MACHINE CONDITION PROGNOSIS USING MULTI-STEP AHEAD PREDICTION AND NEURO-FUZZY SYSTEMS

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ABSTRACT

This paper presents an approach to predict the operating conditions of machine based on adaptive neuro-fuzzy inference system (ANFIS) in association with direct prediction strategy for multi-step ahead prediction of time series techniques. In this study, the number of available observations and the number of predicted steps are initially determined by using false nearest neighbor method and auto mutual information technique, respectively. These values are subsequently utilized as inputs for prediction models to forecast the future values of the machine's operating conditions. The performance of the proposed approach is then evaluated by using real trending data of low methane compressor. The results show that the ANFIS prediction model can track the change in machine conditions and has the potential for using as a tool to machine fault prognosis.

1. INTRODUCTION

The fault progression process of machine usually consists of a series of degradations mainly due to the component wear and fatigue during the operation process. Early detection of incipient faults and foretelling the future states can minimize unplanned breakdown and avoid unnecessary maintenance. Thence, the availability and reliability of machine will be increased. Consequently, machine condition prognosis has been the subject of considerable researches in recent years.

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 identified early before they come to more serious failures that result machine breakdown and repair costs. RUL is the time left before a particular fault will occur or the part needs to be replaced. The techniques related to prognosis can be broadly classified as experience-based, model-based, and data-driven based techniques. From these techniques, data-driven is the promising and effective technique due to its flexibility in generating appropriate model. The outstanding data-driven prognosis approaches are found in references [2-4].

In addition, the more future states are predicted precisely, the more effective the maintenance activities become. For that reason, long-term prediction methodology is considered in machine condition prognosis significantly. There are three strategies mainly used in long-term prediction interpreted as follows: recursive, DirRec, and direct prediction strategy [5]. Recursive and DirRec prediction strategies have the drawback that the accumulated error in previous predicting process will be added in the next step. Consequently, the direct prediction strategy is used in this paper.

Other problems to be dealt with machine condition prognosis are the number of observations (embedding dimension) and the number of predicted values (time delay). The former problem can be solved by using the false nearest neighbour method (FNN) [6]. The latter can be calculated by using auto mutual information (AMI) [7]. After determining the embedding dimension and time delay, ANFIS [8] is utilized as the prediction model for the purposes of forecasting the future operating condition of machine.

2. PROPOSED SYSTEMS

The proposed system for machine condition prognosis comprises four procedures sequentially as depicted in Fig. 1. Data acquisition procedure is used to obtain the vibration data from machine condition. In the data splitting procedure, the trending data attained from previous procedure is split into training set and testing set for different purposes. Training- validating procedure includes the following sub-procedures: determining the time delay and the embedding dimension based on AMI and FNN method, respectively; creating the prediction models and validating those models. In the predicting procedure, long-term direct prediction method is used to forecast the future values of machine condition. The predicted results are measured by the error between predicted values and actual values in the testing set. Models and updated data are also carried out for the next prediction process.

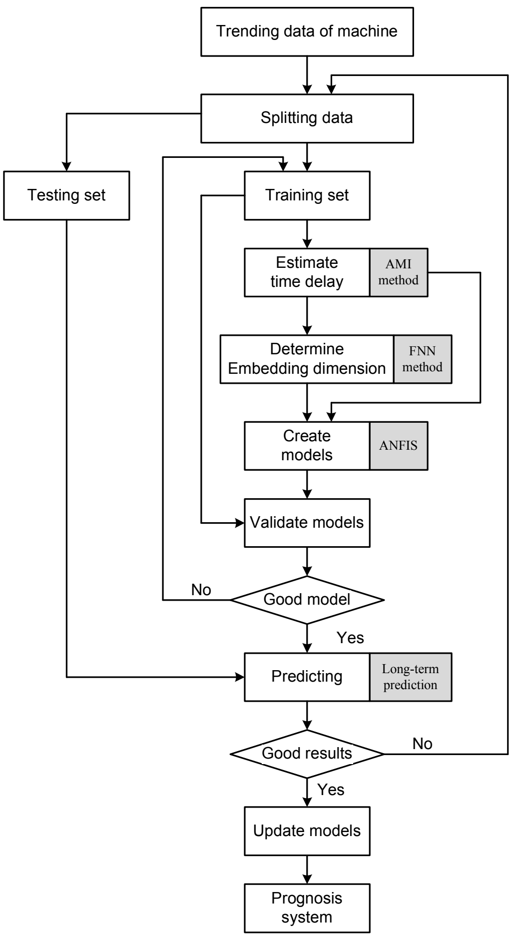


Fig.1 Proposed system for machine condition prognosis

3. EXPERIMENTS

The proposed method is applied to a real system to predict the trending data of a low methane compressor as shown in Fig. 2. Information of the system is summarized in Table 1.

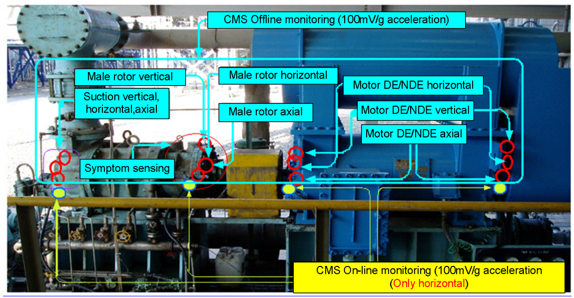


Fig.1 Low methane compressor: wet screw type

Table 1 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

The trending data was recorded from August 2005 to November 2005 which the average recording duration was 6 hours. This data includes peak acceleration and envelope acceleration data and consists of approximately 1200 data points as shown in Figs. 2 and 3, and contains information of machine history with respect to time sequence (vibration amplitude).

The machine is in normal condition during the first 300 points of the time sequence. After that time, the condition of the machine suddenly changes. This indicates that there are some faults occurring in the machine. These faults were identified as the damages of main bearings of the compressor (notation Thrust: 7321 BDB) due to insufficient lubrication.

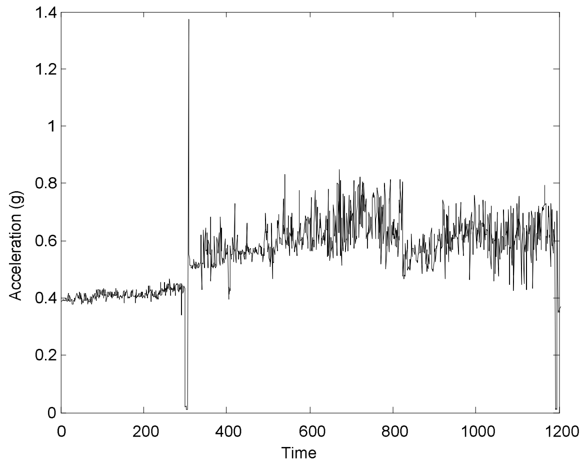


Fig.2 The entire of peak acceleration data of low methane compressor

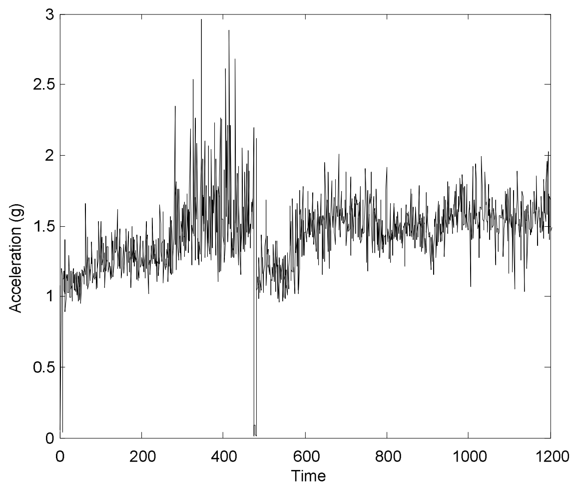


Fig.3 The entire of peak acceleration data of low methane compressor

With the aim of forecasting the change of machine condition, the first 300 points were used to train the system. In order to evaluate the predicting performance, the root-mean square error (RMSE) is utilized as following

$$RMSE = \sqrt{\sum_{i=1}^{N} \left(y_i - \hat{y}_i \right)^2 / N} \qquad (1)$$

where N, y_i, $\hat{y}_i$ represent the total number of data points, the actual value, and predicted value, respectively.

4. RESULTS AND DISCUSSION

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 τ is initially calculated. Theoretically, the optimal time delay is the value at which the AMI obtains the first local minimum. From Fig. 4, the optimal time delay of peak acceleration training data is found as 7. Similarly, 5 is the optimal time delay value of envelope acceleration training data.

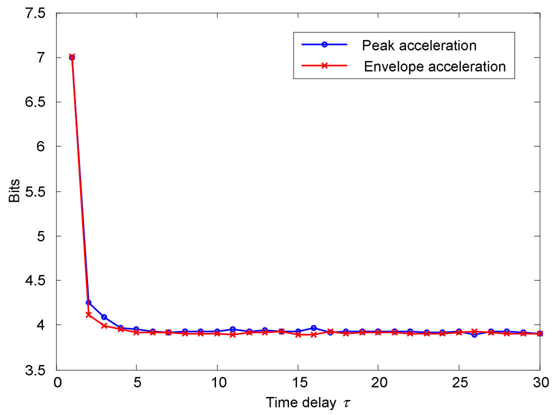


Fig.4 Time delay estimation.

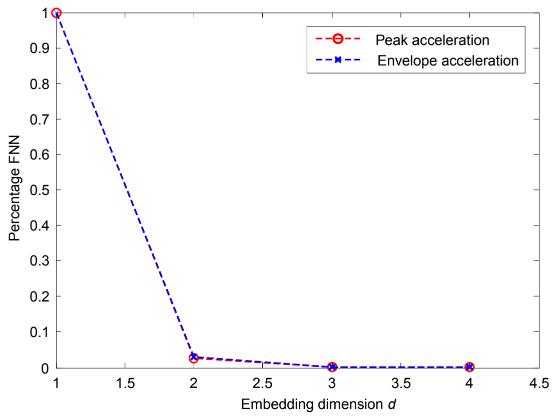


Fig. 5. The relationship between FNN percentage and embedding dimension.

Using FNN method, the optimal time delay τ is subsequently utilized to determine the embedding dimension d. It is noted that the tolerance level R_{tol} and threshold A_{tol} must be initially chosen. In this study, $R_{tol} = 15$ and $A_{tol} = 2$ are used according to the results from

[6]. The relationship between the false nearest neighbor percentage and the embedding dimension for both peak acceleration data and envelope data is shown in Fig. 5. From the figure, the embedding dimension d is chosen as 4 for both data sets where the false nearest neighbor percentage reaches to 0.

After calculating the time delay and embedding dimension, the process of generating the prediction models is carried out. In case of the ANFIS model, the bell shape is chosen for each membership function (MF) and the number of MFs is 2. After executing 100 epochs, all RMS errors of the outputs reach the convergent stage for both the peak acceleration data and envelope acceleration data as shown in Fig. 6. Alternatively, the parameters of MFs, which are premise parameters and consequent parameters, are automatically adjusted through the learning in order that the outputs of ANFIS model match the actual values in training data. The changes of MF shapes are depicted in Fig. 7

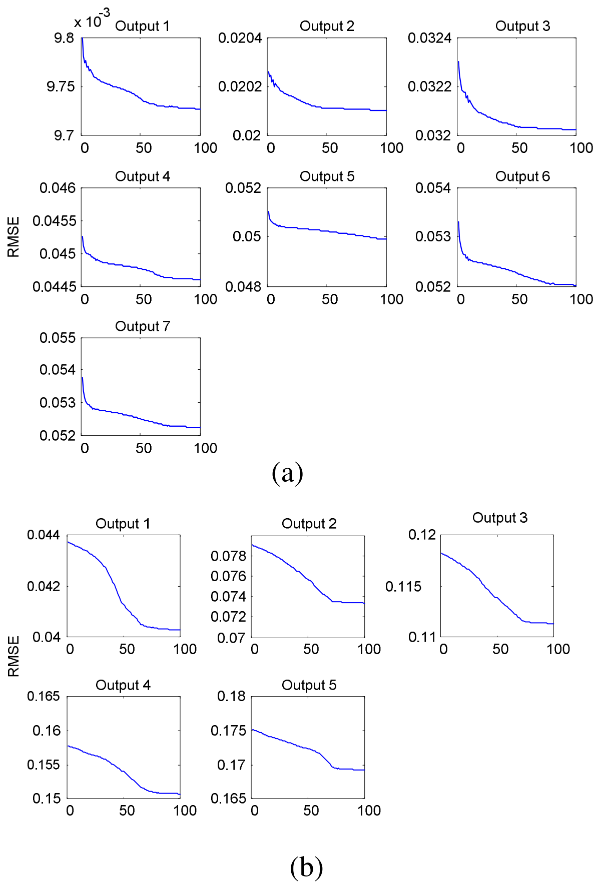


Fig.6 RMSE convergent curve. (a) Peak acceleration, (b) Envelop acceleration.

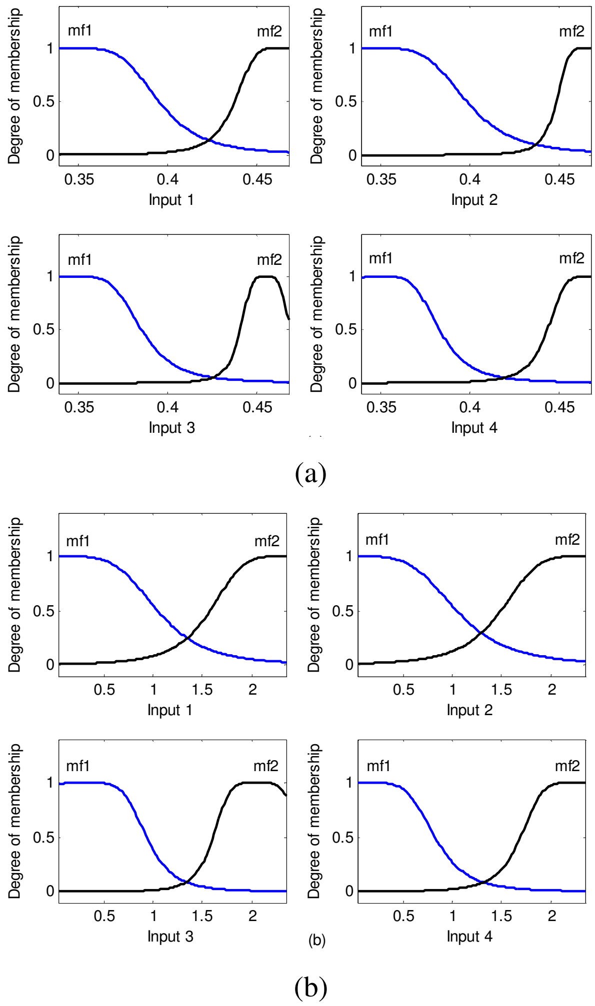
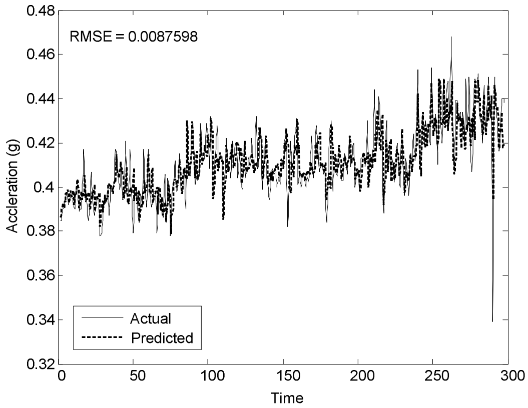


Fig. 7. The changes of MFs after learning. (a) Peak acceleration, (b) Envelope acceleration.

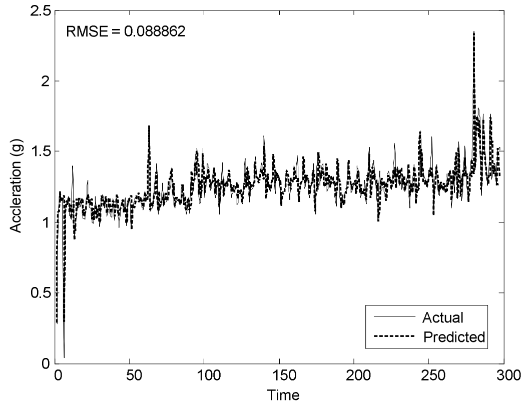
The training and validating results of ANFIS models for both the peak acceleration data and envelope acceleration data are respectively shown in Fig. 8. From these figures, the RMSE values are sequentially 0.00876 and 0.08886. For higher accuracy of RMSEs, the MFs can be increased. Nevertheless, this will also increase the computational complexity and take too much training time.

Fig. 9 shows the predicted results of the ANFIS models for peak acceleration and envelope acceleration data. The RMSE values of the ANFIS model for those data are summarized in Table 2. Obviously, the predicted results of ANFIS models can keep track with the changes of the operating condition of machine more precisely. This is of crucial importance in industrial application for estimating the time-to-failure of equipments. As mentioned above, the predicted results of ANFIS models can be improved by adjusting the parameters of ANFIS.

However, these changes should take into consideration the increase of computational complexity and time-consumption of the training process which may lead to unrealistic application in real life.

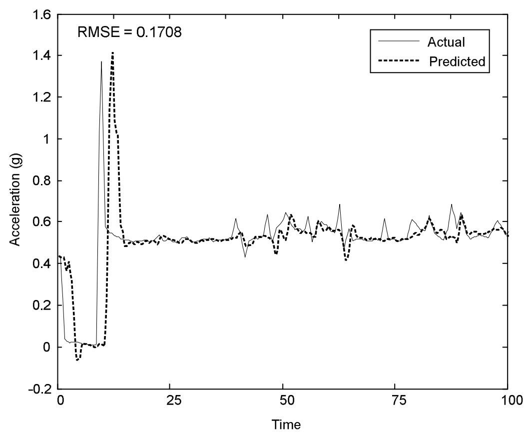


(a)

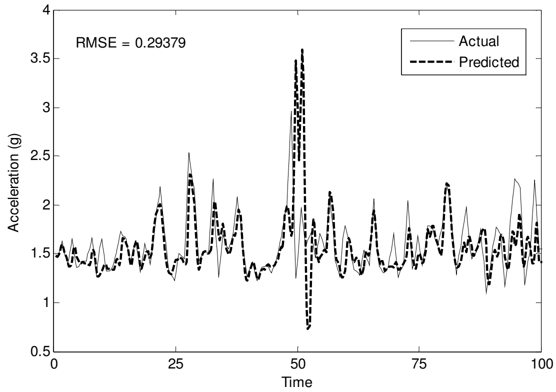


(b)

Fig.8 Training and validating results of ANFIS model (a) peak acceleration data, (b) envelope acceleration data



(a)



(b)

Fig. 9 Predicted results of ANFIS model: (a) peak acceleration data, (b) envelope acceleration data.

Table 2. The RMSEs of predicted results

Data type	Training	Testing
Peak acceleration	0.00876	0.1708
Envelope acceleration	0.08886	0.2938

5. CONCLUSIONS

Machine condition prognosis is extremely essential in foretelling the degradation of operating conditions and trends of fault propagation before they reach the final failure threshold. In this study, multi-step ahead direct prediction for the operating conditions of machine based on data-driven approach has been investigated. The ANFIS prediction model is validated by its ability to predict future state conditions of a low methane compressor using the peak acceleration and envelope acceleration data. The predicted results show that they are capable of tracking the change of machines' operating conditions with acceptable accuracy. The tracking-change capability of operating conditions is of crucial importance in estimating the RUL of industrial equipments. This means that ANFIS has the potential for using as a tool to machine condition prognosis.

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