Tran, Van Tung

Development of intelligent techniques for machine prognostics

DEVELOPMENT OF INTELLIGENT TECHNIQUES FOR MACHINE PROGNOSTICS

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ABSTRACT

The prognostic system plays a crucial role in estimating the remaining useful life of machine components and forecasting of the future states of machines. The techniques related to prognostics consist of statistical-based, model-based, and data driven or intelligence-based. Among these, artificial intelligence is commonly used due to its flexibility in generating appropriate models for the forecasting purpose. This paper presents the development of intelligent techniques for machine health prognostic system in Intelligent Mechanics Laboratory (IML) of Pukyong National University (PKNU), South Korea. These developed techniques include support vector machine, relevance vector machine, Dempster-Shafer theory, decision tree, neuro-fuzzy inference systems. Additionally, they are also combined with other model-based techniques such as autoregressive moving average, proportional hazard model, logistic regression, etc. to fulfill the final goal of prognostic system. Case studies of machine health prognostics are also presented in this paper to show the plausibility of the developed systems.

1. INTRODUCTION

In today's highly competitive marketplace, industries strive to minimize their capital and operational costs by trying to utilize the whole life cycle of their machinery without sacrificing human, production, or environmental safety. Condition-based maintenance (CBM) is most useful in predicting equipment failure and avoiding unnecessary maintenance activities. Prognostics (also called prognosis) is an inherent component of CBM. Prognostics is the ability to assess the current health of a part and predict into the future the health of a part for a fixed time horizon or predict the time to failure. It is critical to the machine for improving safety, planning missions, scheduling maintenance costs and downtime. Being able to perform reliable prognostics is the key to CBM.

Failure prediction that allows the pending failures to be identified before they come to a serious situation, the remaining useful life (RUL) estimation, and the machine degradation assessment of machine are objectives of prognostics. The efforts to accurately determine such objectives have been studied for recent decade. However, this topic is still a challenge of engineering asset management task. A number of techniques and methods have been extensively studied in literature related to the way to assess the degradation parameter or deviation parameter. The published papers which reported the review of machine prognosis are presented in Refs. [1-3]. According to Jardine et al. [2], the approaches to prognostics fall into three main categories: *statistical approaches*, *artificial intelligent approaches*, and *model-based approaches*. Among these, artificial intelligent approaches are more popular due to its flexibility in generating appropriate models. Artificial intelligent prognostics, also known as data-driven prognostics, is a method to generate the model based on training process of prior data, and then predict the future state using one-step or multi-step ahead prediction. On the other hand, model-based prognostics is a method to predict the future condition by using the accurate mathematical models which can be constructed based on the physical fundamentals of a system.

This paper presents research output of developed prognostic techniques at IML-PKNU based on data-driven and model-based techniques. The techniques presented in this paper are relatively new contribution to the machine health prognostics that utilizes intelligent tools such as support vector machine (SVM), relevance vector machine (RVM), Dempster-Shafer theory, decision tree, and adaptive neuro-fuzzy inference system (ANFIS), etc. Furthermore, these intelligent tools are combined with model-based techniques e.g. autoregressive moving average (ARMA), proportional hazard model (PHM), and logistic regression (LR) in order to assess the degradation and estimate the RUL of machine until final failure occurred. Finally, several case studies will be presented to show the plausibility of proposed intelligent machine health prognostics.

2. THE DEVELOPED TECHNIQUES

Various intelligent prognostic methods have been developed for failure prediction and RUL estimation of machine. The following will present their implementations in industrial equipments.

2.1. MACHINE STATE PREDICTION

2.1.1. Support vector machine (SVM)

The theoretical foundation of SVM was developed by Vapnik [4]. Our first study of prognostics was application of SVM for predicting future state condition of machine reported in Ref. [5]. The method of implementation is described in Fig. 1 as follows

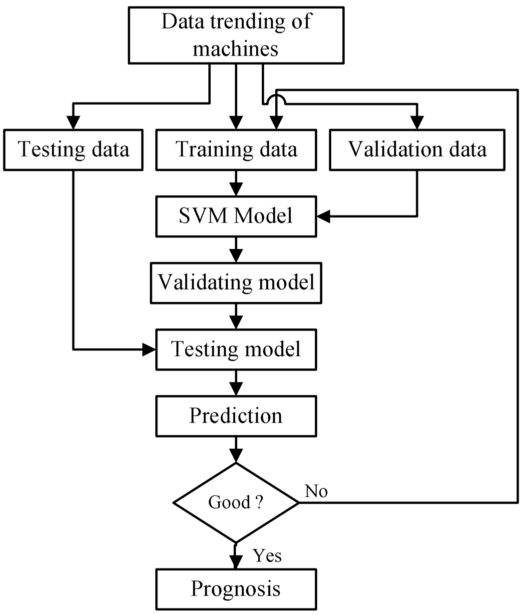


Fig. 1 SVM for prognostics implementation

The data used in this experiment is trending data of machine based on vibration signal which contains data histories of machine until faults occurred. Then, the trending data is divided into three parts: training data, validation data and testing data. The training and validation data are used to build the model for machine fault prognostics system, while the testing data is used to test the validated model. After model validation, the tested model will be obtained. The tested model is used to predict the future data that is never used for training and validation. The quality of prediction result is measured by performance measures e.g., root-means square error RMSE and correlation coefficient R. Prognostics system is obtained if the prediction is successful and passed the user defined criterion of performance measures. This method was successfully implemented in prediction the future state of low methane compressor based on acceleration data (Fig. 2)

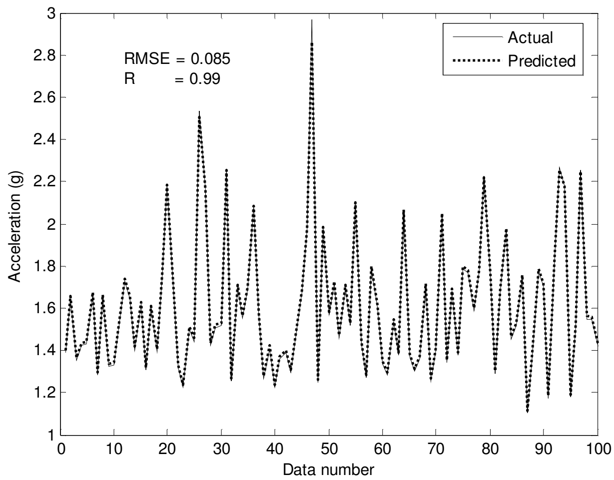


Fig. 2 Prediction of envelope acceleration data

2.1.2. Decision tree (DT)

The implementation of decision tree for machine prognostics has been reported in Ref. [6]. Such paper proposes a method to predict the future conditions of machines based on one-step-ahead prediction of time-series forecasting techniques and regression trees. In that study, the embedding dimension is firstly estimated in order to determine the necessarily available observations for predicting the next value in the future. This value is subsequently utilized for the predictor which is generated by using regression tree technique. The proposed method consists of four steps: data acquisition, data splitting, training-validating and predicting. The flowchart of method is depicted in Fig. 3. The result prediction is presented in Fig. 4.

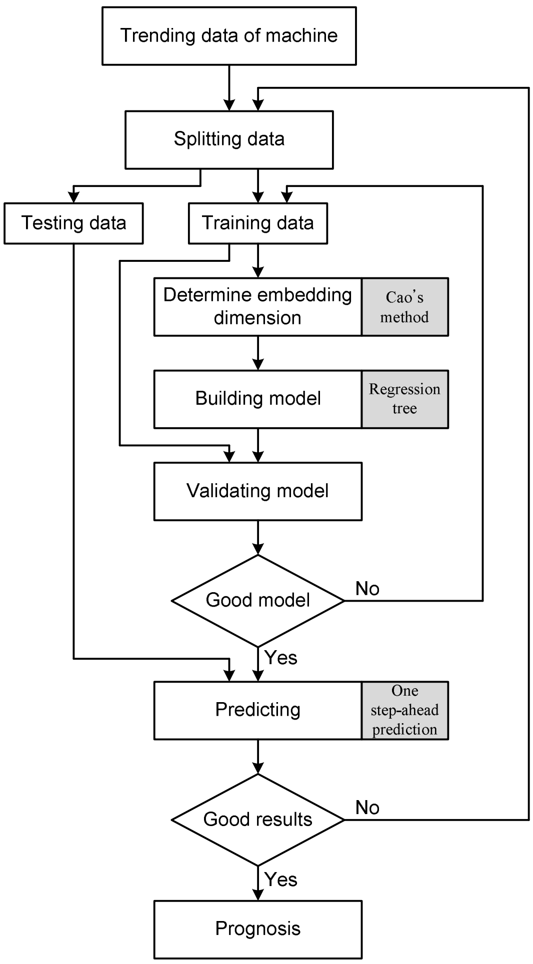


Fig. 3 The prognostic method by DT

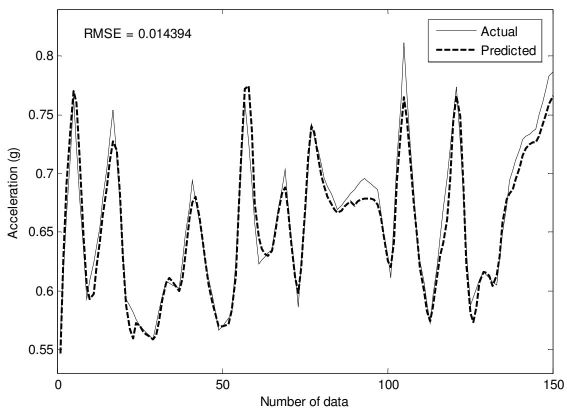


Fig. 4 Predicted results of envelope acceleration data

2.1.3. Dempster-Shafer regression (DSR)

The DSR technique was adopted as a new time-series prediction model for machine prognostics purpose. DSR or evidence regression was introduced by Renaud and Denœux [7] by adopting the subjectivist, nonprobabilistic view of 'Smets' transferable belief model [8]. Basically, the method considers each training sample from the neighborhood of the input vector as a piece of evidence regarding the value of the output. The pieces of evidence are discounted as a function of their distance to the input vector, and pooled using Dempster's rule of combination. This technique was successfully applied to estimate future state condition of low-methane compressor using multi-step ahead prediction. The result is presented in Fig. 5.

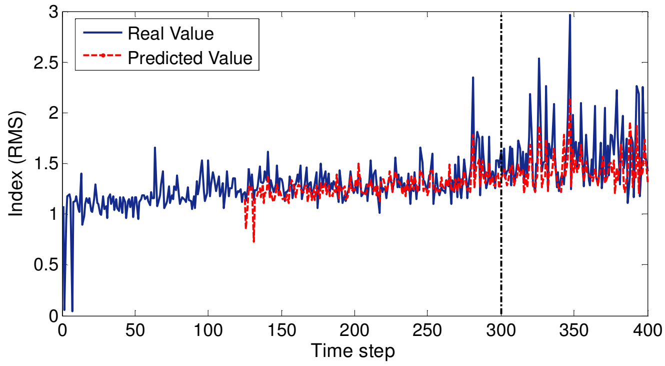


Fig. 5 Prediction of acceleration trend by DSR

2.1.4. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS in association with direct prediction strategy of time series techniques are also utilized for multi-step ahead prediction the machine states [9]. In that study, the number of available observations and the number of predicted steps are initially determined by using false nearest neighbor (FNN) method and auto mutual information (AMI) technique, respectively. This proposed method is mainly similar with previous technique. The results of estimating the number of predicted steps (the time delay) and number of observations are respectively depicted in Figs. 6 and 7. The predicted result of using ANFIS predictor in multi-step ahead is depicted in Fig. 8.

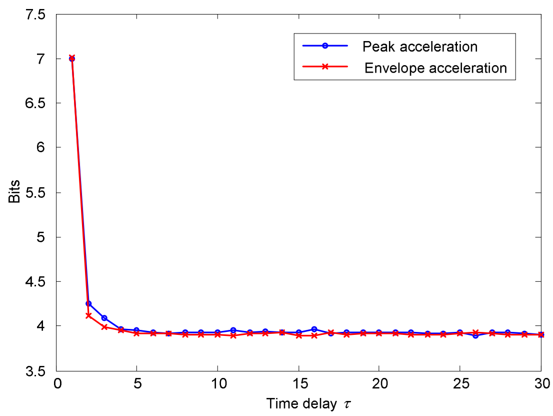


Fig. 6 Time delay estimation

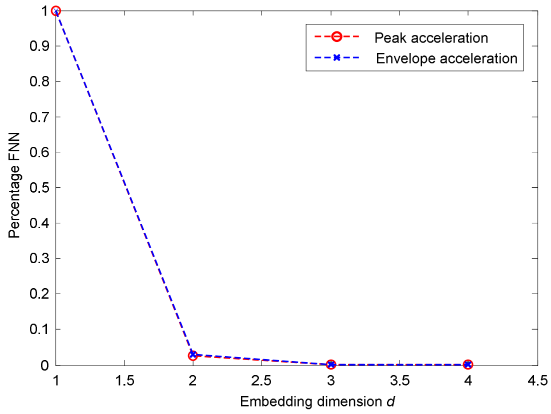


Fig.7 The number of observations

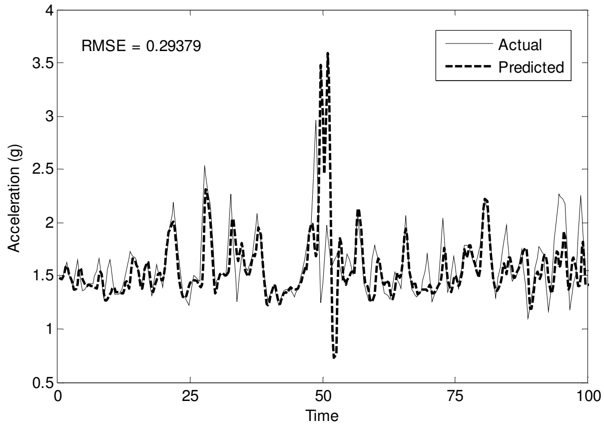


Fig. 8 Predicted results of ANFIS.

2.1.5. ARMA/GARCH

We have also developed autoregressive moving average/ generalized autoregressive conditional heteroscedasticity (ARMA/GARCH) for prognostics health condition of machine [10]. The main idea of implementation is to utilize the linear ARMA model and nonlinear GARCH model to explain the wear and fault condition of machine, respectively. The successful outcomes of the ARMA/GARCH prediction model can give obvious explanation for future states of machine which enhance the worth of machine condition monitoring as well as condition-based maintenance in practical applications. The proposed method is summarized in the flowchart as depicted in Fig. 9.

First, the acquired time-series data e.g., vibration data needs to be made up as stationary data before inputting into ARMA/GARCH model. The stationer data is then divided into two parts: training data and testing data. Training data is used to build forecasting model and to determine the parameters for the ARMA/GARCH model by using the maximum likelihood estimation. Testing data is used to assess the performance capability of the model. After the adequate model is estimated, forecasting is performed to predict the future condition of machine health. The final step is updating the model after one time step prediction to achieve more accurate results and capable to multi-step ahead prediction. The ARMA/GARCH based prognostics system has been successfully applied to predict health condition of low-methane compressor similar with previous example presented in Fig. 10. In this figure, the performance of 1 ~ 4 step-ahead predictions is presented by measuring conditional standard deviation.

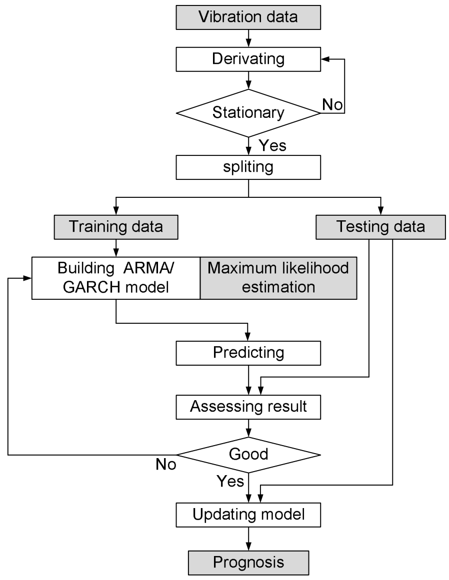
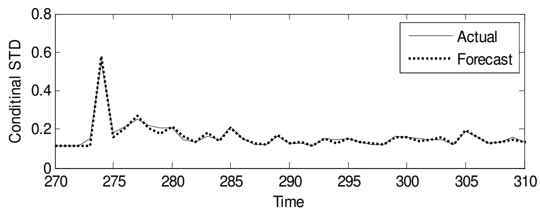
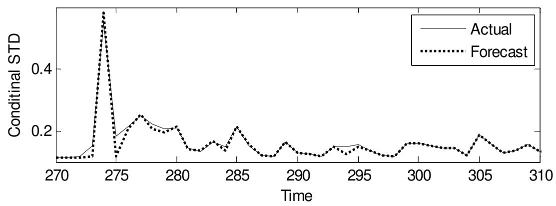


Fig. 9 The ARMA/GARCH prediction model



(a)



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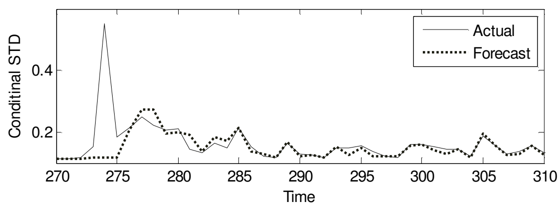

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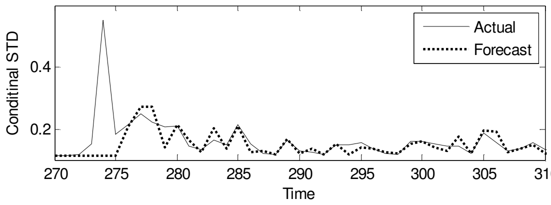

(d)

Fig. 10 The conditional standard deviation forecasts of innovations (a ~ d): using 1 ~ 4 step-ahead prediction

2.2. MACHINE DEGRADATION ASSESSMENT AND RUL ESTIMATION

2.2.1 Logistic regression (LR) and relevance vector machine (RVM)

In our development, we proposed prognostics technique based on LR in order to assess the failure degradation and prediction from incipient failure until final failure occurs [11]. LR is a variation of ordinary regression method which is used when the dependent variable is a dichotomous variable (which is usually represented the occurrence or non-occurrence of some output event, usually coded as 0 and 1).

The goal of LR is to find the best fitting model to describe the relationship between the dichotomous characteristic of the dependent variable and a set of independent variables [12]. The LR was combined by RVM to perform intelligent prognostics system. This method has been applied to predict failure degradation of rolling element bearing as presented in the previous example. The LR calculation and result of prediction are presented in Fig. 11 and Fig. 12, respectively.

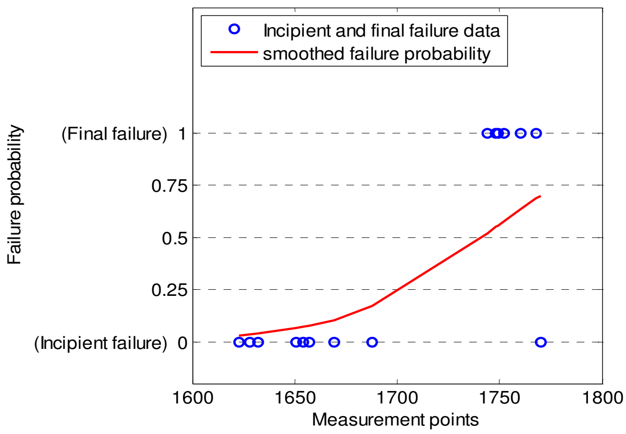

Fig. 11 Logistic regression of data

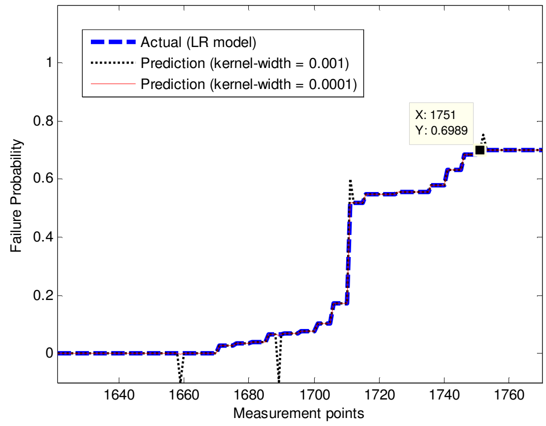

Fig. 12 The result of degradation prediction

2.2.2. Combination of ARMA, PHM, and SVM

In another of our study, a three-stage method for both targets involving machine performance degradation assessment and RUL prediction was proposed. In the first stage, ARMA model, which is one of the system identification techniques, was 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 in association with multi-step ahead direct prediction method of time-series forecasting techniques is utilized to forecast the RUL in the last stage. The flowchart of proposed method and degradation index are depicted in Fig. 13 and 14, respectively.

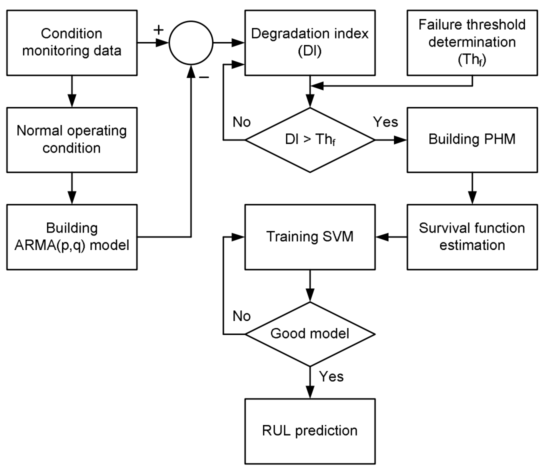

Fig. 13 Schematic diagram of proposed method

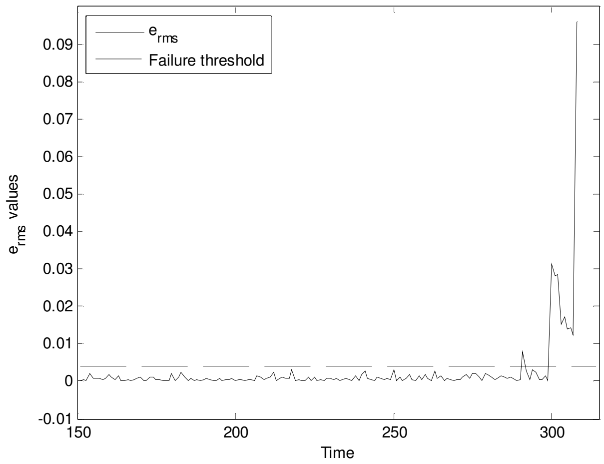

Fig. 14 Degradation index of machine

From this figure, the degradation index can be obviously recognized to the change of machine condition. Therefore, it is adequate to assess the machine degradation. Furthermore, the degradation index also assists in generating PHM and estimating survival function. Fig. 15 presents the forecasting results of RUL using SVM.

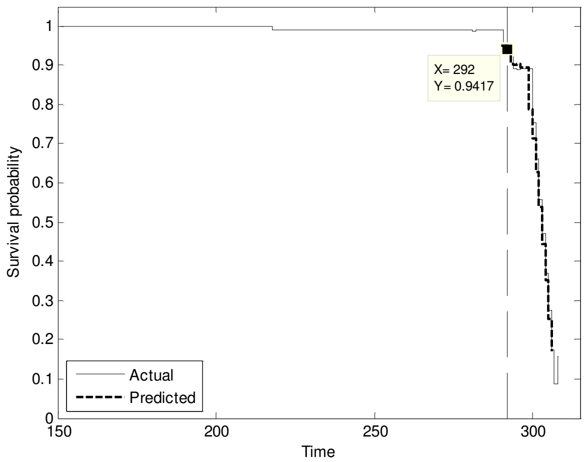

Fig. 15 Predicted results of RUL

3. CONCLUSION

This paper summarizes and reviews research outcomes of machine prognostics study which have been conducted in IML-PKNU, Korea. The developed methods have employed various techniques for estimating failure degradation of machines being studied. Moreover, our developed systems concern with implementation of intelligent systems to obtain high accuracy in predicting health condition of machines. Our developed systems have been tested by experimental data acquired in industry and laboratory scale to present their usefulness. Even though many researchers have been conducted similar research of prognostics, but this area is still open and interesting to be studied. The effort to find research finding of machine prognostics that are effective and reliable in application should be emphasized.

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