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Identification of Bearing Fault Signal based on Adaptive Feature Extraction and Optimal ACROSVKF Classification Model

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Abstract:
The paper proposed a new efficient diagnostic technique for the various fault statuses of roller bearings. This technique identifies the bearing fault exactly by an optimal classification model based on our adaptive features. Firstly, the empirical mode decomposition (EMD) method is used to decompose a non-linear and non-stationary vibration signal into intrinsic mode functions (IMFs). A feature-matrix is then formed by several of the first IMFs with its adaptive statistical characteristics, namely IMFSC. Secondly, the singular value decomposition (SVD) method is used to exploit the meaningful singular values which represent as a feature vector in the original feature-matrix named IMFSC-SVD. The obtained IMFSC-SVD features provide the classifier model with the vital input. Finally, a support vector machine model with a kernel function (SVKF) is optimally trained in the features, learning to identify the respective fault pattern. In the formation of the optimal classifier model, the artificial chemical reaction optimization (ACRO) algorithm is used to find out the best parameter pair of the SVKF classifier model, commonly called ACROSVKF. We experimented on two bearing vibration datasets, and the achieved results demonstrated that the proposed diagnostic technique was effective in terms of identification accuracy and time cost.

Keywords: Bearing component fault diagnosis; Support vector kernel function; Intrinsic Mode Function Statistical characteristics; Artificial Chemical Reaction Optimization Algorithm.

I. INTRODUCTION

In the maintenance of rotating machinery, roller bearings are of more interest than most parts because they usually assume important responsibilities. These systems work especially well under the condition of healthy bearings (HBs). Defects in roller bearings normally occur on the outer-race (OR), inner-race (IR), or roller element (RE), which causes faults in the respective bearing components. These actual fault statuses need to be identified accurately and opportunely to meet the minimal requirement for the production efficiency and to guarantee safety Therefore, an effective of diagnostic technique has been developed to reduce the maintenance cost and improve productivity. Normally, the bearing fault conditions are subjectively detected by vibration signals, which are generated by are operation of roller bearing with fault. Thevibrationsignal is normally non-linear and non-stationary with features which are hidden deeply and cannot be discovered in fact [1]. In past decades, the time-frequency analysis methods have been formulated to probe these data and are applied to feature extraction. The methods include short-time Fourier transform (STFT) [2], Wigner–Ville distribution (WVD) [3], wavelet transform (WT) [4], empirical mode decomposition (EMD) [5, 6], and local mean decomposition (LMD) [7, 8]. Among these methods, EMD is one of the special method and is very well known. EMD was first proposed by Huang in 1998 [9]. It has been extensively studied and widely applied in various areas, such as process control [10], modeling [11], and voice recognition [12]. The EMD method is adequate for processing vibration signals. Moreover, EMD has become more and more attractive in the field of fault diagnosis[6, 13, 14] and it especially impresses on rotating machinery systems. EMD can decompose the vibration signal into a set of Intrinsic Mode Functions (IMFs) and a residual. The first several IMFs contain the most important information of the original signal which needs to be explored. In this work, the authors used statistical characteristics (SCs) to analyze the hidden features of IMFsin the time-domain and frequency-domain, namely IMFSC. The IMFSC is based on the root mean square (Rms), skewness (Sk), kurtosis (Kur), crest factor (CrF), and impulse factor (ImF) in the time domain, while the Shannon entropy $(ShaEn)$ can indicate the vibration energy of the signal in the frequency domain. These obtained IMFSCs then form an adequate IMFSC feature-matrix of the original vibration signal, which is compared with a single feature vector. However, the dimensionality of the feature-matrix can interfere with the further classification stage. We take advantage of Singular Value Decomposition (SVD) to achieve the crucial features of IMFSC, named IMFSC-SVD. These obtained singular values can exactly reflect the actual fault status of the roller bearing. They contain the main information in the original feature-matrix, which represents as a singular feature vector of the original vibration signal. This feature vector then serves as input for the classification model, which is trained to identify the pattern statuses respectively. Support Vector Machine is a new machine learning algorithm proposed by Vapnik and based on statistical learning theory [15]. Support vector machine with kernel function (SVFK) has been proposed to improve the accuracy of the classification. SVKF is a powerful machine learning tool that has been employed in applications such as pattern recognition, time-series forecasting, robotics, and diagnostics [16-20]. Using SVKF for classification purposes not only requires superior input features but also requires an optimal parameter pair (C, σ). These parameter values play an important role in the architectural design of a classifier model with high classification accuracy and stable performance. Recently, evolutionary algorithms such as ant colony optimization (ACO), genetic algorithm (GA), and particle swarm optimization (PSO) have been used to optimize the SVKF's parameter pair [21-23]. However, the reasons why these methods are not ideal and have restrictions have been shown to include the abundance of training samples, the multiple parameters of a particle, and greater time cost [23]. In this study, the objective is to lift restrictions, and we propose the use of the Artificial Chemical Reaction Optimization (ACRO) algorithm to select the best parameter pair $(C, \sigma)$for the SVKF classifier. The ACRO algorithm is a fairly new meta-heuristic introduced by Bilal Alatas [24]. An evolutionary optimization technique conforms to the nature of chemical reactions to search for the optimal solution. In the algorithm, the potential energy and the entropy can be used as the objective function. The operators of ACRO are designed using the crossover and mutation operators. This algorithm has been effectively employed in some applications, such as in the fields of recognition, data mining, and classification rules [24-26]. The efficiencies of ACRO have been demonstrated in solving NP-hard optimization problems. It should be especially noted that the algorithm does not require values to be set for many parameters at the beginning. It only requires the definition of the number of initial reactants. Based on the superiority of the algorithm, the best parameter pair $(C, \sigma)$of the SVKF classifier model is selected, named ACROSVKF. The optimized ACROSVKF classifier model can achieve distinguished performance in classification accuracy with a low time cost. In this model, the IMFSC-SVD feature provides the input for the ACROSVKF classifier in the form of the IMFSC-SVD–ACROSVKF based diagnostic technique, which is then applied to the diagnosis of various roller-bearing faults. The remainder of this paper is organized as follows: Section 2 presents the IMFSC-SVD based adaptive feature extraction. The crucial feature set is extracted from original vibration data to serve as the classifier model. Section 3 presents the main procedures for building the optimal ACROSVKF classifier model using in the proposed diagnostic technique. Section 4 presents two main stages: (1) adaptive feature extraction and (2) pattern classification by the optimal classifier model in architecting the new diagnostic technique. Section 5 presents the experimental results to demonstrate the effectiveness performance based on the diagnostic technique and discussion. Section 6 gives the conclusions based on the research achievements and extended research field.

II. ADAPTIVE FEATURE EXTRACTION BASED ON EMD

In this section, we detail the feature extraction of the original vibration signal. Firstly, the famous self-adaptivemethod EMD decomposes the vibration signalinto the IMFs and a residual. Adaptive IMFSC values are then calculated and form the feature matrix. Finally, the singular values of the feature-matrix can be obtained by the SVD method. It is a feature vector that contains the most crucial information of the original vibration signal.

A. Empirical Mode Decomposition Method

The Empirical Mode Decomposition (EMD) method is an interesting method for analyzing non-stationary, non-linear data and has been applied effectively [6]. EMD analyzes the main signal based on the expansion of the basic functions. These functions are estimated by an iterative procedure called sifting. In other words, the EMD method is used to decompose a signal automatically into a set of band-limited functions, IMFs. Each IMF should satisfy two basic conditions [9]: (1) in the whole data set, the number of extreme points and the number of zero crossings must either be equal or differ by one at most; and (2) at every point, the mean value of the envelopes defined by local maxima and local minima is zero.

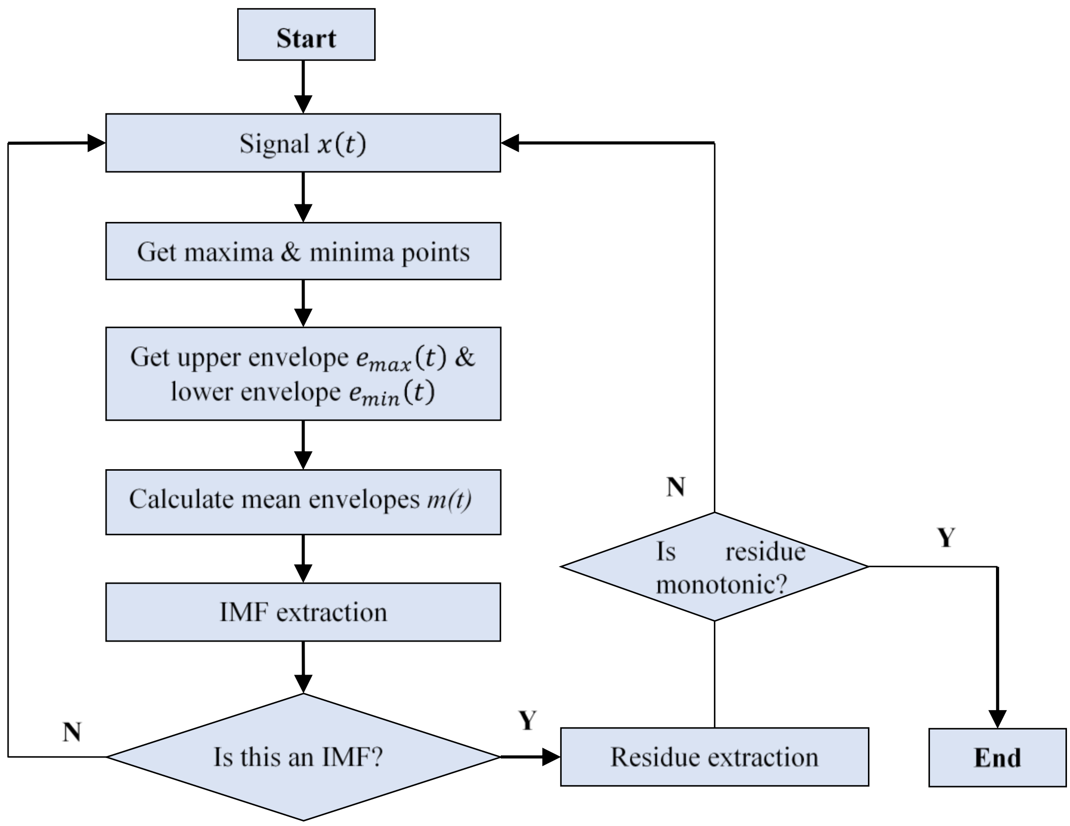

Figure.1. The flow chart of EMD algorithm

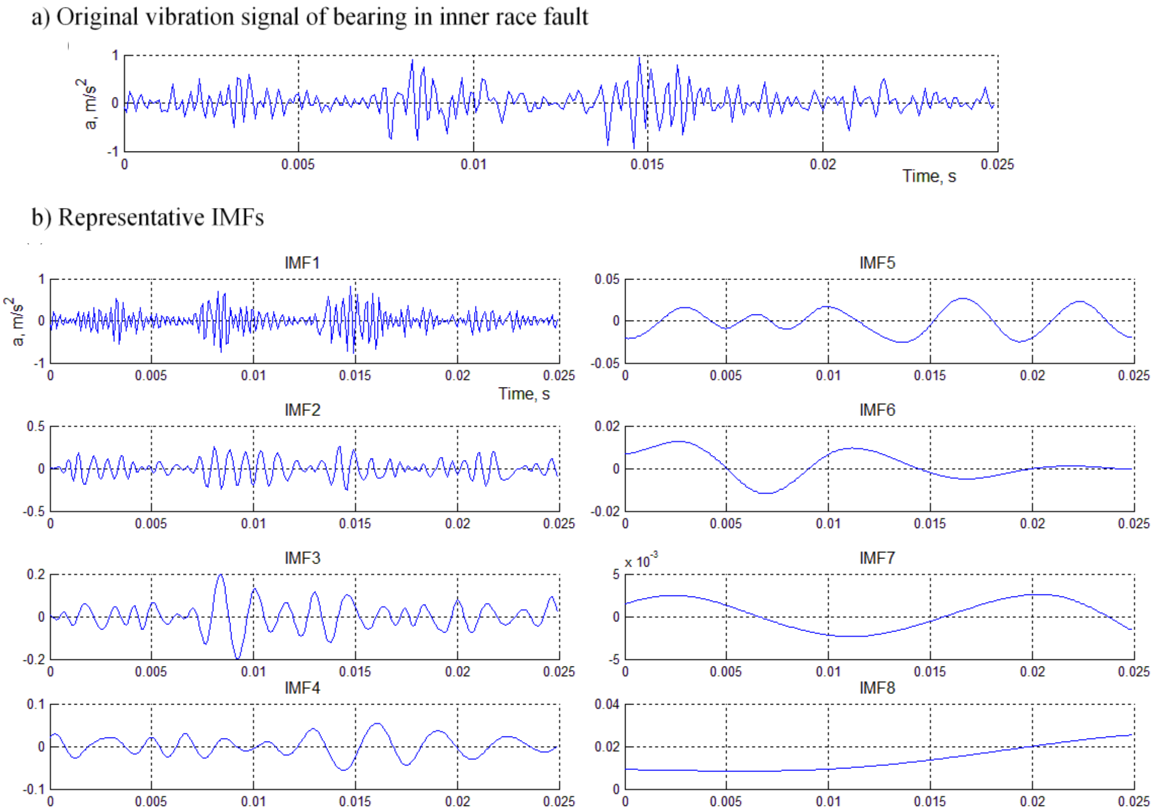

Figure.2. A sample is analyzed by using EMD method

The EMD can separate a segment of a bearing fault signal $x(t)$ into n IMFs: $IMF_1, IMF_2, \ldots, IMF_n$, and a residuesignal r. Hence, $x(t)$ can be reconstructed as a linear combination:

$$x(t) = \sum_{n=1}^{N} IMF_n + r \qquad (1)$$

EMD is a sifting process and is a systematic way to extract IMFs. Figure 1 presents a flow chart of the EMD algorithm. This flow chart can be described as follows:

Given an input signal $x(t), r(t) = x(t), n = 0$,

Step 1: Get the local maximum and local minimum of $x(t)$

Step 2: Get the upper envelope $e_{max}(t)$ by connecting all local maxima through cubic spline functions. Repeat the procedure for the local minima to produce the lower envelope $e_{min}(t)$.

Step 3: Calculate the mean value at every point of the envelopes:

$$m(t) = \frac{1}{2}\left(e_{max}(t) + e_{min}(t)\right) \qquad (2)$$

Step 4: Calculate $h(t) = x(t) - m(t)$. If $h(t)$ satisfies the IMF condition, then $n = n + 1$, $IMF_n = h(t)$ and go to Step 5; else $x(t) = h(t)$, go toStep 1.

Step 5: Let $r(t) = r(t) - IMF_n$. If $r(t)$ is a monotonic function, end the sifting process, else $x(t) = r(t)$ and go back to Step 1. Figure 2 illustrates an example of the EMD process, where Fig. 2(a) shows the bearing vibration signal in the inner race defect and Fig. 2(b) depicts the decomposed IMFs, IMF1 to IMF7, and the residual IMF8. Each of the IMFs includes different frequency bands ranging from high to low and implies a distinct time characteristic scale.

B. IMFSC-SVD based Feature Extraction

In the fault diagnosis systems, the fault feature values of the vibration signal have a crucial role in helping the system to identify the fault status and exactly and quickly. These extracted features must be special and condensed and must express most of the important information of the original vibration signal which will increase capability of the identification process. Figure 3 shows the overall feature extraction and selection based on IMFSC-SVD. EMD decomposes the original vibration signal into the set of IMFs and residual. The obtained IMFs represented explicit and they have a direct relation to the original vibration signal. The first several IMFs are a storehouse for important information. The IMFSCs are analyzed to form a combination feature-matrix that shows all the main information of the vibration signal. It is assumed that$x(t)$ is an original IMF in the time domain and K is the number of amplitude points. IMFSCs are defined as follows:

(1) The root mean square (Rms) is the square root of the average.

$$Rms = \sqrt{\frac{1}{K}\sum_{i=1}^{K} x_i^2} \qquad (3)$$

(2) Skewness (Sk) describes the degree of symmetry of the distribution around its mean $\bar{x}$.

$$Sk = \frac{K}{(K-1)(K-2)} \sum_{i=1}^{K} \left(\frac{x_i - \bar{x}}{Std}\right)^3 \qquad (4)$$

Where: the Std parameter measures the energy in the vibration signal, $Std = \sqrt{\sum_{i=1}^{K}(x_i - \bar{x})^2/(K-1)}$.

(3) The kurtosis (Kur) parameter is used to describe the distribution of the observed data around the mean.

$$Kur = \frac{K(K+1)}{(K-1)(K-2)(K-3)} \sum_{i=1}^{K} \left(\frac{x_i - \bar{x}}{Std}\right)^4 - \frac{3(K-1)^2}{(K-1)(K-2)} \qquad (5)$$

(4) The crest factor (CrF) parameter represents a waveform shape feature of the vibration signal which is indicated by the ratio of the peak value to the Rms value.

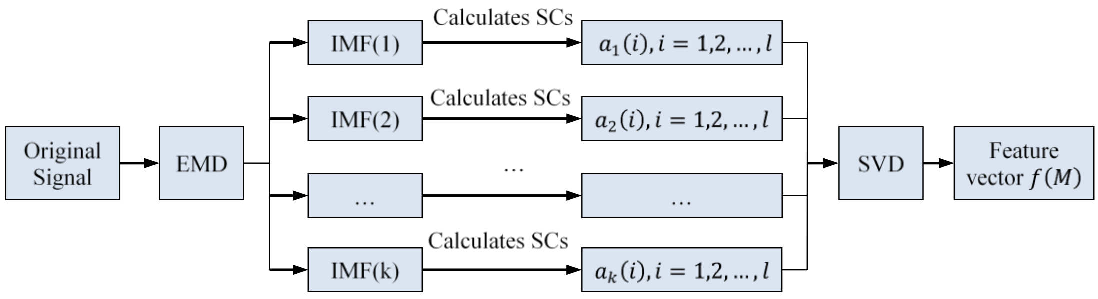

Figure.3. Flowchart of proposed IMFSC-SVD feature extraction

$$CrF = \frac{Peak_{max}}{Rms} \tag{6}$$

(5) The impulse factor (ImF) is defined as follows:

$$ImF = \frac{Peak_{max} - Peak_{min}}{2(Std)} \tag{7}$$

(6) ShaEnindicates the vibration energy in the frequency domain, which is defined as below:

$$ShaEn = -\sum_{k=1}^{K} P_k \log P_k \tag{8}$$

Where: $P_k = |p_i|^2 / \sum_{i=1}^{K} |p_i|^2$ is the distribution of the energy probability for each spectrum component and p_i is a spectrum for $i = 1,2,..,K$, with K the number of spectrum lines.

Table 1 showsa sample feature-matrix IMFSC with a bearing fault condition of an inner-race fault, which is depicted by the waveform in Fig. 2(a). Each row of this table shows the results for one of the six statistical parameters related to Eqs. (3) to (8), respectively. For various fault statuses of roller bearings, IMFSC values are considered for crucial features of the respective vibration signal and are depicted in Fig. 4.

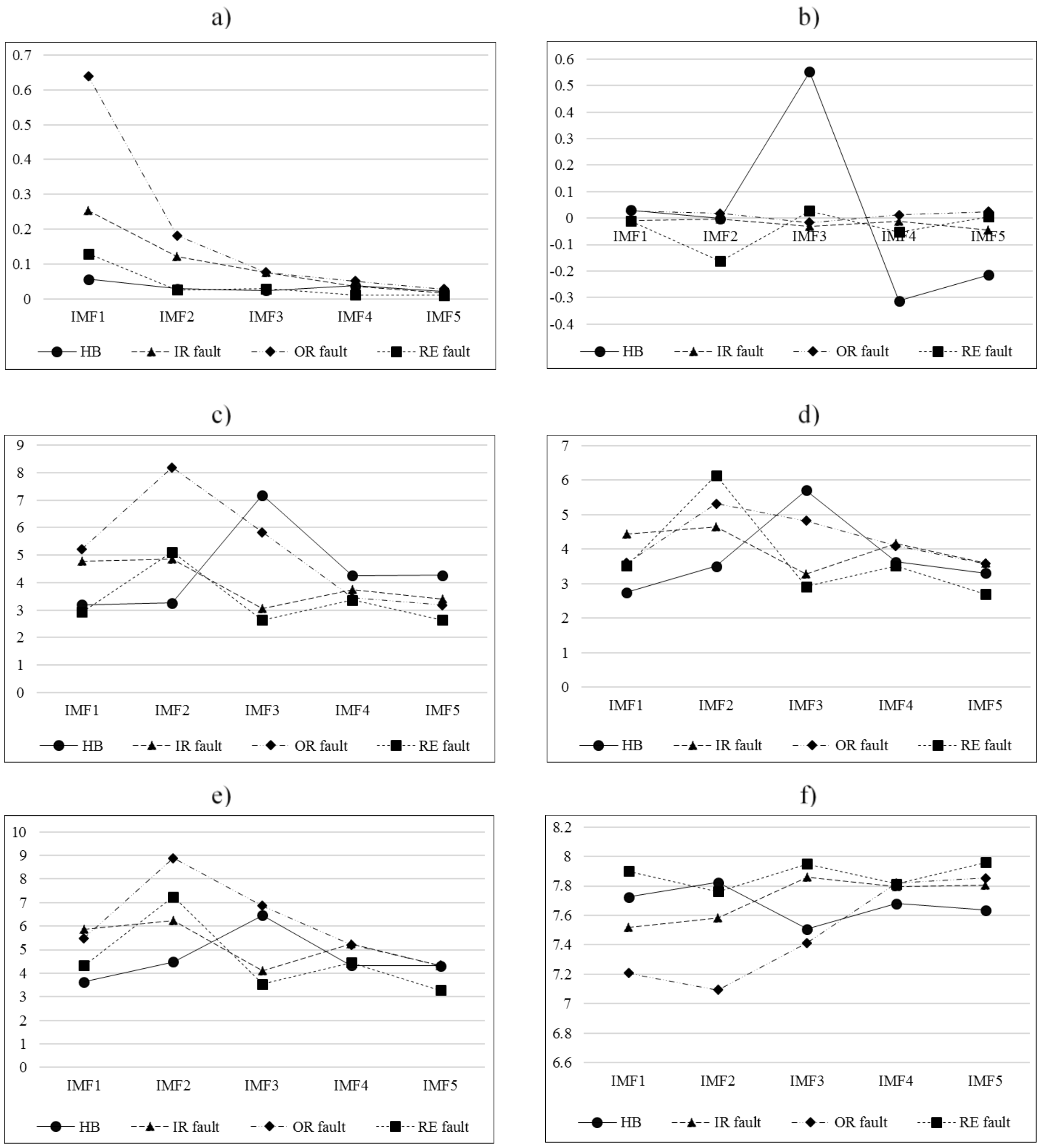

Figure.4. A sample of IMFSC feature values for four bearing statuses
a) Root mean square, b) Skewness, c) Kurtosis, d) Crest factor, e) Impulse factor, f) Shannon Entropy

Table.1. A sampling of feature-matrix imfsc

	Statistical characteristics					
	Rms	*Sk*	*Kur*	*ScF*	*ImF*	*ShaEn*
IMF1	0.2538	-0.0097	4.7809	4.4431	5.8628	7.5164
IMF2	0.1223	-0.0049	4.8497	4.6459	6.2383	7.5814
IMF3	0.0765	-0.0301	3.0621	3.2715	4.1160	7.8604
IMF4	0.0359	-0.0116	3.7563	4.1636	5.2410	7.7956
IMF5	0.0172	-0.0459	3.3901	3.6046	4.3194	7.8059

When performing the fault diagnosis, the feature-matrix needs to represent singular features to aim at diagnostic accuracy and to improve the efficiency of the process. In this work, SVD is used to extract the excellent features based on the IMFSC feature-matrix. IMFSC-SVD exploits the intrinsic characteristics which can give the dominant fault-related information, and the unfitting features of the IMFSC feature-matrix could be ignored. The IMFSC-SVD singular values gained express the conducive features of the original vibration signal which serves as the input of classifier model. Suppose that the first k IMFs obtained are selected to calculate l statistical characteristics according to Eqs. (3) to (8). Variable a is constructed based on the $M^{k\times l}$ feature-matrix, which is expressed as below:

$$M = \begin{bmatrix} a_{11} a_{12} & \cdots & a_{1l} \\ a_{21} a_{22} & \cdots & a_{2l} \\ \vdots \quad \vdots & \ddots & \vdots \\ a_{k1} a_{k2} & \cdots & a_{kl} \end{bmatrix} \qquad (9)$$

By applying SVD to M, the singular values as well as the $f(M)$ fault feature vector are obtained:

$$f(M) = [f_M^1, f_M^2, \dots, f_M^3] \qquad (10)$$

Where: f_M^i are considered as the singular values of M.

The singular values are listed in descending order automatically by the SVD function $f_M^1 \geq f_M^2 \geq \cdots \geq f_M^l$.

III. ARCHITECTING OF THE ACROSVKF CLASSIFICATION MODEL BASED ON ACRO

As mentioned in the first section, this study aims at accurate diagnosis of various bearing fault statuses based on the IMFSC-SVD. We present the ACRO algorithm which is used to build the proposed ACROSVKF classifier model. ThisACROSVKF model obtained the best parameter pair obtained (C, σ) to become the effective model and credible.

A. Support Vector Machine with Kernel Function (SVKF)

In the classification, SVM is a machine learning method which is usually used to solve two-class problems. Suppose that the linear separable sample set is$(x_i, y_i), i = 1,2, \dots, n, x \in R^d$, and $y \in [+1, -1]$ marks the class label. The common form of linear function is $p(x) = \omega x + b$ and the equation describes the separating hyperplane as below:

$$\omega x + b = 0 \qquad (11)$$

The task of SVM is to find the optimal separating hyper plane (OSH) that can separate the samples without error and maximize the distance between both classes and the separating hyperplane, as shown in Fig. 5. To correctly classify the samples of different classes, the OSH must satisfy the condition:

$$y_i[(\omega x_i) + b] - 1 \geq 0, i = 1,2, \dots, n \qquad (12)$$

The margin between the two classes is $(2/\|\omega\|^2)$. Hence, maximizing the margin is equivalent to minimizing$\|\omega\|^2/2$. For the non-linearly separable cases, slack variables ξ_i are introduced and the constraints of Eq. (12) are modified as follows:

$$y_i[(\omega x_i) + b] - 1 + \xi \geq 0, i = 1,2, \dots, n \qquad (13)$$

The generalized OSH is determined by minimizing the following formula:

$$\phi(\omega) = \frac{1}{2}(\omega\omega) + C\left(\sum_{i=1}^{n} \xi_i\right) \qquad (14)$$

Where: C is a value that controls the penalty for misclassified samples. The saddle point of a Lagrange function with Lagrange multipliers gives the solution to the optimization problem under the constraints of Eq. (12). The optimal discriminant function is:

$$f(x) = sgn\{(\omega x) + b\} = sgn\left\{\sum_{i=1}^{n} x_i y_i (x_i, x) + b\right\} \qquad (15)$$

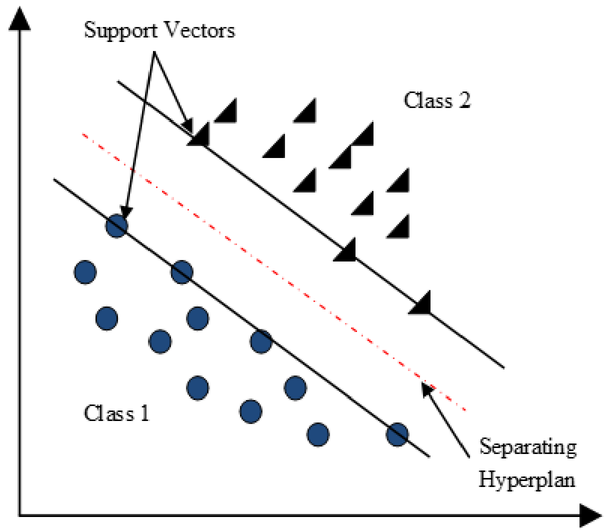

Figure.5. The separating hyperplane of two classes

The Kernel function $K(x, x')$will replace the inner-product in Eq. (13). The original feature space is mapped into a new higher dimensional feature space where the linear inseparability of projected samples is greater. Eq. (12) of the discriminant function is then rewritten as below:

$$f(x) = sgn\left\{\sum_{i=1}^{n} a_i y_i K(x_i, x) + b\right\} \qquad (16)$$

$K(x, x')$ is used with the radial basic function (RBF) as follows:

$$K(x, x_i) = exp\left\{-\frac{\|x - x_i\|^2}{2\sigma^2}\right\} \qquad (17)$$

Where: σ is a Kernel parameter.

SVKF is not only represented by an inner-product type in feature space $K(x, x') = K(\langle x \cdot x' \rangle)$. It is also a translation invariant kernel function as $K(x, x') = K(x - x')$, which is admitted if the function satisfies the conditions [15]:

(i) The symmetry function $K(x, x')$ is the kernel function of a support vector machine if and only if, for all functions $p \neq 0$ that satisfy the preprocessed condition of $\int_{R^d} p^2(\xi) d\xi < \infty$, and we need to satisfy the condition as follows:

$$\iint_{L_2 \otimes L_2} K(x, x') f(x) f(x') dx dx' \geq 0 \qquad (18)$$

(ii) The translation invariant kernel $K(x, x') = K(x - x')$ is an admissive SVKF if, and only if, the Fourier transform of $K(x)$satisfies the condition:

$F[k](\omega) \geq 0,$ Where:

$$F[k](\omega) = \frac{1}{(2\pi)^{d/2}} \int exp(-j(\omega \cdot x)) k(x) dx \qquad (19)$$

The conditions can therefore be utilized for both checking the admissible support vector kernel and constructing new Kernel functions. In this study, we considered using $K(x, x') = K(\langle x \cdot x' \rangle)$. In summary, the classification effect of SVKF is controlled by the parameter pair (C, σ), where the parameter C is mentioned in Eq. (14) and σ is a Kernel parameter mentioned in Eq. (17). These parameter pair values must be appropriately selected to obtain an effective classification accuracy, which can be done by the ACRO algorithm.

B. Artificial Chemical Reaction Optimization (ACRO) Algorithm

The ACRO is an adaptive optimization technique. The stochastic search algorithm of the ACRO is based on the process of natural chemical reactions. A chemical reaction is a process that leads to the transformation of one set of chemical substances into another. Two key reactions in the ACRO are bimolecular and monomolecular reactions [24]. The principle of the ACRO consists of the following five steps [24, 25]:

***Step 1*:** Define the problem and the optimization algorithm parameters.

***Step 2*:** Initialize the reactants and evaluate them.

***Step 3*:** Perform the chemical reactions.

***Step 4*:** Update the reactants.

***Step 5*:** Check the termination criterion.

The optimization problem is specified as follows:

Minimize $f(x)$
Subject to $x_j \in X_j, j = 1,2, \dots, N$
Where: $f(x)$ is an objective function; x is a set of decision variable x_j; and N is the number of decision variables; that is,x_j^{max} and x_j^{min} are the lower and upper bounds of the jth decision parameter respectively for encoding the realvalues. For more details, the reader can refer to [24].

C. Optimal ACROSVKF Classification Model

The ACRO algorithm is used to select best parameter pair (C, σ) in the SVKF classifier model which relates to the overall ability and reliability of the classifier model. The ACRO algorithm performs a search over the whole solution space to find the optimal solution efficiently. The algorithm is also simple since it does not require a continuous differentiable objective function like the gradient-based optimization techniques. The ACRO algorithm can select the best parameter value in the space of all possible parameter values of the training process. These parameters will be used to build an optimal classifier model. The reactants in the optimization algorithm ACRO are represent by the parameters C and σ, which represent the candidate solution. The reactant parameter values and training set are fed to the initial SVKF model. The depreciation function, Eq. (20), is used to evaluate the quality of every element. A better solution has a lower depreciation value. This process is continued until the maximum iteration value is reached. This completes the training phase of the ACROSVKF model, which is implemented as follows:

***Step 1*:** Divide the obtained feature set of vibration signal into the training set and testing set.

***Step 2*:** Perform the initialization, employing the training set
Randomly generate the initial parameter pair (C, σ) for SVKF. Set the maximum iteration number $k_{max} = 50$. Set the iterative variable: $k = 0$ and perform the training process for the next steps.
Set the values for the other parameters: the population size $popup = 5$, the upper bound $u^b = 2^{12}$, and the lower bound $l^b = 2^{-12}$

***Step 3*:** Set the iteration variable by increasing its value by one unit: $k = k + 1$.

***Step 4*: Carry out the fitness evaluation:**

The depreciation function is used to evaluate the quality of every element, which must be designed before searching for the optimal values of the SVKF. Equation (20) is a depreciation function that shows the classification accuracy of the obtained classification model.

$$depreciation(\%) = \left(1 - \frac{Samp_t}{Samp_t + Samp_f}\right) \qquad (20)$$

Where: $Samp_t$ and $Samp_f$ express the number of true and false classified samples, respectively. The desirable value is small, indicating high classification accuracy.

***Step 5*:** Criteria checking if the depreciation function is satisfied or the iteration meet the minimal value, go to step 7. The Optimal classification model ACROSVKF with the most accurate classification results is found. If not, go to the next step.

***Step 6*:** Update the parameter pair (C, σ) with new parameter values and go back to Step 3.

***Step 7*:** At the end of the training procedure, the trained classification model with the optimal parameter pair (C, σ) is obtained. Output the optimal value.

The excellent search capability of ACRO combined with the generalizing capability of SVKF to bring out synergies in the optimized ACROSVKF model. The results in the identification accuracy and time cost demonstrated ability and reliability of ACROSVM model which is based on the patterns of different bearing faults.

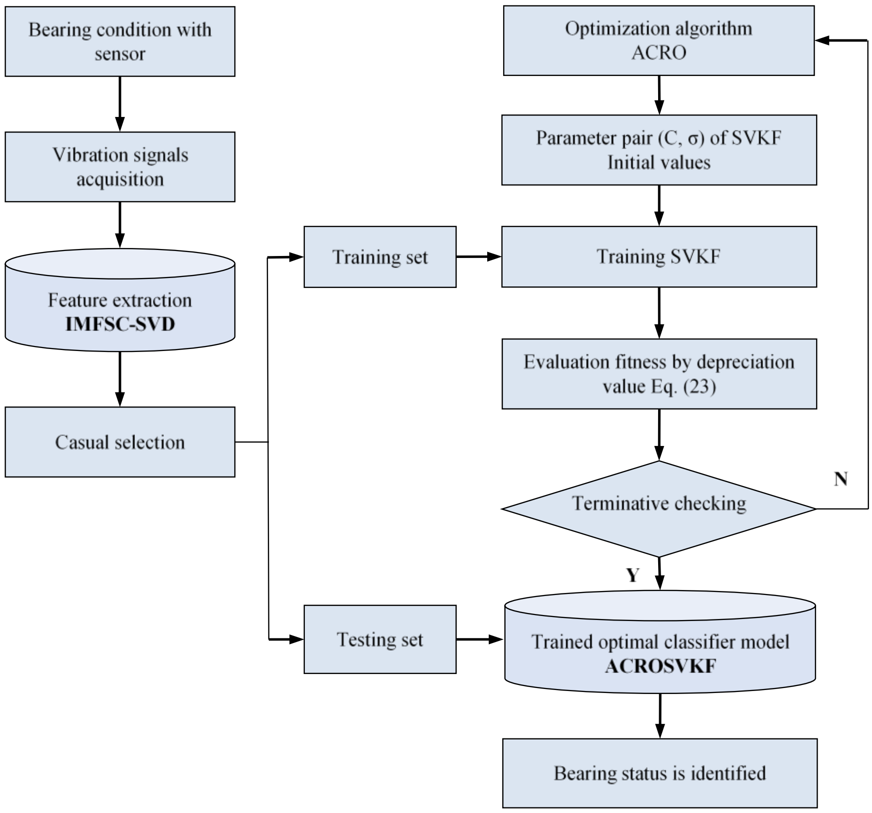

Figure.6. The Architecture of the fault diagnostic technique based on IMFSC-SVD and ACROSVKF

IV. BEARING FAULT DIAGNOSIS BASED IMFSC-SVD-ACROSVKF PROPOSED TECHNIQUE

The proposed technique based on IMFSC-SVD-ACROSVKF is coherently represented in this section. This technique consists of two main stages: (1) adaptive IMFSC-SVD feature-based feature extraction and (2) the optimal ACROSVKF model. Firstly, we use the adaptive IMFSC-SVD feature extraction to extract the meaning and most responsive features of the original vibration signal, which would increase the overall reliability and classification accuracy of the classifier model. Secondly, an optimal ACROSVKF classifier model is then used to identify the fault status with effective identification performance in which the classifier is based on the meta-heuristic ACRO algorithm. The aim of the proposed diagnostic technique IMFSC-SVD-ACROSVKFis to further improve the fault diagnosis performance and make sure the diagnoses are reliable. This technique can be visualized by the flowchart presented in Fig. 6, which can be described as follows:

Step 1**:** Data acquisition the vibration signals of the rolling bearing components with defects are taken by using the accelerometer sensor.

Step 2**: Adaptive feature extraction**
The feature set is generated by the feature extraction method based on the proposed IMFSC-SVD. Firstly, EMD decomposes the original vibration signal into the IMFs and residual. The first several IMFs are analyzed using the statistical features defined in Eqs. (3) to (8), which form a feature-matrix. Based on this feature-matrix, the SVD method extracts the singular features, which constitute an important feature vector of the original vibration signal. The details of this step are presented in Section 2.
Step 3**:** Pattern identification
The obtained feature set is divided into a training set and a testing set. The samples with the respective class labels of the training set are used to train the ACROSVKF. The trained ACROSVKF model with the optimal parameter pair (C, σ) is then evaluated by the testing set which fulfill as pattern classification. The bearing fault diagnostic technique based on IMFSC-SVD-ACROSVKF demonstrated diagnostic accuracy and reliabilityin experiments.

V. EXPERIMENTAL ANALYSIS

In this section, the authors report the results of an extensive performance study for evaluating the proposed IMFSC-SVD-ACROSVKF diagnostic technique. This diagnosis technique is applied to identify various faults of the bearing components with two vibration datasets. In which, the proposed ACROSVKF classifier model specially is stable and unbiased. To show that the classification capability of this model is superior we compared ACROSVKF with other classifier models. All of classifier models are experimented on the different feature sets which extracts by the IMFSC-SVD and EMD-SVD methods to make the comparison.

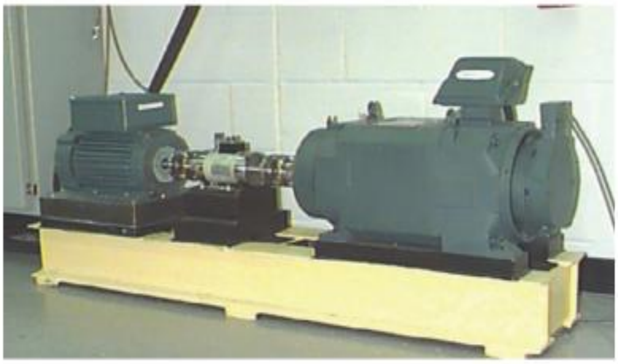

Figure .7. Schematic of the experimental setup

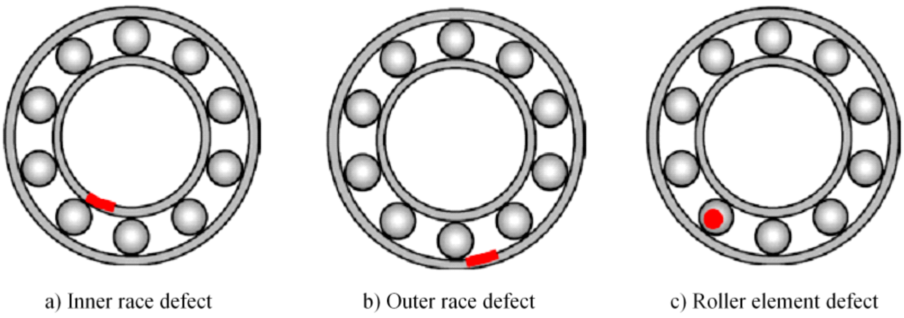

Figure.8. Schematic drawing of bearing fault statuses

Table.2. Classifier models for bearing conditions

Classifier model	Bearing condition			
	HB	IR fault	OR fault	RE fault
ACROSVKF1	**(+1)**	(-1)	(-1)	(-1)
ACROSVKF2	(-1)	**(+1)**	(-1)	(-1)
ACROSVKF3	(-1)	(-1)	**(+1)**	(-1)
ACROSVKF4	(-1)	(-1)	(-1)	**(+1)**

A. Data Acquisition

The first dataset was used in the Bearing Data Center, Case Western Reserve University (Loparo, 2013) with the experimental setup test rig shown in Fig. 7. This consists of a 2-HP Reliance electric motor, a torque transducer, and a dynamometer. The test bearings are installed on a motor shaft which is loaded by the dynamometer. The acquired vibration signal group comprises 100 signals with a sampling frequency of 12 kHz. Its grouping in four bearing conditions is tested for healthy bearings (HBs) and inner-race (IRs), outer-race (OR), and roller element (RE) faults separately. Figure 8 show the test conditions of the roller bearings. The test bearing is placed in DE with a shaft speed of 1797 RPM and has defect with a fault diameter of 0.007 inches and fault depth of 0.011 inches, which are generated by machining using the electro-discharge approach. To further demonstrate the efficacy of the proposed technique, a second dataset is acquired from the test rig in Fig. 9, which consists of a motor connected to a shaft by a coupling. A rotor and two test roller bearings of 6311-type are installed on the shaft. The bearing faults are introduced by laser cutting in the IR or RE with the same slot sizes of $W \times D$ = 0.15×0.13 (mm), respectively. The shaft's rotation speed is steady with a frequency of 25 Hz. The bearing vibration signals are acquired from the acceleration sensor at a sampling frequency of 4096 Hz. The collected vibration signal group is 60 signals in three roller bearing conditions: HB, IR fault, and RE fault, with 20 signals from each tested bearing condition respectively.

B. Results and Discussion

IMFSC-SVD based feature extraction was used to extract the feature set of the acquired vibration dataset. The adaptive parameters according to Eqs. (3)–(8) are used to calculate the statistical characteristics for the first five IMFs which are gained by the EMD in each vibration signal. The SVD is then used to extract the fault feature vector $\sigma(M)$. The obtained feature set is divided into the training and testing sets, which provide the input for the classifier model. The various fault statuses of the roller bearings are respectively identified by the classifier.

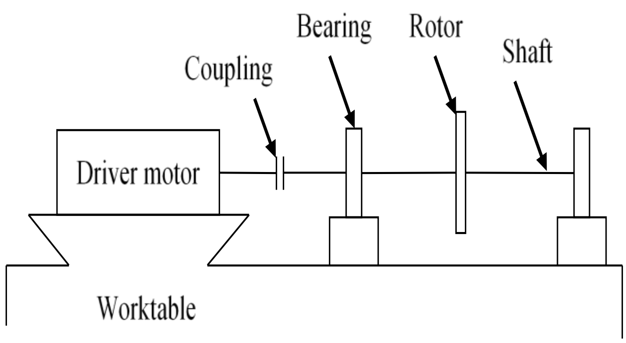

Figure. 9. Schematic drawing of the test rig

Table .3. Detailed information of acrosvkfs for the first dataset

	IMFSC-SVD Features					Patterns		Diagnosis task
						Training	Testing	
ACROSVKF1	21.6573	3.2692	0.5891	0.3805	0.0281	72	28	HB
ACROSVKF2	21.4028	1.7786	0.3114	0.1059	0.015	72	28	IR fault
ACROSVKF3	22.6017	3.6993	0.9713	0.2325	0.0208	72	28	OR fault
ACROSVKF4	20.9642	2.9797	0.294	0.0688	0.0071	72	28	RE fault

Table .4. The second dataset, with detailed information of acrosvkfs

	IMFSC-SVD Features					Patterns		Diagnosis task
						Training	Testing	
ACROSVKF1	20.1174	0.8614	0.3912	0.0387	0.00001	45	15	HB
ACROSVKF2	21.5883	2.3529	0.6258	0.0238	0.000034	45	15	IR fault
ACROSVKF4	23.7767	3.9291	0.9993	0.1585	0.000036	45	15	RE fault

In this study, the ACROSVKF(i), with i = 1, 2, 3, 4, are detailed in Table 2; they are designed to identify the HB, IR fault, OR fault, and RE fault conditions, respectively. It should be noted that the label of bearing status is assigned to (+1) in the status that needs to be identified and other labels of bearing status are assigned to (–1). To demonstrate the superior performance of the ACROSVKF classifier model, we compare ACROSVKF with the GASVKF model based on two feature sets. The majority (72%) of sample data are randomly selected and used for training the classifier and the rest are used for testing the classifier. Tables 3 and 4 show the number of training and testing samples in the two experimental datasets, respectively.

Table .5. Classification results obtained with the different diagnosis technique on the first dataset

	EMD		IMFSC-SVD	
	Diagnosis accuracy (%)	Time (s)	Diagnosis accuracy (%)	Time (s)
ACROSVKF1	80.36	1.8930	**99.64**	1.2158
ACROSVKF2	81.79	2.3657	**93.21**	1.4361
ACROSVKF3	84.64	2.1923	**100.00**	1.2842
ACROSVKF4	78.21	1.9986	**87.50**	1.2307
GASVKF1	76.18	2.6643	85.00	1.9845
GASVKF2	78.57	2.2544	92.50	1.8981
GASVKF3	84.64	2.0012	90.00	1.7977
GASVKF4	77.14	2.3123	80.00	2.0898

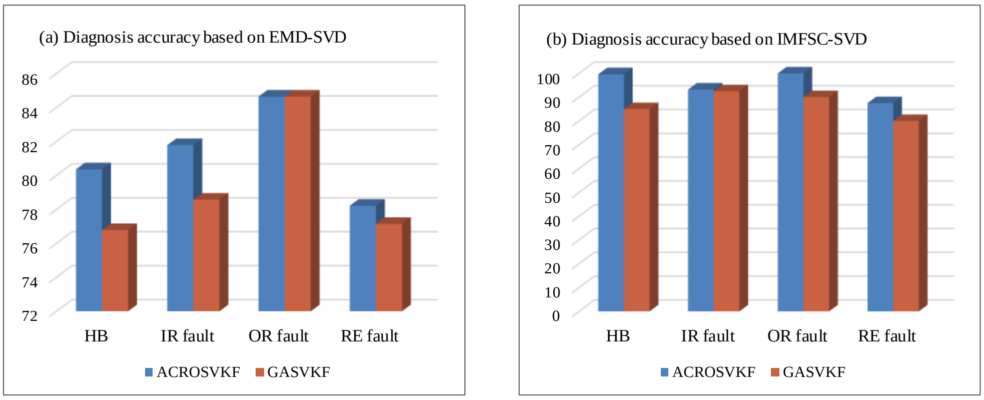

Figure.10. Comparison of diagnostic accuracy of IMFSC-SVD-ACROSVKF with other techniques in the first dataset

The achieved diagnostic results are shown in Tables 5 and 6 for both vibration datasets respectively. Observing these result tables, the ACROSVKF classifier model obtains a higher classification accuracy result in comparison with GASVKF for both feature sets. The achieved IMFSC-SVD feature set expressed the superior quality in the optimal classifier based on the ACRO algorithm which is highlighted in the result tables.

Table .6. Classification results obtained with the different diagnosis technique for the second dataset

	EMD		IMFSC-SVD	
	Diagnosis accuracy (%)	Time (s)	Diagnosis accuracy (%)	Time (s)
ACROSVKF1	88.67	1.4116	**99.33**	1.3965
ACROSVKF2	95.33	0.7199	**100.00**	0.8876
ACROSVKF4	90.00	1.0304	**90.67**	1.0304
GASVKF1	82.00	3.2798	84.67	2.8328
GASVKF2	82.67	3.0873	86.00	2.7168
GASVKF4	74.67	3.1207	76.00	2.8299

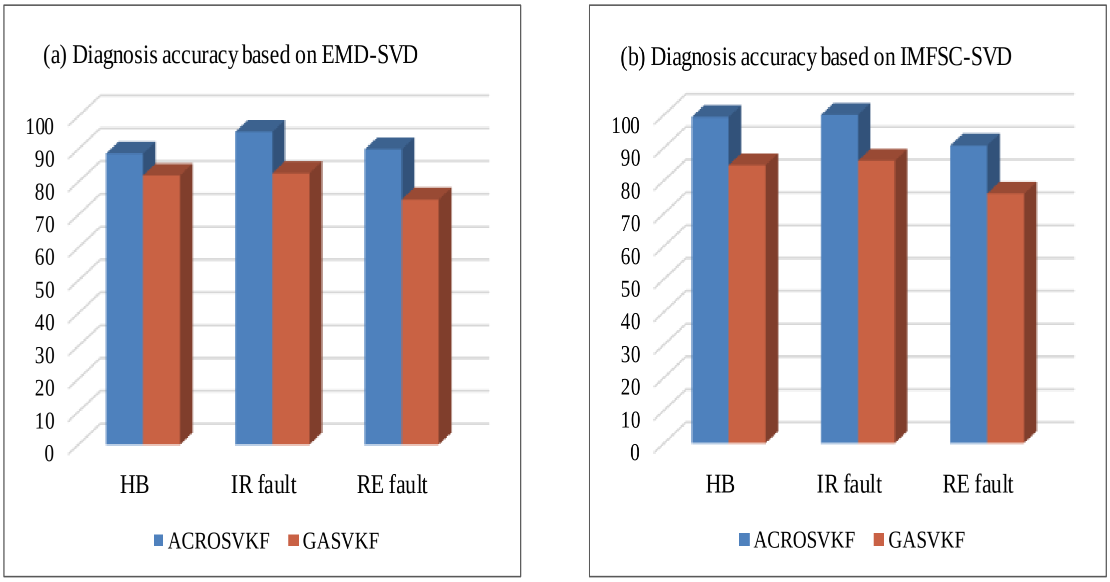

Figure.11. Comparison of diagnostic accuracy of IMFSC-SVD-ACROSVKF with other techniques in the second dataset

From the results in Table 5, based on the IMFSC-SVD feature set, the diagnostic accuracy of the proposed ACROSVKF classifier reached a maximum of 100%, while the GASVKF classifier achieved a maximum of 92.5%. Similarly, the results of Table 6 objectively reveal that the percentage classification accuracy achieved by the IMFSC-SVD-ACROSVKF technique is a significant result. To visualize the comparative results of the different diagnostic techniques, they are clearly depicted in the column chart in Figs. 10 and 11. We would like to emphasize that our proposed diagnostic technique had a lower time cost than the other models, which is also clearly shown in the time columns in Tables 5 and 6.

VI. CONCLUSIONS

The research in this paper is based on a theoretical synthesis and experiments to propose a diagnostic technique for bearing fault statuses. A new diagnostic technique integrates the adaptive feature extraction based on IMFSC-SVD and the ideal ACROSVKF classifier model in experiments. Firstly, the EMD method decomposed the original vibration signals into IMFs, in which each of the first five IMFs is calculated six parameters of statistical characteristic to form the IMFSC feature-matrix.Then, the SVD method is applied to the IMFSC feature-matrix to achieve the crucial IMFSC-SVD features. Finally, these feature values are fed into the optimal ACROSVKF classifier model as the input for performing classification. The classification results showed the effective classification performance. In addition, the proposed methodology in this study is demonstrated in an experimental environmentthrough application to two complex datasets of bearing statuses to identify the actual status. The experimental results showed that the samples are identified exactly with a low time cost. Moreover, the authors are confident that, this technique can be safely applied to other fault identification fields in machinery systems with non-linear, non-stationary data.

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VIII. CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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