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Data-driven approach to machine condition prognosis using least square regression tree †

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Abstract

Machine fault prognosis techniques have been profoundly considered in the recent time due to their substantial profit for reducing unexpected faults or unscheduled maintenance. With those techniques, the working conditions of components, the trending of fault propagation, and the time-to-failure are precisely forecasted before they reach the failure thresholds. In this work, we propose the least square regression tree (LSRT) approach, which is an extension of the classification and regression tree (CART), in association with one-step-ahead prediction of time-series forecasting techniques to predict the future machine condition. In this technique, the number of available observations is first determined by using Cao's method and LSRT is employed as a prediction model in the next step. The proposed approach is evaluated by real data of a low methane compressor. Furthermore, a comparative study of the predicted results obtained from CART and LSRT are carried out to prove the accuracy. The predicted results show that LSRT offers the potential for machine condition prognosis.

Keywords: Least square method; Embedding dimension; Regression trees; Prognosis; Time-series forecasting

1. Introduction

Most machine components are degraded during operation due to wear which is the major reason causing machine breakdowns. Maintenance is a set of activities performed on a machine to sustain it in operable conditions. The most common maintenance strategy is corrective maintenance, which mostly means fix it when it breaks. However, this strategy considerably reduces the availability of machine and high unscheduled downtime. Condition-based maintenance (CBM) which involves diagnostic modules and prognostic modules is an alternative. Prognosis is the ability to predict accurately the future health states and failure modes based on current health assessment and historical trends [1]. There are two main functions of machine prognosis: failure prediction and remaining useful life (RUL) estimation. Failure prediction, which is addressed in this paper, allows pending failures to be early identified before they become more serious failures that result in machine breakdown and repair costs. RUL is the time left for the normal operation before a breakdown occurs or machine condition reaches the critical failure threshold. However, prognosis is a relatively new area and becomes a significant part of CBM [2]. Various approaches in prognosis, which range in fidelity from simple historical failure rate models to high-fidelity physics-based models, have been developed. Fig. 1 illustrates the hierarchy of potential prognostic approaches related to their applicability and relative accuracy as well as their complexity. Each of them has advantages and limitations in application. For example, experience-based prognosis is the least complex, but it is only used in situations where the prognostic model is not warranted due to low failure occurrence rate; trend-based prognosis may be

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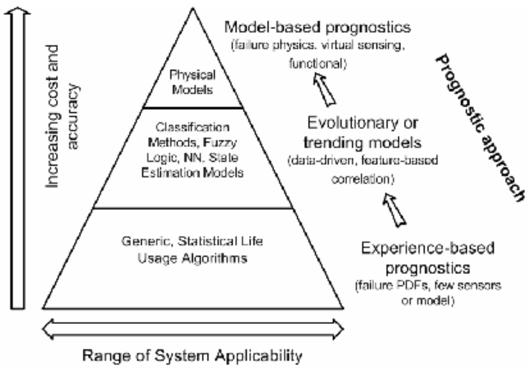

Fig. 1. Fidelity of prognostic approaches.

implemented on the subsystems with slow degradation type faults [3].

In these approaches, data-driven based and model-based are the most considered because they provide higher accuracy and reliability. Nevertheless, model-based techniques require accurate mathematical models of failure modes and are merely applied in some specific components in which each of them needs a different model. Furthermore, a suitable mathematical model is also difficult to establish and changes in structural dynamics can affect the mathematical model, which is impossible to mimic the behavior of systems. Meanwhile, data-driven techniques utilize and require a large amount of historical data to build a prognostic model. Most of these techniques use artificial intelligence which can generate flexible and appropriate models for most failure modes. Consequently, data-driven approaches, some of which have been proposed in references [4-7], are first examined.

In order to predict the machine conditions, the number of future predicting values and the number of observations, so-called embedding dimension d, used for prediction model, are two of the necessary problems to be considered. In the first issue, one-step-ahead or multi-step-ahead prediction of time-series forecasting techniques is frequently used. The prognostic system utilizes available observations to forecast one value or multiple values at a definite future time. Unlike the one-step-ahead prediction, multi-step-ahead prediction is typically faced with growing uncertainties arising from various sources such as the accumulation of errors and the lack of information. Therefore, the more the steps ahead there are, the less reliable the forecasting operation is [7]. In the second issue, the embedding dimension should be chosen large enough so that the prediction model can accurately forecast the future value and not too large to avoid an unnecessary increase in computational complexity. False nearest neighbor method (FNN) [8] and Cao's method [9] are commonly used to determine this value. However, FNN not only depends on chosen parameters and the number of available observations, but also is sensitive to additional noise. Cao's method overcomes the shortcomings of the FNN approach and, therefore, it is chosen in this study.

Classification and regression trees (CART) [10] handle multivariate regression methods to obtain models. These models have proven to be quite interpretable and have competitive predictive accuracy. Moreover, these models can be obtained through a computational efficiency that hardly has a parallel in competitive approaches, turning these models into a good choice for a large variety of data mining problems where these features play a major role [11]. CART is widely implemented in machine fault diagnosis. In the prediction techniques, CART is also applied to forecast the short-term load of the power system [12] and predict the future conditions of machines [13]. Nevertheless, the average value of samples in each terminal node used as the predicted result is the reason for reducing the accuracy of CART. Several approaches have been proposed to ameliorate that CART limitation [14-16]. In this paper, the least square method [17] to improve the prediction capability of CART model is proposed. This improved model is then used to predict the machine conditions.

2. Background knowledge

2.1 Determine the embedding dimension

Assuming a time-series of $x_1, x_2, \ldots, x_N$. The time delay vector is defined as follows [13]:

$$y_{i(d)} = [x_i, x_{i+\tau}, \ldots, x_{i+(d-1)\tau}],\ i = 1, 2, \ldots, N-(d-1)\tau \quad (1)$$

where τ is the time delay and d is the embedding dimension.

Defining the quantity as follows:

$$a(i,d) = \frac{\left\| y_i(d+1) - y_{n(i,d)}(d+1) \right\|}{\left\| y_i(d) - y_{n(i,d)}(d) \right\|} \quad (2)$$

where $\|\cdot\|$ is the Euclidian distance and is given by the maximum norm, $y_i(d)$ means the ith reconstructed vector and $n(i, d)$ is an integer so that $y_{n(i,d)}(d)$ is the nearest neighbor of $y_i(d)$ in the embedding dimension d.

In order to avoid the problems encountered in the FNN method, a new quantity is defined as the mean value of all $a(i, d)$'s:

$$E(d) = \frac{1}{N - d\tau} \sum_{i=1}^{N-d\tau} a(i,d) \tag{3}$$

$E(d)$ is only dependent on the dimension d and the time delay τ. To investigate its variation from d to d+1, the parameter E_1 is given by

$$E_1(d) = \frac{E(d+1)}{E(d)} \tag{4}$$

By increasing the value of d, the value $E_1(d)$ is also increased and it stops increasing when the time series comes to a deterministic process. If a plateau is observed for $d \geq d_0$ then $d_0 + 1$ is the minimum embedding dimension.

Cao's method also introduced another quantity $E_2(d)$ to overcome the problem in practical computations where $E_1(d)$ is slowly increasing or has stopped changing if d is large enough:

$$E_2(d) = \frac{E^*(d+1)}{E^*(d)} \tag{5}$$

where

$$E^*(d) = \frac{1}{N - d\tau} \sum_{i=1}^{N-d\tau} \left| x_{i+d\tau} - x_{n(i,d)+d\tau} \right| \tag{6}$$

According to [8], for a purely random process, $E_2(d)$ is independent of d and equal to 1 for any of d. However, for deterministic time-series, $E_2(d)$ is related to d. Consequently, there must exist some d's so that $E_2(d) \neq 1$.

2.2. Least square regression trees (LSRT)

Regression tree models are sometimes called piecewise constant regression models. Regression trees are constructed by using a recursive partitioning algorithm. Assume that a learning set is comprised of n couples of observation $(y_1, \mathbf{x}_1), ..., (y_n, \mathbf{x}_n)$, where $\mathbf{x}_i = (x_{1_i}, ..., x_{d_i})$ is a set of independent variables and $y_i \in R$ is a response associated with x_i. The regression tree is constructed by recursively partitioning this learning set into two descendant subsets which are as homogeneous as possible until the terminal nodes are achieved.

The split values for the partitioning process are chosen so that the sums of square errors are minimized. The sum of square error of the tth subset is expressed as:

$$R(t) = \frac{1}{n} \left(y - \bar{y}(t) \right) \tag{7}$$

where $\bar{y}(t)$ and n are the mean value of response and the number of samples in that subset, respectively. At each terminal node, the predicted response is estimated by the average $\bar{y}(t)$ of all values y of the response variables associated to that node. This issue is the reason why the prediction accuracy is significantly reduced.

To improve the accuracy of the predicted response, the mean value $\bar{y}(t)$ of response at any node in LSRT is replaced by the local model $f(\boldsymbol{\theta}, \mathbf{x}_i)$, which shows the relationship between the response y_i and a set of independent variables x_i. Hence, the sum of square error of the tth node (subset) in Eq. (7) can be rewritten as:

$$R(t) = \frac{1}{n} \sum_{y_i, \mathbf{x}_i \in t} \left(y_i - f(\boldsymbol{\theta}, \mathbf{x}_i) \right)^2 \tag{8}$$

where $\boldsymbol{\theta}$ is a set of parameters. The local models

Table 1. Local model types in LSRT.

Model type	Description	Parameters
Polynomial	$y = \sum_{i=1}^{n+1} \theta_i x^{n+1-i}$	θ_i
Power	$y = \theta_1 x^{\theta_2}$ $y = \theta_1 + \theta_2 x^{\theta_3}$	$\theta_1, \theta_2, \theta_3$
Fourier	$y = \theta_0 + \sum_{i=1}^{n} \theta_{1_i} \cos(n\omega x)$ $+ \sum_{i=1}^{n} \theta_{2_i} \sin(n\omega x)$	$\theta_0, \theta_{1_i}, \theta_{2_i}$
Sine	$y = \sum_{i=1}^{n} \theta_{1_i} \sin(\theta_{2_i} x + \theta_{3_i})$	$\theta_{1_i}, \theta_{2_i}, \theta_{3_i}$

$f(\boldsymbol{\theta}, \mathbf{x}_i)$ can be either linear or non-linear in which the forms are known with unknown values of parameters as shown in Table 1.

In LSRT, those local models are organized as a set of models. At any node, an appropriate model $f(\boldsymbol{\theta}, \mathbf{x}_i)$ is chosen to fit the independent variable x_i. The values of parameters $\boldsymbol{\theta}$ of each model are initially calculated by using the least square method [17]:

$$\boldsymbol{\theta} = [\mathbf{X}^T \mathbf{X}]^{-1} \mathbf{X}^T \mathbf{y} \tag{9}$$

where $\mathbf{y} = [y_1, ..., y_n]^T$ is the response, $\mathbf{X} = [\boldsymbol{x}_1^T, ..., \boldsymbol{x}_n^T]^T$ is a matrix of independent variables. Furthermore, there could be several appropriate local models that are found. The best models are subsequently chosen based on the minimum of the sum of squares due to error (SSE) and the root mean squared error (RMSE) criteria:

$$\begin{aligned} SSE &= \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \\ RMSE &= \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \end{aligned} \tag{10}$$

where y_i and $\hat{y}_i$ are response values and predicted values given by the local model at that node, respectively. By this improvement, the outputs of terminal nodes are local models that lead to more accurate prediction.

Similarly to CART, LSRT needs to be pruned and have cross-validation carried out in order to avoid the over-fitting and complicated problems. These processes are implemented as in references [13].

3. Proposed system

Normally, when a fault occurs in a machine, the machine conditions can be identified by the change in vibration amplitude. To predict the future state based on available vibration data, a system as shown in Fig. 2 is proposed.

This system consists of four procedures sequentially: data acquisition, data splitting, training-validating model and predicting. The role of each procedure is explained as follows:

Step 1 Data acquisition: acquiring vibration signal during the running process of the machine until faults occur.

Step 2 Data splitting: the trending data are split into two parts: training data for building the model and testing data for testing the validated model.

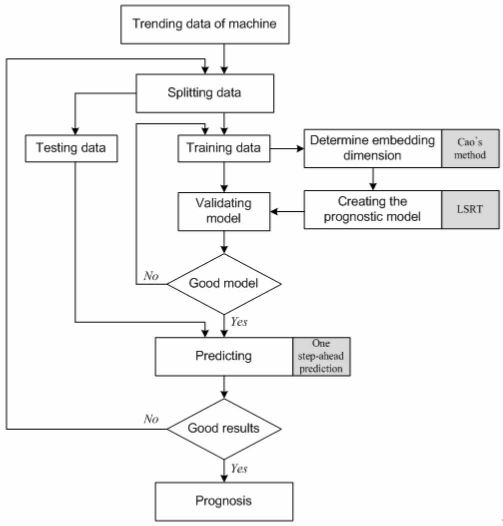

Fig. 2. Proposed system for machine fault prognosis.

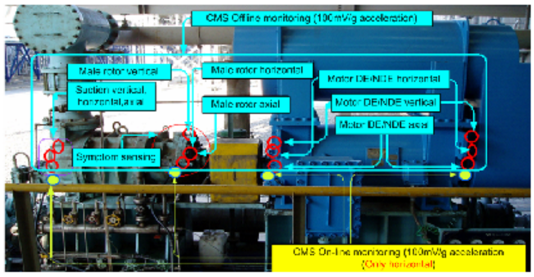

Fig. 3. Low methane compressor.

Step 3 Training-validating: determining the embedding dimension based on Cao's method, building the model and validating the model for measuring the performance capability.

Step 4 Predicting: one-step-ahead prediction is used to forecast the future value. The predicted result is measured by the error between the predicted value and actual value in the testing data. If the prediction is successful, the result obtained from this procedure is the prognosis system.

4. Experiments and results

The proposed method is applied to a real system to predict the trending data of a low methane compressor of a petrochemical plant. This compressor, which is shown in Fig. 3, is driven by a 440 kW motor, 6600 volt, 2 poles and operating at a speed of 3565 rpm.

Table 2. Description of system.

<table>
<tr><th colspan="2">Electric motor</th><th colspan="2">Compressor</th></tr>
<tr><td>Voltage</td><td>6600 V</td><td>Type</td><td>Wet screw</td></tr>
<tr><td>Power</td><td>440 kW</td><td rowspan="2">Lobe</td><td>Male rotor (4 lobes)</td></tr>
<tr><td>Pole</td><td>2 Pole</td><td>Female rotor (6 lobes)</td></tr>
<tr><td>Bearing</td><td>NDE: #6216, DE: #6216</td><td rowspan="2">Bearing</td><td>Thrust: 7321 BDB</td></tr>
<tr><td>RPM</td><td>3565 rpm</td><td>Radial: Sleeve type</td></tr>
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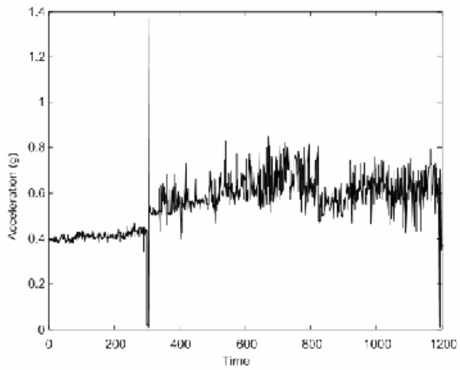

Fig. 4. The entire of peak acceleration data of low methane compressor.

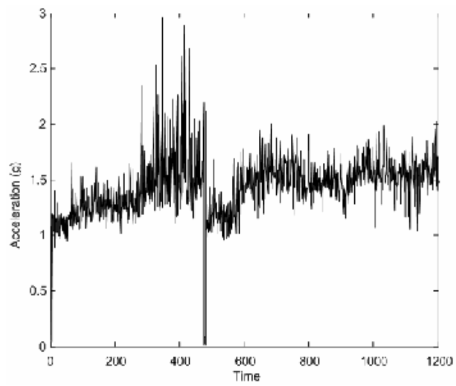

Fig. 5. The entire of envelope acceleration data of low methane compressor.

Other information of the system is summarized in Table 2.

The condition monitoring system of this compressor consists of two types: off-line and on-line. In the off-line system, accelerometers are installed along axial, vertical, and horizontal directions at various locations of drive-end motor, non drive-end motor, male rotor compressor and suction part of compressor. In the on-line system, accelerometers are located at the same

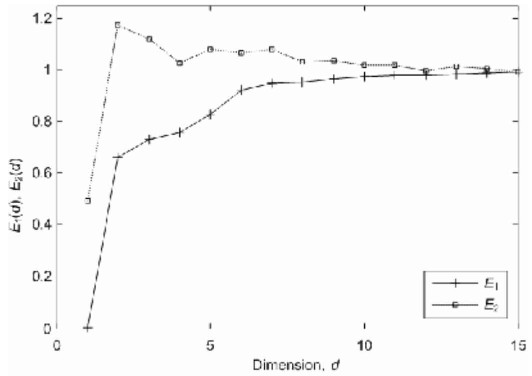

Fig. 6. The values of E_1 and E_2 of peak acceleration data of low methane compressor.

positions as in the off-line system but only in the horizontal direction.

The trending data were recorded from August 2005 to November 2005, which included peak acceleration and envelope acceleration data. The average recording duration was 6 hours during the data acquisition process. Each data record consisted of approximately 1200 data points as shown in Figs. 4 and 5, and contained information of machine history with respect to time sequence (vibration amplitude). Consequently, it can be classified as time-series data.

These figures show that the machine was in normal condition during the first 300 points of the time sequence. After that time, the condition of the machine suddenly changed, indicating that possible faults were occurring in the machine. By disassembling and inspecting, these faults were identified as the damage of main bearings of the compressor (notation Thrust: 7321 BDB) due to insufficient lubrication. Consequently, the surfaces of these bearings were overheated and delaminated [13].

With the aim of forecasting the change of machine condition, the first 300 points were used to train the system. Before being used to generate the prediction models, the time delay and the embedding dimension were initially determined. The time delay was chosen as 1 for the reason that one-step-ahead was implemented in all datasets, while the embedding dimension was calculated according to the method mentioned in section 2.1. Theoretically, the minimum embedding dimension chosen as $E_1(d)$ attains a plateau. In Fig. 6, the embedding dimension is chosen as 6 for the reason that the values of $E_1(d)$ reach saturation.

Subsequent to determining the time delay and em-

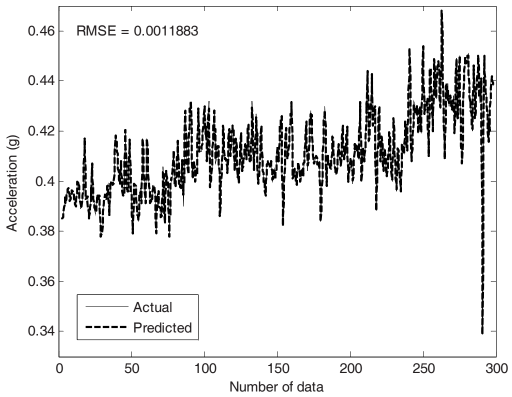

Fig. 7. Training and validating results of peak acceleration data.

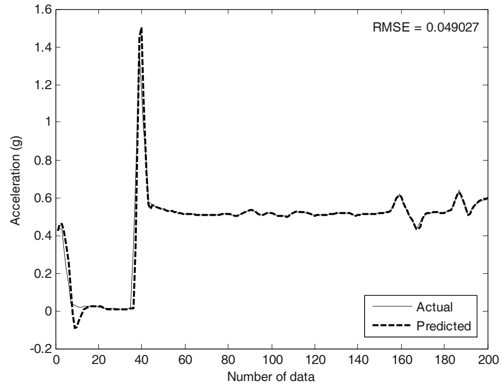

Fig. 8. Predicted results of peak acceleration data using LSRT.

bedding dimension, the process of generating the prediction model was carried out. It is noted that during the process of building the prediction model (regression tree model), the number of response values for each terminal node in tree growing process was 5 and the number of cross-validations was chosen as 10 to select the best tree in tree pruning. Furthermore, in order to evaluate the predicting performance, the RMSE value given in Eq. (10) was used. Fig. 7 depicts the training and validating results of LSRT for peak acceleration data. The actual values and predicted values are almost identical with very small RMSE of 0.00118. It indicates that the learning capability of LSRT model is tremendously positive.

The prediction models obtained from training process were evaluated by using an independent data set. This data set begins at the end point used for training set (from the 300th point) and contains the changing machine condition. Fig. 8 shows the actual-like predicted results of LSRT for peak acceleration data with

Table 3. The RMSE of CART and LSRT.

Data type	Training		Testing	
	CART	LSRT	CART	LSRT
Peak acceleration	0.00062	0.0011	0.1855	0.049
Envelope acceleration	0.00028	0.00015	0.1429	0.101

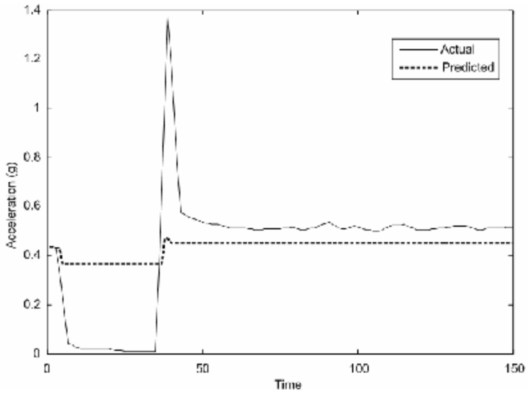

Fig. 9. Predicted results of peak acceleration data using CART.

the small RMSE error of 0.049. Moreover, it can closely track with the changes of the operating condition of the machine that is impossible to obtain with CART as shown in Fig. 9. This is of crucial importance in industrial application for pending equipment failures.

Table 3 shows the remaining results of applying LSRT on envelope acceleration data. It is also depicts the comparison of the RSME between CART and LSRT. According to Table 3, training results of CART are sometimes slightly smaller than those of LSRT, but the testing results of CART are always larger. This indicates the superiority of LSRT in aspect of machine condition prognosis.

5. Conclusions

Machine condition prognosis is extremely significant in foretelling the degradation of working condition and trends of fault propagation. In this study, a machine prognosis system based on one-step-ahead of time-series techniques and least square regression trees has been investigated. The proposed method is validated by predicting future state conditions of a low methane compressor wherein the peak acceleration and envelope acceleration have been examined. The predicted results of the LSRT are also compared with those of traditional CART. From the predicted results, the LSRT model performance is vastly superior to the traditional model, especially in the testing process. Additionally, the predicted results of LSRT are capable of tracking the change of a machine's operating conditions with high accuracy. The tracking-change capability of operating conditions is of crucial importance in pending failures of industrial equipment. The results confirm that the proposed method offers a potential for machine condition prognosis with one-step-ahead prediction.

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