A Framework of an Intelligent Maintenance Prognosis Tool

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Abstract— **The technology of prognosis has become a significant approach but its implementation in maintenance has a major extension. The ability prognosis in the medical area has been established to estimate the future of human health. However, in maintenance, application of prognosis is not yet seen as a practical use for making better maintenance decision. To date, research in this area has been done in proposing prognosis techniques or model but leaving the implementation of prognosis as their future work. In this paper, an overview of prognosis in maintenance is presented. By using the data-driven approach, a framework for implementing of an intelligent maintenance prognosis tool is introduced. The framework utilizes the existing equipment operating performance data in the industry for prognosis process. Next, the framework combines the ability of prognosis in estimating remaining useful life (RUL) of equipment with the maintenance action knowledge to generate a well-received maintenance plan.**

Keywords-component; Maintenance; Condition-based Maintenance(CBM); Prognosis; Data-driven; Remaining useful life (RUL)

I. INTRODUCTION

Preventive Maintenance is the most common maintenance strategy in industry for maintaining and preventing machines from catastrophic failure and breakdown[1]. In preventive maintenance, the determination of maintenance interval is critical. This is because the inefficiency contributes unnecessary maintenance action, premature spare-part replacement, waste in maintenance workers allocation and more interruption in production operation. Traditional preventive maintenance uses time-based parameter such as age-related, operating usage or failure distribution for calculating the maintenance intervals in a preventive maintenance schedule of an equipment[2]. However, Luo et al [2] has addressed that the most of the equipment failures are not related to the amount of usage operation.

As a result, the time-based maintenance intervals are not well-implemented in production to give allocation time to maintenance especially for equipment which continuously produces high volume outputs, expensive spare-parts and limited maintenance workers. Therefore, another strategy for preventive maintenance needs to be carried out.

II. MOTIVATION

Condition-based maintenance(CBM) is gaining its popularity as one of the maintenance solution to improve machine availability and eliminate unnecessary maintenance because of its capabilities in monitoring and detecting potential failures[3, 4]. CBM recommends maintenance actions based on the information collected through condition monitoring variables [5]. Data about failure behavior from suitable condition monitoring variables are able to give information about the actual state of the system[6]. The variables such as vibration, temperature or acoustic that can be obtained through many sophisticated sensors and computerized database software are able to deliver data relating to status and performance equipment. However, the problem is that most of this data is not fully utilized or no practical use [7].

CBM employs diagnostics and prognostics approach for making maintenance decisions [5]. A study conducted by Jardine et al. [5] defines that diagnostics focuses on detection, isolation and identifies failure when they occur while prognostics focuses to predict failure before they occur. In medical field, the role of diagnostics and prognostics are quite common yet efficient. It has been widely used to detect and analyze a particular health problem in human including disease states identification, classification of disease severity, future disease assessment and risk stratification to aid in treatment decisions[8]. In contrast, the approach applied in industry for maintenance today mainly focuses on diagnostic capabilities, in which give only short notice to maintenance engineers soon after sign of failure is detected[9]. Acknowledging the capability of the prognosis approach in failure predicting, prognostics approach in maintenance decision is used in this research in order to provide sufficient time for maintenance planning and reduce unnecessary maintenance action in production plant. In order to understand the use of prognosis, an overview of prognosis in maintenance area is discussed in next section.

III. PROGNOSIS IN MAINTENANCE

Prognosis is a relatively new area and has become a significant function into a maintenance system [10]. From human perspective, it seems that machines fail abruptly. But the fact machines usually go through a measurable sign of failure before occurring [9]. Because of this situation, prognosis is able to use this measurable sign for predicting and estimating the amount of time is left before failure. Thus in the study, prognosis 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 machine condition variable and past operation profile [5]. The observed condition can be attributed from physical characteristics or process performance to its failures. For instance, vibration signature and oil analysis have been successfully used for monitoring the presence of failure in equipment[9]. Other alternative condition parameters that can be used in prognostic are acoustic data, temperature, pressure, moisture, humidity, weather or environment data, etc [5]. These observed condition is subject to data input of the prognosis process.

Currently, prognosis process can be categorized in numerous approaches ranging from historical failure rate models to physics-based models [10]. Based on literature in this study, prognostic approaches can be classified into three basic groups; model-based prognostic, data driven prognostics and experience-based prognostic [2, 10, 11]. Fig. 1 is a proposed taxonomy of prognosis approaches in maintenance.

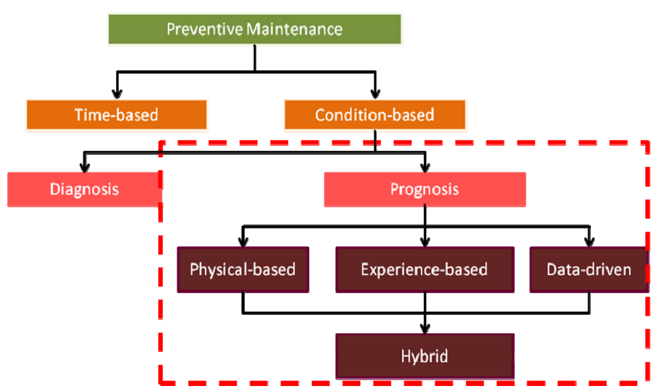

Figure 1. A proposed taxonomy of prognosis in maintenance

A. *Data –driven*

The data-driven approaches use the routinely observed system operating data to track, approximate and forecast the system degardation behavior [12]. Data collected under nominal and degraded condition associated with statistical or artificial intelligence techniques can generate an appropriate prognosis model. With the technology of sophisticated sensors and database software much of the work in data-driven prognosis have been proposed. Vachtsevanos and Wang [13] used dynamic wavelet neural network to predict the failure and estimate the RUL based on the vibration data from cracked bearings. Wang [3] developed a two stage prognosis model by using a Hidden Markov process for estimating an item's life till replacement. Dong and He [4] also used a Hidden Markov Process to estimate RUL of hydraulic pump based data using the growth of contamination stage. Some other research concentrate to produce accurate prognosis results such as Dragomir et al. [14] which utilized Adaptive Neuro-Fuzzy inference for stabilizing the error of prognosis. While the study conducted by Tran et al. [10] used two types of vibration datasets; training and testing into Regression Trees method for machine prognosis, the strength of data-driven techniques is their ability to recode from high level data into low level information for any decisons purpose. However, data-driven approach is highly-dependent on quantity and quality of operational data[15].

B. *Model-based*

Model-based prognosis is an alternative approach for time saving in collecting sufficient quantity and quality of operating data. The model-based prognostic approach is applicable in situations where an accurate mathematical model can be constructed from first principle of system's failure modes[10]. Thus, it requires specific mechanistic knowledge and theory of monitored equipment[5]. A number of applications of model-based design can be found in automotive, aerospace and defence industries. Abbas et al.[16] developed a mechanistic model of Electrical Power Generation and Storage (EPGS) such as battery, generator, electrical loads and voltage controller associated particle filtering technique for estimating RUL. The main advantage of model-based approaches is the ability to understand the physical of the particular system to monitoring [15] Because of that, those developed techniques are merely applied for some specific systems and each of them needs a different mathematical model[10]. Furthermore, an accurate model is so difficult to establish and mimic the real life of the system.

C. *Experience -based*

Experience–based prognosis is an approach which does not depend on equipment's historical data or the output from mechanistic model-based system. The approach solely depends on expert judgment [10]. The study in experience-based prognosis focuses on the development of rule-based model [12]. Kothamasu, and Huang [17] utilized an Adaptive Mamdani Fuzzy method to formulate the expert's knowledge to give the expected result on state of machine. This type of prognosis is not common to be addressed because the prognosis researchers are more focused towards the existence of numerical condition of data.

D. Hybrid

Hybrid approaches are also possible which combines an approach with one or more of the other approaches. For instance, hybrid approach can combine the data-driven approach with one or more of the other approaches[12]. It possibly offers a more reliable and accurate prognostic results [7, 12]. A hybrid technique such as through an understanding of the failures modes and theirs effects of physical model or statistical and learning techniques based on failure progression data (e.g. field failure data) can also be employed to system, or components observed[15]

As a summary of this overview, most published prognosis research in maintenance has stated their intention to do prognostics. Their progress is reported to be in fault detection, but most of them left the prognosis process to future work. Moreover, current prognosis researches are focused on solving the failure prediction problem and only few papers addressed the use of prognosis in maintenance management. Tools used for practical prognosis has also not been well addressed or not yet developed[9]. The recent study from Heng et al.[1] also shows that current prognosis model might only function well under controlled experimental conditions but remain further research for practical applications. Thus, the research focuses to introduce the framework for practically implementing prognosis in maintenance by using the data-driven prognosis concept.

IV. A Framework of An Intelligent Maintenance Prognosis Tool

In this paper, a novel framework on how this intelligent prognosis tools could be applied in maintenance is proposed as shown in fig. 2.

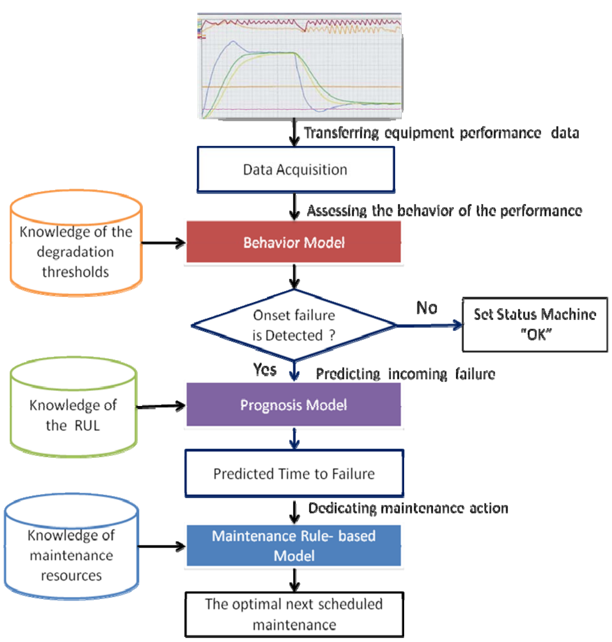

Figure 2. A framework of an intelligent maintenance prognosis tool

In general, the framework consists of four important sub-modules such as data acquisition process, fault identification, prognostic data analysis and maintenance decision process. The details of the framework are described below:

A. Data Acquisition Process

The first step of the framework is data acquisition process. The process is important to obtain the observed condition data. A lot of CBM researchers concentrate to develop the new extremely complex data acquisition architectures [18] . It is however not the focus of this study. The advances in sensing and data measurement technology, automated data collection from multiple sensors installed on equipment or existing database equipment software provide large volume of datasets[4].

In the purposed framework, equipment operating performance datasets are used to find presence of failure or fault. The datasets are obtained through the existing database equipment software based on multiple sensors installed on equipment. The main reason why this study uses the existing database is because it is able to provide a large volume of historical operational performance datasets and supply new operational dataset. Thus, the datasets are potentially used for learning behavior process in order to create new degradation knowledge.

B. Fault Identification

In this framework, all historical datasets from the existing database equipment software will be extracted into a new degradation database. This degradation database can be used to train and construct the new knowledge for generating the degradation threshold process. The threshold can be used as behavior model to identify the presence of failure or fault in a new of equipment operating dataset. The thresholds can be formulated by deploying statistic techniques or artificial learning techniques into the existing historical datasets. Usually, low-level signal processing is good enough to obtain satisfied threshold[5]. The most important part of threshold is that it can decide consistently the level of acceptable l_a or unacceptable l_u in any pattern of the observed operation parameter.

As the second stage of the framework, the new observed dataset can be assessed with the behavior threshold to determine the presence of failure. If the observed condition reading is no longer the control limit of threshold, then the status of equipment intelligently indicate nominal behavior. Thus, the equipment remains available the next operational jobs without requiring any maintenance action. If only the proposed tool indicates fault in the observed dataset, the observed dataset will automatically be moved and used to the prognosis process stage for estimating the occurrence of failure.

C. *Prognosis Process*

Once the observed performance dataset stated that there is a fault based on the level unacceptable control limit of behavior threshold model, next, the research looks at the prognosis process stage. Since the complete historical failure data is available in the existing database, the prognosis model parameter can easily be estimated. In this framework, we assume that by using the observed condition feature such as kurtosis, it is able to provide a prognosis data[4]. Thus the length of sign in unacceptable level x is defined as the independent parameter of our prognosis model and remaining useful life r_i which implies from $t_{failure}$-t_{sign} can be the dependent parameter as shown in Fig. 3.

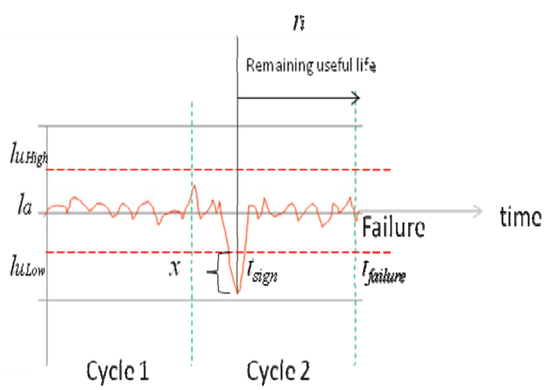

Figure 3. The remaining useful life

As a result, the statistical learning process using simple linear regression in relationship between the r_i and x can generate useful prognosis estimation model. Then, the model can be used for predicting time failure when the assessment new condition equipment operating performance needed.

D. *Maintenance Decision Process*

The proposed framework incorporates with the maintenance decision process. The information about the time to failure or remaining useful life from prognosis process can be used to recommend better maintenance planning. Acknowledging the remaining useful time value, allow the maintenance engineers to have enough time to prepare maintenance resources such as maintenance workers, spare-part and other requirements. Furthermore, this information is very important to production people to acknowledge about the status of equipment before proceeding with the new production jobs into equipments. In the past, without knowing remaining useful life, many industries suffered the material waste and production loss due to equipment breakdown the middle of operation.

As the framework made use data-driven approach, once a quantitative parameter of RUL (unit of time) on the prognosis process has been obtained, the parameter can be easily transformed to a set of critical time level according experience-based information as shown in table 1. This set of level is important and give more impact to the maintenance engineers to understand the need of equipment to be maintained. Using this as the critical level, this research can generate a maintenance rule-based model with other parameters in maintenance to provide more accurate result.

TABLE 1: AN EXAMPLE OF THREE BASICS CRITICALITY LEVEL

r_i(in time unit-hours)	<24	24< r_i<36	More than 36
Criticality level	High	Medium	Low

A variety of intelligent techniques can be embedded into this maintenance module. For an example, by using Fuzzy rule-based which implies IF…THEN rule, it is able to suggest the level of maintenance action needed before the occurrences of failure. However, the content of each maintenance level action should be identified according the company's maintenance capacities.

V. CONCLUSION

In this paper, a framework is designed in this paper in which the existing numeric operating equipment performances can be utilized for learning the behavior of failure. The data are used to generate a behavior threshold for detecting a potential failure given the control limit of acceptance performance. From the behavior threshold model, it can be used to detecting presence of failure given the control limit of acceptance performance. The value generated beyond the acceptance limit is useful for formulating a prognosis parameter. In this framework, the prognosis parameter is the remaining useful life and has the potential to be utilized in the maintenance decision process. Furthermore, testing the framework with the actual dataset associated with the identified techniques is also in this research's future plans.

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