A DATA-DRIVEN PROGNOSTIC MODEL FOR INDUSTRIAL EQUIPMENT USING TIME SERIES PREDICTION METHODS

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ABSTRACT

Condition-based maintenance strategy is considered popular and received high demand in industry to ensure high availability and reliability of equipment in the plant. Prognostic is one of an important functions in condition-based maintenance strategy which is used to predict the future condition of the observed and estimate the remaining useful lifetime (RUL) based on the current and historical condition data. Due to the fact that most of the current automated equipment in industry has the capability to capture and store the condition and process data during operation, the research aimed to formulate a prognostic model based on the integration of the data and predict the series of future condition. This paper presents a data-driven prognostic model to predict the estimated RUL by using condition and process data which are taken from a single unit of equipment. The structure of prognostic model is presented and two time series methods are employed namely Artifical Neural Network and Double Exponential Smoothing in prognostic process. The feasibility of this prognostic model was demonstrated with applying real data from industrial equipment. The result from the model shows that both of the methods are able to extrapolate the extimated RUL and give useful information to the maintenance department to take an appropriate decision.

***KEYWORDS**: Prognostic; Remaining useful lifetime; Condition-based maintenance; Artifical neural network; Double exponential smoothing*

1.0 INTRODUCTION

In recent years, prognostic function has been studied intensely in order to support predictive condition-based maintenance program. Even though many prognostic method and tool have been developed, prognostic were not fully implemented in industry for the purpose of the maintenance (Muller, Suhner, & Iung, 2008). The major setback was

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because there were some difficulties in seeking good reference for the implementation of prognostic in the real industry environment (Heng, Zhang, Tan, & Mathew, 2009). Today, many advanced industrial equipment are having sensor system which are capable of monitoring the operational condition continuously and storing its data in database (Dong & He, 2007). However, due to the lack of understanding about the capability of the equipment, data captured are yet to be further utilized. As these data are typically correlated with the severity of the underlying degradation performance (Elwany & Gebraeel, 2008). Thus, this paper aims to provide a data driven prognostic model based on the existing condition monitoring and operation data to predict the equipment failure and its residual time.

2.0 OVERVIEW OF PROGNOSTIC

Prognostic can be referred as the ability to predict how much time is left or Remaining Useful Life (RUL) before a failure occurs given that an observed equipment condition variable and past operation profile (Jardine, Lin, & Banjevic, 2006). In general, prognostic can be classified into three main approaches namely: physical model-based, experience-based and data-driven based (Tran, Yang, & Tan, 2009). Physical model-based applies mathematical models which are constructed from the first principle of system's failure modes (Tran et al., 2008). Normally, it uses a residual to evaluate performance accuracy between sensed measurement of equipment and the output of mathematical models. The approach is the most preferable method when dealing with time consuming in collecting sufficient quantity and the quality of operating data. However, to develop an accurate mathematical model, a comprehensive mechanistic knowledge and theory of monitored equipment are highly required and most of the models are component–oriented which cannot be applied to the different types of component. Experience–based prognostic approach is based on the use of the probabilistic and stochastic models of life cycle of the equipment. The breakdown information or any related life time data and knowledge from experience during the whole operation period of the equipment are accumulated to form the certain probabilistic function or models (Medjaher & Zerhouni, 2009). Theoretically, this approach is well-presented but in the real implementation, the lifetime data are very difficult to acquire especially on equipment with high reliability which its failure may not occur during the analysis period or only one unit failed before failure. In addition, none of industry will allow its machines or equipment to undergo a breakdown for the purpose of modelling (Xiaoyan & Ping, 2003). Data-driven prognostic approach utilizes historical data to automatically learn a model of system behavior and predict the future condition of degradation values (Schwabacher, 2005). Therefore, the critical challenge in data-driven prognostic approach is continuing to provide a model that is able to generate high validity predicted data for RUL estimation based on all the information acquired. This research aims to propose a data–driven prognostic model that can generate the series of future data with higher accuracy prediction performance.

3.0 THE PROPOSED PROGNOSTIC MODEL

The proposed prognostic model is based on using existing condition operating data from equipment to predict the equipment life time as shown in Figure 1. This model consists of three main modules sequentially: data acquisition, performance degradation assessment, and prognostic model generation. The functionalities of the modules are briefly discussed below.

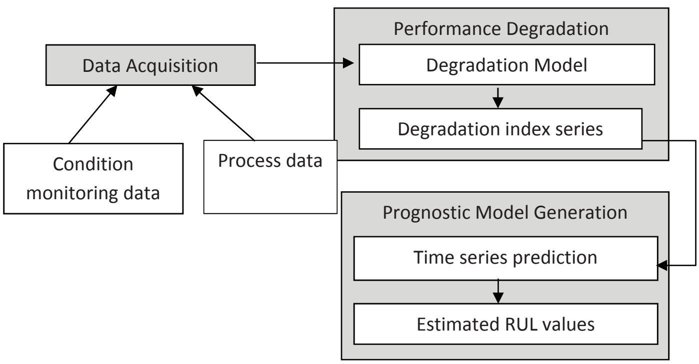

Figure 1. The proposed prognostic model

3.1 Data Acquisition

Data Acquisition is a process of collecting and storing useful data from targeted physical equipment for the purpose of prediction in prognostic (Jardine, et al., 2006). This process is an essential step in the Condition-based Predictive Maintenance (CBPM). Usually, there are two types of data that can be used: event data and condition monitoring data. Event data focuses on the information about when and how failures occur and what kind of the maintenance action can be taken to the observed equipment. On the other hand, condition monitoring data is more flexible which can be attributed from signal characteristics or control process of equipment (Jardine, et al., 2006). For instance, vibration signature, oil analysis and output rate have been successfully used for monitoring the presence of failure in equipment (Lee, Ni et al., 2006; Wang & Hussin, 2008). Other alternative condition parameters that can be used in prognostic are acoustic data, temperature, pressure, moisture, humidity, weather or environment data (Jardine, et al., 2006). These observed conditions are subjected as data input of the prognosis process.

3.2 Performance Degradation Assessment

Performance degradation assessment has been a necessity in development of prognostic as supported by previous studies, for example in Yan et al (2004) & Caesarendra et al (2010). Because of the proposed prognostic model involves the prediction task that contains uncertainty behaviour, thus, it can be more realistic to use a degree of degradation probability for the estimated RUL value (Medjaher & Zerhouni, 2009; Caesarendra et al., 2010). By monitoring the trend of equipment degradation and assessing performance, it allows the degradation behaviour to be analysed and used to understand the failure information. In this paper, the performance degradation assessment is modelled to characterize the identified condition monitoring and process data in data acquisition module to generate degradation index (DI). DI is used as the prognostic parameter in the proposed model. Furthermore, DI would be the key parameter if the failure of equipment is based on the multiple conditions monitoring data.

The transformation of condition monitoring data to the series of degradation index can be accomplished by using a statistical technique namely Logistic Regression (LR). LR is a variation regression method that finds the best fitting model to describe the relationship between dependent dichotomous variable and one or multiple independent variables (Caesarendra et al., 2010). Result of LR which contains the probabilities ranges between 0 and 1 can be used to represent as the series of degradation index (Yan, Koc et al., 2004). A number of researches have investigated the adaptability of LR in engineering especially to assess equipment failure (Yan, Koc et al., 2004; Lee, Ni et al., 2006; Caesarendra et al., 2010). Here, the failure probabilities can be calculated through the function as follows:

$$p(x) = \frac{e^{g(x)}}{1 + e^{g(x)}} = \frac{1}{1 + e^{-g(x)}} \tag{1}$$

where p(x) is the probability of failure, x is an input vector corresponding to the independent variable and g(x) is the logit model which can be defined as:

$$g(x) = \log\left(\frac{p(x)}{1-p(x)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \qquad (2)$$

where g(x) is a linear combination of independent variables, α is the intercept when x=0 and βs are known as the regression coefficients, which can be estimated using a mathematical technique called Maximum Likelihood Estimation. The resulted failure probabilities from the degradation model are subsequently used as the input for developing the prognostic model.

3.3 Prognostic Model Generation

The process of prognostic is accomplished by predicting and extrapolating the dynamic DIs over time from the performance degradation model. A traditional prediction method, which is Autoregressive Moving Average (ARMA) is the most method widely used in time series modelling. However, ARMA models are linear based prediction model and required stationary as the important condition in the time series for conducting prediction process. Because of the stationary assumption, the observation data will be simulated and fitted over and over again within a restricted set of ARMA model parameters. Due to that, these models are only accurate for stationary time series prediction and the robustness of the selected model for a trend and dynamic variance of the degradation process may not appear defensible.

Exponential smoothing technique is a one of successful time series prediction technique that having the property of prediction intervals which is based on the weighted combination of past observation data (Hyndman, 2008). This technique had been extended for handling the time series with trend and known as double exponential smoothing (DES). In detail, exponential smoothing model uses the weighted parameter based on the retention of the observation data. This weighted parameter is known commonly as alpha in which its value is between 0 and 1. The value alpha in the exponential smoothing model can be responsive quickly to changes in the data pattern and can be accomplished in limited observation data. Because of that, the DES method offers more robust and accurate prediction result comparing other time series prediction model. Thus, DES is continuously used in this research to predict the series of future DIs.

However, DES extrapolate from pre-assumed linear form of model, it may not offer good prediction results for a highly dynamic process, when the features extracted from sensor readings display highly irregular behaviour. Therefore, a nonlinear technique is also considered in this research to investigate the performance accuracy in prediction. Artificial Neural Network (ANN) is one of the non-linear information processing techniques that digitized based on biologically inspired computer programs to simulate the way in which the human brain process information (Agatonovic-Kustrin & Beresford, 2000). By using the concept of learning through experience, ANN gathers the information and then detects the patterns and relationship in the data. An ANN architecture constitutes as a computational model that contains hundreds of artificial neurons and connected with coefficients known as weights (Agatonovic-Kustrin & Beresford, 2000) as illustrated in Figure 2. In this study, ANN also is used for predicting the series of the future DIs

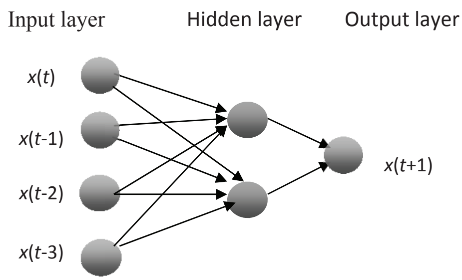

Figure 2. A Neural Network Architecture

However, in order to use an ANN model, two other key parameters need to be considered, namely the number of hidden layer and the number of neurons. A single hidden layer is sufficient to compute a uniform approximation of any continuous function, according to Sun et al., (2010). Therefore, the proposed ANN is composed of an input layer, a hidden layer and an output layer with one output neuron. The logistic function is used as the activation function in the hidden layer and the linear function is used in output layer.

In applying neural network, deciding the number input and hidden neuron has always been an issue. Having a smaller number of hidden neurons tend to leads the performance is not adequate, while having too many neurons may increase the risk of over-fitting of the data and impede generalization. Ultimately, the selection of the architecture of a neural network comes down to trial and error (Heaton, 2008). In this paper, the early stopping method is used in the trial and error procedure to determine the number of input neuron and hidden neuron. Here, the training data is trained iteratively with increase in the number of input and output. The iteration process is stopped when the training result is higher than it was last trained. This training result is based on statistical analysis namely root mean square error (RMSE). RMSE can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(x_t - \bar{x}_t\right)^2} \qquad (3)$$

where n is length of time series data, x_t represents the target values and x_t represents actual values.

After the best ANN architecture is identified, the training dataset are used for training the network in adjusting the synaptic weights. Once the network is completely trained, the weights are frozen and the network is ready to predict and extrapolate failure probability. In order to validate the predicting performance of network, a set of validation data is used by comparing the network output with the target output. The performance of network is then compared with the DES technique to evaluate the prediction capability of ANN. Here, RMSE defined by Equation 3 is utilized for accuracy comparison.

4.0 INDUSTRIAL APPLICATION AND RESULTS

The proposed methods have been implemented in the industrial equipment called autoclave burner. The main function of the burner is to generate heat and energy for heating system in the autoclave as shown in Figure 3 .

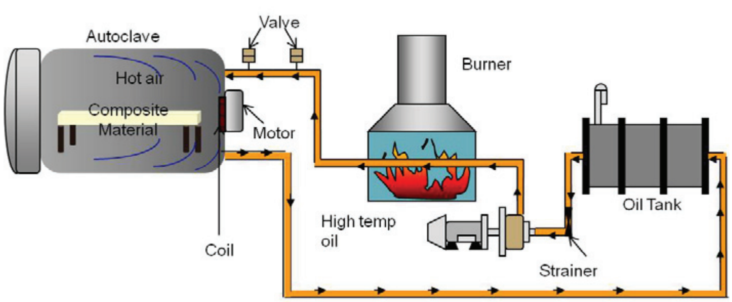

Figure 3. Curing process of autoclave

The process of an autoclave basically removes the air from inside the chamber, creates an increased temperature through the use of heating elements, and creates an increased pressure inside the chamber at the same time as shown in Figure 3. Fuel oil is used to generate heat and energy for the heating system in the autoclave. Therefore the temperature of fuel oil needs to be consistent during the autoclave curing process. One of the major failures of the burner is excessive heating of oil due to the clogging of carbon black in the burner strainer. Thus, the proposed prognosis model is to predict RUL by trending series of degrdation index of the autoclave burner.

Extensive investigations have been made in order to identify condition monitoring parameters that are well related with burner failure. Based on the recommendation from the industry's maintenance experts, maximum temperature (*max_temp*) is utilized as a condition monitoring parameter to monitor condition of autoclave's burner air temperature parameter called AIRTC. From the condition normal and faulty autoclave's burner, performance degradation model is generated using logistic regression method as in Equation (1) and (2) and the series of degrdation index is estimated from the model. Figure 4 illustrates the series of degradation index of the autoclave burner based on a single condition *max_temp*.

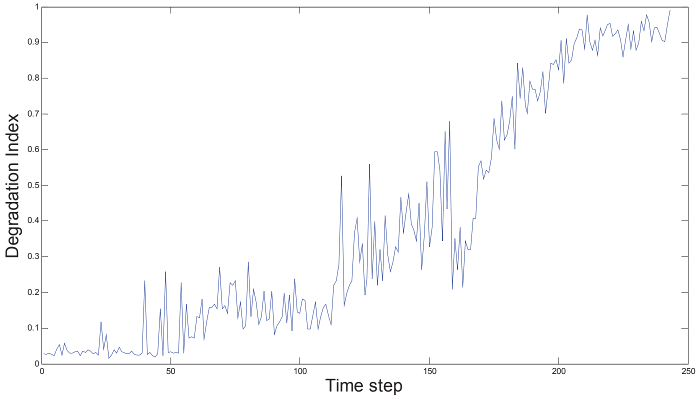

Figure 4. The generated degradation index

For extrapolating the estimated RUL values, the available condition data were used to train the prognostic and the rest of DI point were employed for validation model. Figure 5 and Figure 6 shows the extrapolation process from ANN and double exponential smoothing respectively.

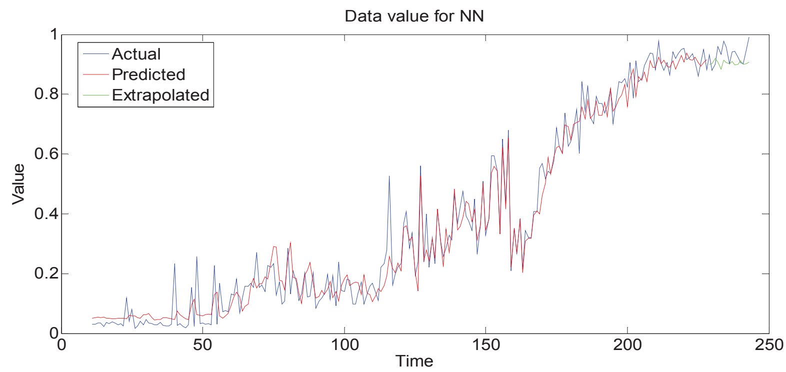

Figure 5. The prediction of DI from ANN

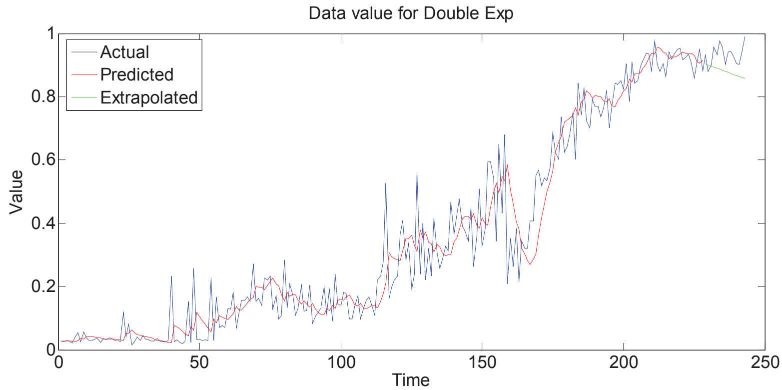

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Figure 6. The prediction of DI from DES

In order to show the efficiency of the predictive ability, the ANN model is examined and compared with Double exponential model. The performance comparison results are presented in Table 1.

Table 1. Performance Comparison

	9		**15**		**21**	
	3 -day		5-day		7-day	
Model	Training	Validation	Training	Validation	Training	Validation
ANN	0.05925	0.03292	0.05435	0.04212	0.05750	0.03226
DE	0.08059	0.03029	0.08138	0.06414	0.08233	0.03669

As shown in Table 1, according to RMSE measurement, it indicates that ANN model offers a minimum error variance and adequate for failure prediction for more series of estimated RUL values based on degradation index. By having more estimated values in advance, the maintenance engineers would have sufficient time to adjust their production line flow and prepare the maintenance necessary actions.

5.0 CONCLUSION

A data-driven prognostic model for predicting future condition equipment has been described and applied through an industrial case study. The proposed methods are based on the time-series prediction techniques to extrapolate the remaining useful life data. In this paper, the prognostic model has been accomplished by using Double Exponential Smoothing and Artificial Neural Network methods. The prediction performance of both methods is also compared and evaluated. With the RUL, the maintenance people are able to construct the maintenance plan efficiently. Finally, the maintenance cost policy would be required to perform the optimal maintenance decision. Thus, one critical direction for the future research relates to the integration of prognostic model with maintenance cost for practical decision making.

6.0 ACKNOWLEDGEMENT

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