Tạp chí Khoa học và Công nghệ, Số 70, 2024

A NEW ROLLER BEARING FAULT DIAGNOSIS METHOD BASED ON MVMD-RMS AND DE-LSSVM

AO HUNG LINH

Faculty of Mechanical Engineering, Industrial University of HCM City

** Corresponding author: aohunglinh@iuh.edu.vn*

DOIs: https://doi.org/10.46242/jstiuh.v70i4.4763

Abstract. This research introduces a novel method for roller bearing fault diagnosis based on the Least Squares Support Vector Machine (LSSVM) with parameters optimized using the Differential Evolution (DE) algorithm, referred to as DE-LSSVM. Initially, the Multivariate Variational Mode Decomposition (MVMD) method decomposes the acceleration vibration signals from roller bearings into component functions. Subsequently, these functions extract initial feature matrices using the root mean square (RMS) method. Finally, these values serve as input vectors for the DE-LSSVM classifier. Experimental results illustrate that the proposed method exhibits lower test error rates and reduced computational time when compared to other methods using the same collected data.

Keywords. Multivariate variational mode decomposition; fault diagnosis; root mean square; differential evolution; least square support vector machine.

1 INTRODUCTION

The roller bearing is an interposed element between the stationary part and the rotating part. A roller bearing failure can lead to a terrible failure, so roller bearing failure diagnosis plays a key role in guaranteeing continued system operation. Therefore, the diagnosis of roller bearing faults is the focus of this paper. Roller bearing failure diagnosis consists of three stages: data collection, feature extraction, and pattern recognition, of which these latter two stages play a significant role. When a bearing failure appears, fault characteristic information extraction is strenuous because of non-stationary feature of the roller bearing vibration signal. Feature extraction includes signal decompositions and feature extraction. The signal decomposition methods consist of Empirical Mode Decomposition (EMD) [1], Local Mean Decomposition (LMD)[2], Local-scale Characteristic Decomposition (LCD)[3]. In general, these methods decompose a vibration signal into the sum of component and residual signals. However, these methods suffer from drawbacks, including end effects and mode mixing during the sifting process, rendering them inefficient for roller bearing vibration signals. Recently, Naveed Ur Rehman et al. proposed the method to decompose the signal, namely Multivariate Variational Model Decomposition (MVMD)[4]. This method overcomes the shortcomings of the EMD, LMD, and LCD methods and gives high efficiency. MVMD utilize for denoising, blink removal from EEG signal, multi-fault diagnosis [5-8].

The component signals are feature extracted to form feature matrices using the methods of frequency ratio analysis [9], energy entropy [10], single value decomposition method (SVD) [11] and autoregressive (AR) model [12]. The feature extraction stage aims to reduce the input matrix size for the patten recognition step. In this paper, the root mean square (RMS) is used to extract features of the roller bearing signal.

Pattern recognition methods include using discriminable predictive model class discrimination (VPMCD) [13], k-nearest neighbor[14], hidden Markov model[15], artificial neural networks (ANNs) [16] and support vector machines (SVM) [17]. The disadvantage of VPMCD is difficult to set the variable parameters of a model. The disadvantage of the k-nearest neighbor method is computationally expensive and lazy learning. Hidden Markov models do not explicitly catch the time in a specified state due to their Markovian behavior. The support vector machine method has more advantages than ANN, meaning it has high generalizability with few numbers of training samples. This is very suitable when dealing with technical problems, but it is awfully expensive to collect large numbers of samples. LSSVM proposed by Suyken [11] is a modified version of SVM to reduce the computational workload. Using the LSSVM in the process of training, a least squares error function is recommended to obtain a linear set of equations in dual space. Thus, the data training problem is reduced to just solving a set of linear equations instead of quadratics like in SVM. LSSVM shows performance in prediction accuracy, fast computation, and high classification. However, the challenge for LSSVM users is the selection of the parameters of this model. The parameters of this model include the penalty factor and Kernel parameter. Usually, the selection of these parameters is based on heuristic search algorithms. Heuristic algorithms are often used to select and search for parameters for LSSVM, such as Genetic Algorithm (GA)[18], Differential Evolution algorithm (DE)[19], Particle Swarm Optimization (PSO)[20]. Differential Evolution algorithm showed outstanding advantages in solving optimization problems when compared with GA and PSO algorithms. In there, we propose using the DE algorithm as a tool for optimal parameters selection for the LSSVM classifier.

In this paper, we use MVMD method combined with RMS operator for feature extraction and DE-LSSVM classifier for fault identification. Firstly, the MVMD method decayed the bearing acceleration vibration signals into component functions. Then these component functions are extracted into a feature matrix by the RMS operator. The feature matrices are used as the input matrix for the LSSVM classifier. The parameters of the LSSVM set are optimized by the DE to generate the DE-LSSVM classifier. The experimental results showed the DE-LSSVM classifier gave lower test error results and shorter time when are compared with the GA-LSSVM and PSO-LSSVM classifiers with the same input data. The paper is arranged as follows: Section 1 shows MVMD method and RMS, Section 2 presents DE Algorithm, Section 3 presents optimization of LSSVM parameters based on DE. Section 4 presents the application of DE-LSSVM to diagnose bearing failure and the experimental process along with the results presented in section 5. Section 6 presents the conclusion of the paper.

2 MVMD-RMS

2.1 Multivariate Variational Mode Decomposition (MVMD)

The MVMD method is an adaptive orthogonal signal decomposition method for the multivariable or multichannel data set [4]. It is the extension of the VMD [21] algorithm and is a powerful method for sampling and anti-interference. The main idea of MVMD is to take out assume *K* quantity of multivariable modulation vibrations $u_k(t)$ from the input data $x(t)$ containing *N* data channels, that is, $x(t) = [x_1(t), x_2(t), \ldots x_N(t)]$

$$x(t) = \sum_{k=1}^{K} u_k\ (t) \tag{1}$$

where $u_k(t)=\{u_1(t), u_2(t),\ldots, u_k\}$.

The fitness function of MVMD becomes the multivariate expansion of the fitness function used in the corresponding VMD optimization problem and is showed by equation:

$$g = \sum \left\| \partial_t\left[e^{-j\omega_k t} u_k^*(t)\right]\right\|_2^2 \tag{2}$$

in which $u_k^*(t)$ is the analytic signal corresponding to $u_k(t)$, ω_k is a single frequency component and is used in the harmonic mixing of the whole vector $u_k(t)$.

This function *g* can be represented as follows:

$$g = \sum \sum \left\| \partial_t\left[u_{k,n}^*(t) e^{-j\omega_k t}\right]\right\|_2^2 \tag{3}$$

in which $u_{k,n}^*(t)$ includes channel number *n* and mode number *k*.

The problem of MVMD can be presented:

$$\min_{\{u_{k,n}\},\{\omega_k\}} \left\{ \sum \sum \left\| \partial_t\left[u_{k,n}^*(t) e^{-j\omega_k t}\right]\right\|_2^2 \right\}$$
$$s.t. X_N \sum_k u_{k,n}(t)\, , n = 1,2, \ldots, N \tag{4}$$

The Lagrange multiplier method and the quadratic penalty method are included in Eq.4 to transform the constrained variable problem into the unconstrained variable problem. The Lagrange parameter L is represented as follows:

$$L(\{u_{k,n}\}, \{\omega_k\}, \lambda_n) = \alpha \sum_{k=1}^{K} \sum_{n=1}^{N} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_{k,n}^*(t)\right] e^{-j\omega_k t} \right\|_2^2 + \sum_{n=1}^{N} \left\| x_n(t) - \sum_{k=1}^{K} u_{k,n}\,(t)\right\|_2^2 + \sum_{n=1}^{N} \langle \lambda(t), x(t) - \sum_{k=1}^{K} u_k\,(t)\rangle \tag{5}$$

where, α is the balancing parameter of the ‘‘data-fidelity’’ constraint.

Details of the MVMD method are presented in [4]. The number of component functions $u_k^*(t)$ determines the signal decay time and the classification time of the LSSVM classifier. The larger the number of component functions, the higher the computational time cost. In this paper, we choose the number of component functions to be 4 because important information is often contained in the first components. After decomposing the bearing acceleration vibration signal into component functions, in the next step, these component functions are extracted into characteristic matrices by the root mean square operator.

2.2 Root Mean Square

The signal *x(t)* has been decomposed with MVMD into n u_k. If n u_k achieves by using the MVMD method to divide the roller bearing oscillation signal, it will make RMS of the n u_k to become [RMS_1,RMS_2, . . . ,RMS_n] equivalent. As the {$u_1(t)$,$u_2(t)$,...,$u_n(t)$} include different frequency components, Z={Z_1,Z_2,...,Z_n}, forms an amplitude distribution in the frequency domain of roller bearing vibration signal, and then the corresponding MVMD RMS is designated as

$$Root\ Mean\ Square \qquad RMS = \sqrt{\frac{1}{n}\sum_{k=1}^{n}|u_k|^2} \tag{6}$$

Fig. 1 (a), (b), (c), and (d) show the roller bearing acceleration vibration signals with 4 conditions: Normal, inner-race fault, out-race fault, and ball fault, respectively. Table 1 shows that RMS of each roller bearing vibration signal is different because of the uncertain amplitude distribution and frequency range. Therefore, the LSSVM classifier will be effective in identifying roller bearing conditions based on these RMS values.

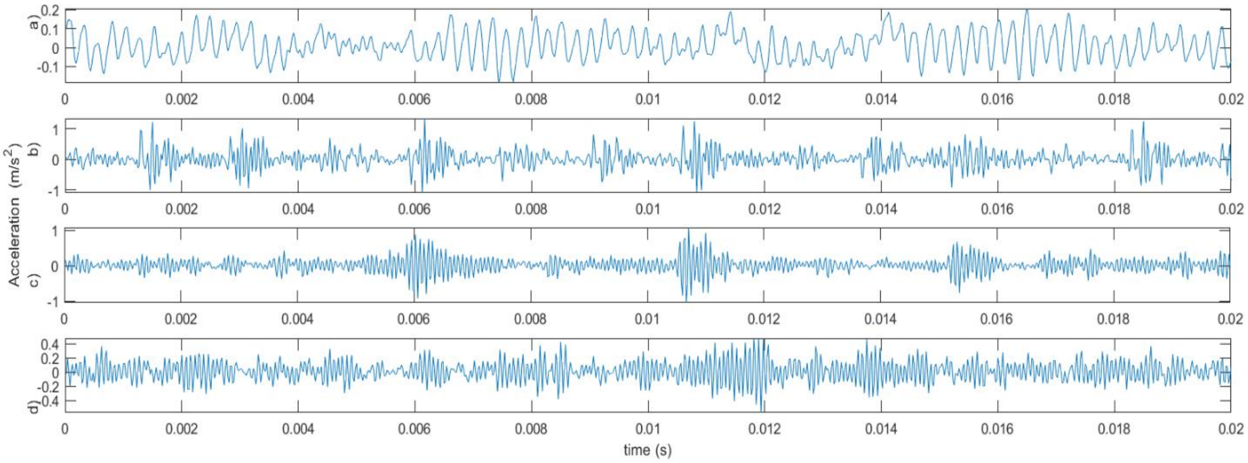

Figure 1: The vibration acceleration signals of the normal
(a), inner-race fault (b), outer-race fault (c), and ball fault roller bearing (d)

Table 1: The MVMD Root Mean Square of the vibration signals of the roller bearing with different faults.

Inner-race fault ($\times10^3$)	Out-race fault ($\times10^3$)	Ball fault ($\times10^3$)	Normal ($\times10^3$)
21.40	16.53	18.61	27.66

3 DIFFERENTIAL EVOLUTION (DE)

The DE is a heuristic search algorithm that includes 3 basic genetic operators: mutation, crossover, and selection to produce test individuals. The DE algorithm consists of six steps as follows[22]: (i) Problem definition and algorithm parameters; (ii) Initialization; (iii) Mutation; (iv) Crossover; (v) Selection ; (vi) End. The procedure of the DE algorithm is shown in Fig. 2.

Problem definition and algorithm parameters:

$$\min f(x) \tag{7}$$
$$subject\ to\ \boldsymbol{x}_i \in R_i = [l_i, u_i], i = 1,2, \dots N$$

where *f(x)* is a fitness function, **x** =(x_1,x_2,...,x_N) is the vector of decision variables, R_i is the range of feasible values for the i-th decision variable, and N is the number of decision variables, l_i and u_i are the lower and upper bounds of the i-th decision variable, respectively;

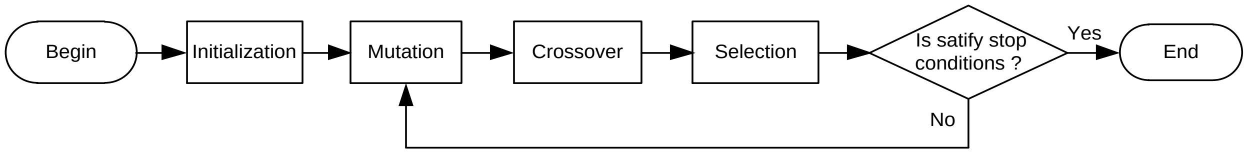

Figure 2: Flowchart of DE algorithm

4 DE BASED LSSVM PARAMETERS OPTIMIZATION

4.1 Least square support vector machine (LSSVM)

Suykens et al. proposed LSSVM to reduce the computationally assigned work of SVM by using equality constraints [23]. This method figures out the solution for convex optimization problems with fine abstraction ability for the optimal separate hyperplane. Suppose $\{(x_i, y_i)|i=1,2,\ldots,l\}$ as the training set of sample numbers is l. The sample of x_i , $i=1,2,\ldots,l$ corresponds to one output $y_i \in (-1,1)$, the objective function and constraint condition are shown as follows:

$$\begin{cases} \min \; J(w,e) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{i=1}^{l} e_i^2 \\ s.t.\; y_i(w^T\varphi(x_i)+b) = 1 - e_i, \quad i = \{1,2,\ldots,l\} \end{cases} \tag{8}$$

where, e_i are slack variables and $\gamma \geq 0$ is a penalty factor.

The training results are decided by values selection of γ. Therefore, it is important to search for the optimal value for γ. This parameter should be modified conscientiously. The Lagrange function can be defined:

$$L(w,b,e,\alpha) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l} \alpha_i \{y_i(w^T\varphi(x_i)+b) - 1 + e_i \tag{9}$$

where, the α_i values are the Lagrange multipliers, which can be positive or negative. The optimal condition is as follows:

$$\frac{\partial L}{\partial w} = 0; \frac{\partial L}{\partial b} = 0; \frac{\partial L}{\partial e_i} = 0; \; \frac{\partial L}{\partial \alpha_i} = 0 \tag{10}$$

The matrix equation can be obtained as follows:

$$\begin{bmatrix} 0 & Y^T \\ Y & \Omega + \frac{I}{\gamma} \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \bar{I} \end{bmatrix} \tag{11}$$

where $Y^T = [y_1, y_2, \ldots, y_l]$; I is unit matrix; $\bar{I} = [1;1;\ldots;1]$; $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_l]$; $\Omega = y_i y_j \varphi^T(x_i)\varphi(x_j) = y_i y_j K(x_i, x_j)$; $K(x_i, x_j)$ is Kernel function of SVM; $i, j=1,2,\ldots N$.

The LSSVM classifier in the dual space can be obtained as follows:

$$f(x) = sgn\left[\sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + b\right] \tag{12}$$

The Gauss radial basic function (RBF) is used to increase LSSVM performance and generalization, as represented as follows:

$$K(x, x_i) = exp\left(\frac{-\|x - x_i\|^2}{2\sigma^2}\right) \tag{13}$$

where σ is a Kernel parameter.

Summary, the parameter pairs (γ, σ) affect the classification efficiency of LSSVM. The proper selection of these two parameters will impact on LSSVM learning performance. Therefore, the DE algorithm is utilized to optimize these parameters to achieve high classification accuracy.

4.2 Parameters optimization of LSSVM based on DE

As mentioned in previous studies [12,13], LSSVM parameters strongly influence the classifier performance. The selection of optimal parameters for LSSVM is mainly based on user experience. In here, we propose to use DE algorithm to find the LSSVM optimal parameters.

The parameter pairs (γ, σ) are considered as optimization variables, while the test error is a suitable measure of the optimization problem. In here, the objective function is the test error of the LSSVM and is represented as follows:

$$G(\gamma, \sigma) = \mathrm{Test}_{\mathrm{Error}_{\mathrm{LSSVM}}}(\gamma, \sigma) \tag{14}$$

where $G(\gamma, \sigma)$ is a fitness function and $Test_{Error_{LSSVM}}(\gamma, \sigma)$ is define:

$$Test_{Error_{LSSVM}} = \frac{Number\ of\ incorrect\ classification\ in\ validation\ samples}{Total\ number\ of\ samples\ in\ validation\ set} \quad (15)$$

In general, the DE was integrated into the LSSVM training procedure to obtain the optimal parameters for minimizing the test error and generalization capability of the LSSVMs. In the first generation, each individual is randomly obtained. Normally, the LSSVM algorithm calculates the corresponding output weights matrix for each individual. Then, DE can be applied to find the fitness measurement for each individual in the population. This process was repeated until the stopping condition was satisfied. When the evolution is finished, the optimal parameters of the LSSVM are ready to conduct the classification. The procedure of DE-LSSVM algorithm is shown as follows (Fig.3):

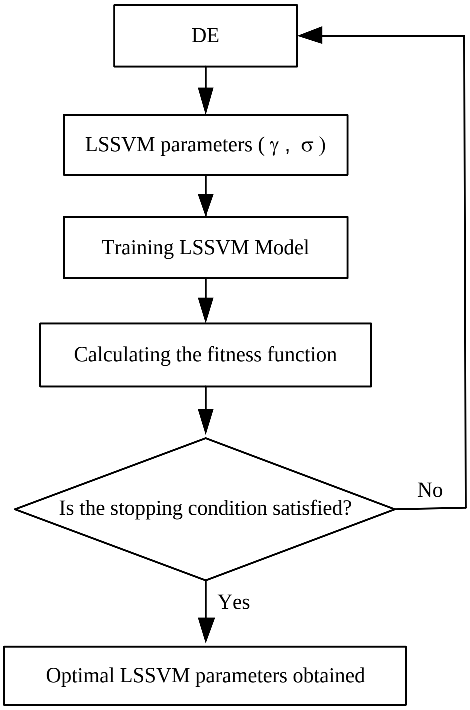

Figure 3: The parameter optimization flowchart of LSSVM based on DE

4.2.1 Parameters analysis of SVM

To analyze the influence of parameters on the generalization performance of SVM, we take the RBF kernel as an example and plot the test error surfaces, test error boundaries with gamma and sigma parameters ranging from 0 to 1000 on the dataset.

The test error boundary is indicated on the right of Fig.4, where the x-axis and y-axis represent γ and σ, respectively. Meanwhile, the test error surfaces are displayed on the left, with the x-axis and y-axis representing γ and σ, respectively. Each grid node in the (x, y) plane of the test error is an abbreviation for a parameter combination, and the z-axis represents the test error value obtained for each parameter combination. Because there are multiple local minima in these test error plots, finding the optimal parameter combination is not straightforward. The test error is lower in one region and significantly higher on both sides of the lower region. This makes it convenient for us to use an optimization procedure to achieve the optimal parameters for the SVM. Figure 4 has many local optimal points, so this article uses DE to solve the global optimization problem for SVM.

4.2.2 Parameter setting for algorithms

Parameters of the DE algorithm were configured as follows: Population Size (NP): 20; Mutation Scale Factor (F): F = 0.4 + (1 - 0.4) * rand; Crossover Probability (CR): 0.9; Maximum Number of Generations

(Max_Gen): 100; Termination Criteria: 10^{-6}; Crossover Method: rand/1.

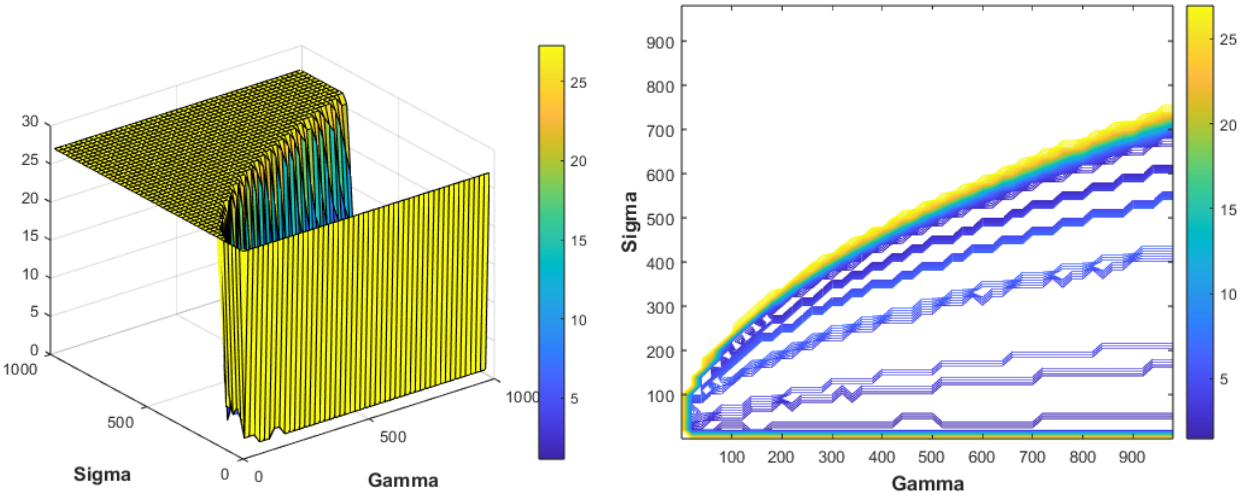

Figure 4: Test error surface and contour with parameters on dataset

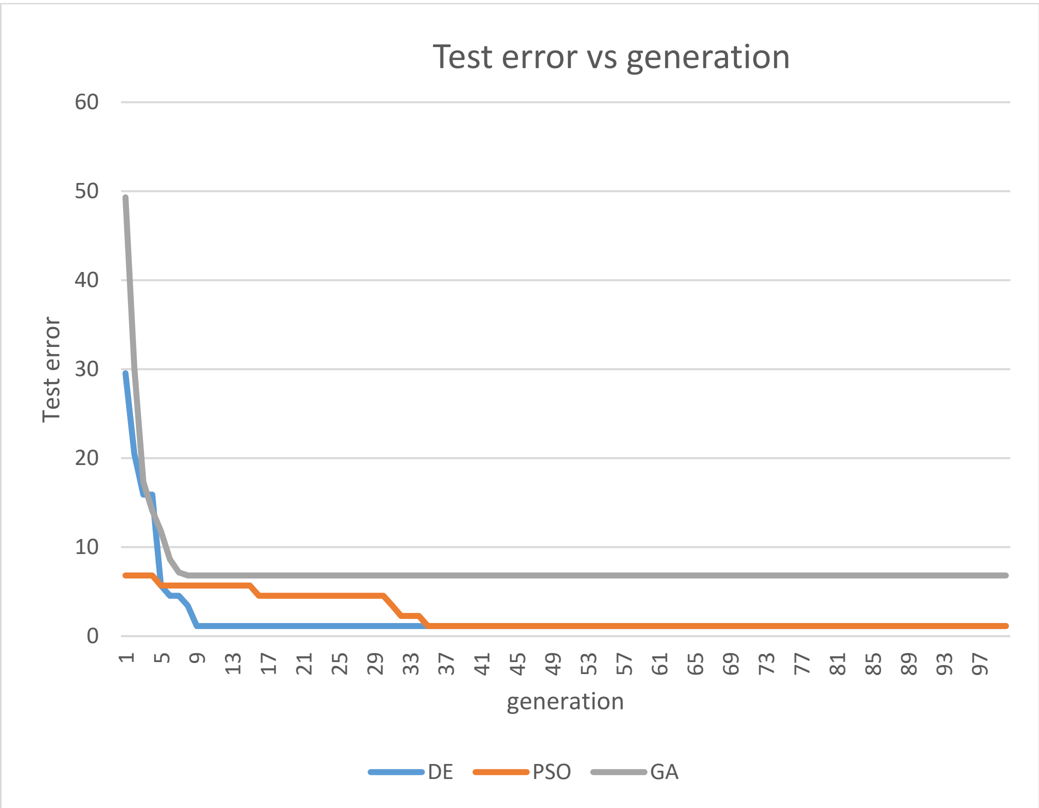

Figure 5: Investigate the convergence of the algorithms

Parameters of the PSO algorithm were fixed with the values given in the Ref. [24, 25]; that is, W =0.75, $c_1 = c_2 = 1.5$, the numbers of particles was 20, and the iteration count was 100. Parameters of the GA algorithm were configured as follows: Population Size (NP): 20; Maximum Number of Generations (Max_Gen): 100; Termination Criteria: 10^{-6}.

5 APPLICATION OF DE-LSSVM TO ROLLER BEARING FAULT DIANOSIS

5.1 Data Acquisition

The data for this paper is provided by the Case Western Reserve University Bearings Data Center Website (CWRUBDCW) with permission from Professor Loparo [26] (Fig.6). The test stand included a 2 hp Reliance Electric motor, a torque transducer/encoder, a dynamometer, and control electronics. The sample frequency was 485063 Hz and the motor speed was 1797 rpm. The deep groove ball bearing manufactured by SKF was used in this test stand. The type of roller bearing is 6205-2RS JEM. The test bearings of electro-discharge machining with fault diameters of 0.007 inches were selected. The roller bearings with the four conditions (normal (NOR), inner-race fault (IRF), outer-race fault (ORF), and ball fault (BF)) include 432 samples. The number of collection samples is divided into 3 parts, one part for testing and 2 parts for training and valiation. Table 2 shows collection of vibration signal samples.

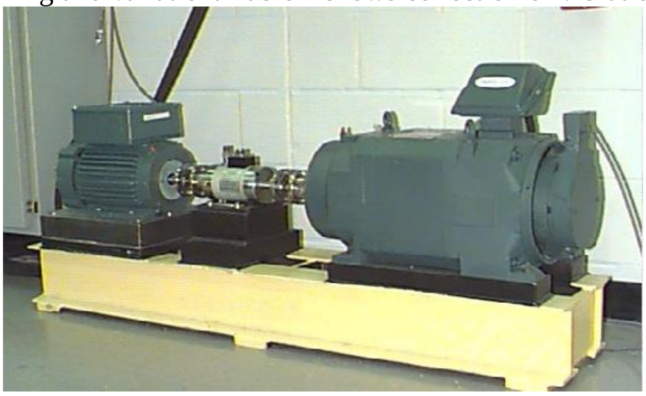

Figure 6: Roller bearing vibration data collection model, extracted from [26]

Table 2: Collection of vibration signal samples

Roller bearing conditions	Class	Collection samples	Training samples	Test samples
Inner-race fault (IRF)	1	108	72	36
Outer-race fault (ORF)	2	108	72	36
Ball fault (BF)	3	108	72	36
Normal (NOR)	4	108	72	36

5.2 Application

From the above analysis, we can see the MVMD-RMS of the roller bearing vibration signals with different operating conditions and failure modes are distinctly different. In this paper, the fault characteristic of each u_k is adopted as DE-LSSVM input vector. It can effectively determine the working condition and fault patterns of the bearing. The flow chart of the roller bearing fault diagnosis method based on MVMD-RMS and DE-LSSVM is shown in Fig. 7. The steps to conduct the experiment are as follows:

(1) Use the MVMD to decompose the roller bearing vibration signals into a number of component functions u_k . Because the main information of the fault roller bearing was mainly included in the first four components, the first four components u_k were selected to form the initial feature vector matrix.

(2) Calculate the RMS_i of the component functions u_k by using *Eq. (6);*

(3) Build feature vector Z with the RMS as element, namely MVMD-RMS vector

$$\sum Z = [RMS_1, RMS_2, \ldots, RMS_m] \qquad (16)$$

(4) Divide the feature vector data into three groups: the training, the validation, and the testing groups with a 60%, 20%, and 20% distribution, respectively.

(5) Evaluate the similarity of data by calculating the max min value.

(6) Train and validate the DE-LSSVM classification model to classify the actual roller bearing fault conditions. After this process, the optimal parameters of DE-LSSVM are γ and σ, which are used to test the samples. A set of DE-LSSVM(i) *i*=1,2,3,4 are constructed to identify bearing conditions IRF, ORF, BF and NOR listed in Table 3. In order to define the condition of roller bearing, DE-LSSVM1 was first used to separate the IRF condition from another condition by setting these conditions as y = +1 and the other conditions as y = −1. Second, $DE\text{-}LSSVM_2$ was used to separate the ORF condition from other conditions by setting outer-race fault as y = +1 and the other conditions as y = −1. Third, $DE\text{-}LSSVM_3$ was used to separate the BF condition from other condition by setting BF as y = +1 and the other conditions as y = −1. Because the data set had only got four conditions that needed to be identified, the rest was NOR condition.

6 RESULT AND DISCUSION

Table 4 indicates that the dataset exhibits similar values for the training, validation, and test sets, with X_i representing the dataset. Consequently, strong training and validation outcomes can be expected to yield favorable test results.

Fig. 4 demonstrates that the convergence speed of DE is superior to that of PSO or GA. DE reached a validation error value of 1.1363 in the 10^{th} generation, whereas PSO attained the same value in the 35^{th} generation. GA, on the other hand, reached a validation error value of 6.8182 in the 8^{th} generation.

Table 3 : Classifier DE-LSSVM model

Classifier model	Roller bearing condition			
	IRF	ORF	BF	NOR
DE-LSSVM$_1$	(+1)	(-1)	(-1)	(-1)
DE-LSSVM$_2$	(-1)	(+1)	(-1)	(-1)
DE-LSSVM$_3$	(-1)	(-1)	(+1)	(-1)
DE-LSSVM$_4$	(-1)	(-1)	(-1)	(+1)

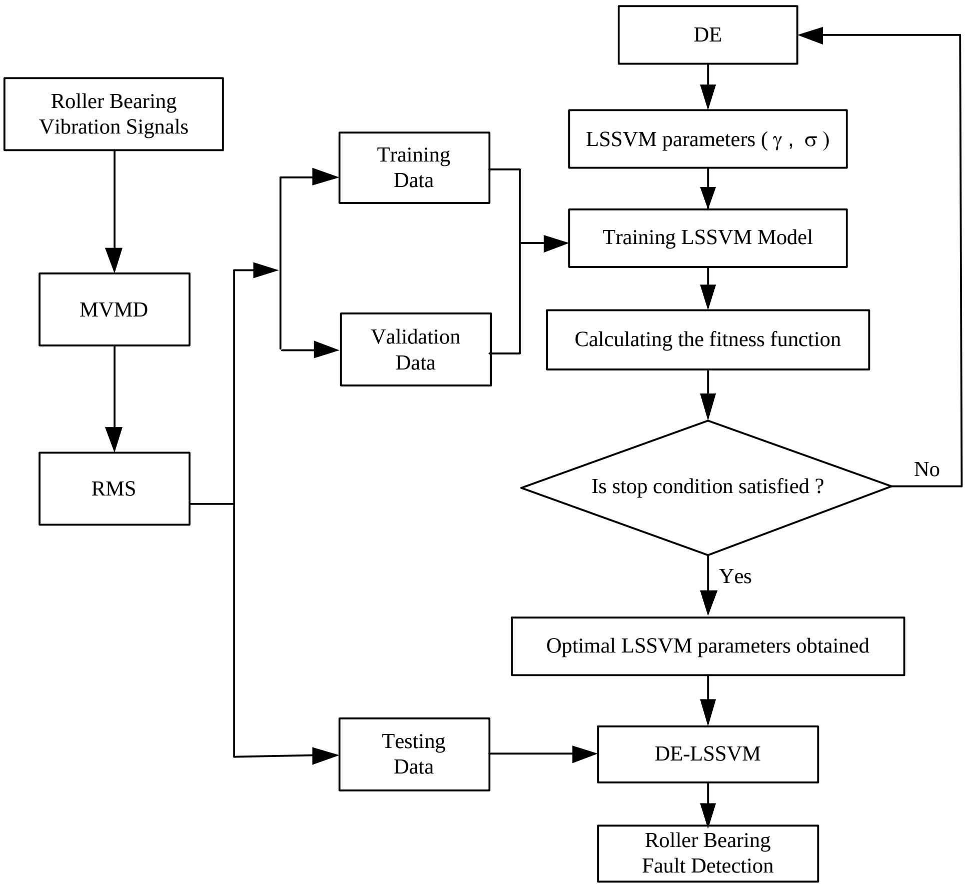

Figure 7: Roller bearing fault detection method based on MVMD-RMS and DE-LSSVM

The results of classification are presented in Table 5. To ensure a fair performance evaluation comparison, we have compared the proposed method with PSO-LSSVM and GA-LSSVM. Subsequently, DE-LSSVM was utilized to identify various patterns. The classification results of the validation samples based on MVMD preprocessing can be found in Table 6, and they are compared with those obtained using PSO-LSSVM and GA-LSSVM classifiers. Table 6 also includes the optimal parameters for the classifiers of the three methods.

The γ and σ values of each classifier are presented in Table 6, in which the classification results of the proposed method give an error equal to PSO-LSSVM and lower than GA-LSSVM with the validation data set. However, as shown in Fig.5, the convergence speed of DE-LSSVM is faster than PSO, so it gives better classification results in the test data set. The classification results in the test set are presented in Table 7. At the same time, the program running time of the MVMD-RMS-DE-LSSVM method is shorter than the MVMD-RMS-PSO-LSSVM and MVMD-RMS methods -GA-LSSVM.

Table 4: Evaluate the similarity of the data.

Class	Group	X1		X2		X3		X4	
		Min	Max	Min	Max	Min	Max	Min	Max
1	Train	0,018958	0,02297	0,08562	0,093926	0,131234	0,150696	0,132914	0,175929
	Validate	0,018753	0,021577	0,08467	0,095441	0,132929	0,151107	0,134901	0,160531
	Test	0,018347	0,021681	0,085316	0,094438	0,136541	0,151989	0,138503	0,160235
2	Train	0,013713	0,019971	0,017538	0,094156	0,091671	0,200456	0,073445	0,167629
	Validate	0,01426	0,018398	0,018203	0,092711	0,098826	0,175419	0,070551	0,148737
	Test	0,014137	0,018452	0,01822	0,086627	0,100457	0,189511	0,083109	0,137662
3	Train	0,013093	0,018984	0,018052	0,022713	0,045982	0,094449	0,068838	0,121215
	Validate	0,013448	0,020102	0,017858	0,022344	0,046407	0,095181	0,074325	0,108941
	Test	0,013065	0,018696	0,01855	0,021636	0,045447	0,084691	0,072277	0,112296
4	Train	0,016944	0,036421	0,047963	0,064346	0,014935	0,017217	0,000905	0,028515
	Validate	0,019665	0,034381	0,051281	0,06075	0,015266	0,016644	0,001642	0,027754
	Test	0,019928	0,030895	0,042808	0,061649	0,015223	0,016655	0,001376	0,034011

Table 5: Classification results of MVMD-RMS and DE-LSSVM method

Test samples	MVMD-RMS 1	MVMD-RMS 2	MVMD-RMS 3	MVMD-RMS 4	DE - SVM1 classifier	DE - SVM2 classifier	DE - SVM3 classifier	Identification results
(1) IRF	0.0214	0.0882	0.1445	0.1519	(+1)			Inner-race fault
(2) IRF	0.0208	0.0927	0.1415	0.1469	(+1)			Inner-race fault
(3) IRF	0.0200	0.0889	0.1387	0.1385	(+1)			Inner-race fault
(4) IRF	0.0230	0.0877	0.1385	0.1360	(+1)			Inner-race fault
(5) IRF	0.0219	0.0888	0.1479	0.1513	(+1)			Inner-race fault
(6) ORF	0.0178	0.0188	0.1575	0.1128	(-1)	(+1)		Outer-race fault
(7) ORF	0.0187	0.0535	0.1328	0.0887	(-1)	(+1)		Outer-race fault
(8) ORF	0.0183	0.0727	0.1736	0.1363	(-1)	(+1)		Outer-race fault
(9) ORF	0.0181	0.0628	0.1976	0.0873	(-1)	(+1)		Outer-race fault
(10) ORF	0.0171	0.0185	0.1533	0.0831	(-1)	(+1)		Outer-race fault
(11) BF	0.0186	0.0197	0.0492	0.1026	(-1)	(-1)	(+1)	Ball fault
(12) BF	0.0201	0.0201	0.0597	0.0870	(-1)	(-1)	(+1)	Ball fault
(13) BF	0.0186	0.0201	0.0567	0.0964	(-1)	(-1)	(+1)	Ball fault
(14) BF	0.0185	0.0210	0.0494	0.0866	(-1)	(-1)	(+1)	Ball fault
(15) BF	0.0190	0.0201	0.0460	0.0989	(-1)	(-1)	(+1)	Ball fault
(16) NOR	0.0293	0.0589	0.0154	0.0017	(-1)	(-1)	(-1)	Normal
(17) NOR	0.0296	0.0513	0.0157	0.0181	(-1)	(-1)	(-1)	Normal
(18) NOR	0.0331	0.0608	0.0161	0.0020	(-1)	(-1)	(-1)	Normal
(19) NOR	0.0314	0.0558	0.0163	0.0208	(-1)	(-1)	(-1)	Normal
(20) NOR	0.0307	0.0608	0.0155	0.0016	(-1)	(-1)	(-1)	Normal

7 CONCLUSION

Because bearing failure signals are non-stationary, this paper proposes a failure diagnosis method based on MVMD-RMS and DE-LSSVM. Initially, MVMD is used to preprocess various signal types into component functions. Subsequently, the RMS operator is employed to characterize these component functions, generating the input matrix for the LSSVM classifier. This input matrix serves as the training and testing data for the LSSVM classifier. Upon training, DE-LSSVM determines the optimal pair of values (γ, σ) for testing. The test results indicate that the proposed method exhibits the highest accuracy with the shortest processing time when compared to other methods. A limitation of this method is the limited dataset; training and testing are only conducted on known data. In the future, the author plans to introduce noise to the dataset to create a more comprehensive and generalized dataset.

Table 6: The comparing results of the classification of bearing failure of the classifiers MVMD-RMS-DE-LSSVM with MVMD-RMS-PSO-LSSVM and MVMD-RMS-GA-LSSVM methods.

Method	Classifier 1		Classifier 2		Classifier 3		Overall Error in Validation set %
	Optimal γ	Optimal σ	Optimal γ	Optimal σ	Optimal γ	Optimal σ	
MVMD-RMS-DE-LSSVM	831,806967	33,3375934	336,0741023	9,211096724	108,4409528	80,37404999	1,1363
MVMD-RMS-PSO-LSSVM	802,953382	51,687694	213,8031374	2,73251705	600,2212078	110,798935	1,1363
MVMD-RMS-GA-LSSVM	670,46784	293,614855	265,5473938	139,277208	908,5352424	246,2118214	6,8182

Table 7: The comparing result means of the classification of bearing failure of the classifiers MVMD-RMS-DE-LSSVM with MVMD-RMS-PSO-LSSVM, and MVMD-RMS-GA-LSSVM methods.

Method	Cost time total (s)	Test error mean (%)
MVMD-RMS-DE-LSSVM	43.6716	0.2273
MVMD-RMS-PSO-LSSVM	235.6504	2.3864
MVMD-RMS-GA-LSSVM	61.9047	8.7500

ACKNOWLEDGMENT

The author thanks Professor K. A. Loparo of Case Western Reserve University for allowing the use of data from the Bearing Data Center for this paper.

REFERENCES

[1] N. Huang *et al.*, The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences,* vol. 454, pp. 903-995, 1998,

[2] J. S. Smith, The local mean decomposition and its application to EEG perception data, (in eng), *Journal of the Royal Society, Interface,* vol. 2, no. 5, pp. 443-454, 2005,

[3] J. Z. Junsheng Cheng, Yu Yang, A nonstationary signal analysis approach-The local characteristic-scale decomposition method, *Journal Vibration Engineering,* vol. 25, no. 2, pp. 215–220, 2012,

[4] N. Rehman and H. Aftab, *Multivariate Variational Mode Decomposition*. 2019.

[5] P. Cao, H. Wang, and K. Zhou, Multichannel Signal Denoising Using Multivariate Variational Mode Decomposition With Subspace Projection, *IEEE Access*, vol. 8, pp. 74039-74047, 2020,

[6] K. Naveed, S. Mukhtar, and N. U. Rehman, Multivariate Signal Denoising Based on Generic Multivariate Detrended Fluctuation Analysis, in *2021 IEEE Statistical Signal Processing Workshop (SSP)*, 2021, pp. 441-445.

[7] C. Zisou, G. Apostolidis, and L. Hadjileontiadis, *Noise-Assisted Multivariate Variational Mode Decomposition*. 2021.

[8] Z. Li, Y. Lv, R. Yuan, and Q. Zhang, Multi-fault diagnosis of rotating machinery via iterative multivariate variational mode decomposition, *Measurement Science and Technology,* vol. 33, no. 12, p. 125104, 2022/09/07 2022,

[9] H. Ao, J. Cheng, Y. Yang, and T. K. Truong, The support vector machine parameter optimization method based on artificial chemical reaction optimization algorithm and its application to roller bearing fault diagnosis, *Journal of vibration and control,* vol. 2013, no. 2013, 2013,

[10] H. Ao, J. Cheng, K. Li, and T. K. Truong, A Roller Bearing Fault Diagnosis Method Based on LCD Energy Entropy and ACROA-SVM, *Shock and Vibration,* vol. 2014, no. 2014, pp. 1-6, 2014,

[11] J. Cheng, D. Yu, J. Tang, and Y. Yang, Application of SVM and SVD Technique Based on EMD to the Fault Diagnosis of the Rotating Machinery, *Shock and Vibration*, vol. 16, p. 519502, 2009,

[12] C. Junsheng, Y. Dejie, and Y. Yu, A fault diagnosis approach for roller bearings based on EMD method and AR model, *Mechanical Systems and Signal Processing*, vol. 20, no. 2, pp. 350-362, 2006/02/01/ 2006,

[13] R. Raghuraj and S. Lakshminarayanan, VPMCD: variable interaction modeling approach for class discrimination in biological systems, *FEBS Lett*, vol. 581, no. 5, pp. 826-30, 2007,

[14] J. Tian, C. Morillo, M. Azarian, and M. Pecht, Motor Bearing Fault Detection Using Spectral Kurtosis Based Feature Extraction and K-Nearest Neighbor Distance Analysis, *IEEE Transactions on Industrial Electronics*, vol. 63, pp. 1-1, 01/01 2015,

[15] M. Yuwono, Y. Qin, J. Zhou, Y. Guo, B. G. Celler, and S. Su, Automatic bearing fault diagnosis using particle swarm clustering and Hidden Markov Model, *Engineering Applications of Artificial Intelligence*, vol. 47, 03/30 2015,

[16] W. S. McCulloch and W. Pitts, A logical calculus of the ideas immanent in nervous activity, *The bulletin of mathematical biophysics*, vol. 5, no. 4, pp. 115-133, 1943,

[17] V. N. Vapnik, *The Nature of Statistical Learning Theory; Springer: New York*. 1995.

[18] X. Pan, Z. Xing, C. Tian, H. Wang, and H. Liu, A method based on GA-LSSVM for COP prediction and load regulation in the water chiller system, *Energy and Buildings*, vol. 230, p. 110604, 2021,

[19] B. Lin and X. Gu, Soft sensor modeling based on DE-LSSVM, *Huagong Xuebao/Journal of Chemical Industry and Engineering (China)*, vol. 59, pp. 1681-1685, 2008,

[20] X. Gao, H. Wei, T. Li, and G. Yang, A rolling bearing fault diagnosis method based on LSSVM, *Advances in Mechanical Engineering*, vol. 12, no. 1, p. 1687814019899561, 2014,

[21] K. Dragomiretskiy and D. Zosso, Variational Mode Decomposition, *IEEE Transactions on Signal Processing*, vol. 62, no. 3, pp. 531-544, 2014,

[22] R. Storn and K. Price, Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces, *Journal of Global Optimization*, vol. 11, no. 4, pp. 341-359, 1997,

[23] J. A. K. Suykens and J. Vandewalle, Least Squares Support Vector Machine Classifiers, *Neural Processing Letters*, vol. 9, no. 3, pp. 293-300, 1999,

[24] F. Ardjani, K. Sadouni, and M. Benyettou, Optimization of SVM MultiClass by Particle Swarm (PSO-SVM), in *2010 2nd International Workshop on Database Technology and Applications*, 2010, pp. 1-4.

[25] K. Chandramouli and E. Izquierdo, *Image Classification using Chaotic Particle Swarm Optimization*. 2006, pp. 3001-3004.

[26] L. K. A. (2003, 1 Nov.). *Bearings vibration dataset*, *Case Western Reserve University*. Available: https://engineering.case.edu/bearingdatacenter/download-data-file (Accessed on September 10, 2022)

PHƯƠNG PHÁP MỚI CHẨN ĐOÁN KHUYẾT TẬT Ổ BI DỰA TRÊN TOÁN MVMD-RMS VÀ DE-LSSVM

AO HUNG LINH

Khoa Công nghệ Cơ khí, Trường Đại học Công nghiệp Thành phố Hồ Chí Minh

Tác giả liên hệ: aohunglinh@iuh.edu.vn

Tóm tắt. Nghiên cứu này đề xuất một phương pháp mới trong việc chẩn đoán khuyết tật ổ bi bằng cách sử dụng máy véc tơ hỗ trợ bình phương tối thiểu (LSSVM). Các tham số của LSSVM được tối ưu hóa bằng thuật toán tiến hóa vi phân DE-LSSVM. Đầu tiên, tín hiệu dao động của ổ bi được phân rã thành các hàm con bằng phương pháp phân rã mô hình biến đổi đa biến (MVMD). Sau đó, các hàm này được chuyển thành các ma trận đặc trưng bằng phương pháp giá trị hiệu dụng thực (RMS). Cuối cùng, các ma trận này được sử dụng làm dữ liệu đầu vào cho bộ phân loại DE-LSSVM. Kết quả thực nghiệm cho thấy rằng phương pháp mới này cung cấp độ chính xác cao trong việc nhận dạng khuyết tật ổ bi, đồng thời giảm thiểu thời gian cần thiết cho quá trình nhận dạng so với các phương pháp truyền thống trên cùng tập dữ liệu.

Từ khóa. Phương pháp phân rã mô hình biến đổi đa biến; chẩn đoán hư hỏng; giá trị hiệu dụng thực; thuật toán toán tiến hóa vi phân; máy véc tơ hỗ trợ bình phương tối thiểu.

Received on: 07/09/2023
Accepted on: 01/11/2023