An intelligent condition-based maintenance platform for rotating machinery

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ABSTRACT

Maintenance is of necessity for sustaining machinery availability and reliability in order to ensure productivity, product quality, on-time delivery, and safe working environment. The costly maintenance strategies such as corrective maintenance and scheduled maintenance have been progressively replaced by superior maintenance strategies in which condition-based maintenance (CBM) is one of the delegates. This strategy commonly consists of sequent modules such as data acquisition, signal processing, feature extraction and feature selection, condition monitoring, etc. However, approaches in literature which have been developed for each module and implemented for different applications are standalone instead of a comprehensive system. Furthermore, these approaches have been demonstrated in a laboratory environment without any industrial validations. For these reasons, an intelligent algorithm based CBM platform is proposed in this paper to be applied for rotating machinery easily and effectively. Subsequently, two case-studies are presented in order to evaluate the effectiveness of this platform in industrial applications.

1. Introduction

A failure in industrial equipment results in not only the loss of productivity but also timely services to customer, and they may even lead to safety and environmental problems. This emphasizes the necessity of maintenance in manufacturing operations. Maintenance can sustain the reliability and availability of product equipments, improve the product quality, increase productivity, and undertake the safety requirements. However, the general opinion is that *maintenance is a necessary evil* or *nothing can be done to improve maintenance costs*. Indeed, the cost of maintenance contributes a large part of the total operating and production cost in specific capital-intensive industries. For example, maintenance cost as a percentage of totals

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value-added could be up to 20-50% for mining, 15-25% for primary metal and 3-15% for processing and manufacturing industries (Campbell, 1995). Additionally, with the augment of mechanization and automation, many modern plants have installed flexible automatic computer-controlled and unmanned equipments, the maintenance costs have been increased substantially. Consequently, an efficient and reasonable maintenance strategy is necessary for implementation so that the minimum maintenance costs could be attained.

The maintenance strategies could be broadly classified into two categories, namely corrective maintenance (CM) and preventive maintenance (PM) (Tsang, 1995; Lebold et al., 2003), and summarized in Table 1. CM, also known as breakdown maintenance, is frequently performed by unplanned activities and implemented after the occurrence of an obvious functional failure, malfunction, or breakdown of the equipment. Its actions can store the functional capabilities of failed components by either repairing the defect or replacing the new ones. PM involves scheduled maintenance and condition-based maintenance (CBM). Scheduled maintenance is periodically carried out by lubricating, calibrating, refurbishing, inspecting, and checking equipment for each fixed period of time to lessen the deterioration leading to faults. This helps prevent the functional failures by replacing critical components at regular intervals which are shorter than their expected useful lives. However, random stoppages of equipment in CM or frequent replacements of the expensive components before the end of their lives in scheduled maintenance result in high cost of maintenance.

CBM is a method to reduce the uncertainty of maintenance activities that frequently encounter in other strategies. In CBM, equipment operating conditions are continuously monitored to identify the need for maintenance in real time. The actual preventive actions are only taken when an incipient failure is supposed to have been detected. Therefore, CBM can significantly reduce the maintenance costs by reducing the number of unnecessary scheduled PM operations if properly established and effectively implemented. For that reason, CBM has been received great attention of researchers and practical maintainers.

Table 1 Maintenance approaches.

Generally, a CBM system comprises a number of functional modules: sensing and data acquisition, signal processing, feature extraction and feature selection, condition monitoring and health assessment, diagnostics, prognostics, decision reasoning, and human system interface. Therefore, in order to implement CBM system, it is required to integrate a variety of hardware and software components. In recent times, these components have been continuously improved to be applied and practiced in different applications by several researches. In case of hardware component, thanks to the fast forwarding development of sensor industry, not only the price and the size of sensors have been reduced but also more tasks have been performed in benchmarking with the conventional ones. A new sensor generation which involves micro-

electromechanical systems and smart sensors has been employed for CBM to improve the sensor reliability and accuracy. Owing to the advantages of mutual information from multiple sensors, sensor fusion techniques are commonly engaged to lead the superiority. In case of software component, numerous standalone approaches have been fruitfully developed to implement the CBM system for rotating machinery. Most of these approaches focus on fault diagnostics and prognostics and fall into three main categories: statistical-based, model-based, and data driven-based. The applications of these approaches for rotating machinery could be found in the studies of Jardine (Jardine et al., 2006) and Heng (Heng et al., 2009).

Even though standalone approaches in progress have been developed in literature, there are several fundamental opportunities to be considered:

- Most of existing approaches are able to apply for specific equipment. A scalable methodology or systematic toolbox for generic machinery does not exist.
- Several developed algorithms have been demonstrated in a laboratory environment without any industrial validations.
- Currently, methods are generally focused on solving the failure prediction issue. Tools for system performance assessment and degradation prediction have not been well addressed. Furthermore, estimating the remaining lifetime of machinery is still a challenge of prognostics.
- There is no available platform that can be applied for various rotating machinery.

In recent years, several methods in our studies have been developed and applied for various rotating machinery in the range of signal processing to prognostics. For instance, wavelet transform and statistical method, which were used to extract salient features from raw noise and vibration signals, were combined with self-organizing feature map, learning vector quantization and support vector machine (SVM) for detecting and classifying faults of reciprocating refrigerator compressors (Yang et al., 2005). An expert system, namely VIBEX, was proposed to aid plant operators in diagnosing the cause of abnormal vibration for rotating machinery (Yang et al., 2005). The decision tree in this system was used as an acquisition of structured knowledge to obtain the diagnosing rules from decision table which is built by the cause-symptom matrix. The integration of case-based reasoning with other methods such as Petri nets, adaptive resonance theory, the learning strategy of Kohonen neural network, etc was introduced to the fault diagnosis of induction motors (Yang et al., 2004). Other our works in diagnostic area could be found in references (Niu et al., 2007; Widodo et al., 2007; Niu et al., 2008; Widodo et al., 2008; Tran et al., 2008; Son et al., 2009). Alternatively, in prognostic area, we have proposed numerous models for forecasting future states (Tran et al., 2008; Tran et al., 2009; Niu et al., 2009; Pham et al., 2010; Caesarendra et al., 2010), assessing the degradation (Niu & Yang, 2010; Pham et al., 2010; Caesarendra et al., 2010).

Although most of our researches were validated in industrial equipment, they still were

standalone approaches. In order to compensate for the remaining shortcomings mentioned above, a systematic platform based on intelligent algorithms, namely intelligent CBM (I-CBM), is proposed in this study. This platform consists of sequent modules: data acquisition, signal processing, feature extraction and feature selection, condition monitoring and health assessment, fault diagnostics, and prognostics. Two case-studies are presented to perform the effectiveness of this platform in industrial application.

2. Intelligent condition-based maintenance architecture

The architecture of I-CBM platform is shown in Fig. 1. This platform contains modules with the aim of converting the rotating machinery signals into the useful information for the maintainers to take remedial actions, inspect the conditions, and conduct a repair on the defect before the catastrophic failure occurs. In each module, many applicable algorithms could be appropriately selected to obtain the best result. As depicted in Fig. 1, data can be obtained from the sensors installed on the machinery for condition monitoring or manually input working conditions. Subsequently, these data are transformed into features by selecting appropriate algorithms for signal processing, feature extraction, and feature selection. In the feature space, a proper algorithm is employed for each task of classifying the type of faults, performing the degradation, and forecasting the remaining lifetime of machinery. In order to easily and conveniently implement the proposed I-CBM, a toolbox has been developed which the main user interface is shown in Fig. 2 and the algorithms used for each module of this toolbox is summarized in Table 2. A brief introduction of these modules is given as follows:

Fig. 1. The architecture of I-CBM platform.

Fig. 2. The main user interface of I-CBM platform.

Table 2 Algorithms in I-CBM.

Data acquisition: A major challenge confronted with CBM is that how the functional symptoms are monitored in terms of measurable machinery states. Data are a requirement for this challenge. Data acquisition is a process of collecting and storing useful data from target system to monitor the condition, diagnoses the faults, and prognosticate the future states and remaining lifetime. According to (Jardine et al., 200), data used for CBM could be categorized into two main types: event data and condition monitoring data. The former includes the information on what has happened (e.g., installation, breakdown, overhaul, etc.) and what has been done (e.g., minor repair, preventive maintenance, oil change, etc.) to the machinery. The latter is the measurements related to the health condition/states of the machinery. Condition monitoring data is very versatile which could be vibration, acoustic, oil analysis, temperature,

pressure, moisture, humidity, weather or environment data, etc. In this platform, vibration and current data are commonly used due to the easy-to-measure signals and analysis.

Signal processing: is a process of removing distortions and restoring the original shape of signals, removing sensor data which is not relevant, transforming the signal to make relevant features more explicit. Many methods could be applied for this process in I-CBM platform, for example wavelet transform, fast Fourier transforms (FFT) which is demonstrated in Fig. 3.

Fig. 3. FFT for vibration signals.

Feature representation: Data obtained from signal processing process is rarely usable in its raw form due to the huge dimensionality. The huge dimensionality causes not only difficulties of data storage but also data transfer. Therefore, representing data as features is the demand for reduce the huge dimensionality. Feature representation or feature calculation module is a sub-module of feature-based techniques, as shown in Fig. 4, and plays a crucial role in attaining the performance of I-CBM platform. Here, the represented features include time domain features (e.g. root mean square, variance, shape factor, skewness, kurtosis, crest factor, etc.), frequency domain features (e.g. content at the feature frequency, the amplitude of FFT spectrum, etc.). Fig. 5 presents an example of feature representation module for vibration signals.

Fig. 4. The user interface of module of feature-based techniques.
Fig. 5. An example of feature representation module.

Feature extraction and/or feature selection: Total features obtained in the previous process can cause cures of dimensionality and peaking phenomenon that greatly degrade the classification accuracy. Feature extraction can be viewed as a pre-pruning process to choose a small subset of total features that is necessary and sufficient to describe the overall operations of machine systems. The importance of feature extraction is not only to reduce the search space, but also to speed up the process of classification and also to improve the quality of classification. The extracted feature vectors will serve as one of the essential inputs to fault diagnosis and prognosis algorithms. In this platform, common algorithms used for feature extraction are principal component analysis (PCA), independent component analysis (ICA), kernel PCA, kernel ICA, linear discriminant analysis, etc., as an example shown in Fig. 6. Even though dimensionality is reduced by the feature extraction process, each feature set contains many redundant or irrelevant features as well as salient features in feature space. Consequently, feature selection process is of necessity to find an optimal subset of features that maximizes information content or predictive accuracy. Fig. 7 is the result obtained from feature selection process.

Fig. 6. An example of feature extraction in I-CBM platform.

Fig. 7. The result of feature selection in I-CBM platform.

Diagnostics: This module is used for analyzing the pattern embedded in the features to determine the root causes of previous observed faults or degradation. In order to attain this purpose by using the I-CBM platform, several classification methods are applied. Furthermore, the maintainers can compare the performance of each method to certainly affirm the condition of machine. Fig. 8 describes the diagnosing results of induction motor faults.

Health assessment: The health status and the degradation of machinery are performed in this module by using condition parameters. It also provides the unacceptable level or the failure threshold for the operations so that the appropriate actions will be taken to avoid the consequences of failure before the failure occurs.

Prognostics: Prognostics is the ability to predict the remaining lifetime, future health states, or reliability of machinery based on current health assessment and historical trends. Thus, there are two main functions of prognostics: failure prediction and remaining lifetime estimation. Failure prediction allows the pending failures to be identified before they come to a serious situation. Remaining lifetime is the time left before a particular fault will occur or any part needs to be replaced. The techniques related to prognostics can be classified as experience-based, model-based, and data driven-based. The prognostics module of I-CBM platform addresses both these functions in which most of methods belong to data driven-based techniques. Fig. 9 shows a forecasted result of kurtosis feature of bearing by using ARMA/ GARCH model (Pham et al., 2010).

Fig. 8. Performance of each method for fault diagnostics of induction motor.

Fig. 9. Forecasted result of machine state.

3. Industrial case-studies

Two industrial case-studies are presented to demonstrate the applications of proposed platform for rotating machinery. In the case of diagnostics, induction motor is considered due to its indispensable roles in several industrial applications. The faults of induction motor may not only cause the interruption of production operation but also increase costs, decrease product quality and effect safety of operators. Most common faults of induction motors are bearing failures, stator winding failures, broken rotor bar or cracked rotor end-rings and air-gap irregularities (Acosta et al., 2006). To diagnose these faults in this case-study, a combination of wavelet transform and SVM, namely W-SVM, are employed. In the case of prognostics, a low

methane compressor which is an important equipment in petrochemical plant is used as an object for investigation. Self-organizing map (SOM) and failure threshold determination are used for assessing the degradation of machine and setting an alarm, respectively. Once the degradation value is higher than failure threshold, the Cox's proportional hazard model (PHM) (Cox, 1972) in association with SVM is triggered to forecast the remaining lifetime of machine.

3.1. Rotating machinery fault diagnostics

3.1.1. Data acquisition and feature calculation

Data acquisition was conducted on induction motor of 160 kW, 440 V, 2 poles as shown in Fig. 10. Six accelerometers were installed along vertical, horizontal and axial directions to pickup vibration signal at drive-end and non drive-end. The maximum frequency of the used signals and the number of sampled data were 60 Hz and 16384, respectively. The condition of induction motor is briefly summarized in Table 3. Each condition was labeled as class from 1 to 7. There are totally 126 features calculated from 6 signals, 21 features and 98 samples calculated from 7 conditions, 14 measurements.

Fig. 10. Data acquisition of induction motor.
Table 3 Condition of induction motor.

3.1.2. Feature extraction

Structure of three first original features, those are mean, RMS, and shape factor are plotted in Fig. 11. This figure shows the performance of original features which are containing overlap in some conditions. To make original features well clustered, applying component analysis is suggested in this study. Component analysis via ICA, PCA, and their kernel are used to extract and reduce the feature dimensionality based on eigenvalue of covariance matrix as described in Fig. 12. After performing component analysis, the features have been changed into independent and principal components, respectively. The first three independent and principal components from PCA, ICA, and their kernel are plotted in Fig. 13. It can be observed that the clusters for seven conditions are separated well. It indicates that component analysis can perform feature extraction and all at once do clustering each condition of induction motors.

Fig. 11. Original features.
Fig. 12. Feature reduction using component analysis.
Fig. 13. The first three principal and independent components.

According to the eigenvalue of covariance matrix, the features are changed into component analysis and reduce only 5 component analysis needed for classification process. The other

features are discarded due to small of eigenvalue of covariance matrix. The selected component analysis is then used as input vectors for W-SVM classifier to diagnose the faults of induction motor.

3.1.3. Result and discussion

The SVM based multi-class classification is applied to perform the classification process using one-against-all methods. Vapnik (Vapnik, 1982) describe a method which used the projected conjugate gradient algorithm to solve the quadratic programming (QP) problem in SVM. In this study, 1 and 10^{-7} are assigned to the parameter C (bound of the Lagrange multiplier) and λ (condition parameter for QP method), respectively. Furthermore, wavelet kernel function using Daubechies series is performed. The parameter δ in wavelet kernel refers to number of vanishing moment and is set 4. In the training process, the data set is also trained using RBF kernel function as comparison. The parameter γ for bandwidth RBF kernel is user defined equal to 0.5.

The complex separation boundaries of W-SVM are presented in Fig. 14. In these figures, the circle refers to the support vector that states the correct recognition in W-SVM. Each condition of induction motor is well recognized using Daubechies wavelet kernel. In the classification process using W-SVM, each condition of induction motors can be clustered well. The good separation among conditions shows the performance of W-SVM doing recognition of component analysis from vibration signal features.

The performance of classification process is summarized in Table 4. All data set come from component analysis are accurately classified using Daubechies wavelet kernel and SVM and reached accuracy 100% in training and testing, respectively. SVM using RBF kernel function with kernel width $\gamma = 0.5$ is also performed in classification for comparison with Daubechies wavelet kernel. The results show that the performance of W-SVM is similar to SVM using RBF kernel function, those are 100% in accuracy of training and testing, respectively. In the case of number support vectors, SVM with RBF kernel function needs lower than W-SVM except kernel PCA.

Fig. 14. Separation boundaries of W-SVM.

Table 4 Results of classification.

3.2. Rotating machinery prognostics

3.2.1. Data acquisition

Methane compressor shown in Fig. 15 is important equipment used in petrochemical industry where normal production flow is required to maintain. Due to the importance of this machine, condition monitoring and prognostics are of necessity to sustain its operation. This

compressor is driven by a 440 kW motor, 6600 V, 2 poles and operating at a speed of 3565 rpm. Other information of the system is summarized in Table 5.

The condition monitoring system of this compressor consists of two types: off-line and on-line. In the off-line system, the acceleration sensors are installed along axial, vertical, and horizontal directions at the locations of drive-end motor, non drive-end motor, male rotor compressor and suction part of compressor. In the on-line system, acceleration sensors are located at the same places as in the off-line system but only in the horizontal direction. Vibration signal was recorded from August 2005 to November 2005. The average recording duration was 6 hours during the data acquisition process.

Fig. 15. Low methane compressor.

Table 5 Information of the system.

3.2.2. Machine health assessment and failure threshold determination

After acquiring vibration signal, RMS and envelope features used in this study are extracted. RMS is a common feature, even the only indicator used in ISO 10816 and ISO 7919 for machinery condition monitoring and alarming. Envelope is useful to detect glitches (narrow pulse signals). Both of the two features are often used for condition monitoring of rotating machinery as plotted in Figs. 16 and 17. In these figures, the machine was obviously in normal operating condition during the first 300 points of the time sequence. At the 291st point, the machine condition significantly reduced in comparison with other points. After the 300th point, the machine suddenly changed the condition and was broken down at the 308th point. Thus, there was a process of degrading from normal operating state to failure state in this compressor.

Fig. 16. The entire peak acceleration data of low methane compressor.

Fig. 17. The entire envelope acceleration data of low methane compressor.

To perform this degradation, a process of normalization is conducted to transform values of features into a common scale and group them as input set for feature-fusion. SOM neural network is employed to combine the input set into a single out indicator which is minimum quantization error (MQE) (Qiu et al., 2003), as shown in Fig. 18. Comparing with the plots of RMS and envelope features, MQE indicator maintains a more steady state than envelop curve, whilst enhances a degradation trend than RMS curve, which is especially appropriate for initial fault detection and health degradation prediction. Additionally, MQE indicator in Fig. 18 can be obviously recognized the sudden increase from the 300th point. This appropriates to the sudden change of RMS feature mentioned above as well as indicates the abnormal value at the 291st point. Therefore, MQE is adequate to assess the machine degradation.

Fig. 18. Machine health indicator.

The next step is to determine the failure threshold so that the prognostic module is triggered. Further reading the method for determining this threshold could be found in reference (Ginart et al., 2006). Failure threshold is also employed to attain the censored data which is used for generating the PHM in the next process. This data consists of a series of "0" and "1" values indicating the normal condition and failure condition, respectively.

3.2.3. Remaining lifetime estimation

To estimate the remaining lifetime, The Cox's PHM is built based on the censored data obtained from previous step. The parameters of this PHM are estimated as $\beta_1 = -0.8042$ for RMS feature and $\beta_1 = 0.1062$ for envelope feature. Hazard rate and survival function estimation of this PHM are depicted in Figs. 19 and 20, respectively. In Fig. 19, the hazard rate gradually increases with respect to time. From the 300th point, the hazard rate significantly changes because of the rapid growth of RMS values. Thus, the more the hazard rate increases, the less the reliability is.

Fig. 19. Hazard rate estimation.

Fig. 20. Survival function estimation.

After attaining the survival function, the process of training and forecasting by using SVM in association with time-series forecasting techniques is carried out. The multi-step ahead direct prediction method [20] of time-series forecasting techniques is applied for this study. The values of survival function up to 291st point are used to train SVM model in which the Gaussian kernel $K(x, y) = \exp(-|x - y|^2 / (2\sigma)^2)$ is employed. The other predefined parameters ε and C are set to 0.001 and 500, respectively. Moreover, 5-fold cross validation is also applied to choose the best SVM model. The predicted results of 17 points from the 292nd point where the machine commences degrading the state are depicted in Fig. 21. Even though the multi-step ahead is employed, the predicted results is closely resemble with the actual values. From the predicted results, the remaining lifetime could be estimated by using the predefined survival probability for fault. For example, if this value is chosen as 0.2, the point where predicted result reaches for 0.2 is 306th. This means the predicted remaining lifetime of machine after degrading state occurred is 84 hours $((306 - 292) \times 6 = 84)$ while the actual remaining lifetime is 84 hours (the 306th point). As a result, the prognostic module of I-CBM platform can estimate accurately the remaining lifetime of the methane compressor.

Fig. 21. Forecasting results.

4. Conclusions

This study proposes the I-CBM platform based on standalone data-driven approaches as a comprehensive system for rotating machinery. This platform contains necessary modules to adequate the request for CBM system involved hardware and software components. A toolbox has also been developed as a software component to easily and conveniently implement this platform in application. Two industrial cases are used to validate the effectiveness of the I-CBM platform. The accurate results obtained from these cases indicate that the I-CBM platform can fulfill the shortcomings of previous approaches i.e. systematic tool for various rotation machinery, performance degradation assessment, remaining lifetime estimation, and industrial validation.

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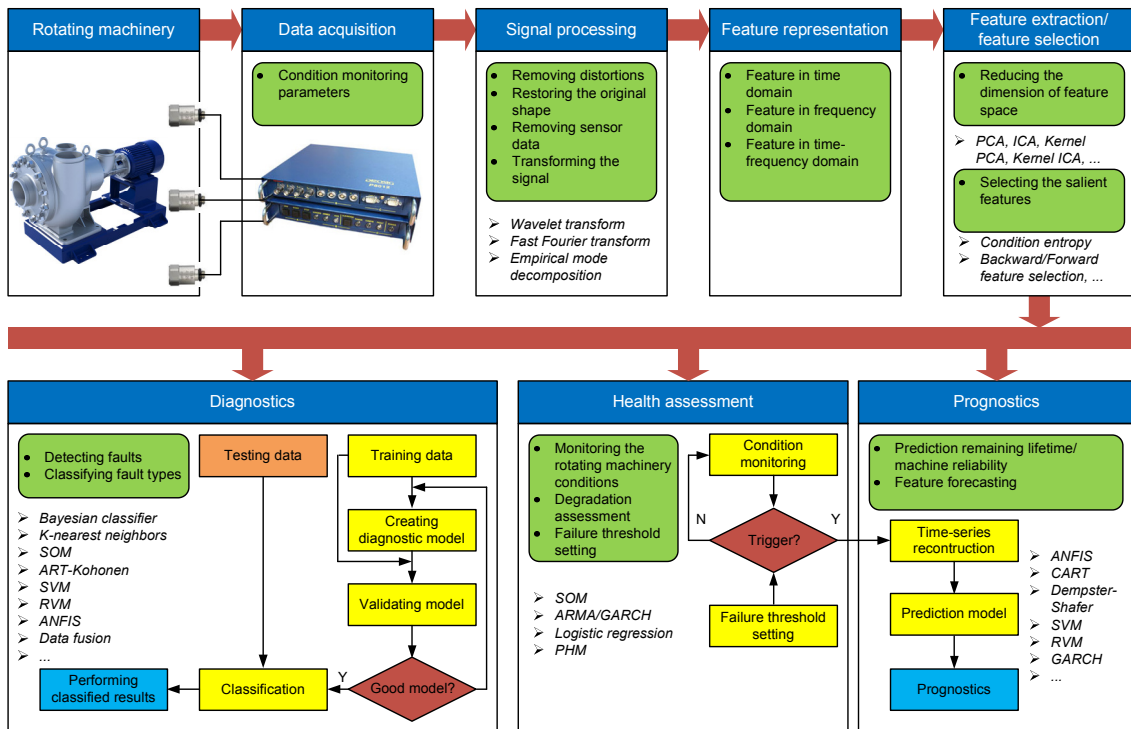
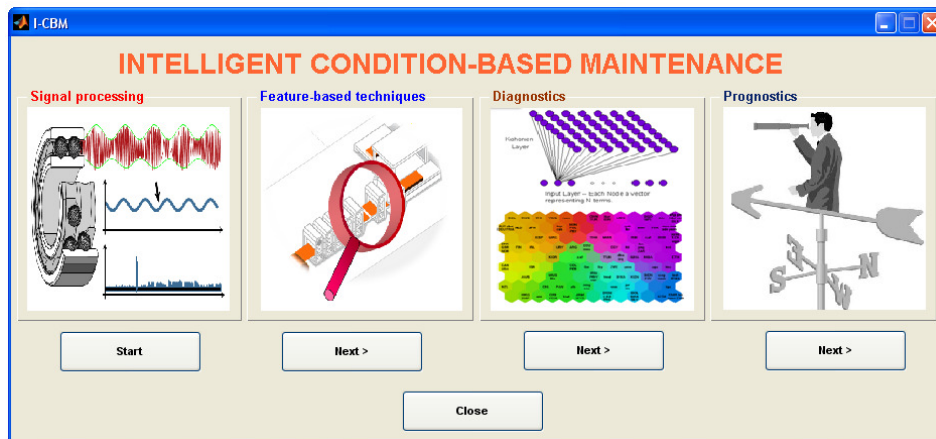**Fig. 1.** The architecture of I-CBM platform.

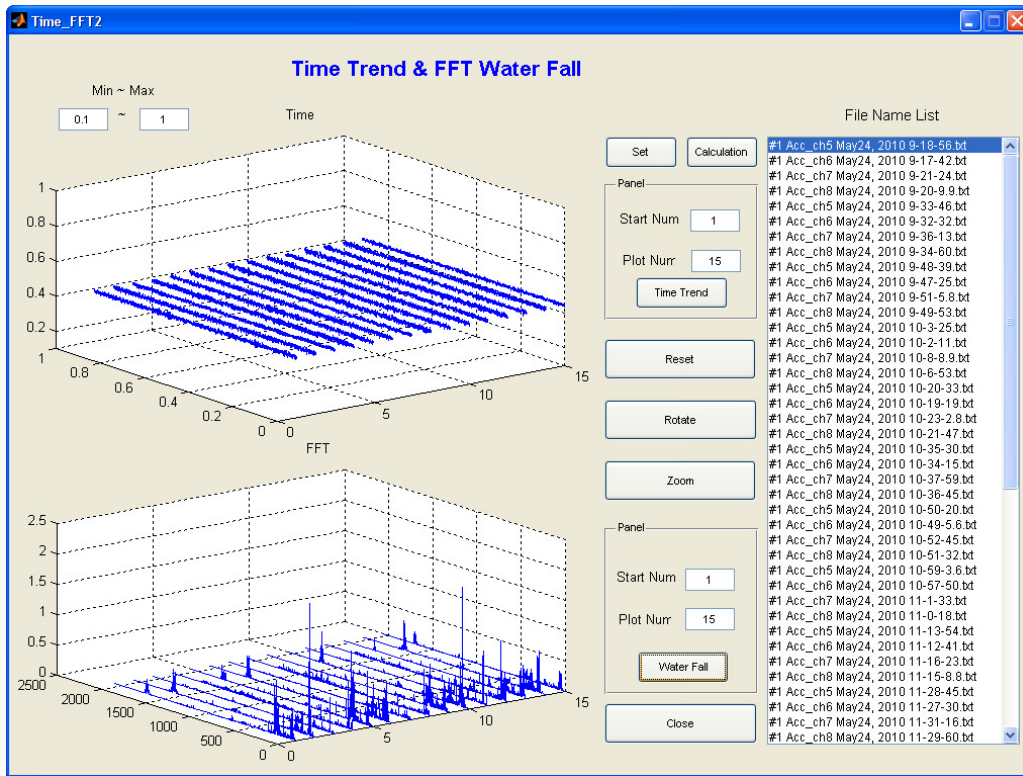**Fig. 2.** The main user interface of I-CBM platform.

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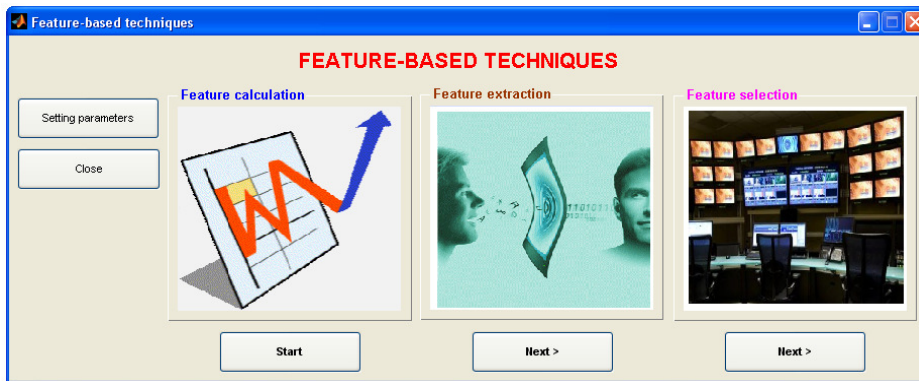**Fig. 3.** FFT for vibration signals.

Fig. 4. The user interface of module of feature-based techniques.
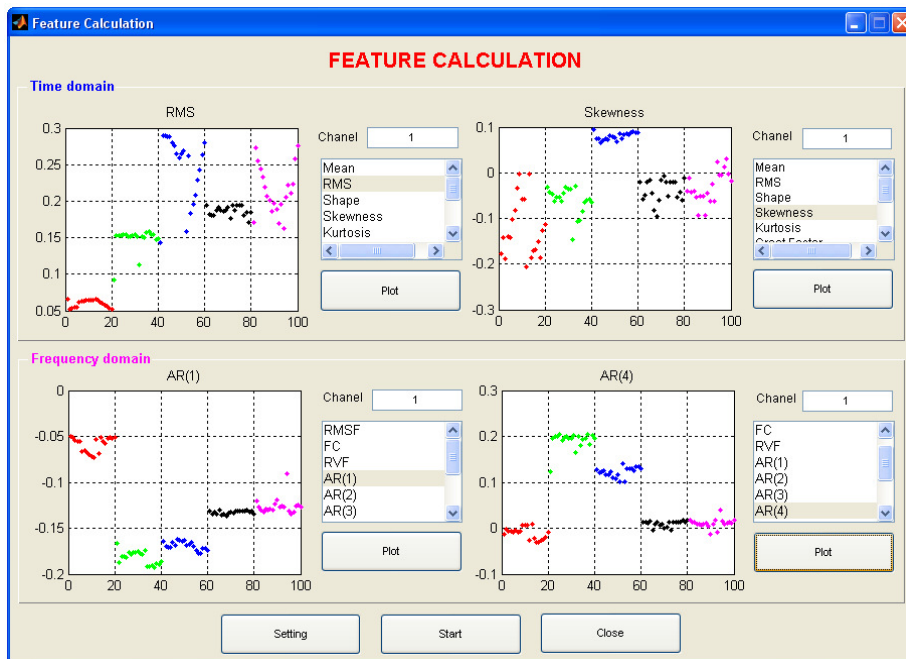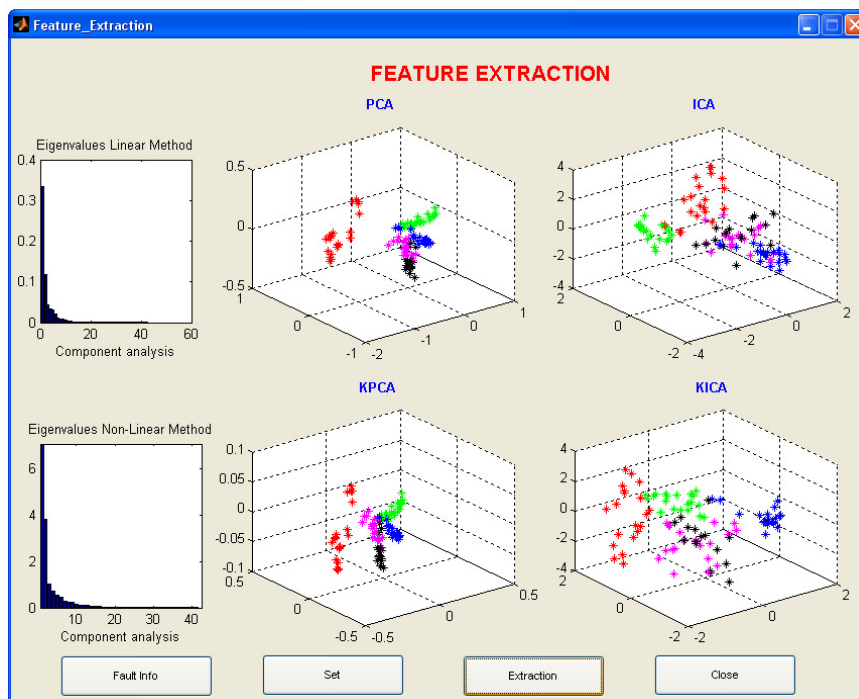
Fig. 5. An example of feature representation module.
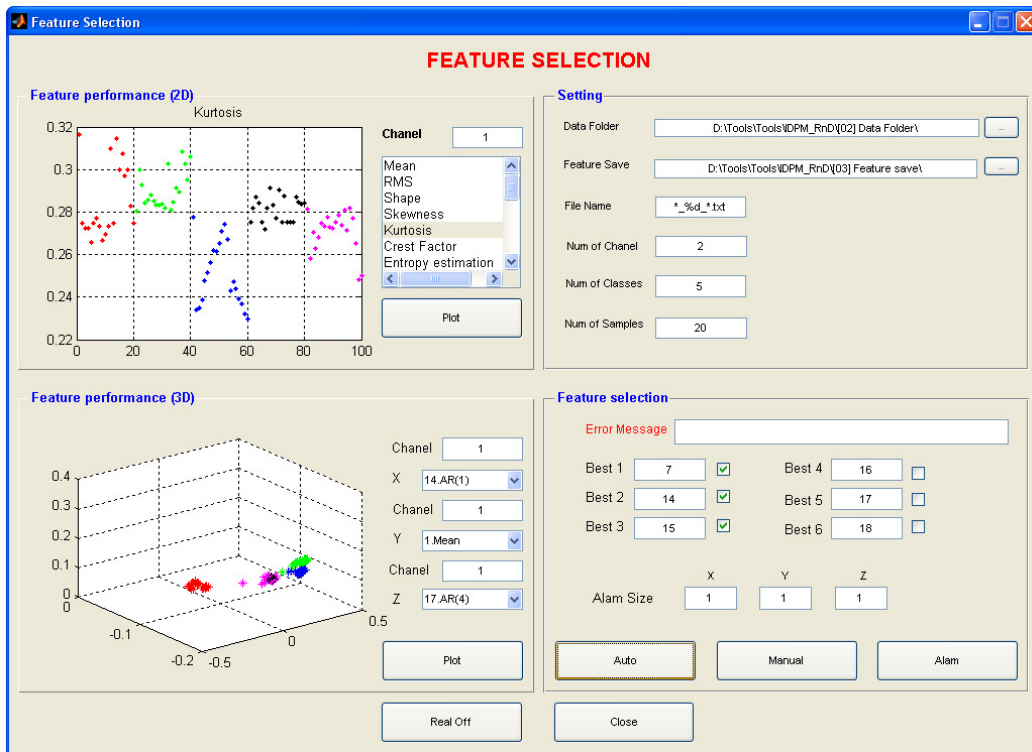

Fig. 6. An example of feature extraction in I-CBM platform.

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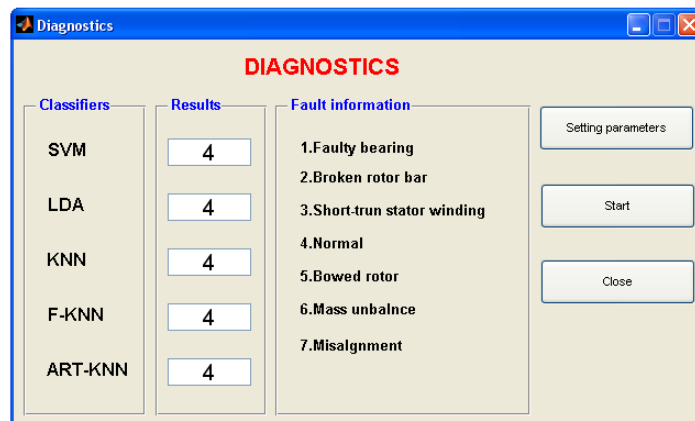**Fig. 7.** The result of feature selection in I-CBM platform.

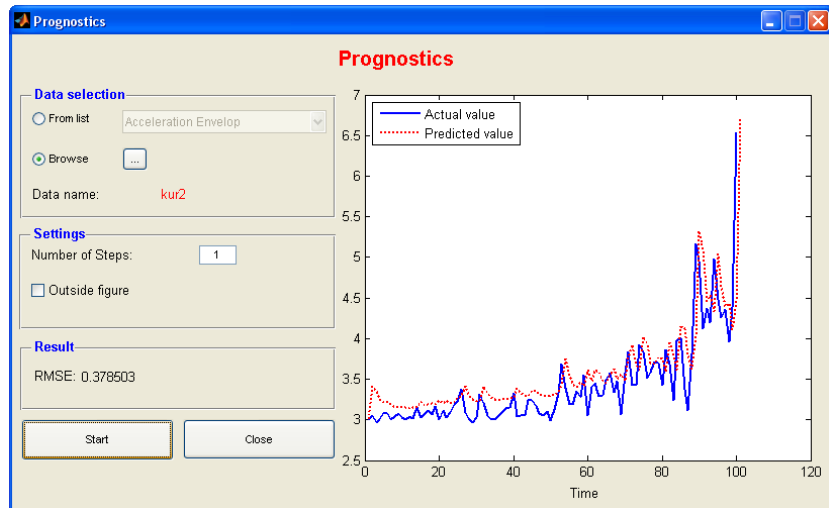**Fig. 8.** Performance of each method for fault diagnostics of induction motor.

Fig. 9. Forecasted result of machine state.
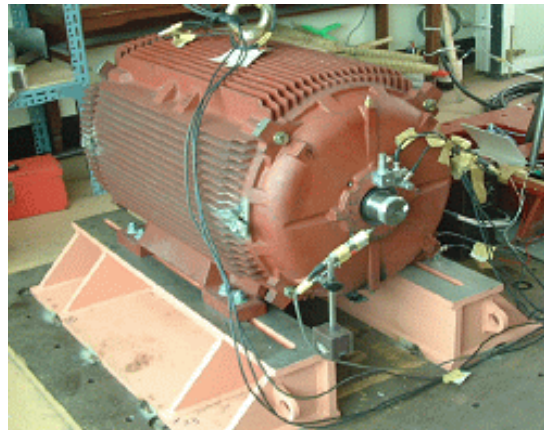
Fig. 10. Data acquisition of induction motor.

Fig. 11. Original features.

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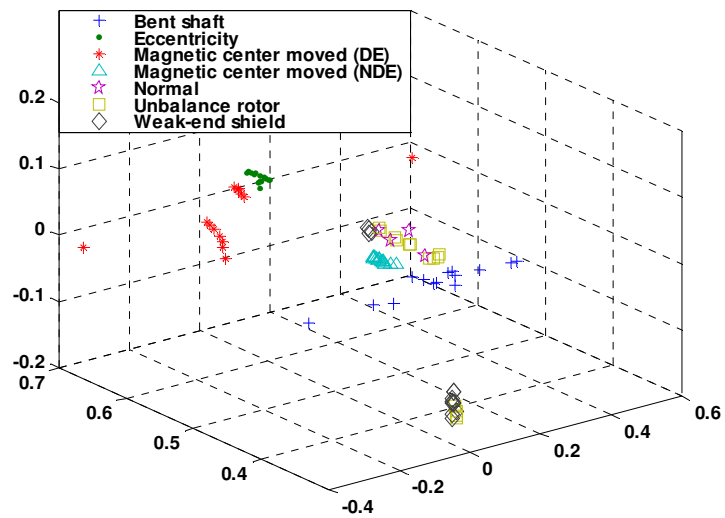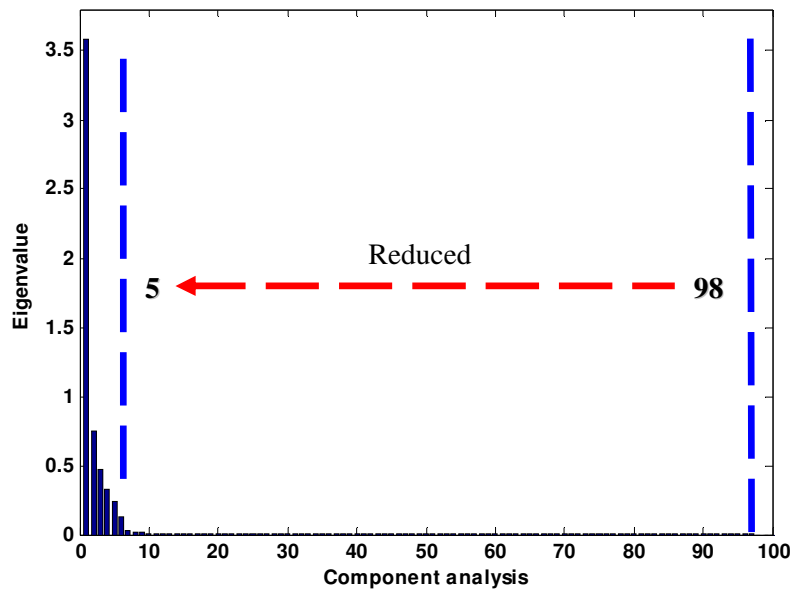
Fig. 12. Feature reduction using component analysis.
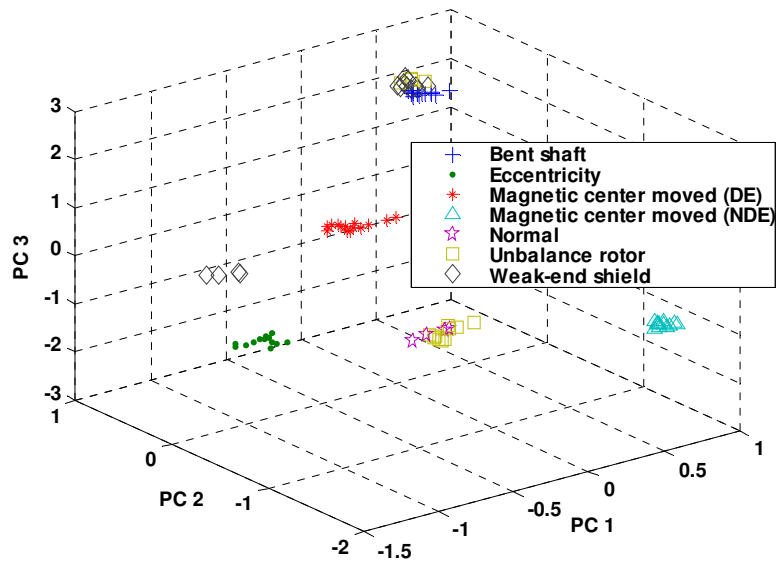
(a) Principle components
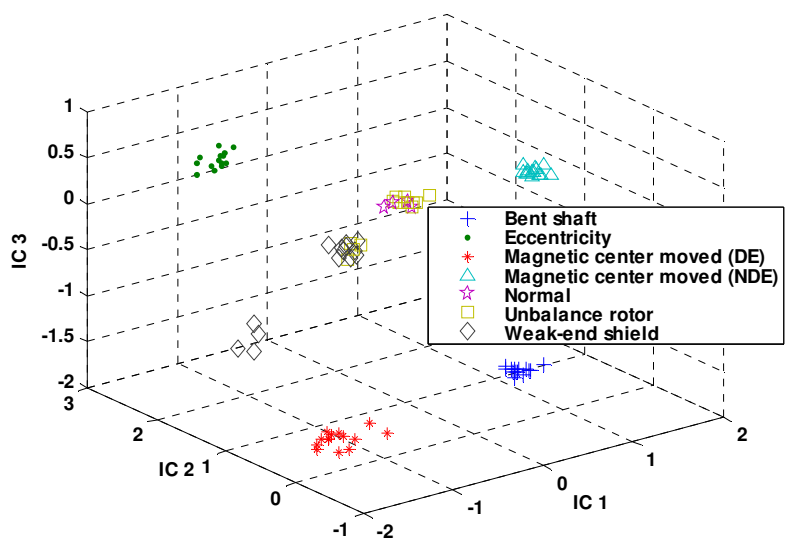
(b) Independent components
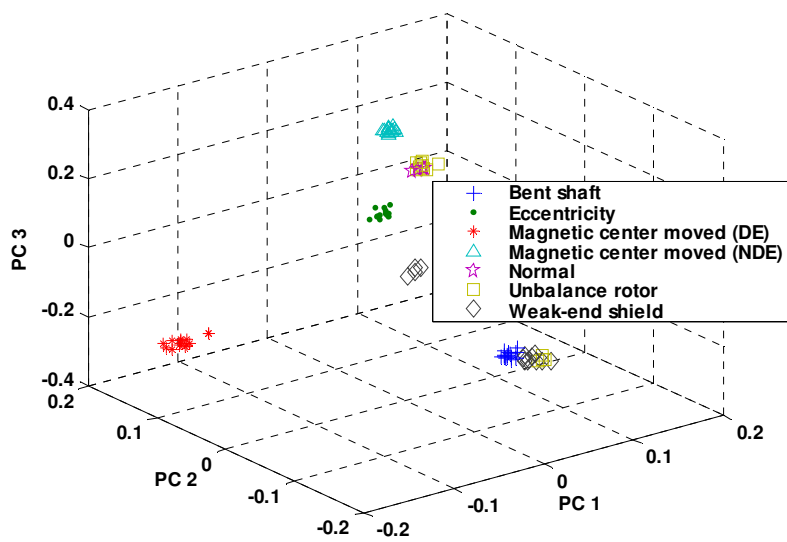
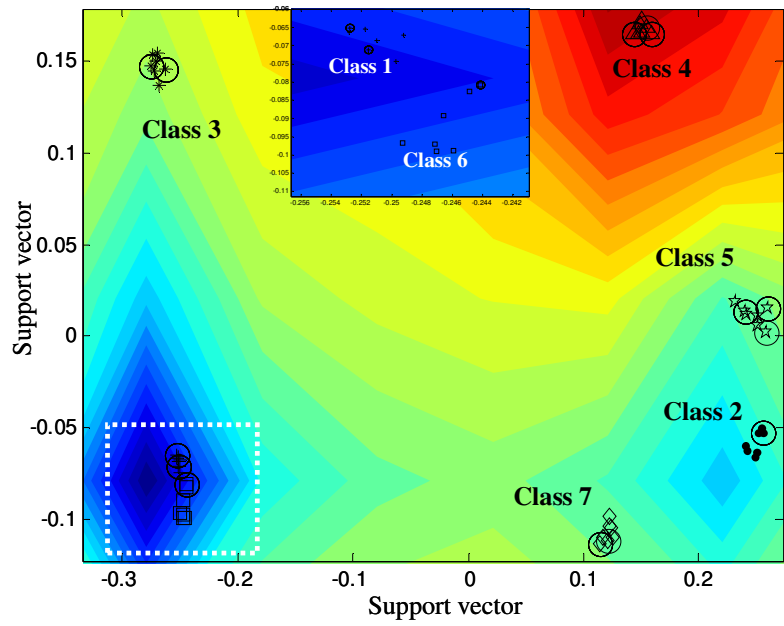(c) Kernel principle components
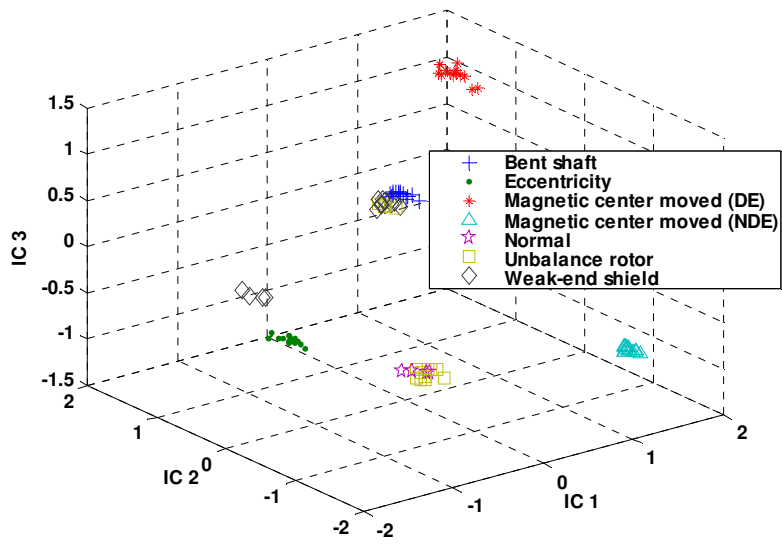
(d) Kernel independent components

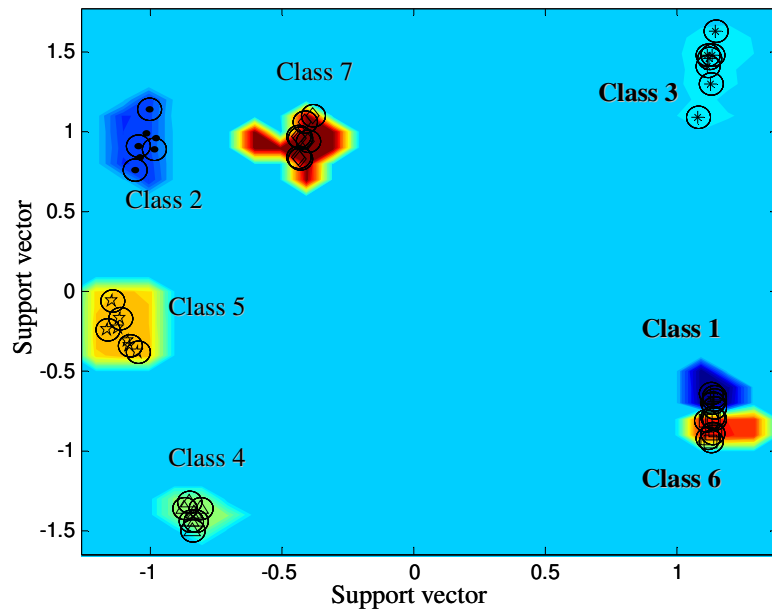**Fig. 13.** The first three principal and independent components.
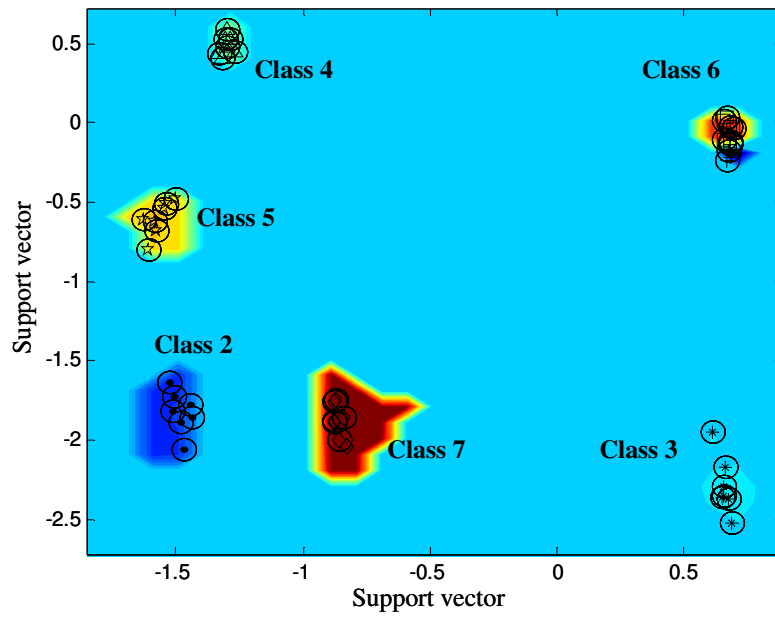
(a) Daubechies kernel with PC data

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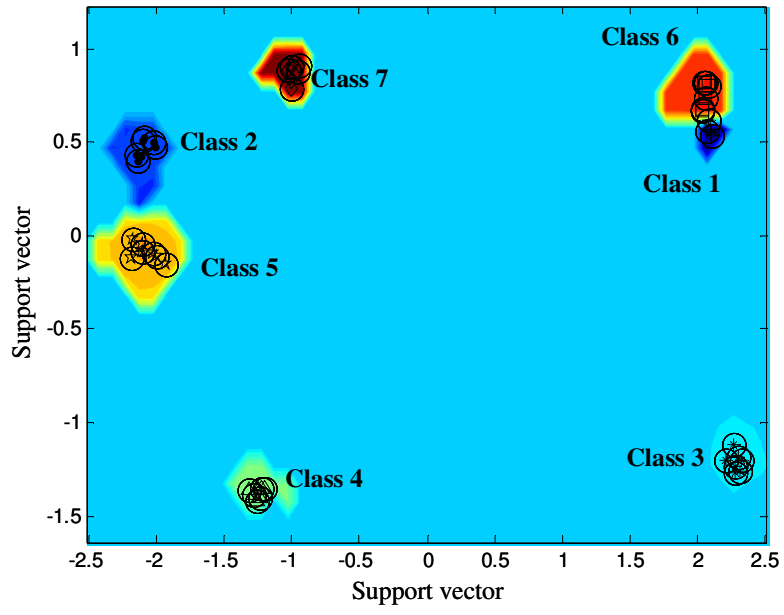
(b) Daubechies kernel with IC data

(c) Daubechies kernel with kernel PC data

(d) Daubechies kernel with kernel IC data
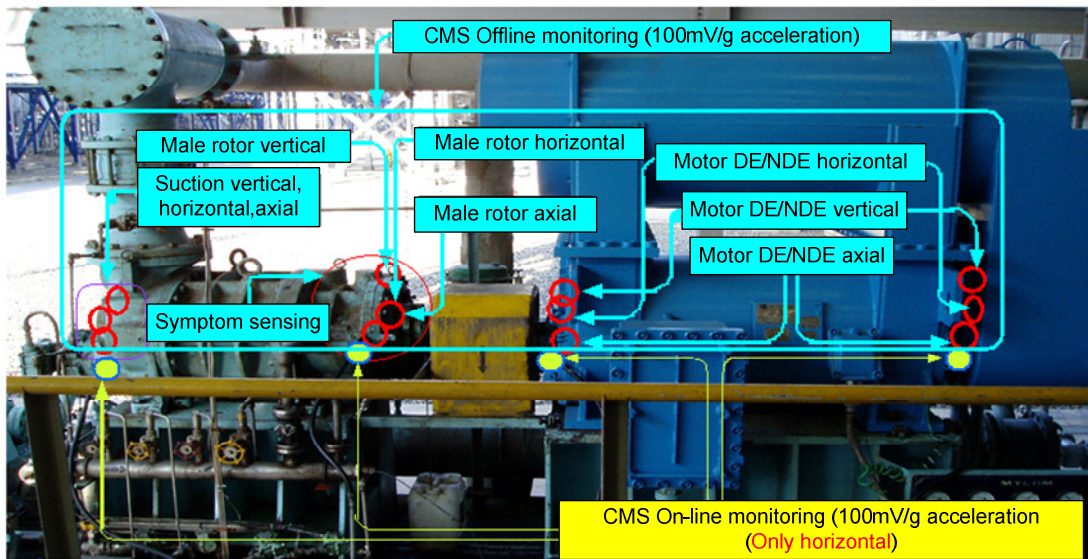
Fig. 14. Separation boundaries of W-SVM.

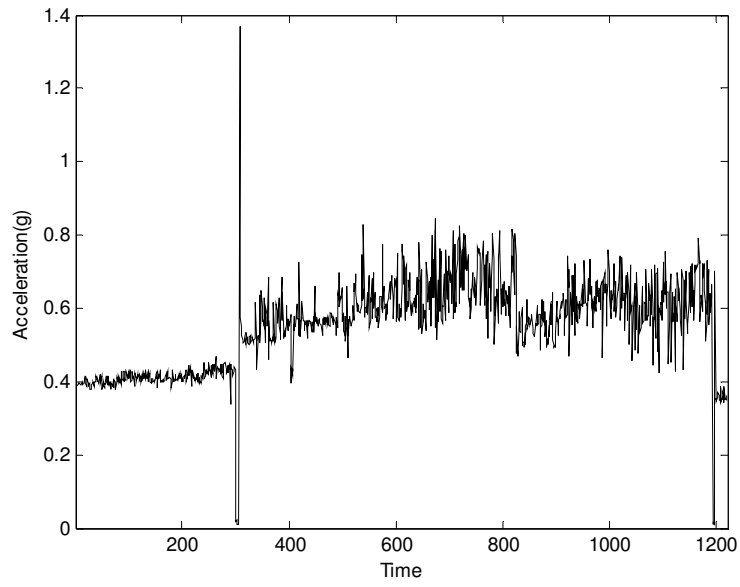
Fig. 15. Low methane compressor.

Fig. 16. The entire peak acceleration data of low methane compressor.
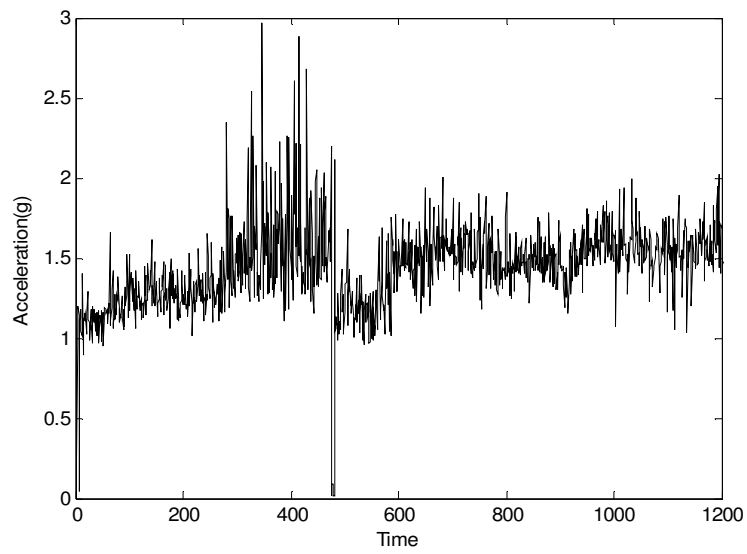

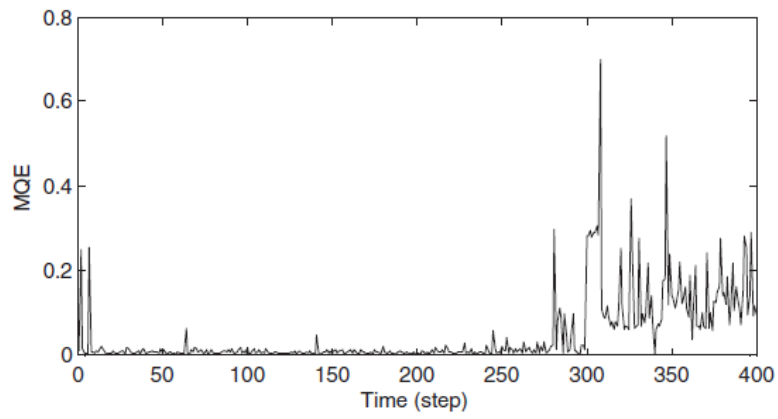**Fig. 17.** The entire envelope acceleration data of low methane compressor.
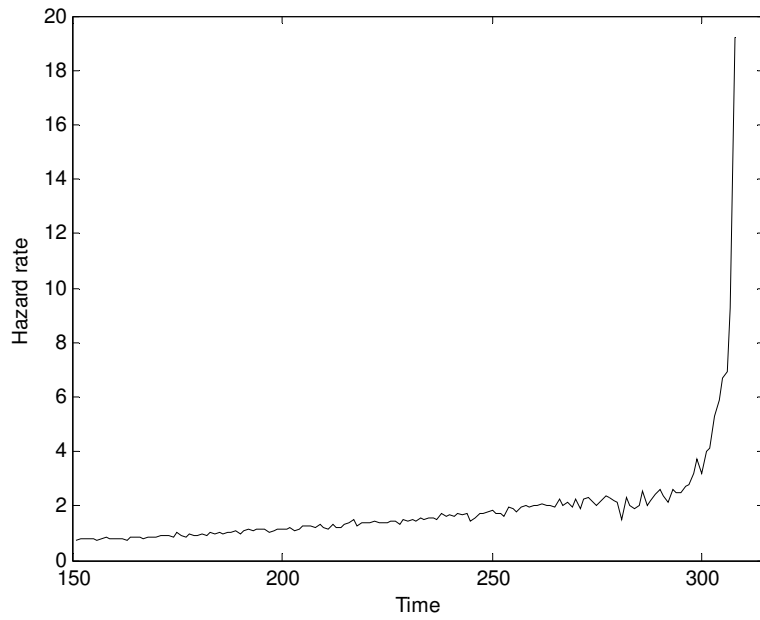
Fig. 18. Machine health indicator.

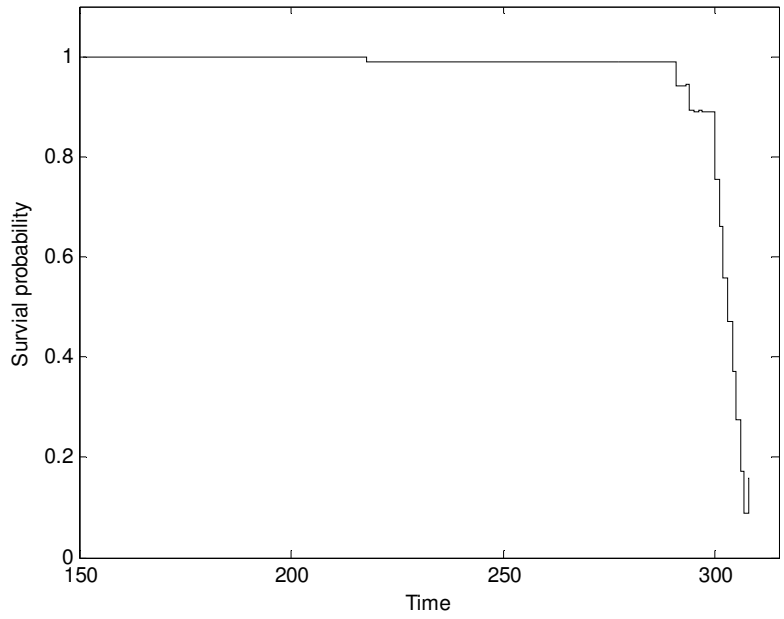

Fig. 19. Hazard rate estimation.

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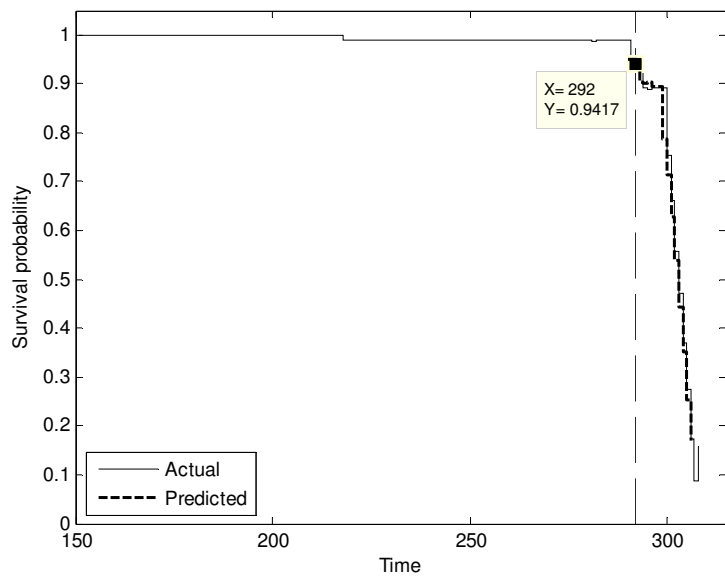**Fig. 20.** Survival function estimation.

Fig. 21. Forecasting results.

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Table 1

Maintenance approaches.

Maintenance strategy	Frequency of maintenance	Criteria of initiating maintenance	Condition assessment	Results
Corrective	Unscheduled	Upon failure/ work stoppage to fix immediate problems	Unusual	• Unpredictable asset availability and reliability
Preventive	Pre-scheduled	Prescribed based on failure history or test data	Unusual/ manual data collection	• Maintenance performed more often than may be necessary
Condition-based	Just-in-time	Prescribed based on statistical patterns in operating parameters	Continuous/real-time sensor monitoring and data collection	• Maintenance performed when necessary • Highest asset availability and reliability of mission-critical assets • Continuous data collection

Table 2

Algorithms in I-CBM.

Module name	Methods
Signal processing	Wavelet transform
	Fast Fourier transform
	Empirical mode decomposition
Feature representation	Time domain analysis
	Frequency domain analysis
	Time-frequency domain analysis
Feature extraction	Principal component analysis (PCA)
	Independent component analysis (ICA)
	Kernel PCA
	Kernel ICA
	Fisher discriminant analysis (FDA)
	Linear discriminant analysis (LDA)
	Generalized discriminant analysis (GDA)
	Clustering techniques
Feature selection	Individual feature evaluation based on space distribution
	Condition entropy
	Backward feature selection
	Forward feature selection
	Branch and bound feature selection
	Plus l-take away r feature selection
	Floating forward feature selection
	Distance evaluation technique
	Taguchi method-based feature selection
	Genetic algorithm
Diagnostics	Linear classifier
	Quadratic classifier
	Bayesian classifier
	k-nearest neighbors
	Self-organizing feature map neural network
	Learning vector quantization neural network
	Radial basic function neural network
	ART-Kohonen neural network
	Support vector machine (SVM)
	Decision tree
	Random forest
	Adaptive neuro-fuzzy integrated system (ANFIS)
	Data fusion system
Prognostics	Adaptive network-based fuzzy inference system (ANFIS)
	Classification and regression trees (CART)
	Dampster-Shafer regression
	Autoregressive moving average (ARMA)
	Generalized autoregressive conditional heteroscedasticity (GARCH)
	Relevance support vector machine (RVM)
	Support vector machine (SVM)
	Logistic regression
	Proportional hazard model

Table 3
Condition of induction motor.

Class No.	Condition	Description	Others
1	Bent rotor	Maximum shaft deflection	1.45mm
2	Eccentricity	Static eccentricity (30%)	Air-gap: 0.25 mm
3	MCDE	Magnetic center moved (DE)	6 mm
4	MCNDE	Magnetic center moved (NDE)	6 mm
5	Normal	No faults	-
6	Unbalance	Unbalance mass on the rotor	10 gr
7	Weak-end shield	Stiffness of the end-cover	-

Table 4
Results of classification.

Kernel	Accuracy (training/test), %				Number of SVs			
	IC	PC	Kernel IC	Kernel PC	IC	PC	Kernel IC	Kernel PC
Wavelet Daubechies	100/100	100/100	100/100	100/100	35	39	39	17
RBF-Gaussian ($\gamma = 0.5$)	100/100	100/100	100/100	100/100	22	22	25	33

Table 5
Information of the system.

Electric motor		Compressor	
Voltage	6600 V	Type	Wet screw
Power	440 kW	Lobe	Male rotor (4 lobes)
Pole	2 Pole		Female rotor (6 lobes)
Bearing	NDE:#6216, DE:#6216	Bearing	Thrust: 7321 BDB
RPM	3565 rpm		Radial: Sleeve type