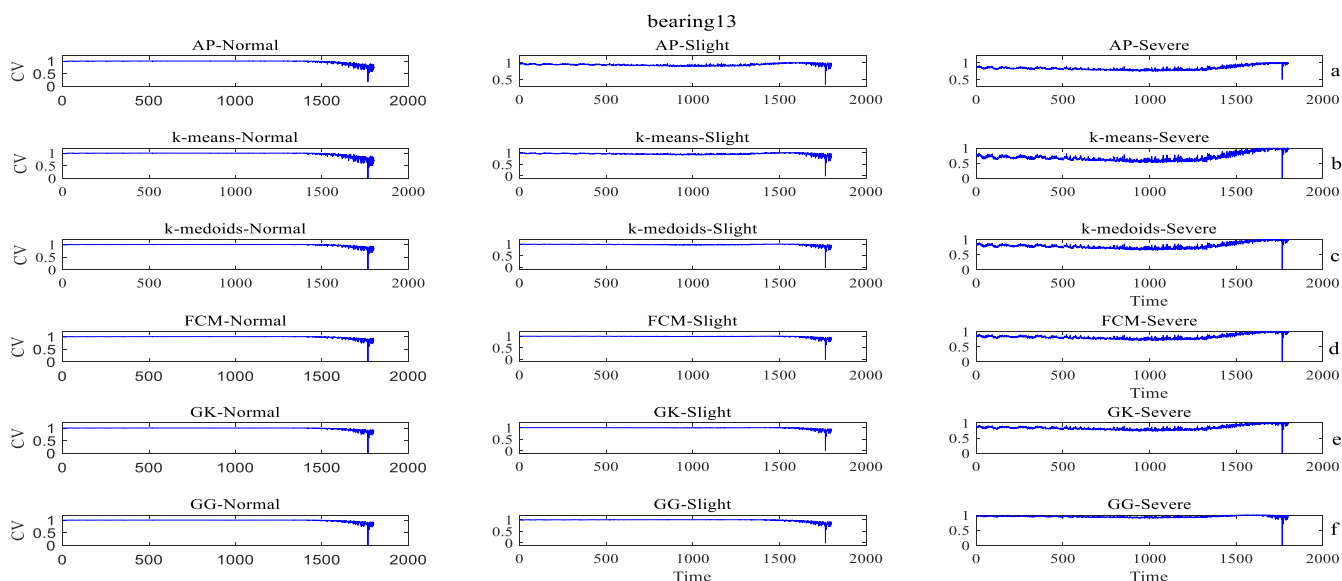

FIGURE 13. CV values calculated for bearing 13 by various clustering methods (a): AP; (b): k-means; (c): k-medoids; (d): FCM; (e): GK; (f): GG.

generates very different CV curve. For instance, Fig. 15 presents the CV curves of bearing 11 when cluster is initialized as 2 and 3 for the k-means method. When there are only two clusters, although it is still possible to distinguish the normal and severe states, the CV curve associated with the normal state first decreases and then increases, which indicates the bearing state is not stable. Moreover, early-stage detection of the commencement of the slight status in bearings enables the maintenance personnel adequate time to execute the rehabilitation actions. In comparison, the proposed method presents almost identical CV curve, but is free of the trouble to initiate the cluster number.

The performance of k-medoids, FCM and GK are less satisfying. When there are three clusters, namely for bearing 11, 13 and 14, these methods are not always capable of differentiating the slight status. Take bearing 11 for example, the CV value of normal and slight statuses from the three methods are all very close to 1, making it difficult to tell the actual bearing states.

For GG method, it simply fails for all bearings. For bearing 11, 12 and 13, the CV values for all states are 1, making it impossible to determine the bearing states. For bearing 14, the CV value of normal and slight statuses are not distinguishable.
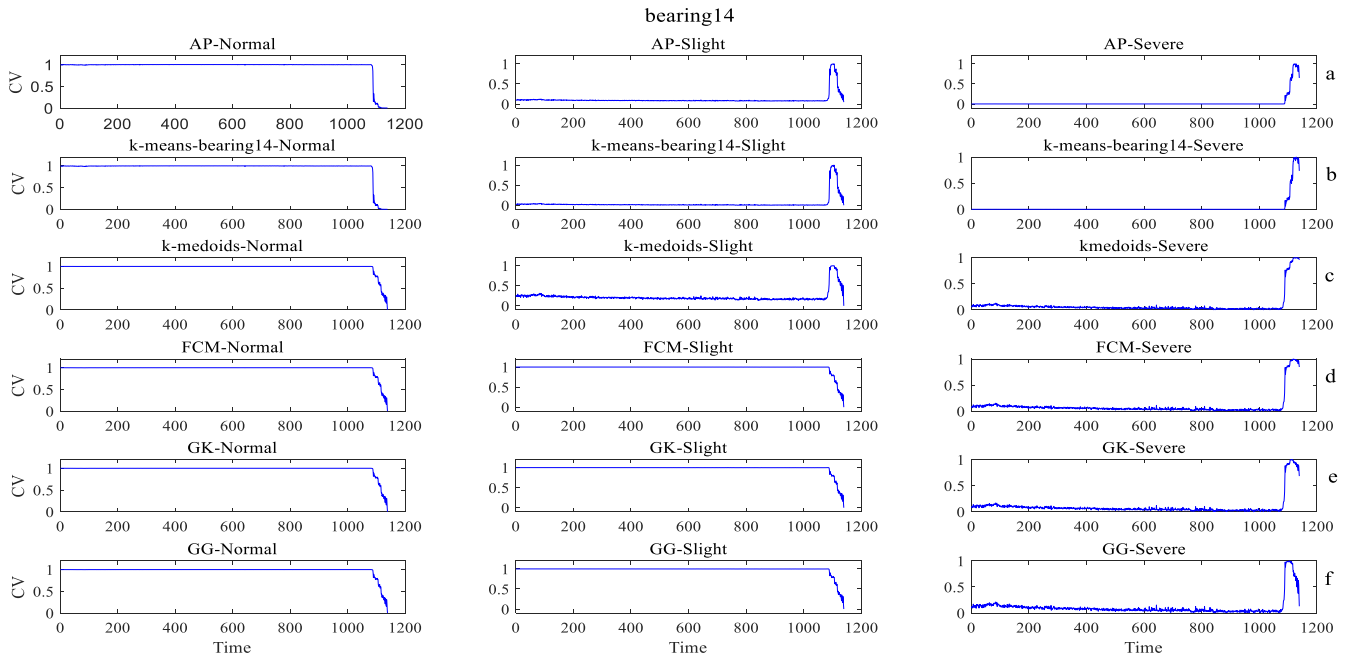
FIGURE 14. CV values calculated for bearing 14 by various clustering methods.
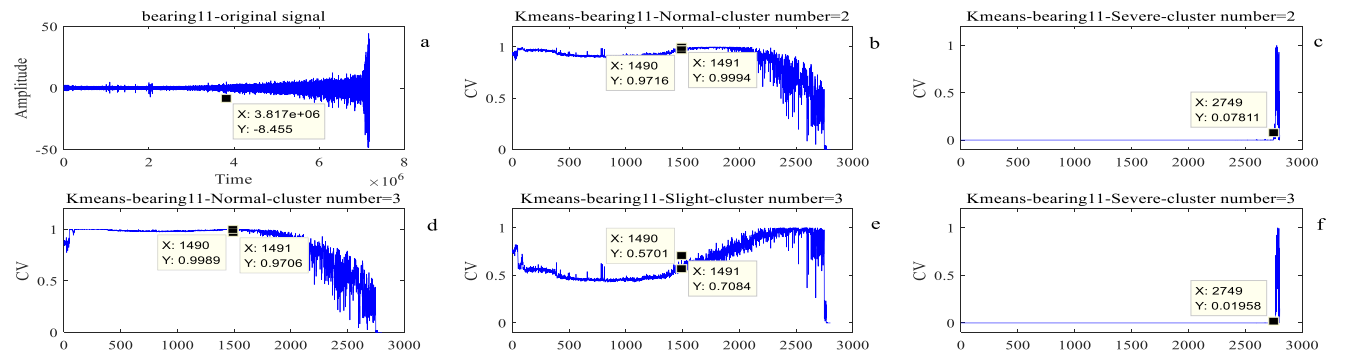

FIGURE 15. CV curves calculated by k-means with different preset clustering numbers.

These experimental results indicate that the PDA performance of AP clustering is the same as k-means with cluster number a priori and is superior to those of k-medoids, FCM, GK, and GG despite of pre-determined cluster number.

E. COMPARISON WITH RMS AND KURTOSIS
In this section, the performance of the proposed method is compared with the time-domain features RMS and kurtosis. Fig. 16 and Fig. 17 show the results of RMS and kurtosis, respectively.

In Fig. 16(a) and Fig. 16(b), some noise can be seen in the normal condition, for example in the CV values before the 1490th sample for bearing 11 and before the 828th sample for bearing 12, 13, and 14, which adds to the difficulties in distinguishing the bearing state transition point. In contrast, the CV curve from the proposed method is clearer and more

stable for the normal condition, as in Fig. 8 and Fig. 9. Moreover, when bearing 11 transits from normal to slight at around the 1490th sample in Fig. 9(a), there is a sharp increase of CV value. For the RMS method, it increases steadily at the 1490th sample, with no obvious features observed. While the drastic change of CV value in Fig. 9 provides the user with evidence of bearing status transition, especially from normal to slight, the RMS plot is smoother, thus provides less information, which is also verified on bearing 13 and 14, see Fig. 9 and Fig. 16 for detail.

From Fig. 17(a), (b) and (c), kurtosis plot introduces even larger fluctuations in the normal state than KMS plot, which is again undesirable. What's more, little information can be extracted from Fig. 17 to determine the bearing state transition point as compared with the proposed method in Fig. 9.
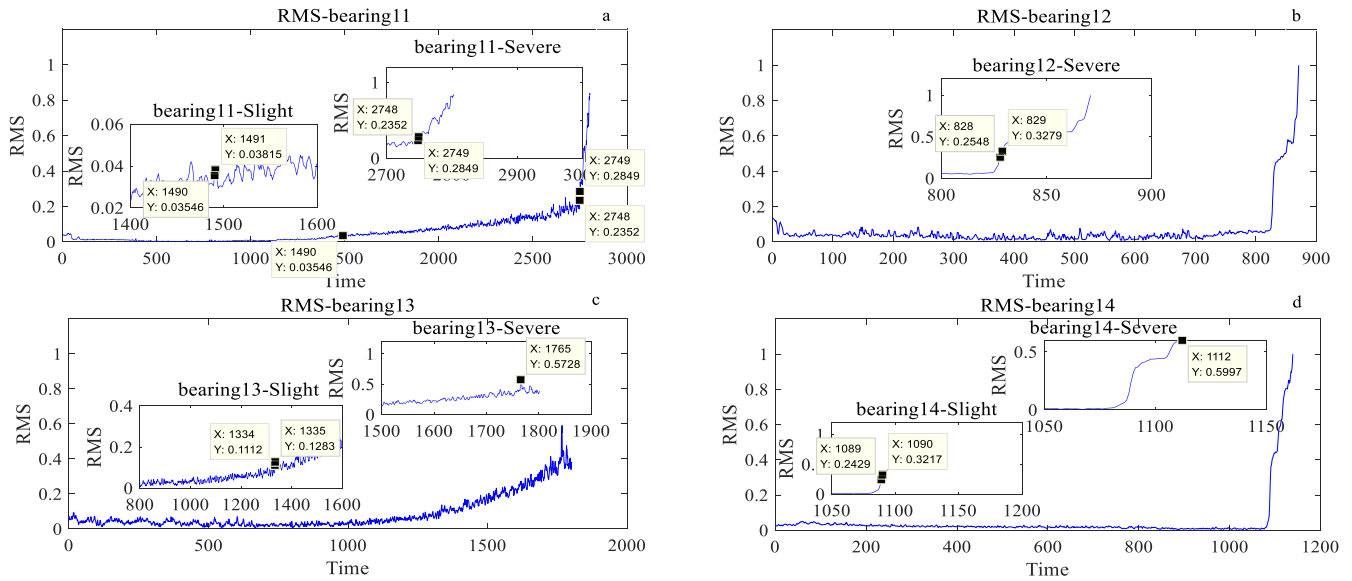
FIGURE 16. RMS results for different bearings (a): Bearing 11 (b): Bearing 12 (c): Bearing 13 (d): Bearing 14.
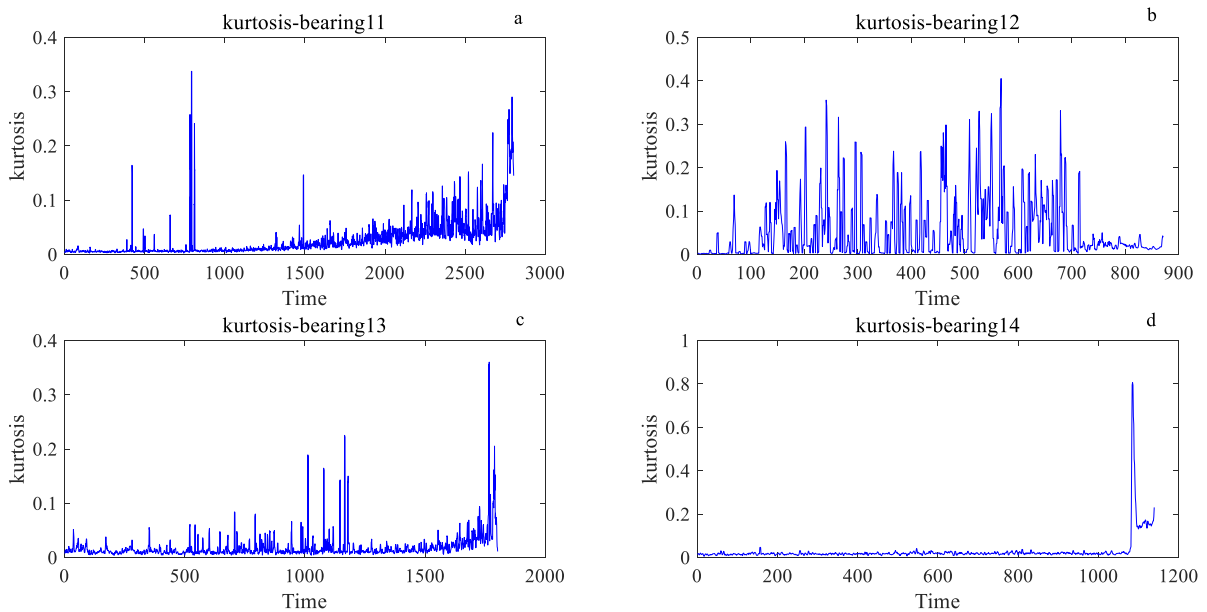

FIGURE 17. Kurtosis results for different bearings (a): Bearing 11 (b): Bearing 12 (c): Bearing 13 (d): Bearing 14.

Reinforcing the conclusions above, these results demonstrate that the PDA ability of AP clustering is superior to that of RMS and kurtosis.

V. CONCLUSION

This paper presents a new method for bearing PDA. First, EEMD is used to decompose the bearing vibration signal into IMFs. Second, the SV values obtained from the IMFs are used to extract and calculate the degeneration vector of the bearing. Then the extracted features are subject to AP clustering to determine the cluster center. Finally, CV as a health indicator was calculated from the distance between each sample and the cluster center point under the normal state to implement the bearing PDA. Compared with traditional clustering method, the newly employed AP method doesn't require a pre-determined cluster number and is demonstrated experimentally to truly identify all the cluster centers for all bearings. The performance of proposed framework was also compared with traditional methods k-means, k-medoids, FCM, GK, and GG, and temporal features such as RMS and kurtosis. When cluster number is known a priori, the k-means and the proposed method yields almost identical results.

Otherwise it is shown that the AP method provides superior CV index than those methods in reflecting slight changes in degradation status.

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