An Appropriate Approach for Misalignment Fault Diagnosis Based on Feature Selection and Least Square Support Vector Machine

H. Ahmadi, A. Moosavian, and M. Khazaee

***Abstract*—** A study is presented to diagnosis of misalignment fault using feature extraction and selection technique and support vector machine (SVM) classifier. The time-domain vibration signals of a compressor with normal and misalignment conditions in driven end (DE) are gained for feature extraction. The features are extracted by using the statistical and vibration parameters. Then stepwise backward selection is applied for selecting the significant features. The selected features are used as inputs to the classifier for two-class (normal or misalignment) identification. The roles of stepwise backward selection technique and SVM classifier are investigated. The results indicate the potential of the proposed intelligent method in misalignment fault diagnosis of the compressor.

***Keywords*—** Fault diagnosis, Misalignment fault, Feature selection, Support vector machine.

I. Introduction

CONDITION monitoring of rotating machinery is important in terms of system maintenance and process automation [1]. Reliability has always been an important aspect in the assessment of industrial products. By development of technology, cost of time-based preventive maintenance increased thus, new approaches in maintenance such as condition-based maintenance (CBM) developed. Machine condition monitoring has long been accepted as one of the most effective and cost-efficient approaches to avoid catastrophic failures of machines [2,22]. Precise and high accuracy assessment of machinery condition results in fewer stoppages and better product quality and reduces maintenance costs for plants. Thus, they can optimize workforce and implement more efficient operations [3-19].

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Most of machinery used in the modern world operates by means of rotary components which can develop failures. The monitoring of the operative conditions of rotating machinery provides a great economic improvement by decreasing maintenance costs, as well as improving the safety level. So, it is essential to analyze the external information so as to evaluate the internal components state which, generally, are inaccessible without disassemble the machine [21].

Fault diagnosis improves the reliability and availability of an existing system. Since various failures degrade relatively slowly, there is potential for fault diagnosis at an early step. This avoids the sudden, total system failure which can have serious consequences. Fault diagnosis provides more information about the nature or localization of the failure. This information can be used to minimize downtime and to schedule adequate maintenance proceeding.

In recent years, on-line fault diagnostic systems have been gaining considerable amount of business potential. The need for automating industrial processes and reducing the cost maintenance has simulated the research and extension of faster and robust fault diagnosis. Attempts have been created towards classification of the most common type of rotating machinery problem [23].

Vibration analysis is one of the main techniques used to the non-destructive diagnosis and identification of various defects in rotary machines. Vibration analysis provides early information about progressing malfunctions for future monitoring purpose.

Rotating machineries are used considerably utilized in the manufacturing of industrial products. Shafts as a key rotating motion transmission component, plays a critical role in industrial applications. Therefore, attracts research interests in condition monitoring and fault diagnosis of this equipment [20]. Importance of shafts and bearings in condition monitoring of the machine is undeniable, thus, processing and analysis of acoustic and vibration signals of the shafts and bearings is the common way of extracting reliable representative of the machine condition.

Misalignment faults are one of the foremost causes of failures in rotating machinery. One of the major effects of misalignment between rotors in drive system is the production of rotor preload in a specific radial direction. Consequently, misalignment produces a constant radial force, which pushes the rotor to the side. The rotor becomes displaced from the original position and can move to higher eccentricity ranges inside the bearings and seals. It is possible for the rotor to become bowed and rotate in a bow configuration [4-5]. This means that misalignment could change the nominal air gap length thus introducing dynamic air gap eccentricity in the drive motor. However, this type of fault is believed to be the second cause of bearing failure and considered to be the main cause of static or/and dynamic air gap eccentricity, which can result in a contact between rotor and stator.

In this work, an appropriate procedure for misalignment fault diagnosis was implemented. In this method, experimental vibration signals for normal and misalignment situations was obtained. Statistical and vibration functions were applied for feature extraction. The superior features were selected by using stepwise backward selection. Finally support vector machine was used for classification of two-class. Figure 1 shows the diagram of the proposed method for condition monitoring. For this research, Matlab 7.6 Software was used.

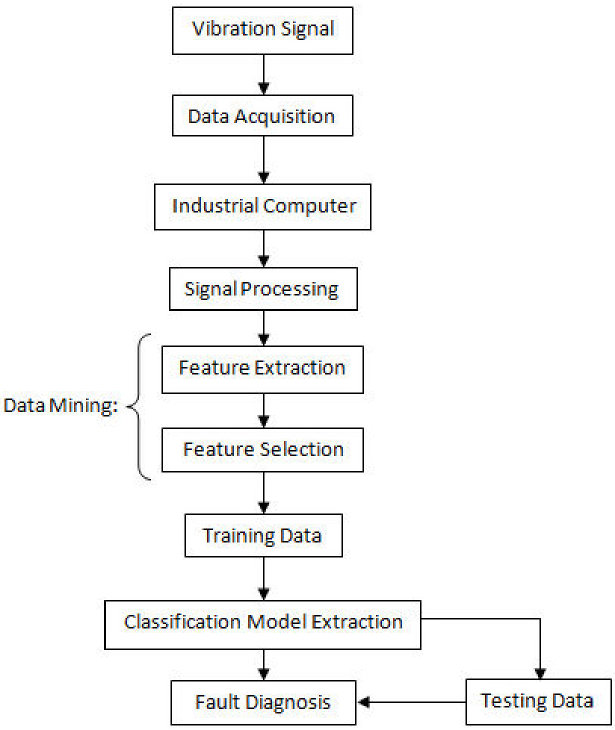

Fig. 1 The schematic of the diagnostic method

II. Experimental System

The experimental system was a compressor with the power of 1360W which worked on 2979 rpm. The sensor used is an accelerometer (VMI-102 model) which was installed horizontally on the bearing housings of a NPP2 compressor shaft to collect the vibration signals. The vibration signals in frequency-domain were directly measured for two condition of journal-bearing by on-line monitoring. The sensor was connected to the signal-conditioning unit (X-Viber FFT analyzer), where the signal goes through a charged amplifier. The software SpectraPro-4 that accompanies the signal-conditioning unit was used for recording the signals directly in the computer. Root Mean Square (RMS) of the vibration acceleration (g) was calculated for the vibration signals. The sampling rate was 8192 Hz for this work. Figure 2 show shows the set of sensors and data acquisition system that employed in this work.

Fig 2 Data acquisition system

III. Material And Methods

A. Fast Fourier Transform

The frequency domain refers to a display or analysis of the vibration data as a function of frequency. The time domain vibration signal is typically processed into the frequency domain by applying a Fourier transform, usually in the form of a Fast Fourier transform (FFT) algorithm. The principal advantage of this format is that the repetitive nature of the vibration signal is clearly displayed as peaks in the frequency spectrum at the frequencies where the repetition takes place [6].

B. Feature Extraction

Vibration signals contain a large set of data for each sample therefore some statistical and frequency domain functions are applied to reduce feature vectors. Feature extraction method is a dimensionality reduction technique is widely applied in condition monitoring. 30 features were extracted from RMS values of vibration velocity of signals by using the statistical and vibration parameters. Some of used parameters are: Maximum, Minimum, Average, Root Mean Square (RMS), Standard Deviation (Stdv), Variance (Var), 5th Momentum (5th M), sixth momentum (6thM), Crest Factor, Skewness, Kurtosis etc [7]. Some of these features are shown in Table 1.

C. Feature Selection

Stepwise selection is a method that moves in eitherdirection, dropping or adding variables at the various step.

Feature Description	Formula	Feature Description	Formula
Mean value	$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$	Third central moment	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^3}{n}$
Standard deviation	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2}$	Forth central moment	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{n}$
Root mean square	$\sqrt{\frac{\sum_{i=1}^{n}(x_i)^2}{n}}$	Kurtosis	$\frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2)^2}-3$
Skewness	$\frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^3}{(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2)^{3/2}}$	FM4	$\frac{n\sum_{i=1}^{n}(x_i-\bar{x})^4}{(\sum_{i=1}^{n}(x_i-\bar{x})^2)^2}$

Table 1. Some features and their formulas

Backward stepwise selection involves starting off in a backward approach and then potentially adding back variables if they later appear to be significant. The process is one of alternation between choosing the least significant variable to drop and then re-considering all dropped variables (except the most recently dropped) for re-introduction into the model [8]. This means that starting with all the variables, stepwise backward selection removes the variable which leads to the smallest increase in prediction error. Variable removal stops when the new candidate model significantly increases the prediction error. Significance is measured by a partial F-test. In this work, twice feature selection is performed. First the value of p (significance level) is 0.5 with linear model and second the value of p (significance level) is 0.2 with linear model. In the first step 8 features was selected. In the second step 2 features was selected.

D. Support Vector Machine

The Support Vector Machines (SVM) have been developed by Vapnik and are gaining popularity due to many appealing features, and promising empirical performance. SVM, based on statistical learning theory, is a proper technique for solving a variety of learning and function assessment problems. SVM have been successfully applied to a number of applications such as machine condition monitoring, face detection, verification, and recognition, object detection and recognition, handwritten character and digit recognition, text detection and categorization, speech and speaker verification, recognition, information and image retrieval, etc.

SVM has become an increasingly popular technique for machine learning activities including classification, regression, and outlier detection. Detailed reviews on SVM are available elsewhere [9,10]. The idea of using SVM for separating two classes is to find support vectors (i.e. representative training data points) to define the bounding planes, in which the margin between the both planes is maximized [11].

Support vector machines (SVM) were originally designed for binary (2-class) classification. In binary classification, the class labels can take only two values: 1 and -1. Figure 3 shows the classification of binary SVM. Also, SVM has been recently applied to solve multi-class problems.

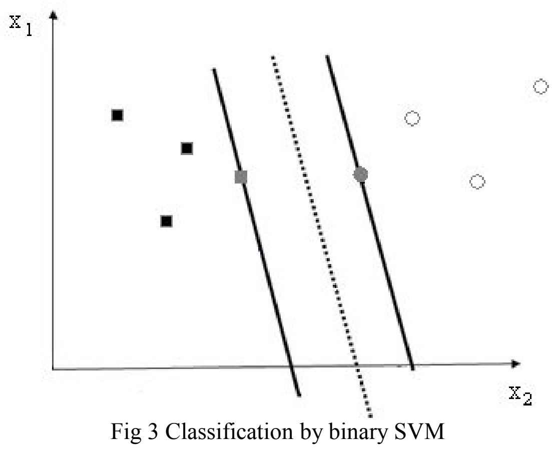

Fig 3 Classification by binary SVM

Given a training set of N data points $\{y_k, x_k\}_{k=1}^{N}$, where $x_k=R^n$ is the k th input pattern and $y_k=R^n$ is the k th output pattern, the support vector method approach aims at constructing a classifier of the form:

$$y(x) = sign\left[\sum_{k=1}^{N} \alpha_k y_k \psi(x, x_k) + b\right] \quad (1)$$

where α_k are positive real constants and b is a real constant. For $\psi(.,.)$ one typically have the following choices:

$\psi(x, x_k) = x_k^T x$ (linear SVM);

$\psi(x,x_k) = (x_k{}^T x + 1)^d$ (polynomial SVM of degree *d*);
$\psi(x,x_k) = \exp\left\{-\|x - x_k\|^2 / 2\sigma^2\right\}$ (RBF SVM);
$\psi(x,x_k) = \tanh[\kappa x_k{}^T x + \theta]$ (two layer neural SVM);

where σ, κ and θ are constants. The classifier is constructed as follows. One assumes that

$$\begin{aligned} &w^T\varphi(x_k) + b \geq 1 \quad \text{if} \quad y_k = +1 \\ &w^T\varphi(x_k) + b \leq -1 \quad \text{if} \quad y_k = -1 \end{aligned} \tag{2}$$

which is equivalent to

$$y_k[w^T\varphi(x_k) + b] \geq 1 \tag{3}$$

where $\varphi(.)$ is a nonlinear function which maps the input space into a higher dimensional space. However, this function is not explicitly constructed. In order to have the possibility to violate (3), in case a separating hyperplane in this higher dimensional space does not exist, variables ξ_k are introduced such that

$$\begin{aligned} &y_k[w^T\varphi(x_k) + b] \geq 1 - \xi_k \\ &\xi_k \geq 0 \quad , \quad k = 1,...,N \end{aligned} \tag{4}$$

According to the structural risk minimization principle, the risk bound is minimized by formulating the optimization problem

$$\min_{w,\xi_k} \partial_1(w,\xi_k) = \frac{1}{2}w^T w + c\sum_{k=1}^{N}\xi_k \tag{5}$$

subject to (4). Therefore, one constructs the Lagrangian

$$\ell_1(w,b,\xi_k;\alpha_k,\upsilon_k) = \partial(w,\xi_k) - \sum_{k=1}^{N}\alpha_k\{y_k[w^T\varphi(x_k) + b] - 1 + \xi_k\} - \sum_{k=1}^{N}\upsilon_k\xi_k \tag{6}$$

by introducing Lagrange multipliers $\alpha_k \geq 0$, $\upsilon_k \geq 0$ ($k = 1,...,N$) The solution is given by the saddle point of the Lagrangian by computing

$$\max_{\alpha_k,\upsilon_k}\min_{w,b,\xi_k} \ell_1(w,b,\xi_k;\alpha_k,\upsilon_k) \tag{7}$$

One obtains

$$\begin{aligned} &\frac{\partial\ell_1}{\partial w} = 0 \to w = \sum_{k=1}^{N}\alpha_k y_k\varphi(x_k) \\ &\frac{\partial\ell_1}{\partial b} = 0 \to \sum_{k=1}^{N}\alpha_k y_k = 0 \\ &\frac{\partial\ell_1}{\partial\xi_k} = 0 \to 0 \leq \alpha_k \leq c \quad , \quad k = 1,...,N \end{aligned} \tag{8}$$

which leads to the solution of the following quadratic programming problem

$$\max_{\alpha_k} Q_1(\alpha_k;\varphi(x_k)) = -\frac{1}{2}\sum_{k,l=1}^{N} y_k y_l \varphi(x_k)^T\varphi(x_l)\alpha_k\alpha_l + \sum_{k=1}^{N}\alpha_k \tag{9}$$

such that

$$\sum_{k=1}^{N}\alpha_k y_k = 0 \quad , \quad 0 \leq \alpha_k \leq c \quad , \quad k = 1,...,N$$

The function $\varphi(x_k)$ in (9) is related then to $\psi(x,x_k)$ by imposing

$$\varphi(x)^T\varphi(x_k) = \psi(x,x_k) \tag{10}$$

which is motivated by Mercer's Theorem.

Note that for the two layer neural SVM, Mercer's condition only holds for certain parameter values of κ and θ.

The classifier (1) is designed by solving

$$\max_{\alpha_k} Q_1(\alpha_k;\psi(x_k,x_l)) = -\frac{1}{2}\sum_{k,l=1}^{N} y_k y_l \psi(x_k,x_l)\alpha_k\alpha_l + \sum_{k=1}^{N}\alpha_k \tag{11}$$

subject to the constraints in (9). One does not have to calculate w nor $\varphi(x_k)$ in order to determine the decision surface. Because the matrix associated with this quadratic programming problem is not indefinite, the solution to (11) will be global [12].

Furthermore, one can show that hyperplanes (3) satisfying the constraint $\|w\|/2 \leq a$ have a VC-dimension h which is bounded by

$$h \leq \min([r^2 a^2], n) + 1 \tag{12}$$

where [.] denotes the integer part and r is the radius of the smallest ball containing the points $\varphi(x_1),...,\varphi(x_N)$. Finding this ball is done by defining the Lagrangian

$$\ell_2(r,q,\lambda_k) = r^2 - \sum_{k=1}^{N}\lambda_k(r^2 - \|\varphi(x_k) - q\|^2 / 2) \tag{13}$$

where q is the center of the ball and λ_k are positive Lagrange multipliers. In a similar way as for (5) one finds that the center is equal to $q = \sum_k \lambda_k\varphi(x_k)$, where the Lagrange multipliers follow from:

$$\max_{\alpha_k} Q_2(\lambda_k;\varphi(x_k)) = \sum_{k,l=1}^{N}\varphi(x_k)^T\varphi(x_l)\lambda_k\lambda_l +$$

$$\sum_{k=1}^{N} \lambda_k \varphi(x_k)^T \varphi(x_k) \quad (14)$$

such that

$$\sum_{k=1}^{N} \lambda_k = 1$$
$$\lambda_k \geq 0 \quad , \quad k = 1,...,N \quad (15)$$

Based on (10), Q_2 can also be expressed in terms of $\psi(x_k, x_l)$. Finally, one selects a support vector machine with minimal VC dimension by solving (11) and computing (12) from (14) [13].

E. Least Square Support Vector Machine

Least Squares Support Vector Machine (LS-SVM) is reformulations to standard SVM [14-15] which lead to solving linear KKT systems. LS-SVM is closely related to regularization networks [16] and Gaussian processes but additionally emphasizes and exploits primal-dual interpretations. Links between kernel versions of classical pattern recognition algorithms such as kernel Fisher discriminant analysis and extensions to unsupervised learning, recurrent networks and control [17] are available. LS-SVM alike primal-dual formulations are given to kernel PCA, kernel CCA and kernel PLS. For very large scale problems and on-line learning a method of Fixed Size LS-SVM is proposed, based on the Nyström approximation with active selection of support vectors and estimation in the primal space. The methods with primal-dual representations have also been developed for kernel spectral clustering, data visualization, dimensionality reduction and survival analysis [18].

In this section we introduce a least squares version to the SVM classifier by formulating the classification problem as

$$\min_{w,b,e} \partial_3(w,b,e) = \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{k=1}^{N} e_k^{\ 2} \quad (16)$$

subject to the equality constraints

$$y_k [w^T \varphi(x_k) + b] = 1 - e_k \quad , \quad k = 1,...,N \quad (17)$$

One defines the Lagrangian

$$\ell_3(w,b,e;\alpha) = \partial_3(w,b,e) - \sum_{k=1}^{N} \alpha_k \{ y_k [w^T \varphi(x_k) + b] - 1 + e_k \} \quad (18)$$

where α_k are Lagrange multipliers (which can be either positive or negative now due to the equality constraints as follows from the Kuhn-Tucker conditions. The conditions for optimality

$$\begin{aligned}
&\frac{\partial \ell_3}{\partial w} = 0 \rightarrow w = \sum_{k=1}^{N} \alpha_k y_k \varphi(x_k) \\
&\frac{\partial \ell_3}{\partial b} = 0 \rightarrow \sum_{k=1}^{N} \alpha_k y_k = 0 \\
&\frac{\partial \ell_3}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma e_k \quad , \quad k = 1,...,N \\
&\frac{\partial \ell_3}{\partial \alpha_k} = 0 \rightarrow y_k [w^T \varphi(x_k) + b] - 1 + e_k = 0 \quad , \quad k = 1,...,N
\end{aligned} \quad (19)$$

can be written immediately as the solution to the following set of linear equations

$$\begin{bmatrix} I & 0 & 0 & -Z^T \\ 0 & 0 & 0 & -Y^T \\ 0 & 0 & \gamma I & -I \\ Z & Y & I & 0 \end{bmatrix} \begin{bmatrix} w \\ b \\ e \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vec{1} \end{bmatrix} \quad (20)$$

where $Z = [\varphi(x_1)^T y_1; ...; \varphi(x_N)^T y_N]$, $Y = [y_1; ...; y_N]$, $\vec{1} = [1; ...; 1]$, $e = [e_1; ...; e_N]$, $\alpha = [\alpha_1; ...; \alpha_N]$. The solution is also given by

$$\begin{bmatrix} 0 & -Y^T \\ Y & ZZ^T + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{1} \end{bmatrix} \quad (21)$$

Mercer's condition can be applied again to the matrix $\Omega = ZZ^T$, where

$$\Omega_{kl} = y_k y_l \varphi(x_k)^T \varphi(x_1) = y_k y_l \psi(x_k, x_1) \quad (22)$$

IV. Results And Discussion

Figure 3 shows the vibration signals obtained for different conditions of the compressor. It can be found that the overall vibration values of compressor for fault condition are more. Root mean square (RMS) of vibration velocity (mm/sec) in four measurements was higher than standard value (Figure 4, Table 3). The first and second dataset (8*122*2 and 2*122*2) consisting of 8 and 2 selected features, respectively, 122 samples and two conditions (normal and misalignment) were divided into two subsets, training set and test set. The training set and test set consist of 90 and 32 samples, respectively. For LS-SVM, the target values were specified as 1 and -1, respectively, representing normal and faulty conditions. In this work, The RBF kernel is used (σ2 =0.2, γ=10). Figure 5 shows the output model of LS-SVM for 2 selected features. The result of classification accuracy is given in Table 2. The classification accuracy for the 8 features was better. But Computation time for the 2 features was a little lower than the 8 features.

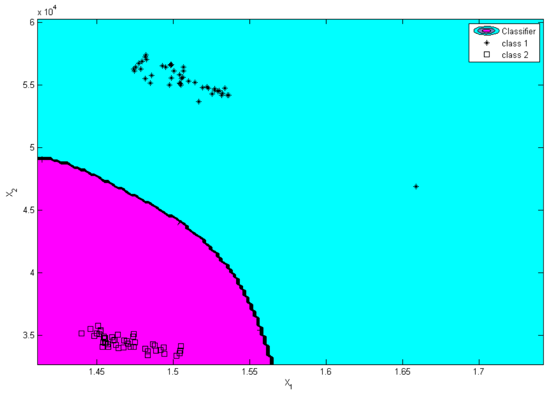

Fig 5 The model of the LS-SVM for second significance level in feature selection

By attention to this result, it can be found that the FFT is the one of useful signal processing technique. Also, using enough and correct features could will result in powerful inputs for classifier and raise its diagnosis accuracy. Gaining the excellent performance indicate proper selection of SVM classifier and its parameters.

Table 2. Accuracy of classification for twice feature selection

Number of feature	Train data	Test data
8	100%	96.88%
2	100%	93.75%

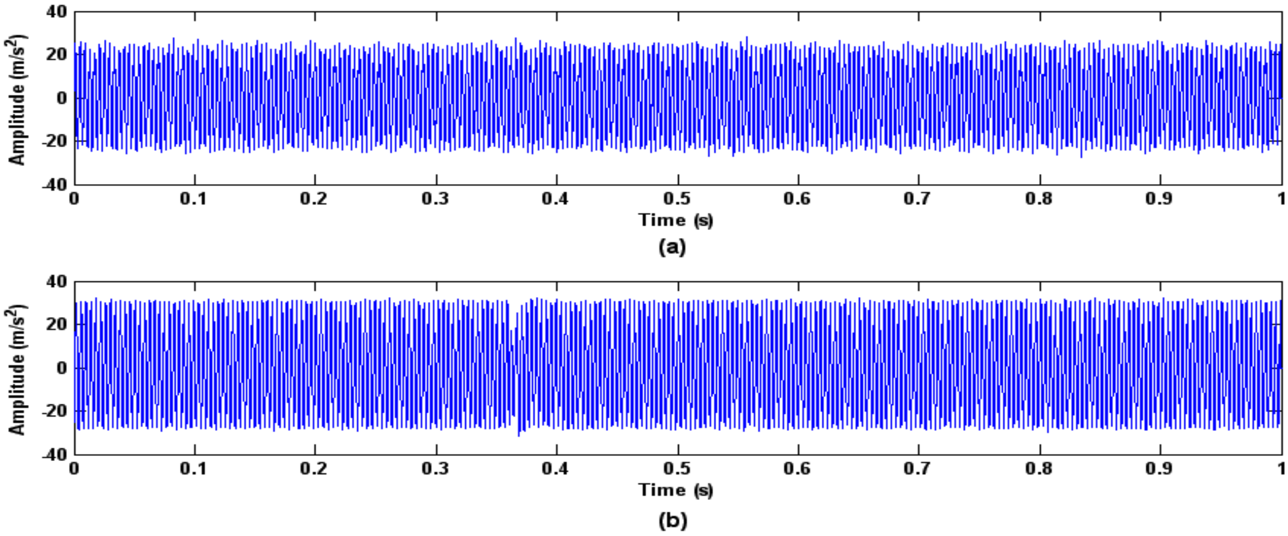

Fig 3 Vibration signals for two conditions of compressor: (a) normal, (b) misalignment

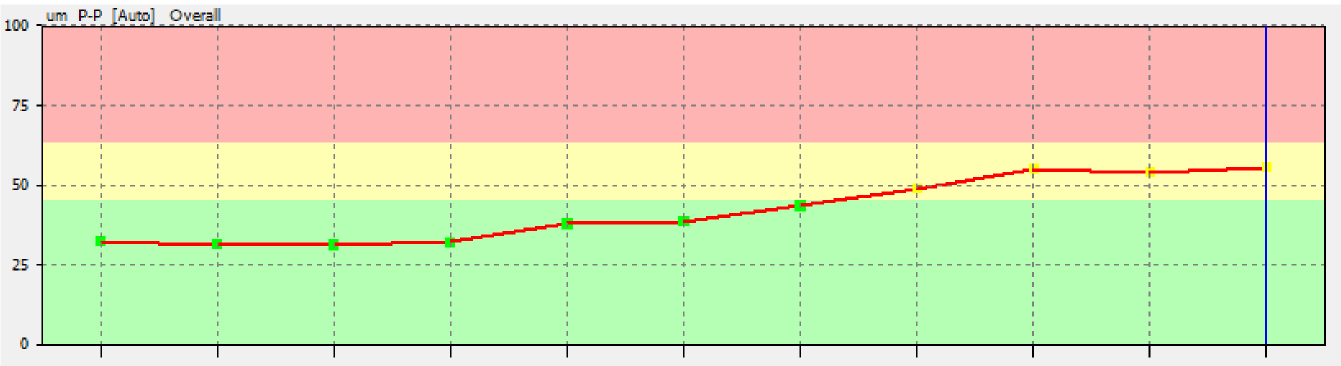

Fig 4 Overall vibrations of driven end (DE) of compressor

Test	Measuring date	RMS of vibration velocity (mm/s)	Bearing Condition	Alarm status
1	2011/07/08 12:35	32.5	1.53	Ok
2	2011/07/08 12:36	31.47	1.47	Ok
3	2011/07/09 12:37	31.43	1.47	Ok
4	2011/07/09 13:38	32.15	1.51	Ok
5	2011/07/10 12:47	37.98	1.56	Ok
6	2011/07/10 13:48	38.67	1.61	Ok
7	2011/07/10 14:55	43.61	2.81	Ok
8	2011/07/13 13:06	49.08	3.56	Warning
9	2011/07/13 14:47	55.26	4.23	Warning
10	2011/07/13 15:03	54.21	4.08	Warning
11	2011/07/13 15:30	55.77	4.39	Warning

Table 3. Result of measurement of compressor

V. CONCLUSION

A procedure was presented for diagnosis of misalignment fault using LS-SVM classifier and twice features selection from 30 extracted features. Two significance level of p=0.5 and p=0.2 were considered in stepwise backward selection. In first and second step, 8 and 2 features are selected, respectively. The RBF kernel was used ($\sigma2$ =0.2, γ=10) for LS-SVM. The accuracy of classification for each two significance level was showed in Table 1. The performance of LS-SVM was studied. The results show that the SVM is a strong classifier for fault diagnosis of rotary machine. Also, the results demonstrate the ability and reliability of proposed method in condition monitoring of compressor.

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REFERENCES

[1] L. Xinsheng, L. A. Kenneth, "Bearing fault diagnosis based on wavelet transform and fuzzy inference," *Mechanical Systems and Signal Processing* 18, pp. 1077–1095, 2004.

[2] H. Bang-Fu, "Smart maintenance system for three-phase power transformer via fuzzy logic approach," *International Journal of Circuits, Systems and Signal Processing*, issue 4, vol. 5, pp. 370-381, 2011.

[3] B. Bagheri et al., "Implementing discrete wavelet transform and artificial neural networks for acoustic condition monitoring of gearbox," *Elixir Mech. Engg* 35, pp. 2909-2911, 2011.

[4] A. H. Bonnett, T. Albers, "Squirrel Cage Rotor Options for AC Induction Motors," *IEEE Transactions on Industry Applications*, vol. 37, pp. 1197-1209, 2001.

[5] O. V. Thorsen, M. Dalva, "A Survey of Faults on Induction Motors in Offshore Oil Industry, Petrochemical Industry, Gas Terminals, and Oil Refineries," *IEEE Transactions on Industry Applications*, vol. 31, pp. 1186-1196, 1995.

[6] C.K. Mechefske, *Machine condition monitoring and fault diagnostics*, pp 1-35, 2005.

[7] B. Samanta, K. R. Al-Balushi, and S. A. Al-Araimi, "Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection," *Engineering Applications of Artificial Intelligence* 16, pp. 657–665, 2003.

[8] The LOGISTIC Procedure, Chapter 39, Overview, SAS OnlineDocä: Version 8, pp. 1903-2040.

[9] E. M. Jordaan, Development of robust inferential sensors, industrial application of support vector machines for regression. Ph.D. thesis, Technische Universiteit Eindhoven, 2002.

[10] V. Vapnik, *The nature of statistical learning theory*, New York: Springer-Verlag, 1995.

[11] L. H. Chiang, M. E. Kotanchek, and A. K. Kordon, "Fault diagnosis based on Fisher discriminant analysis and support vector machines," *Computers and Chemical Engineering* 28, pp. 1389- 1401, 2004.

[12] R. Fletcher, *Practical Methods of Optimization*, John Wiley and Sons: Chichester and New York, 1987.

[13] J. A. K. Suykens, J. Vandewalle, "Least Squares Support Vector Machine Classifiers," *Neural Processing Letters* 9, pp. 293–300, 1999.

[14] C. Cortes, V. Vapnik, "Support-vector network," *Machine Learning* 20, pp. 273-297, 1995.

[15] Van Gestel et al., "Benchmarking least squares support vector machine classifiers," *Machine Learning*, vol. 54, no. 1, pp. 5–32, 2001.

[16] T. Evgeniou, M. Pontil, T. Poggio, "Regularization networks and support vector machines," *Advances in Computational Mathematics* 13(1), pp. 1–50, 2000.

[17] J. A. K Suykens, J. Vandewalle, "Recurrent least squares support vector machines," *IEEE Transactions on Circuits and Systems-I* 47(7), pp. 1109–1114, 2000.

[18] K. De Brabanter et al., LS-SVMlab Toolbox User's Guide version 1.8, ESAT-SISTA Technical Report 10-14, 2011.

[19] A. Moosavian, H. Ahmadi, and A. Tabatabaeefar, "Condition monitoring of engine journal-bearing using power spectral density and support vector machine," *Elixir Mech. Engg* 43, pp. 6631-6635, 2011.

[20] K. Kerdprasop, N. Kerdprasop, "A data mining approach to automate fault detection model development in the semiconductor manufacturing process," *International Journal of Mechanics*, issue 4, vol. 5, pp. 336-344, 2011.

[21] H. Ahmadi, A. Moosavian, "Fault Diagnosis of Journal-Bearing of Generator Using Power Spectral Density and Fault Probability Distribution Function," Innovative Computing Technology , Communications in Computer and Information Science, vol. 241, part 1, pp. 30-36, 2011.

[22] H. Ahmadi, K. Mollazade, "A practical approach to electromotor fault diagnosis of Imam Khomaynei silo by vibration condition monitoring," *African Journal of Agricultural Research* 4, pp. 383-388, 2008.

[23] A. Dabkevičius, N. Naginevičiūtė, and E. Kibirkštis, "Non-destructive identification of vibrations of cardboard boxes," *Journal of Vibroengineering*, vol. 13, issue 4, pp. 886-890, 2011.

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