Study on Condition Based Maintenance Using On-Line Monitoring and Prognostics Suitable to a Research Reactor

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ABSTRACT

The purpose of this paper is to look into a more effective way for how condition based maintenance using on-line monitoring and prognostics can be applied to the components/systems in the field of a research reactor, which has been demanded to upgrade or modify the existing MMIS. The requirements of the contemporary diagnostics and prognostics herein are briefly introduced and then an assessment of the actual application to a research reactor is reviewed.

1. INTRODUCTION

The requirements for equipment qualification applied to the nuclear industry have been getting stricter and more challenging in particular since the Fukushima accident. This also strongly influences Research Reactors (RRs) as well as Nuclear Power Plants (NPPs). Most RRs have been recently forced to be modernized or refurbished for lifetime extension or uprating. On the other hand this demand could provide a great opportunity to realize the Condition Based Maintenance (CBM) where the diagnosis and prognosis technique is applied to the upgraded Human-Machine Interface (HMI) system. The health monitoring for the component and system is definitely considered important but the CBM using a suitable prognostic technique should be established in the RR in the near future as found in (NUREG/CR-6895, 2006).

The advantage of CBM is its direct contribution to minimize the cost and prevent unnecessary downtime compared with regular based maintenance. In addition, it also helps to minimize the risk of radiation exposure as low as reasonably achievable owing to less frequency of access to radiation zones and gain invisible benefit such as reducing public anxiety caused from a reactor shutdown. If only utilization of the on-line monitoring technology for system health and prognostics can be maximized, it will be readily possible to predict the estimated Remained Useful Life (RUL) to set up the optimized conditional maintenance plan using an on-line monitoring technique and verified prognostics.

The most remarkable feature in a RR is to have different aspects from a NPP in the case of the operating conditions such as a specific temperature and pressure boundary. The condition in the RR is considerably moderated owing to lower temperature and pressure compared with the NPP case, and it is literally interpreted that the environmental conditions are not severe and therefore so many parts of requirement are under discussion in order to apply to the graded approach. These points are expected to make it easier for the RR to have more various experiments and available application.

2. PROGNOSTICS AND CONDITION BASED MAINTENANCE

Prognosis can be defined as the prediction of future health states and failure modes based on current health assessments, historical trends and projected usage loads on the equipment and/or process according to recent trends as shown in (Singer, R.M., K.C. Gross, J.P. Herzog, R.W. King, and S.W. Wegerich, 1996). These prognostics are inevitable factor to realize the CBM because the CBM is developed by considering the degradation progression. The main idea of CBM is to utilize the system's or component's degradation information extracted and identified from on-line monitoring instruments to minimize the system downtime by balancing the risk of failure and achievable profits. The decision making in CBM focuses on how effectively the predictive maintenance is performed as shown in (IAEA-TECDOC-1625, 2009).

2.1. Diagnostic-Prognostic Process

As mentioned above, the current failure mode, its cause and effect as well as its extent of degradation are very important for exact prognostics. To determine the RUL of a component, it is inevitable to know and understand the following necessary information in advance: (a) degraded state of the component, (b) cause of initiating the degradation, (c) severity level of the degradation, (d) degradation progress speed from its current state to functional failure (e) method to classify novel events related with degradation, and (f) other factors (e.g. measurement noise) affecting the estimate of the RUL as found in (ISO 13381-1, 2004). If these prerequisites are well prepared, it will be followed by a diagnostic-prognostic process. It is significant to classify several steps into the diagnostics with using data preprocessing and prognostics with the RUL determination as shown in Figure 1.
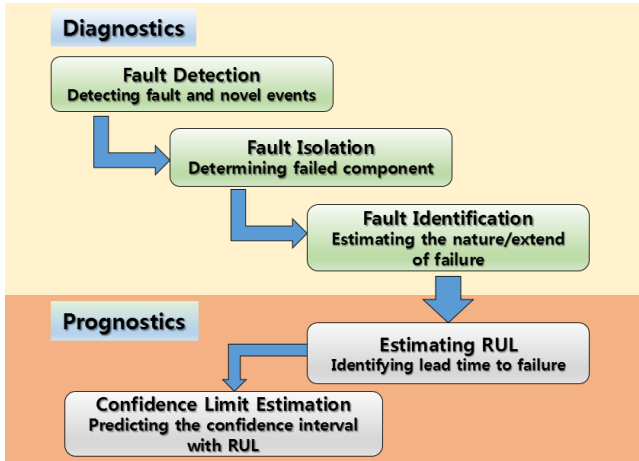

Figure 1. Process step of diagnostics and prognostics.

In diagnosis stage, faults including novel events are detected and abnormal operating conditions are reported upon fault detection. After fault isolation a specific component which is under failure is identified at the stage of fault identification, the extent and nature of the fault is estimated. In the prognosis stage, a time to failure is evaluated based on the fault identification and the appropriate confidence limit is calculated.

2.2. Selection of Suitable Prognostic Model

The CBM program is determined by decision making subject to the operating goal and management plan. The prognostic model should be carefully selected to take the characteristics of the system into account especially for the actual operating conditions. For this reason we have to consider the prognostics in detail and how to implement the prognostics model in a case by case manner.

2.2.1. Prognostics Types by Implemented Sequence

The prognostics type can be classified by three different activities such as existing failure mode prognostics, future failure mode prognostics and post-action prognostics, which are called steps 1 through 3 prognostics, respectively, as they involve an increasing level of modelling and implementation complexity. Step 1 provides estimates for the RUL of components subject to how each diagnosed failure mode is going. Step 2 evaluates the postulated effects of identified failure mode on other potential failure modes in order to evaluate the worst case scenario for the affected components/systems. Step 3 assesses how aforementioned models are affected by maintenance actions at last. As each prognostic level requires the accurate and reliable outputs from the preceding step the likelihood of success is sure to increase. This approach increases a potential enhancement to prognostic capability.

2.2.2. Implementing Prognostics Model

A modified classification approach is proposed here that was specifically designed for the RUL prediction as shown in Figure 2, which is categorized into four main groups and a few numbers of subgroups. Knowledge-based models assess the correlation between observed measurements and a databank of previously defined failures using an expert system or a fuzzy rule as mentioned in (G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess and B. Wu, 2006). The determined life expectancy models literally estimate the RUL of components based on the deterioration under known operating condition using a stochastic model and statistical model such as an auto-regressive moving average and proportional hazards model. Artificial neural networks compute an estimated output for the RUL from a mathematical representation, which has been derived from observation data rather than through a physical understanding. Finally, the physical model represents the behavior of the degradation process based on physical laws as remarked in (G. Vachtsevanos, F. L Lewis, M. Roemer, A. Hess and B. Wu, 2006).
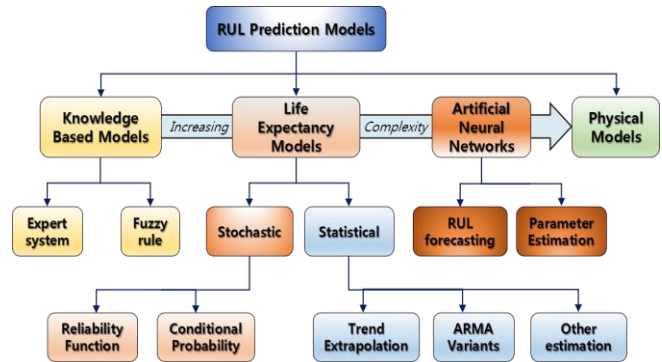

Figure 2. Main model categories for RUL prediction

Ultimately a model selection requires that all advantages and weak points be understood and more importantly how well

the actual system operating condition is reflected in the process of model selection.

3. APPROACH FOR APPLICATION TO RESEARCH REACTOR

There are a number of approaches to realize the optimal condition based maintenance, and among them, an on-line monitoring instrument channel calibration is a very simple but effective way to adjust the maintenance term, although it is not exactly the tracking system condition. It is used to identify invalid sensor data that seem faulty due to zero readings, missing data, jump, noise, etc. In addition, sensor anomalies, such as drift and a slow response can be accounted for in validating an array of raw data. Three channels of data from the pressure transmitter are herein introduced, which are used for measuring the hydrogen of the cold neutron source system in a RR.

3.1. On-line Monitoring Data Analysis for the CNS

These pressure transmitters in the CNS of an RR have three redundant sensors, which it means it can perform calibration monitoring, consistency checking, and signal validation. In addition, with redundant sensors, calibration monitoring can be performed using simple averaging techniques as proposed in (M.carnero, 2006). The deviation from the holistic mean among groups of transmitters can be monitored online, and upper/lower limits can be set to trigger alarms if the deviation exceeds that expected for drift candidacy. The signals are subject to pre-set limits of operation. If a value were to exceed these limits, an alarm would be raised, thus indicating the drift.

When analyzing the regularly sampled data through six months, as shown in Figure 3, each channel has shown the hydrogen value staying within a normal range through the whole duration except for certain outliers. There is a just a little deviation between the holistic mean and all channels of values.
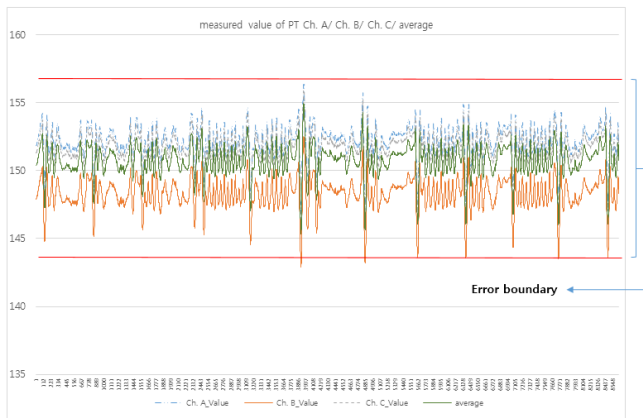

Figure 3. Collected data for on-line monitoring application

The most important thing is to identify how much the drift of the instrument is in progress, and a drift analysis shows that

the results from on-line monitoring are better than one from an off-line data analysis. This implies that the maintenance plan and period for a relevant sensor can be adjusted only if the uncertainty on this instrument is fully considered, which can affect both the performance and accuracy of on-line monitoring technique, which utilize the data gathered using the instrument channels as introduced in (A. Yamada & S. Takata, 2002).

3.2. Diagnostics and Prognostics Applied to RR

In a research reactor the critical rotating machines such as a Primary Cooling System (PCS) pump are monitored either continuously or by periodic vibration measurements. This is to monitor the shaft displacement and the vibration level of the PCS pump frame. The Vibration Monitoring System (VMS) is designed to provide an alarm signal to the Main Control Room when the vibration level exceeds the allowable limit as commented in (W. Wu, J.Hu and J. Zhang, IEEE, 2007). It also provides information to be used in analyzing the status of the PCS pump, which incorporates the electrical, mechanical, operational, and environmental condition for detecting the symptom of the shaft crack, and misalignment and rotor balancing, as shown in Figure 4.
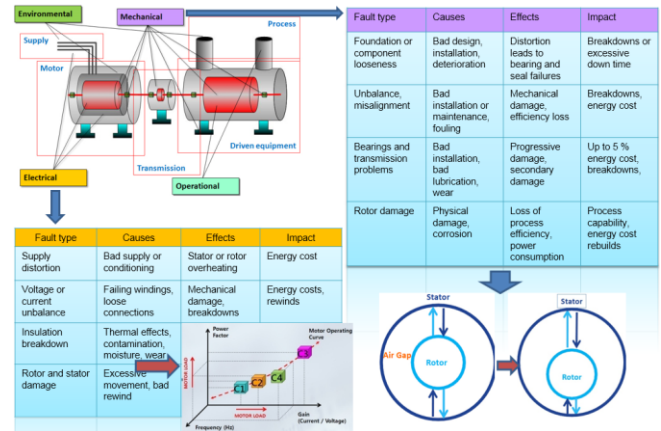

Figure 4. VMS principle and configuration

The change in the internal characteristics of a motor(eg. Short winding) will cause the real motor transfer function to change. In the case of mechanical fault detection, if it is assumed that an unbalance occurs, it causes the rotating rotor/stator gap to change, which will make the amplitude modulation shown in the sidebands appear around the line frequency in the spectrum, as shown in Figure 5. For more accurate fault detection, sufficient terms of the learn phase are needed, and after this initial learning, the VMS begins to be monitored as found in (S.J. Engel, B.J. Gilmartin, K. Bongort and A. Hess, IEEE, 2000). Through this VMS, we can recognize the symptoms of the component failure in advance before the fault is worse to exceed the tolerance. However, it was actually found to be a little difficult to predict the RUL in the only this manner. This results in difficulties to confirm the maintenance schedule which has to

be estimated upon the system performance. This is because the prognostics in an RR currently depend on a knowledge-based system such as an expert system.
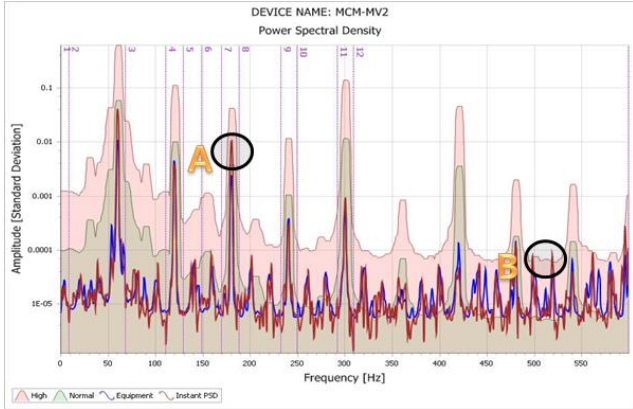

Figure 5. Anomalies estimated from PSD

3.3. Comparison of Prognostics Candidacy

There are many prognostics available to the system in the RR, as aforementioned here, which has an advantageous condition of relatively low temperature, pressure, and radiation level. This enables us to have a large number of opportunities to try in the application of advanced prognostics. This is because the structure of the RR is simpler, which makes it easier for a design change than an NPP. To summarize this, the environmental condition is more moderate in an RR, and a simplified system, components, and structure for the experiment is considered the optimal conditions for testing and verifying whether the prognostics is available in various actual operating conditions.

Table 1. Comparison between prognostics models.

Prognostics Model	Anticipated Advantage to RR	Anticipated Disadvantage to RR
Knowledge Based Expert System	Easy to develop and understand	1. High dependency on experts 2. No confidence limit 3. Not possible to predict exact RUL
Reliability Function	1. Numerous software option 2. Confidence Limit available	1. Demand of too big sample size 2. Not possible to prior to actual failure
Artificial Neural Networks	1. Available under large noises 2. RUL model is available	1. Data is complex or symbolic 2. Temporal input is not available due to learning period
Physical Models	High accuracy in RUL prediction	1. Physical model is hardly available

Table 1 shows a comparison of the prognostics model, which is narrowed down as suitable to apply to the system in the RR. From the viewpoint of RUL, it is the best way to adapt the Artificial Neural Network (ANN) or physical model, but in terms of cost and benefit, an expert system or reliability function is a good alternative to prognostics as proposed in (J. Lee, J. Ni, D. Djurdjanovic, H. Qiu, and H. Liao, 2006).

3.4. Consideration of Uncertainty

The obvious obstacle of acquiring the exact prediction of RUL as well as accurate diagnosis is the inherent uncertainty of the objective. In order to establish the condition based maintenance (CBM) with elegance, it is required to analyze uncertainty associated with the deterioration process and ambiguity of future operation. However it is a difficult task to deal with this uncertainty because it arises from a variety of sources, and is filtered through complicated non-linear system dynamics. In order to find out the resolution, several uncertainty representations such as interval mathematics, and fuzzy have been already introduced.

4. CONCLUSION

On-line monitoring for redundant instrument channels is applied to the CNS of a research reactor for hydrogen trip parameters, and it shows the contribution of this result to adjust the maintenance schedule more efficiently. The aforementioned vibration monitoring system is used for a kind of prognostics suitable to a research reactor, and prominent prognostics models suitable to the research reactor were proposed to exploit this application, and consideration of the uncertainty was shortly addressed. Thanks to the high performance of new prognostics methodology, the application of the on-line monitoring and prognostics to the research reactor seems to be very bright in the near future.

REFERENCES

NUREG/CR-6895, Technical Review of On-Line Monitoring Techniques for Performance Assessment, Volume1: State-of-the-art, 2006

Singer, R.M., K.C. Gross, J.P. Herzog, R.W. King, and S.W. Wegerich, "Model-Based Power Plant Monitoring and Fault Detection: Theoretical Foundations," Proc. 9th Intl. Conf. on Intelligent Systems Applications to Power Systems, 1996

IAEA-TECDOC-1625 Research Reactor Modernization and Refurbishment, 2009

ISO 13381-1, Condition Monitoring and Diagnostics of Machines-prognostics – part1: General Guidelines: International Standards Organization, 2004

G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess, B. Wu, Intelligent Fault Diagnosis and Prognosis for

Engineering Systems, John Wiley and Sons Inc., Hoboken, New Jersey, 2006.

G. Vachtsevanos, Lewis, F. L., Roemer, M., Hess, A. & Wu, B. (2006). Intelligent Fault Diagnosis and Prognosis for engineering system, Hoboken, NJ: John Wiley & Sons, Inc

M.carnero. An evaluation system of the setting up of predictive maintenance programs, Reliability Engineering and System Safety, 2006

A. Yamada, S. Takata, Reliability improvement of industrial robots by optimizing operation plans based on deterioration evaluation, Annals of CIRP 51/1 (2002) 319–322.

W. Wu, J.Hu, J. Zhang, Prognostics of machine health condition using an improved ARIMA-based prediction method, IEEE, Harbin, China, 2007, pp. 1062–1067.

S.J. Engel, B.J. Gilmartin, K. Bongort, A. Hess, Prognostics, the real issues involved with predicting life remaining, in: Aerospace Conference Proceedings, vol. 6, IEEE, 2000,

J. Lee, J. Ni, D. Djurdjanovic, H. Qiu, H. Liao, Intelligent prognostics tools and e-maintenance, Computers in Industry 57 (6) (2006) 476–489

BIOGRAPHIES

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