

Neural Network Prognostics Model for Industrial Equipment Maintenance

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Abstract—This paper presents a new prognostics model based on neural network technique for supporting industrial maintenance decision. In this study, the probabilities of failure based on the real condition equipment are initially calculated by using logistic regression method. The failure probabilities are subsequently utilized as input for prognostics model to predict the future value of failure condition and then used to estimate remaining useful lifetime of equipment. By having a time series of predicted failure probability, the failure distribution can be generated and used in the maintenance cost model to decide the optimal time to do maintenance. The proposed prognostic model is implemented in the industrial equipment known as autoclave burner. The result from the model reveals that it can give prior warnings and indication to the maintenance department to take an appropriate decision instead of dealing with the failures while the autoclave burner is still operating. This significant contribution provides new insights into the maintenance strategy which enables the use of existing condition data from industrial equipment and prognostics approach

Keywords—component; neural network; prognostics; failure probability; maintenance.

I. INTRODUCTION

There is an increase of research attention in prognostics because of its capability to predict the equipment failure. Hence, many prognostics method and tool have been developed in recent time. For example, Yan et al. [1] developed the prognostics implementation algorithm and have implemented it in an elevator door motion system. Tran et al. [2] used prognostics method to predict the trending condition data of a low methane compressor. However, most prognostics model were not fully implemented in industry for the purpose of the maintenance and only work well in experimental environment [3]. One of the main reasons of this shortcoming is the failure prognostics model is based on linear model as in [1, 2], whereas equipment failures involve nonlinear process. In that case, having a nonlinear approach is much appropriate. In addition, the integration of the prognostic model with maintenance decision policy still remains invisible [4].

Recently, many advanced equipment in the industry are having sensor system which are continuously monitoring operational condition and storing data in its database [5].

However, due to the lack of understanding about the capability of the equipment, data are not fully utilized. As these data are typically correlated to the severity of the underlying degradation performance [6], therefore, the paper demonstrated a neural network prognostic model based on the real condition monitoring data to predict equipment failure and its life time for assisting maintenance decision.

II. PROGNOSTICS OVERVIEW

Equipment prognostics refer as the ability to predict Remaining Useful Life (RUL) before a failure can occur given that an observed equipment condition variable and past operation profile [7]. In general, prognostics can be classified into three main approaches namely: physical model-based, experience-based and data-driven based [8]. Physical model-based require accurate mathematical models which are constructed from the first principle of system's failure modes [9]. This approach focuses on the residual assessment 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 process 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 more of the component-oriented which cannot be applied for the different types of component. Experience-based prognostic solely depends on expert judgments and less complex than physical model-based [9]. Essentially, the approach establishes the rule-based model of the equipment [10]. Nonetheless, the approach is not well addressed in the area of equipment prognostics due to the researchers tend to focus on the existence of degraded condition data which provide higher accuracy and reliability [2]. Data-driven prognostic approach utilizes historical data to automatically learn a model of system behavior [10]. Then, the model is used to predict the RUL. The main challenge with this approach is to obtain sufficient historical condition data to the development of prognostic model.

Since the most advanced industrial equipment are having the historical condition operating data in its database, therefore this paper used data-driven approach to utilize these data to develop a prognostics method by using neural-network in assisting industrial maintenance decision.

III. NEURAL NETWORK MODEL

Neural Network (NN) is biologically inspired computer programs which are designed to simulate similar mechanism of human brain information processing [11]. By using the concept of learning through experience, NN gathers the knowledge and then identifies the patterns and relationship in data. The NN structure constitutes as a computational model that contains hundreds of artificial neurons and connects with coefficients known as weights [11]. Fig. 1 shows the model of an NN structure. The input signals, x_1, x_2, \dots, x_n are propagated through the network with the weight. The weight w_1, w_2, \dots, w_n are for connection between neurons input and neuron hidden, and the combination of input signals and weights are passed through an activation function to produce the output value of the neuron y_k .

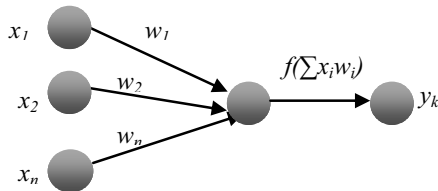


Figure 1. Neural network structure

The use of NN have been widely applied in time series prediction [12]. In this paper, the time series prediction model applied Feedforward Neural Network (FNN) and employed a sliding window over the input sequence. In order to construct the multi-step prediction, the model employs previous predicted value to forecast the future values iteratively until the expected future values are obtained. This multi-step prediction can be illustrated generally in Fig. 2.

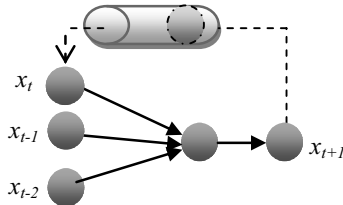


Figure 2. The concept of multi-step prediction

This multi step prediction technique is able to predict a series of predicted value based on the required number of time step d . The prediction technique utilizes the previous values to forecast iteratively of the future d time step values. Given the observation $y_t = [x_{t-r+1}, x_{t-r+2}, \dots, x_t]$, the first future value can be predicted by using:

$$\hat{y}_{t+1} = f(y_t) = f(x_{t-r+1}, x_{t-r+2}, \dots, x_t) \quad (1)$$

where r denotes the number of inputs or the size of sliding window dimension. For predicting the next value, the same prediction model can be given:

$$\hat{y}_{t+2} = f(x_{t-r+2}, x_{t-r+3}, \dots, \hat{y}_{t+1}) \quad (2)$$

Then, the procedure repeats recursively depending on the required number of time series d .

$$\hat{y}_{t+d} = f(x_{t-r+d}, x_{t-r+d+1}, \dots, \hat{y}_{t+d-1}) \quad (3)$$

In prognostics, this multi-step prediction provides the failure probabilities from the beginning until the final failure of equipment in which the RUL can be estimated. In the following section, the approach of proposed prognostic model for industrial equipment maintenance is described.

IV. THE PROPOSED PROGNOSTICS MODEL

The prognostic model is based on using existing condition operating data from equipment to predict the equipment life time and decide time to perform maintenance as shown Fig. 3.

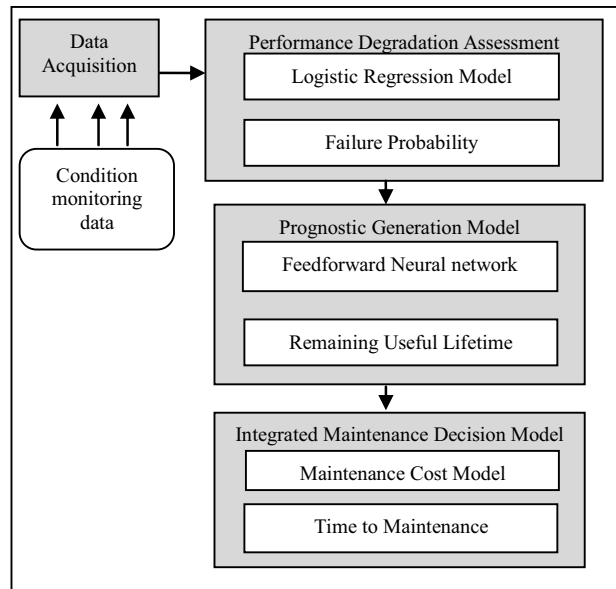


Figure 3. The proposed prognostics model

This model consists of four main modules sequentially: data acquisition, performance degradation assessment, prognostic model generation and integrated maintenance decision. The functionalities of the modules are briefly discussed in the following subsections.

A. Data Acquisition

Data Acquisition is a process of collecting and storing useful data from targeted physical equipment for the purpose of prediction in prognostic [7]. 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 and condition monitoring data. Event data focuses on the information of when and how failures can occur and which the maintenance action needs to be taken to the observed equipment. Conversely, condition monitoring data is more flexible which can be attributed from signal characteristics or control process of equipment [7]. For instance, vibration signal, oil analysis and output rate have been successfully used for monitoring the presence of failure in equipment [13]. Other alternative condition parameters that can be used in prognostic are acoustic data, temperature, pressure, moisture, humidity, weather or environment data [7]. These observed conditions are subjected to data input of the prognosis process. The proposed implementation model makes use of the historical condition operating data under nominal and degraded condition.

B. Performance degradation assessment

Performance degradation assessment has been a necessity in development of prognostic as supported by previous studies, for example in [14] and [1]. By monitoring the trend of equipment degradation and assessing performance, it allows the degradation behavior to be analyzed and used to deliver the failure information. In this paper, the performance degradation assessment is used to characterize the identified condition monitoring data in data acquisition module to failure probabilities (FPs). FP is used as the prognostic parameter in the proposed implementation model due to the behavior of failure is uncertain [14]. Furthermore, failure probability can be made as key parameter if the failure of equipment is based on the multiple conditions monitoring data. Here, all the identified conditions data can be combined in the calculation of failure probability.

Regarding these purposes, the transformation of original condition monitoring data to failure probability 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 [14]. As the final result of LR is the probabilities ranges between 0 and 1, it is able to represent failure probability of equipment [1, 13, 14]. Because of that, LR technique is used in this paper to assess equipment condition to failure based on failure probability.

Here, the failure probability can be calculated through the function as follows:

$$p(x) = \frac{e^{g(x)}}{1 + e^{g(x)}} = \frac{1}{1 + e^{-g(x)}} \quad (4)$$

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:

$$g(x) = \log\left(\frac{p(x)}{1 - p(x)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \quad (5)$$

where $g(x)$ is a linear combination of independent variables, α is the intercept when $x=0$ and β s 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.

C. Prognostics generation model

The process of prognostic is accomplished by predicting and extrapolating the dynamic FPs over time from the performance degradation model using FNN. In order to use FNN, three other key parameters need to be considered, namely the number of hidden layer, the choice of activation functions and the number of neurons.

As a single hidden layer is capable to compute a uniform approximation of any continuous function [15], hence the proposed FNN architecture is composed of an input layer, a hidden layer and an output layer with one output neuron. In order to introduce nonlinearity into the network model, nonlinear activation functions are needed. Thus, the *logistic* and *tanh* functions can be used as a combination of activation function from input layer to the output layer.

In applying neural network, deciding the number input hidden neuron has always been an issue. Having a smaller number of hidden neurons tend to lead ineffective performance, 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 [16]. In this paper, the forward selection method is used in the trial and error procedure to determine the number of input neuron and hidden neuron together with final combination in activation functions. Here, the training data is trained iteratively with the increase in the number of input and output and the activation functions are changed respectively until the error produced by the network is minimum based on root mean square error (RMSE) which can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (x_t - \bar{x}_t)^2} \quad (6)$$

where n is length of time series data, x_t represents the target values and \bar{x}_t represents actual values. After the FNN 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 predicted output.

D. Integrated Maintenance Decision Model

From the FNN prognostic model, the series of predicted failure probabilities can be calculated to represent the continued degradation process of equipment. This continued degradation process is used to formulate the failure time distribution $f(t)$. This failure distribution is primarily used in maintenance model which normally focuses to determine the optimal maintenance action time. The process of formulating the failure time distribution is generated based on the curve fitting procedure.

The curve fitting is successfully applied in several studies in order to derive the trend and fitted function from time series of data [17, 18]. Also it enables analysis of general cumulative germination data and have been used widely for all types of system [19]. Due to this, curve fitting is used adaptively in this study to trend and approximate the failure distribution from the predicted value of prognostics. This approximated failure distribution is further used in maintenance cost model in order to find the optimal time to maintenance. In this case, the maintenance cost model in [20] has been used.

The optimal time to maintenance performed on the considered minimum cost per unit with two maintenance strategy decisions which are preventive maintenance and corrective maintenance. Both maintenance strategies take negligible cost but suppose that the cost of corrective maintenance is higher than the cost of preventive maintenance since the corrective maintenance is likely to be more expensive and complex especially when it carried out at certain failure level. Therefore, the trade-off between both maintenances can give the critical threshold to trigger a preventive maintenance action on the basis of the observed equipment failure probability. Let C_p and C_c denote the preventive and corrective maintenance cost respectively. The total maintenance cost per unit of time can be defined as:

$$C(t) = \frac{1}{\Delta t} C_p (1 - F(t)) + C_c F(t) \quad (7)$$

where $F(t)$ is the probability density function of failure distribution $f(t)$ for the equipment during a unit time length Δt . By integrating with maintenance cost model in the prognostic method, the essential decision of maintenance to determine the time to maintenance using the condition-based approach can be obtained.

V. IMPLEMENTATION & RESULT

The proposed method has been implemented in the industrial equipment which is called autoclave burner. The main function of the burner is to generate heat and energy for heating system in the autoclave as shown in Fig. 4. The detail of the autoclave burner operation is discussed in detail

in [21]. 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 failure probabilities of the autoclave burner.

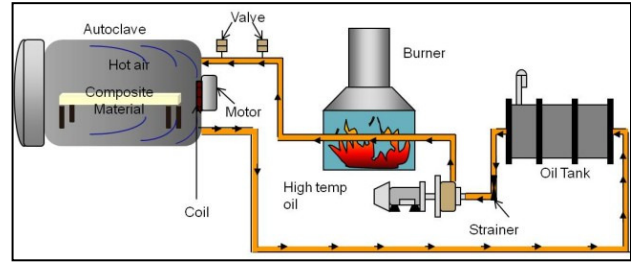


Figure 4. The process of autoclave burner

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 industrial maintenance experts, currently maximum temperature (max_temp) is utilized as a condition monitoring parameter to evaluate the condition of autoclave's burner. The expert judgment is also required to decide the normal and faulty condition of burner in order to formulate degradation model. Current findings by experts show that the $max_temp \leq 285$ degree Celsius represent the normal condition that is equal to 0, and $max_temp > 285$ degree Celsius represents faulty condition which is equal to 1. From the condition normal and faulty set, a performance degradation model is generated using logistic regression method as in (4) and (5) and the failure probabilities are estimated from the model. Fig. 5 illustrates the overall performance failure probability of the autoclave burner based on a single condition max_temp .

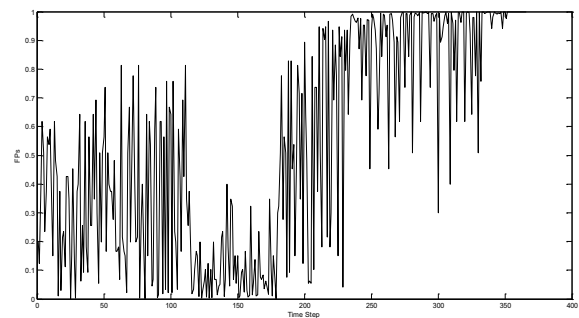


Figure 5. The generated failure probabilities

In the prognostics generation model module, the first 120 data point is neglected to avoid the initialization effect and incomplete time to failure due to maintenance. The next dynamic FPs ranging from 0 until the first value of 1 are selected as the dataset to develop the prognostic model. In order to evaluate the predicting performance of FNN, this selected dataset is divided into training and validation

dataset. In this study, 115 data points are used as training dataset and 5 data points are used as validation dataset.

For FNN prediction model construction, the combination of activation function and the number of the neuron in input and hidden layer should be determined. The training data is initially trained with one input neuron and one hidden neuron in a combination activation functions. The RMSE recorded for every increment in number of neuron together with the change of combination activations functions before the minimum RMSE is identified. The overall result revealed that the optimal numbers of input and hidden nodes were 10 and 10 respectively with the best combination of activation functions are the *logistic* function in hidden layer and the *tanh* function is output layer. With these numbers of neurons and the identified activation functions, a FNN prediction model was constructed. The actual and predicted FP value for the degradation of burner is generated, as shown in Fig.6.

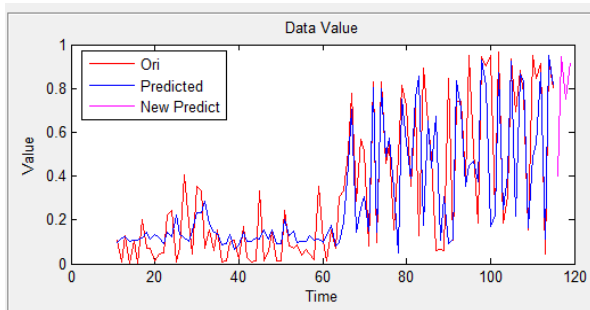


Figure 6. Failure probability prediction

From Fig. 6 the prediction of FPs using FNN shows almost identical trend with the actual series of FPs at approximately 60 time step onwards with the minimum error as shown in Fig.7. This prediction is also able to extrapolate the next 5 data points. These extrapolate data points show that the prediction is able to reach the final failure probability at almost same time in validation dataset. By extrapolating future outputs, the equipment useful life time can be obtained in advanced.

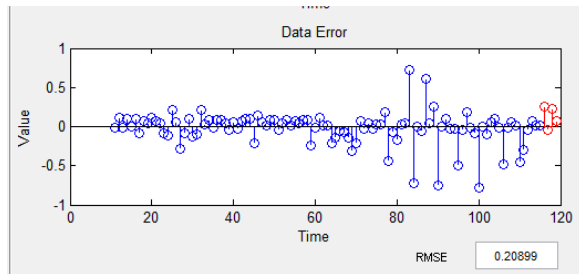


Figure 7. Prediction Error-RMSE

From the FNN model, the predicted failure probabilities are used to generate the failure time distribution by using curve fitting procedure. Four distributions are considered namely; linear, quadratic, cubic and exponential. Table 1 is the result of R-square and RMSE of four main distributions

are given in Table I. It can be found that cubic distribution are satisfied at 58% ($R\text{-square} = 0.5842$) with the smallest $RMSE = 0.1832$

TABLE I. TABLE OF FITS

Distribution	R-square	RMSE
Linear	0.5261	0.1956
Quadratic	0.5311	0.1945
Cubic	0.5842	0.1832
Exponential	0.5069	0.2013

From this curve fitting procedure, the cubic failure time distribution $f(t)$ is identified as the best fit distribution to represent the predicted failure probability gives :

$$f(x) = p_1x^3 + p_2x^2 + p_3x + p_4 \quad (9)$$

By using (9) and the identified coefficients values from curve fitting process, the probability density function $F(t)$ can be obtained. By combining the $F(t)$ into the maintenance cost policy from (7), the total cost per unit time can be calculated. With the minimum of total cost per unit time, the best time to perform maintenance can be decided as shown in the Fig 8.

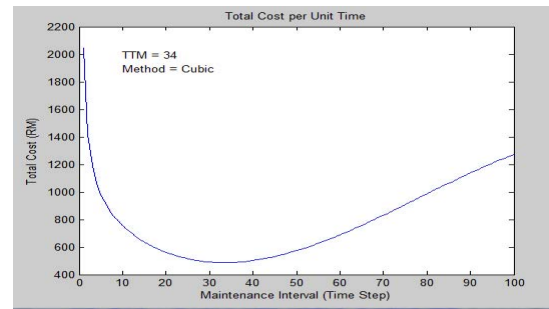


Figure 8. The optimal maintenance time

As illustrated in Fig. 8, the minimum maintenance interval based on minimum total cost per unit time $C(t)$ is 340 hours (one time step =10 running hours) with the cost would at RM 487 for the following set of unit maintenance costs $C_p = RM 1200$ and $C_c = RM 5000$.

VI. DISCUSSION

In this paper, the neural network prognostic model has demonstrated to obtain the RUL estimation based on the failure probabilities. With this tremendous FPs, the failure distribution can be fitted and able to generate failure distribution which can be used in the maintenance model for deciding maintenance time. It is found that the neural network prognostic model can prognosis the autoclave burner from normal to failure stage and able to be integrated with maintenance cost model in order to suggest the optimal

time to perform maintenance action which is at 320 hours. Having this result, the engineer in the industry can estimate the lifetime of equipments hence deciding to stop or continue the operation. Furthermore, by obtaining the optimal time to maintenance, it can improve the maintenance program in terms of cost and resources (i.e. maintenance staff and spare part) by reducing the unnecessary maintenance activity on the autoclave burner. Thus it is shown that the quality of maintenance can be achieved with proper planning.

VII. CONCLUSION

In practical maintenance program, the implementation of prognostic method is still small and needs a lot of the practical effort. The major contribution of this paper is to demonstrate neural network prognostics model for supporting maintenance decision by utilizing the existing condition data from real industrial equipment. The model has shown promising result and be able to improve the implementation of prognostics approach in maintenance. Future work includes validating the proposed model to other types of equipment in the industry.

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REFERENCES

- [1] J. Yan, M. Koc, and J. Lee, "A prognostic algorithm for machine performance assessment and its application". *Production Planning & Control*, Vol. 15, 796-801, 2004.
- [2] V. T. Tran and B. S. Yang, "Data-driven approach to machine condition prognosis using least square regression tree". *Journal of mechanical science and technology*, Vol. 23, 1468-1475, 2009.
- [3] A. Heng, S. Zhang, A. Tan, and J. Mathew, "Rotating machinery prognostics: State of the art, challenges and opportunities". *Mechanical Systems and Signal Processing*, Vol. 23, 724-739, 2009.
- [4] A. Muller, M. Suhner, and B. lung, "Formalisation of a new prognosis model for supporting proactive maintenance implementation on industrial system". *Reliability Engineering and System Safety*, Vol. 93, 234-253, 2008.
- [5] M. Dong and D. He, "Hidden semi-Markov model-based methodology for multi-sensor equipment health diagnosis and prognosis". *European Journal of Operational Research*, Vol. 178, 858-878, 2007.
- [6] A. Elwany and N. Gebraeel, "Sensor-driven prognostic models for equipment replacement and spare parts inventory". *IIE Transactions*, Vol. 40, 629-639, 2008.
- [7] A. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance". *Mechanical Systems and Signal Processing*, Vol. 20, 1483-1510, 2006.
- [8] V. Tran, B. Yang, and A. Tan, "Multi-step ahead direct prediction for the machine condition prognosis using regression trees and neuro-fuzzy systems". *Expert Systems with Applications*, Vol. 36, 9378-9387, 2009.
- [9] V. Tran, B. Yang, M. Oh, and A. Tan, "Machine condition prognosis based on regression trees and one-step-ahead prediction". *Mechanical Systems and Signal Processing*, Vol. 22, 1179-1193, 2008.
- [10] M. Schwabacher, "A survey of data-driven prognostics". in *Proceedings of the AIAA Infotech@ Aerospace Conference*. 2005. Arlington, USA: Citeseer.
- [11] S. Agatonovic-Kustrin and R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research". *Journal of pharmaceutical and biomedical analysis*, Vol. 22, 717-727, 2000.
- [12] Y. Tan and A. Van Cauwenberghe, "Neural-network-based d-step-ahead predictors for nonlinear systems with time delay". *Engineering applications of artificial intelligence*, Vol. 12, 21-35, 1999.
- [13] J. Lee, J. Ni, D. Djurdjanovic, H. Qiu, and H. Liao, "Intelligent prognostics tools and e-maintenance". *Computers in industry*, Vol. 57, 476-489, 2006.
- [14] W. Caesarendra, A. Widodo, and B. Yang, "Application of relevance vector machine and logistic regression for machine degradation assessment". *Mechanical Systems and Signal Processing*, Vol. 24, 1161-1171, 2010.
- [15] Y. Sun, V. Babovic, and E. Chan, "Multi-step-ahead model error prediction using time-delay neural networks combined with chaos theory". *Journal of Hydrology*, Vol., 2010.
- [16] J. Heaton, *Introduction to Neural Networks for Java: Heaton Research Inc*, 2008.
- [17] B. Bradley, R. Jacob, J. Hermance, and J. Mustard, "A curve-fitting technique to derive inter-annual phonologies from time series of noisy NDVI satellite data". *Remote Sensing of Environment*, Vol. 106, 137-145, 2007.
- [18] P. Jonsson and L. Eklundh, "Seasonality extraction by function fitting to time-series of satellite sensor data". *Geoscience and Remote Sensing, IEEE Transactions on*, Vol. 40, 1824-1832, 2002.
- [19] R. V. L. Joosen, J. Kodde, L. A. J. Willems, W. Ligterink, L. H. W. Van Der Plas, and H. W. M. Hilhorst, "germinator: a software package for high throughput scoring and curve fitting of Arabidopsis seed germination". *The Plant Journal*, Vol. 62, 148-159, 2010.
- [20] A. Grall, C. Berenguer, and L. Dieulle, "A condition-based maintenance policy for stochastically deteriorating systems". *Reliability Engineering & System Safety*, Vol. 76, 167-180, 2002.
- [21] S. A. Asmai, B. Hussin, A. S. H. Basari, and N. K. Ibrahim, "Equipment Condition-based Prognosis Using Logistic Regression :An Industrial A Case Study". in *4th Asia-Pacific International Symposium on Advanced Reliability*. 2010. Wellington, New Zealand: Mc Graw-Hill, Dec, 2010.