Machine performance degradation assessment and remaining useful life prediction using proportional hazard model and support vector machine

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ABSTRACT

Machine performance degradation assessment and remaining useful life (RUL) prediction are of crucial importance in condition-based maintenance to reduce the maintenance cost and improve the reliability. They provide a potent tool for operators in decision-making by specifying the present machine state and estimating the remaining time. For this ultimate purpose, a three-stage method for assessing the machine health degradation and forecasting the RUL is proposed. In the first stage, only the normal operating condition of machine is used to create identification model for recognizing the dynamic system behavior. Degradation index which is used for indicating the machine degradation is subsequently created based on the root mean square of residual errors. These errors are the difference between identification model and behavior of system. In the second stage, the Cox's proportional hazard model is generated to estimate the survival function of the system. In the last stage, support vector machine, which is one of the remarkable machine learning techniques, in association with time-series techniques is utilized to forecast the RUL. The data of low methane compressor acquired from condition monitoring routine is used for validating the proposed method. The result shows that the proposed method could be used as a reliable tool to machine prognostics.

Keywords: Prognostics, Performance degradation, Remaining useful life, Proportional hazard model, Support vector machine.

1. Introduction

Machinery operation generally consists of a series of states which are transient, normal operating, and degrading before fault occurrences. Among these, even degrading state plays an important role in maintenance activity, it is not a root cause of the machine breakdown. However, it does decline the performance reliability and increase the potential for faults and failures. Once the failure degradation has been detected, the remaining lifetime of machinery needs to be predicted in order that system operators implement the timely maintenance actions to avoid the catastrophic failures.

In order to estimate the remaining useful life (RUL), condition-based maintenance (CBM), one of the efficient maintenance strategies, has been recently received considerable attention in modern industries. In CBM, prognostics is of necessity and gradually becomes a key component due to its capability to foretell the remaining operation life, future machine state, or probability of reliable machine operation based on the data acquired from condition monitoring process [1]. Additionally, more advanced prognostics are being focused on performance degradation monitoring and assessment so that failure can be predicted and prevented. According to [2], three crucial steps are necessary to fulfill the goal of prognostics. Firstly, the defect or abnormality should be able to be detected at an early stage. Secondly, the machine performance degradation should be assessed robustly and tracked continuously. Finally, the RUL and possible failure mode of the machine should be effectively predicted. Therefore, the key challenges of implementing machine prognostics are machine performance degradation assessment and RUL prediction in which the former is a critical procedure to the latter.

Lately, several considerable efforts which range from data-driven based techniques to model-based techniques have been implemented to develop methods and tools for these challenges. Qiu et al. [2] developed a robust performance degradation method for rolling element bearing. This method based on a combination of wavelet filter and self-organizing map (SOM) in which the former was used for enhancing weak signal for fault identification whilst the latter was applied for performance degradation assessment. Lee et al. [3, 4] applied a pattern discrimination model based on a cerebellar model articulation controller (CMAC) neural network to monitor and assess performance degradation in a robot. Lin et al. [5] combined traditional reliability modeling methods with vibration-based monitoring techniques and CMAC neural network in an integrated system to perform the machine reliability and determine the health status of machine. The results of CMAC were then verified by Weibull proportional hazard model. Xu et al. [6] proposed a fuzzy-based extension of CMAC neural network to analyze two types of machine degradation severities: the network was trained by signals from different levels of machine degradation severity, and the network was only trained by signals of machine normal state. Other neural network-based approaches to assess bearing performance degradation and forecast the RUL were presented by Gebraeel et al. [7] and Huang et al. [8]. Liao and Lee [9] proposed a method which combined wavelet packet analysis, principal component analysis, and Gaussian mixture model to define performance index. This index was determined based on the overlap between the distribution of the baseline feature space and that of the testing feature space. An extension of support vector machine (SVM), namely least squares SVM, was used for assessment of machine performance degradation proposed in reference [10]. Using fuzzy *c*-means (FCM) clustering method is a trendy approach to assess the machine performance degradation. Huang et al. [11] proposed a combined model in which wavelet packet transform was used to process raw signals, the Fisher criterion was applied for feature selection, and FCM was utilized to assess and classify the performance of machine. Pan et al. [12] proposed an FCM-based method for bearing performance assessment. This method comprised lifting wavelet packet decomposition for feature extraction and FCM for bearing performance degradation assessment. In case of model-based techniques, proportional hazard model (PHM) and logistic regression model (LRM) which are related to multiple degradation features were implemented to perform machine reliability indices and enable machine RUL forecast [13]. Other applications of LRM to realize machine performance assessment and RUL prediction could be found in references [14-16].

Generally, these above approaches can indicate the performance degradation of machine as well as assist in forecasting the machine RUL. However, some existing disadvantages lead to difficulty of applying these approaches to real industrial equipment. FCM, SVM, and back propagation neural network need to be trained by historical data including both normal and failure operation to generate the assessment models, which is costly or inapplicable in industrial area. SOM and CMAC neural network assessment models could be created by using only normal operation data which is more beneficial. Nevertheless, they are either not intuitive enough to reflect degradation degree or seriously influenced by some parameters defined by user, which makes it unpractical [12]. Moreover, these approaches only focused on the machine performance degradation assessment without RUL prediction which is the ultimate goal of prognostics. Performance degradation assessment and RUL prediction methods based on PHM and LRM also need data of whole machine life. This is impossible in case of newly installed machine operating in normal condition. Yan et al. [15] proposed a solution for this problem by using technician's experience for acceptable level or unacceptable level to predefine the probability thresholds. However, these levels are non-scientific and human intuitive.

In this study, a three-stage method for both targets involving machine performance degradation assessment and RUL prediction is proposed. In the first stage, autoregressive moving average (ARMA) model [17], which is one of the system identification techniques, is generated by using only normal operating data to identify the behavior of the complex system. Degradation index defined as the root mean square of residual errors is then used to indicate the machine degradation. The residual errors are the different outputs between identification model and behavior of system. By this degradation index, operators or maintainers could define the failure threshold for the system. In the second stage, the Cox's PHM is established to estimate the survival function of system. Finally, support vector machine, which is one of the remarkable machine learning techniques, in association with multi-step ahead direct prediction method of time-series forecasting techniques is utilized to forecast the RUL in the last stage.

2. Background knowledge

2.1. Autoregressive moving average (ARMA)

ARMA (p, q) forecasting model for time-series y_t is given as follows:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \phi_j \varepsilon_{t-j} + \varepsilon_t \qquad (1)$$

where c is a constant, p is the number of autoregressive orders, q is the number of moving average orders, φ_i is autoregressive coefficients, ϕ_j is moving average coefficients and ε_t is a normal white noise process with zero mean and variance σ^2.

Box and Jenkins [17] proposed three iterative steps to build ARMA models for time series: model identification, parameter estimation and diagnostic checking. The elaborate information of each step could be found in reference [18]. In order to determine the orders of ARMA model, autocorrelation function (ACF) and partial autocorrelation function (PACF) are commonly used in conjunction with the Akaike information criterion. Additionally, maximum likelihood estimation [19] in association with ACF and PACF is another technique which could be used to estimate these ARMA orders. Nevertheless, these methods are manual and empirical. In this study, the ARMA orders are automatically estimated by applying an ameliorated method proposed by Broersen. The technique of this method could be elaborately found in references [20, 21].

2.2. Cox proportional hazard model and survival function

The semi-parametric Cox's PHM [22] is the most commonly used model in hazard regression. It has been successfully applied to survival analysis in medical areas and reliability predictions in accelerated life testing. The basic approach in the proportional hazard modeling assumes that the hazard function consists of two parts: time dependence and time independence. The former describes how hazard changes over time whilst the latter describes how hazard relates to factors. The hazard function can be written as follow:

$$\lambda(t \mid z) = \lambda_0(t)\exp(\beta^T z) \qquad (2)$$

where z is the vector of time dependent covariates, $\lambda_0(t)$ denotes an arbitrary unspecified baseline hazard function, and $\beta = (\beta_1, \ldots, \beta_p)^T$ is the vector of regression coefficients. These coefficients are generally estimated by maximizing the partial likelihood function without specifying the baseline hazard function $\lambda_0(t)$. The partial likelihood function is given as:

$$L(\beta) = \prod_{i=1}^{n} \left(\frac{\exp(\beta^T z_i)}{\sum_{j \in R(t_i)} \exp(\beta^T z_j)} \right)^{\delta_i} \qquad (3)$$

where $R(t_i) = \{j : t_j \geq t_i\}$ denotes the risk set at time t_i.

Note only that the uncensored times contribute their factor to the partial likelihood. However, both censored and uncensored observations appear in the denominator, where the sum over the risk set includes all individuals which are still at risk immediately prior to t_i. Let $\hat{\beta}$ denote the maximum partial likelihood estimate of β. The corresponding log likelihood function $l(\beta)$ = $\ln L(\beta)$ can be written as:

$$l(\beta) = \sum_{i=1}^{n} \delta_i (\beta^T z_i) - \sum_{i=1}^{n} \delta_i \ln\left(\sum_{j \in R(t_i)} \exp(\beta^T z_j) \right) \tag{4}$$

The first derivative of $l(\beta)$ is given by:

$$U(\beta) = \frac{\partial l}{\partial \beta} = \delta^T Z - \sum_{i=1}^{n} \delta_i \frac{\sum_{j \in R(t_i)} \exp(\beta^T z_j) Z_{(j,.)}}{\sum_{j \in R(t_i)} \exp(\beta^T z_j)} \tag{5}$$

where $\delta = (\delta_1, \ldots, \delta_n)^T$ denotes the vector of censoring indicators, Z is the ($n \times p$) matrix of covariate values, $Z_{(j,.)} = z_j^T$.

The negative of the second derivative of $l(\beta)$ is the information matrix $I(\beta)$. Let $1_{R(t_i)} \in \Re^n$ denote the indicator vector of the risk set $R(t_i)$. This means the jth element of $1_{R(t_i)}$ is 1 when $t_j \geq t_i$, and 0 in otherwise. The information matrix takes the form:

$$I(\beta) = \frac{\partial^2 l}{\partial \beta^2} = \sum_{i=1}^{n} \frac{\delta_i}{w_i(\beta)^2} \bar{Z}(i)^T [w_i(\beta) diag\{\exp(Z\beta)\} - \exp(Z\beta)\exp(Z\beta)^T] \bar{Z}(i) \tag{6}$$

where $w_i(\beta) = 1_{R(i)}^T \exp(Z\beta)$ are scalars, $diag(.)$ denotes the diagonal matrix, and $\bar{Z}(i) = diag\{1_{R(i)}\} Z$. The matrix $\bar{Z}(i)$ are modifications of the design matrix Z, setting the rows of $\bar{Z}(i)$ to zero when the corresponding observation in not in the risk set for time t_i. The value $\hat{\beta}$ that maximizes Eq. (3) can usually be obtained by a Newton-Raphson iteration utilizing equation $U(\beta) = 0$ and Eq. (6).

In reliability, the cumulative baseline hazard function $\Lambda_0(t) = \int_0^t \lambda_0(s) ds$ that represents the probability to analyze the system fails at time t_i can be estimated by:

$$\hat{\Lambda}_0(t) = \sum_{i: t_i \leq t} \frac{\delta_i}{\sum_{j \in R(t_i)} \exp(\hat{\beta}^T z_j)} \tag{7}$$

The survival function $S(t \mid z)$ of an individual with the covariate values z is given by $S(t \mid z) = S_0(t)^{\exp(\beta^T z)}$. Therefore, the estimated survival function can be obtained by substituting $\hat{S}_0(t) = \exp(-\hat{\Lambda}_0(t))$ and $\hat{\beta}$, which is described as follow:

$$\hat{S}(t \mid z) = \exp(-\hat{\Lambda}_0(t))^{\exp(\hat{\beta}^T z)} \tag{8}$$

2.3. Support vector machine for regression

Presented by Vapnik [23], the support vector machine (SVM) was originally applied to pattern recognition problems. Then, SVM model has been successfully extended for dealing with regression problems [24], called support vector regression (SVR). In SVR, the basic idea is to map the data $\boldsymbol{x}$ into a higher-dimensional feature space via a nonlinear mapping and then to perform linear regression in this space. Given a data set $\{(x_i, d_i), i = 1,..., N\}$ (x_i is the input vector, d_i is the desired value, N is the total number of data patterns), the regression function is expressed as follows:

$$y = f(x) = w\phi(x) + b \tag{9}$$

where $\phi(x)$ denotes the feature of the inputs, w and b are the coefficients. These coefficients are estimated by minimizing the following regularized risk function:

$$R_{SVM}(C) = \frac{1}{2}\|w\|^2 + C\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(d_i, y_i) \tag{10}$$

$$L_\varepsilon(d_i, y_i) = \begin{cases} |d_i - y_i| - \varepsilon & \text{if } |d_i - y_i| \geq \varepsilon \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

The first term $\frac{1}{2}\|w\|^2$ is called the regularized term and used to estimate the flatness of the function. The second term $C(1/N)\sum_{i=1}^{N} L_\varepsilon(d_i, y_i)$ is the so-called empirical error, which is measured by the ε-insensitive loss function (11). ε is called the tube size of SVM, and C is the regularization constant determining the trade-off between the empirical error and the regularized term. C and ε are both user-defined parameters and are empirically selected. Two positive slack variables which are ξ and ξ^* are introduced to representing the distance from desired values to the corresponding boundary values of the ε-tube. Eq. (10) is lead to the following constrained form:

$$\text{Minimize } \; R_{SVM}(w, \xi, \xi^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi + \xi^*) \tag{12}$$

Subject to

$$d_i - w\phi(x_i) - b_i \leq \varepsilon + \xi_i, \quad w\phi(x_i) + b_i - d_i \leq \varepsilon + \xi_i^*, \quad \xi, \xi^* \geq 0, \quad i = 1, ..., N$$

Finally, by introducing Lagrange multipliers and exploiting optimality constrains, Eq. (9) is transformed into the form rewritten as follow:

$$f(x, \alpha_i, \alpha_i^*) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(x, x_i) + b \tag{13}$$

where α_i, α_i^* are called Lagrange multiplier which satisfy the equality $\alpha_i \alpha_i^* = 0, \alpha_i \geq 0, \alpha_i^* \geq 0$ and obtained by maximizing the dual function (12) which Karush-Kuhn-Tucker conditions are applied.

The dual Lagrange form of Eq. (12) is given by:

$$R(\alpha_i,\alpha_i^*)=\sum_{i=1}^{N}d_i(\alpha_i-\alpha_i^*)-\varepsilon\sum_{i=1}^{N}(\alpha_i+\alpha_i^*)-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)K(x_i,x_j) \tag{14}$$

with the constrains:

$$\sum_{i=1}^{N}(\alpha_i-\alpha_i^*)=0,\quad 0\le\alpha_i\le C,\quad 0\le\alpha_i^*\le C,\quad i=1,\ldots,N \tag{15}$$

where $K(x_i, x_j)$ is the kernel function.

The value is equal to the inner product of two vectors x_i and x_j in the feature space $\phi(x_i)$ and $\phi(x_j)$, which means $K(x_i, x_j) = \phi(x_i)\cdot\phi(x_j)$. Any function satisfied Mercer's condition [23] can be used as the kernel function. The common kernel functions used to SVM approaches are linear, polynomial, and Gaussian which is employed in this study.

3. Proposed method for performance degradation assessment and RUL forecasting

The proposed method employed to assess the machine performance degradation and forecast the RUL is depicted in Fig. 1. It comprises three steps involving system behavior identification, survival time estimation, and RUL prediction. In order to apply this method, machine condition monitoring process is firstly carried out to acquire the machine condition. The data obtained from condition monitoring process are then used as the inputs for the proposed method. The role of each step is summarized as follows:

Step 1 (System behavior identification): in this step, the data obtained from the normal operating condition of system is used to generate an identification model. This model will mimic the behavior of the system in the future states. Based on the residual errors which are the difference between the real system behavior and identification model, the degradation index is defined. The failure threshold is also determined by operators or maintainers. This step will be continued until occurrence of that the degradation index is higher than the failure threshold.

Step 2 (Survival time estimation): The Cox's PHM is created to estimate the survival time of system once the degrading mode occurred.

Step 3 (RUL prediction): Based on the survival time data, SVM in association with time-series prediction techniques is trained to forecast the system RUL.

Fig. 1. Schematic diagram of proposed method.

4. Application and results

4.1. Data acquisition

The proposed method is applied to forecast the RUL based on the data acquired from condition monitoring routine of a low methane compressor of a petrochemical plant. The compressor shown in Fig. 2 is driven by a 440 kW motor, 6600 volt, 2 poles and operating at a speed of 3565 rpm. Other information of the system is summarized in Table 1.

Fig. 2. Low methane compressor.

Table 1 Information of the system

To monitor the machine condition, several kinds of signals could be used e.g. vibration, acoustic, oil analysis, temperature, pressure and moisture, etc. Amongst these, vibration signal is the most commonly acquired data due to the easy-to-measure signals and analysis. That is the reason why vibration signal was also applied for the condition monitoring system of this compressor. Characteristics of vibration signal can be described by its large variety of feature such as root mean square, kurtosis, crest factor, cepstrum, envelope spectrum, etc. However, numerous of previous researches in literature have shown that each feature is only effective for a certain defect at a certain stage. Thus, which feature to be selected for machine fault prognosis in general and machine degradation in particular is still a challenge which needs more investigation. In this study, peak and envelope accelerations are used as vibration features of condition monitoring. These features were recorded from August 2005 to November 2005. The average recording duration was approximately 6 hours during the data acquisition process. Each data record consisted of 1200 data points as shown in Figs. 3 and 4. Consequently, these data contain information of machine history with respect to time sequence.

Fig. 3. The entire peak acceleration data of low methane compressor.

Fig. 4. The entire envelope acceleration data of low methane compressor.

4.2. Results and discussions

As indicated in Fig. 3, the machine was obviously in normal operating condition during the first 300 points of the time sequence in which the machine condition at the 291th point significantly reduced in comparison with other points. After the 300th point, the machine suddenly changed the condition. Due to the lack of the expertise and/or historical fault data for this complex system to assist operators in determining the necessary activities, this compressor was broken down at the 308th point. To avoid the occurrence of catastrophic failure series, the compressor was stopped after the 308th point so that the necessary maintenance activities can be performed. According to the result of inspection, the occurred faults were the damage of main journal bearings because of insufficient lubrication which leads to overheated and delaminated surfaces of these bearings [25]. After being repaired, the compressor operated and the acquisition process was going on continuously. The data of the 309th point onwards are the condition monitoring values after maintenance. In this work, even more than 1200 data points were shown, only the data before the compressor being broken are used for indicating the machine degradation and RUL estimation purposes.

As mentioned in the previous section, the first step of proposed method is to create the identification model, which ARMA model is applied here, based on normal operating condition to mimic the behavior of system. For that reason, 308 points included normal operating state and degrading state of both peak and envelope accelerations are split into two parts, namely identifying and validating, as an example shown in Fig. 5. In indentifying process, 150 points of data which are taken from 300 points in normal operating state are used to generate ARMA model. A problem frequently encountered in this process is to determine the orders of ARMA model. Using the method mentioned in section 2.1, ARMA (4, 3) and ARMA (6, 5) models are obtained in correspondence with peak and envelope acceleration data. The coefficients of these models of peak and envelope data are φ_p = {1, -0.2408, -0.2667, -0.6316}; ϕ_p = {1, -0.058, -0.2726} and φ_e = {1, 0.0311, -0.1426, -0.1226, -0.1679, -0.4622}; ϕ_e = {1, 0.0844, -0.1741, -0.1002, -0.0487}, respectively. Afterward, this identification model is used to estimate the dynamic behavior of machine for the remaining points (158 points). The residual errors which are the difference between the machine behavior and identification model are gained. The degradation indexes depicted in Fig. 6 is defined as the root mean square of residual errors, denoted by e_{rms}:

$$e_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_{ih})^2}, \; i = 1, ..., N \tag{16}$$

where N is total number of observations, y_i is the ith value of machine behavior, and y_{ih} is the ith value obtained from ARMA model.

Fig. 5. Splitting process of peak acceleration data.

Fig. 6. Root mean square of residual errors (degradation index): (a) Peak acceleration data, (b) Envelope acceleration data.

In Fig. 6 (a), the degradation index is recognized to suddenly increase from the 300th point of peak acceleration data. This not only appropriates to the sudden changed value mentioned above but also indicates the abnormal value at the 291th point. Conversely, it will be challenging to determine the change condition during the first 300 points by using envelope acceleration data (Fig. 6(b)). Obviously, degradation index of peak acceleration is adequate to assess the machine degradation and the first 308 points of peak acceleration data are chosen to reveal the machine performance degradation in this study.

In order to estimate the RUL of machine, the unacceptable level or the failure threshold is necessary to be set up. Normally, the failure threshold can be determined by using the international standards (ISO 13381-1, ISO 10816 and ISO 7919) with historic experiences of monitored machine for proper adjustment. However, the ISO standards so far are limited in root mean square indicator of vibration signals, and solely used for general sizes and mounting of the machinery such as pump, electric motor, compressor and turbine, which limit prevalent application. Even different indicators are used, each of them has its own threshold setting scheme and makes the threshold setting become difficult. In this study, a new method is proposed for determining the failure threshold based on the degradation index. This threshold is chosen by considering all values of degradation index during the normal operation state, for example 0.004 in this work. Moreover, the failure threshold is also employed to attain the censored data which is used for generating the PHM. This data consists of a series of “0” and “1” values indicating the normal condition and failure condition, respectively.

Once the degradation index is higher than the failure threshold, the degradation state has been initiated. Thereafter, Cox’s PHM is built bases on the censored data obtained from previous step. In this study, two kinds of features $z_1(t)$ and $z_2(t)$ are used and denoted as peak and envelope features, respectively. The parameters of PHM are estimated as β_1 = -0.8042 and β_1 = 0.1062. Hazard rate and survival function estimation are depicted in Figs. 7 and 8, respectively. In Fig. 7, the hazard rate gradually increases with respect to time though the peak acceleration values still approximately remain in the same average value. This could be the increment of envelope which affects the hazard rate function. From the 300th point, the hazard rate significantly changes because of the rapid growth of peak acceleration values. Thus, the more the hazard rate increases, the less the reliability is.

Fig. 7. Hazard rate estimation.

Fig. 8. Survival function estimation.

After attaining the survival function, the predicting process in which SVM in association with time-series forecasting techniques is carried out. There are two categories of predicting strategy: short-term prediction (one-step prediction) and long-term prediction (multi-step prediction). In long-term prediction, three methods could be commonly used: Recursive, DirRec, and Direct which their detailed description could be found in reference [26]. In this study, the multi-step ahead direct prediction method is applied. In fact, multi-step prediction plays a crucial role in prognosis by providing information of RUL. However, it is also a challenging task for time series prediction matter. In multi-step prediction techniques, the predicting model is only learned by the behavior of machine from the past until the present. Then, this model is applied for estimating unknown values in the future. Accordingly, the values of survival function from the 151th to 291th point (normal state) 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. After being trained, SVM model is utilized to forecast the future values of survival function from the 292th point where the machine commences degrading the state. Fig. 9 is depicted the results of predicting process. As shown in Fig. 9, even though the multi-step prediction is employed, the predicted results can track the reduction of reliability with the root mean square error (RMSE) of 0.33674. From the predicted results, the RUL of machine could be estimated by using the predefined survival probability for fault. For example, if this probability is chosen as 0.2, the point where predicted result reaches for 0.2 is 308th. This means the predicted RUL of machine after degrading state occurred is 96 hours ((308 − 292) × 6 = 96) while the actual RUL is 84 hours (the 306th point). The accuracy can be evaluated using the follow formula:

$$\text{Accuracy} = \left(1 - \frac{\left|t_{predicted} - t_{actual}\right|}{t_{predicted}}\right) \times 100\% = \left(1 - \frac{96 - 84}{96}\right) \times 100\% = 87.5\%$$

Even if the accuracy is optimistic and acceptable in industrial application, the predicted RUL lags behind actual RUL. This is a common problem encountered in implementing the multi-step prediction techniques. The lag of predicted RUL in comparison with actual RUL leads to inaccurate estimation of the machine left time and inappropriate decision making, in time, among options of taking no action, repair or replacement. However, multi-step prediction is of necessity for real application of machine prognosis. For further improvement of predicting accuracy, a feasible method is proposed in which the predicted value has been moved backward with an interval of the average lag as shown in Fig. 10. As a result, the predicted results and actual values of survival function is closely resemble with the accuracy of 100%. This proposal can be acceptable due to the manifestation of improving the predicted results

Fig. 9. Predicted results.

Fig. 10. Predicted results after improvement.

5. Conclusions

In this study, the method is proposed for assessing the health degradation and forecasting the RUL based on only the normal operating condition of machine. This method consists of three stages in which ARMA identification model, Cox's PHM, and SVM are combined in an integrated tool. In the first stage, only the normal operating condition of machine is used to create ARMA model for recognizing the dynamic system behavior. Base on the difference between identification model and behavior of system, degradation index is generated to indicate the machine status and determine the failure threshold. In the second stage, the Cox's proportional hazard model is built to estimate the survival function of the system once the degradation index is higher than the failure threshold. In the last stage, support vector machine association with time-series techniques is utilized to forecast the RUL. Furthermore, the feasible method is also proposed for further improvement of predicting accuracy. The data of low methane compressor acquired from condition monitoring routine is used for appraising the proposed method. The high accuracy of predicted results indicates that the proposed could be used as a reliable tool to machine prognostics.

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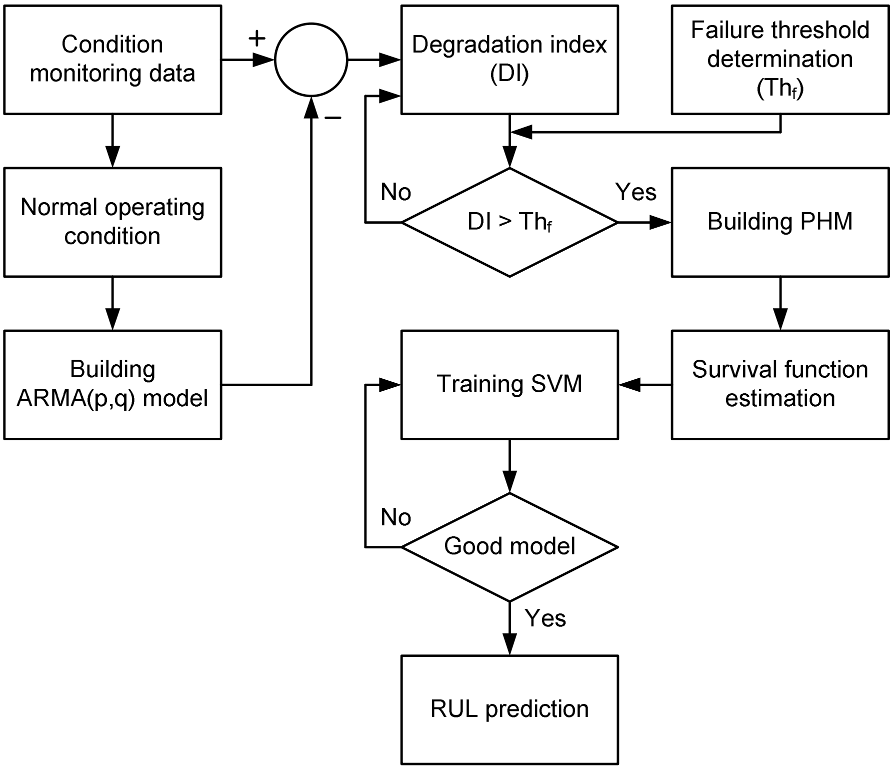


Fig. 1. Schematic diagram of proposed method.

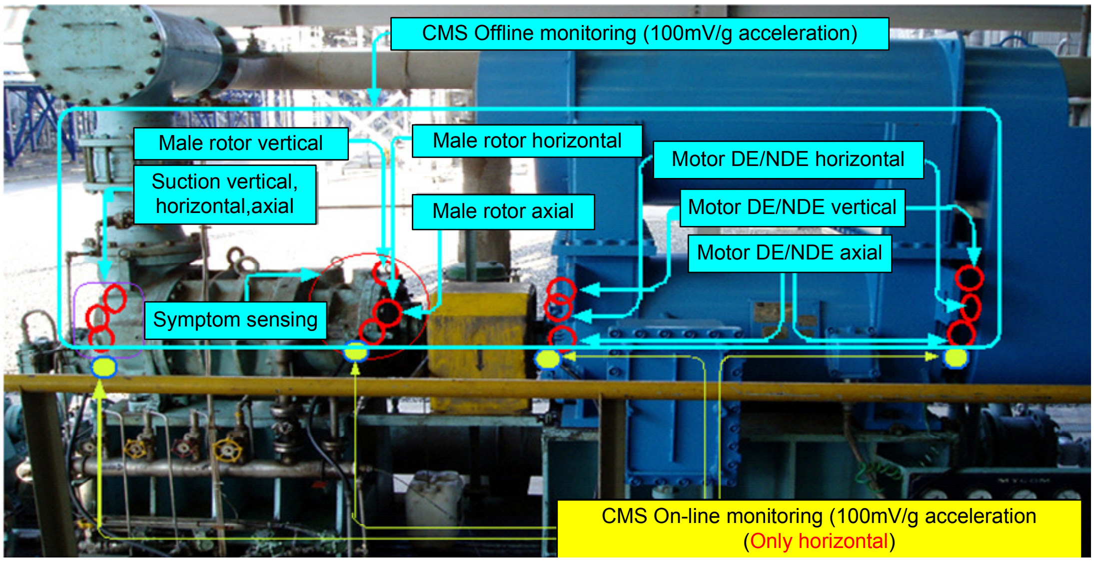


Fig. 2. Low methane compressor: wet screw type.

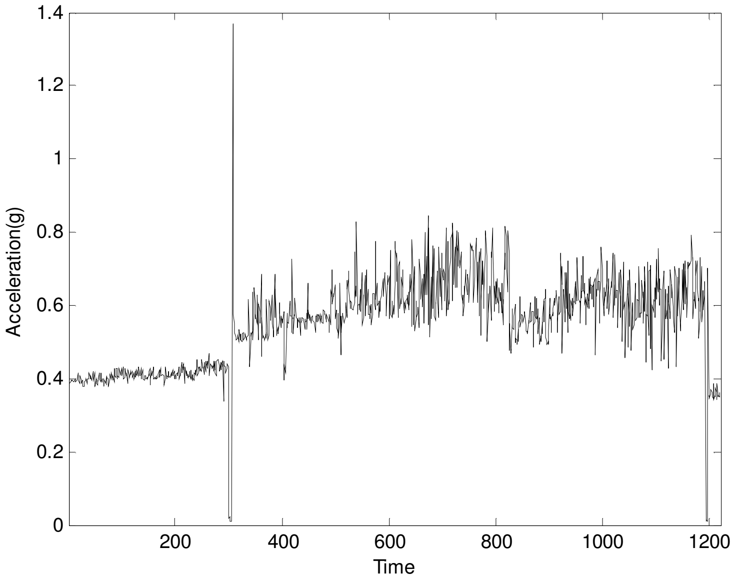


Fig. 3. The entire peak acceleration data of low methane compressor.

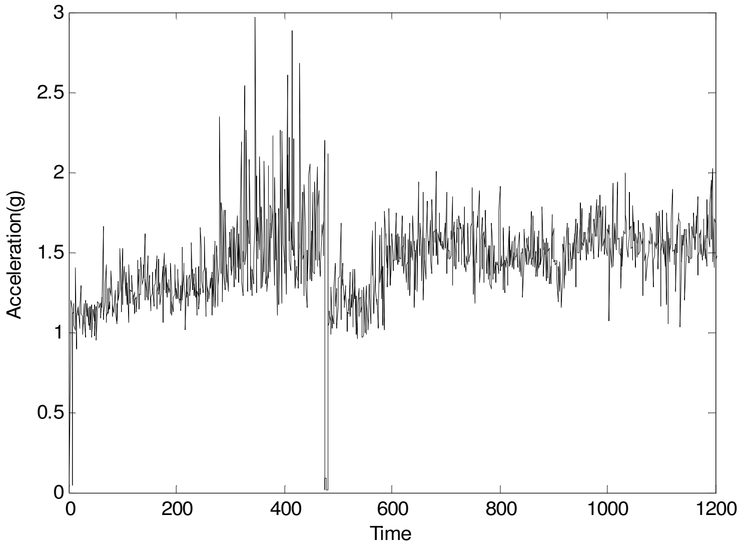


Fig. 4. The entire envelope acceleration data of low methane compressor.

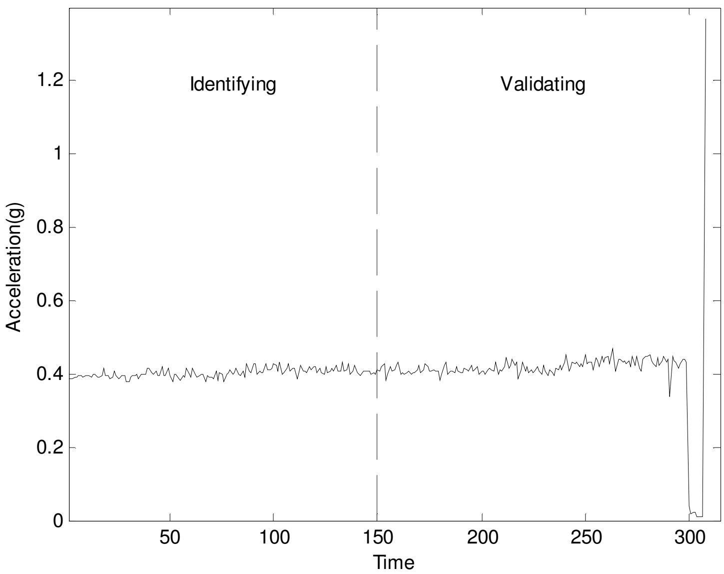
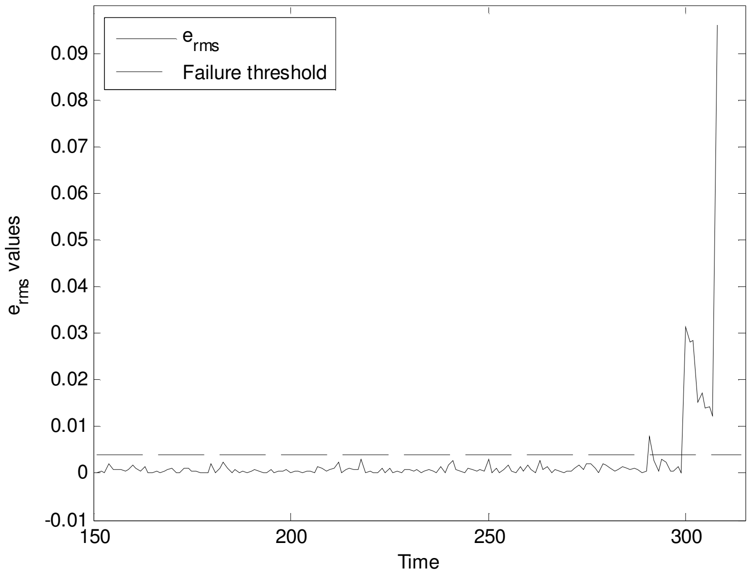
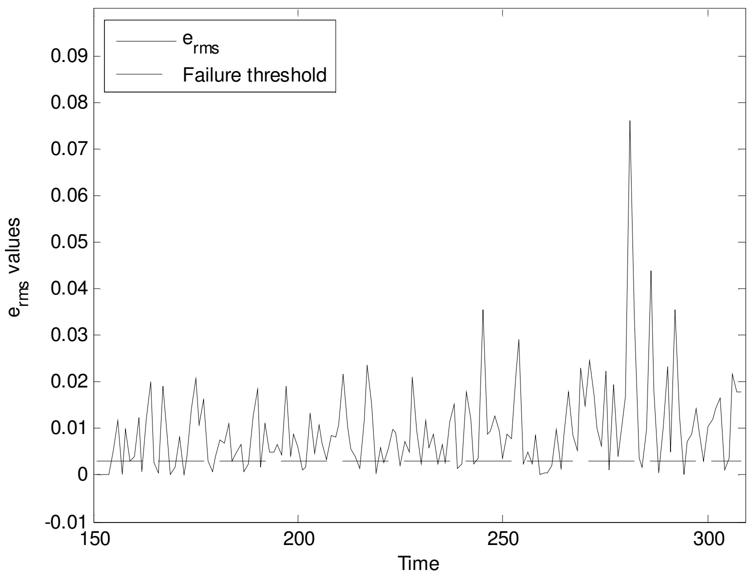


Fig. 5. Splitting process of peak acceleration data.



(a)



(b)

Fig. 6. Root mean square of residual errors (degradation index): (a) Peak acceleration data, (b) Envelope acceleration data.

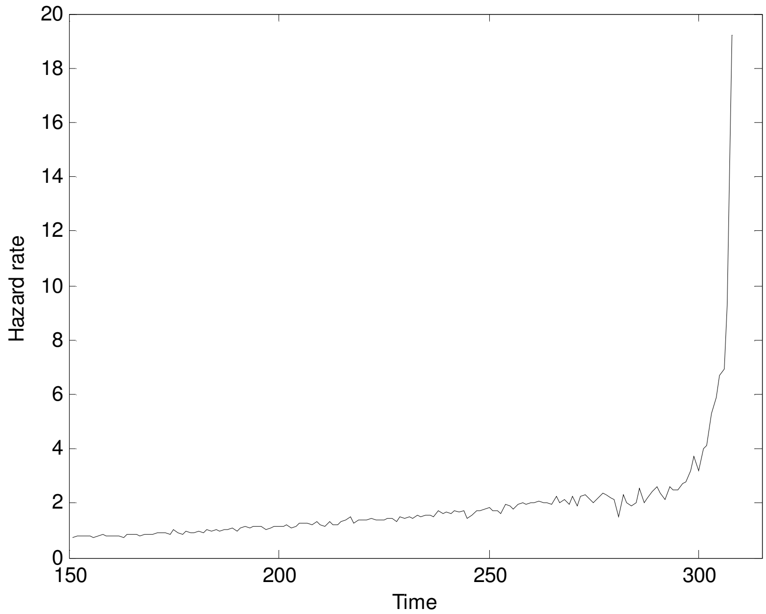


Fig. 7. Hazard rate estimation.

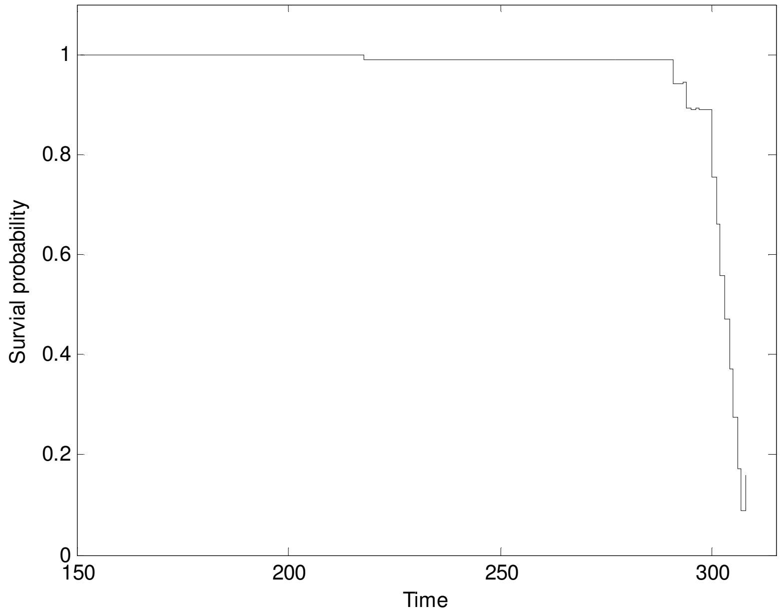


Fig. 8. Survival function estimation.

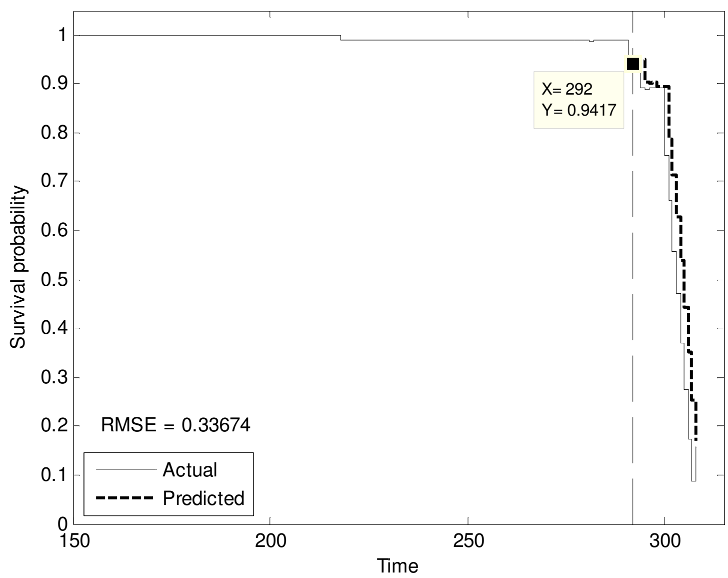


Fig. 9. Predicted results.

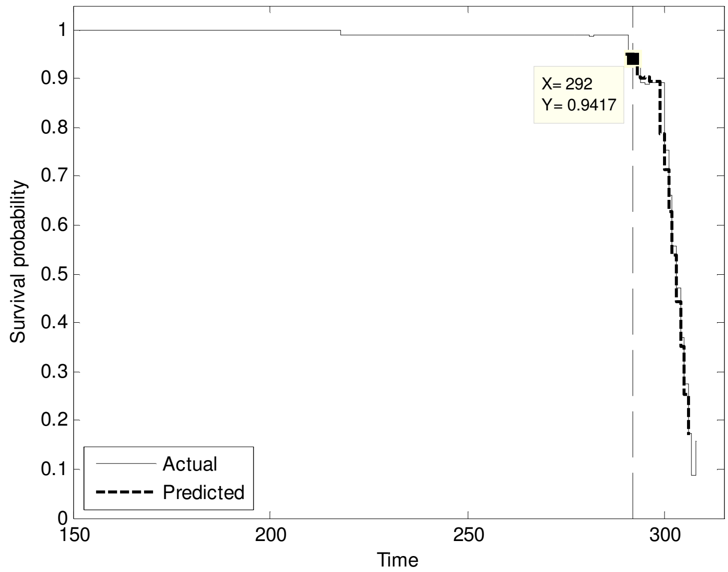


Fig. 10. Predicted results after improvement.

Table 1
Description of 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