CONDITION-BASED MAINTENANCE (CBM) IN NUCLEAR POWER: A SURVEY

***Mamuni Arya*[1], *Jibananda Jena*[2],**
[1, 2]*Gandhi Institute for Education & Technology, Bhubaneswar*

Keywords:
Condition-based maintenance
Monitoring
Diagnostics
Prognostic
Maintenance stakeholders

A B S T R A C T

Condition-based maintenance (CBM) is a maintenance approach centered on performing maintenance tasks according to the health status of the system. It has been widely adopted across various industries due to its effectiveness. This paper conducts a comprehensive survey focusing on the implementation of condition-based maintenance within the nuclear industry.

The survey systematically examines the key phases of CBM, namely monitoring, diagnostics, and prognostics. A thorough review is conducted on each of these aspects, encompassing both the existing practices within the nuclear sector and the ongoing research endeavors aimed at developing new methods and technologies.

By providing insights into current practices and the scope of research in condition-based maintenance within the nuclear industry, this survey aims to equip maintenance stakeholders and researchers with a comprehensive understanding of the field.

Contents

Copyright @ 2019 Authors

1. Introduction

Maintenance has evolved over time as advancement in technology and fast-growing research has been put into building more efficient and reliable systems. In the early days of production, the approach to maintenance was that of ''fix it after it fails" method. This was because simple machines were employed in production and demand was not so high. Therefore, the industries could afford to have downtimes; this type of maintenance is ter- med corrective maintenance. The periods after the world war II, the world began to experience great advancement in technology and the industries had more complex machines, the demands got higher and down times could mean being out of business. Asa result, maintenance approach has evolved from the corrective approach to a new approach, which is the preventive mainte- nance. The preventive type of maintenance from the 1970's, which is the periodic maintenance, involved scheduling maintenance at regular intervals to avoid failure. Over time as technology kept advancing, interest has shifted from ''avoiding failure" type of maintenance to a more cost-effective maintenance. This hasbrought about another type of preventive maintenance, which is the condition-based maintenance (CBM). CBM involves undertak- ing maintenance activities based on the health/ condition/level of degradation of the system/ equipment. In Table 1, the summary of how maintenance has evolved over time and the characteristics of the different types of maintenance is portrayed (Moubray, 1995; Agency, 2007).

CBM has found wide applications in many industries like aerospace, electronics, chemical industry, military and many critical facilities with good results. This paper intends to explore the state of CBM in the nuclear industry.

This paper is organized in seven (9) sections. The first section is the introduction. The second section explores CBM in the nuclear industry. The third section explains the state of monitoring. The fourth section describes detection in the nuclear industry, while the fifth section discusses diagnostics in the nuclear industry. The sixth section explicates the state of prognostics in the nuclear industry. The seventh and eight section discusses the different modelling methods used in CBM, and also strength, weakness, opportunity and threat (SWOT) analysis of these modelling methods. The last section is the conclusion.

2. Condition-based maintenance (CBM) in the nuclear industry

The nuclear industry is a major contributor to the world electricity. The nuclear industry does not just produce electricity, but it provides clean energy, which is free of greenhouse gases. Electricity from the nuclear plant is used mostly for base-load because it is reliable and steady. The nuclear power contribution to world electricity as at 1999 was 17% (Davies et al., 2000). Davies et.al mentioned that this percentage will most likely reduce in the coming decades due to challenges faced in the nuclear industry. This projection is a reality today because data from 1999 to 2015 has shown a decreasing trend of nuclear contribution to the world electricity. This is depicted in the Fig. 1 below. In the the last decade the contribution from nuclear power has been decreasing as given by world energy outlook (IEA, 2017).

One major factor affecting the nuclear power plant (NPP) is producing electricity in a cost-effective manner without jeopardizing safety (which is of highest priority in the nuclear industry). InNPPs, the cost of operations and maintenance (O&M) is about 60–70% of the total cost of generation (Coble et al., 2012). There- fore, to reduce the cost of producing electricity, one importantaspect to look at is the maintenance. For the NPP to compete suc- cessfully with other energy sources, the nuclear industry must reduce the cost of generating electricity, which can be made possi- ble through a condition-based maintenance strategy.

CBM has been widely used in other critical facilities like the aerospace, naval ships with very good outcomes. In addition, in the nuclear industry, places like the USA and Europe have incorporated CBM to their maintenance strategy and this has resulted in reduced maintenance cost and increased output. Bond et al. intheir analyses suggested that applying CBM to all key equipmentin legacy power plants in the United States will result in fleet-wide savings of over $1 billion per year (Bond et al., 2011). With CBM, the NPP will optimize its performance, as maintenance willbe done only when the plant condition requires it. Many of the NPPs across the world are ageing and are pressing for life extensionwhich makes ageing management one of the key issues in the nuclear industry (Pelo, 2013). At present, CBM is playing a key rolein the NPP life extension programmes in the United States.

NPP equipment is majorly categorized into three (3), which are, structures, systems and components (SSC). These SSCs are further

Table 1
Types of Maintenance system and their characteristics.

Maintenance system					
Maintenance type		Period	Basis	Approach	Outcomes
Corrective		1950s	Failure	Fix it after it fails	❖ Downtimes ❖ Unplanned outages ❖ High cost of operation ❖ High cost of production ❖ High cost of repairs ❖ Lots of emergencies ❖ Unsatisfied customer ❖ Stressed management
Preventive	Time based	1970s	Regular intervals	Service/ repair at intervals	❖ Reduced downtimes ❖ Planned maintenance ❖ Costly maintenance ❖ Lower cost of operation ❖ Replacement of good parts ❖ Less emergencies ❖ Unnecessary maintenance ❖ Satisfied customer ❖ Unsatisfied management
	Condition based	Current practice	Plant condition	Service/repair based on level of degradation	❖ Reduced downtimes ❖ Planned maintenance ❖ Cost effective maintenance ❖ Lower cost of operation ❖ Replacement of only bad component parts ❖ Increased production ❖ Plant life extension ❖ Less emergency activities ❖ Satisfied customer ❖ Satisfied management

Copyright @ 2019 Authors

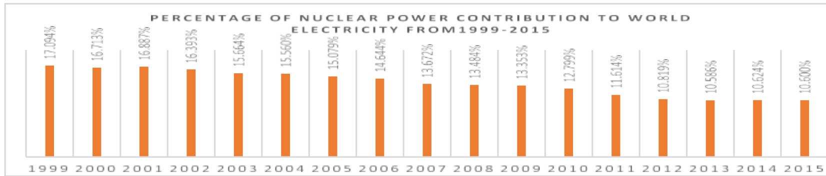

Fig. 1. Percentage of nuclear power contribution to world electricity from1999-2015.

classified as active and passive. The active SSCs are the ones that move and the passive SSCs are the non-moving ones. Maintenance is carried out based on these categories in line with their design and functions. Maintenance program in the nuclear industry is a combination of policies, processes and procedures that inform the type of maintenance that should be used for the plant structures, systems or components (SSCs). For the NPP to be operated safely there is a need for an effective maintenance. Maintenance in the NPP entails different activities which include surveillance, inspection, testing, service, overhaul, repairs and part replacements.

Implementing CBM in the nuclear industry is quite different from other industries because of the unique nature of the nuclear industry. The factors that have made the nuclear industry unique are listed below. Part of these factors are beneficial to the application of CBM while the others account for the reason CBM has not been widely applied in the industry.

- The nuclear industry has safety systems that are normally being monitored and tested extensively, which provides a wealth of data of the plant condition, thereby reducing the cost that is required for monitoring and surveillance. This is a very useful factor that can aid the implementation of CBM in the nuclear industry (Chapin et al., 1999).
- The nuclear industry, in particular, is highly regulated owing to the risks associated with plant accidents and radiation exposure to the public. The introduction of any new technology that impacts safety and protection systems in an NPP is scrutinized to such an extent that many systems never get implemented (Agency, 1999). This particularly has caused the foot-dragging in adopting CBM in the nuclear industry but this can be over- come by introducing CBM systematically by starting with components that are of less concern to the regulators. So this would have made the technology of interest to be well tested, proven and trusted enough to be used in other safety-related applications.
- The NPP has built-in redundancy and spare capacity. This also will aid CBM as it will make decision making easier when problems are detected.
- The ageing management of key components is a major issue as some of the components have become obsolete and no longer being produced and the stringent regulatory process of the nuclear industry does not allow the use of just any off- the-shelf component (Pelo, 2013).

CBM entails; condition monitoring, detecting, diagnostics and prognostics. The first stage of CBM is monitoring which involves surveillance, testing, using special equipment and techniques in knowing the state of the plant. The results from condition monitoring will help in detecting any abnormality in the plant operations. The next step in CBM is diagnostics which involve characterizing the detected abnormality, i.e. locating and knowing the magnitude of the fault. The results of monitoring, detection and diagnostics canbe analyzed through different methods to project and determine the possible time of failure of the equipment which is the estima- tion of the remaining useful life. The results from all these stagesof CBM can help the maintenance personnel to make a useful deci- sion about the type and time of maintenance to be done. Fig. 2 below shows the different stages of CBM. The state of each of the stages in the nuclear industry is discussed in the following sections.

3. State of condition monitoring in the nuclear industry

Monitoring is a very crucial aspect of condition-based maintenance. It is the foundation of CBM. Every other aspect of CBM depends on the output of plant monitoring. The effectiveness of CBM depends largely on how accurate the monitoring process is done. This section covers a review on the state of research on different monitoring techniques employed in the nuclear industry.

The monitoring practices in NPP are mostly conservative due to the unique safety requirements of the industry, which results in more expenses, but nuclear plants in the US and Europe have started adopting condition-based monitoring which is referred to as the On-line condition monitoring (OLM). OLM implies that the plant is being monitored and is available at the time, which means the nuclear plant is in operation, active and in service. Online in the nuclear industry also means that the system is operating in either start-up, normal steady-state operation or shutdown transient. With OLM, monitoring is being done in an un-intrusive, non-destructive and in-situ without obstructing the operations of the nuclear plant. OLM of the nuclear plant SSCs helps in detecting and diagnosing any abnormality in start-ups, normal operations and transient conditions. OLM gives the nuclear plant operator, information on the state of the plant and maintenance personnel, data for the necessary action to take. Series (2013) explains in details the different online monitoring technique in the nuclear industry.

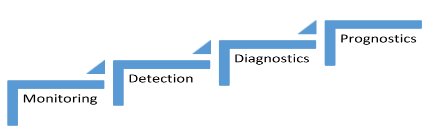

Fig. 2. Stages in condition-based maintenance.

Copyright @ 2019 Authors

Hines and Davis (2005) conducted a 'lessons learned' exercise on NPP on-line monitoring systems. They investigated state of condition monitoring system in the U.S. nuclear industry and highlighted the enormous research that has been put into the application of different online monitoring techniques. From their work, it can be observed that early focus of condition monitoring was on sensor calibration monitoring. They also explained that the emphasis now is presently on both sensor and equipment monitoring.

Majorly, data from on-line monitoring in nuclear plants, areused in checking vibration in reactor internals, measuring core sta-bility margins, leak detection, verify plant thermal performance, anticipate failures of rotating equipment, verify proper operation of valves, and identify and locate loose parts within the reactor system (Series, 2013). The recent research on the different types of monitoring techniques used in the NPP are discussed below:

3.1. Vibration monitoring

Monitoring vibration signals from the different SSCs of the nuclear plant can be an indicator of the state and health of these SSCs. Vibration monitoring involved measuring and analysing signals from the vibration sensors, which are typically accelerometers for high-frequency vibrations and neutron detectors for low-frequency vibrations. Several methods have been developed in literature on monitoring these vibration signals in different parts of the NPP. Many of the methods have been compared with the conventional monitoring techniques and have yielded desirable results. Some areas of application include the monitoring of vibra- tions in the reactor coolant pump carried out by Liu et al. (2015). Intheir work they developed a technique on flywheels in main cool- ant pumps using Hilbert- Huang transform (HHT) algorithm. Their results showed that the proposed method would be effective in condition-based maintenance of reactor main coolant pump. Koo and Kim (2000) also worked on vibration monitoring within reactor coolant pumps. There vibration monitoring system involved the introduction of a Wigner distribution (WD) which was used in analysing vibration signals. They compared their method, which was developed with WD to conventional methods based on Fourier transform. Their study showed vibration signals using WD are easier to analyse. Other notable research in monitoring vibrations in RCP include those carried out by Lebold et al. (2005), Prasad et al. (2002), Qinghu et al. (2009) and Ko and Kim (2013). Vibration monitoring is also used in monitoring the turbine blade conditions. (Rao and Dutta, 2010) described a method based on vibration signal analysis of the turbine casing. Their approach resulted in an early indication of vibration or failures in the nuclear plant turbine blades and in more economic manner. De Pauw et al. (2013) in their research carried out an estimation of the performance ofthe different vibration monitoring methods used for measuringflow-induced vibrations on a fuel pin mock-up. Maekawa et al.(2016) presented a non-contact measurement technique for vibra- tion stress in piping. Kong et al. (2014) also studied vibrations in piping systems. Czibók et al. (2003) monitored control rod vibra- tion signals for degradation. A review of vibration signal tech- niques used in the nuclear industry can be seen in Sinha (2008).

3.2. Acoustic monitoring

Acoustic monitoring involves the different methods used in measuring the acoustic emissions (AEs) of different processes and components in a nuclear facility (Series, 2013). While acoustic emissions (AEs) are transient elastic waves that originate from a speedy release of strain energy which is due to a damage/deformation inside or on the surface of a material (Matthews, 1983). Several techniques are being used in measuring and analysing AEs for monitoring different parts of the nuclear plant some of the research work include investigation using an acoustic monitoring system for timely detection of check valves was carried out by Lee et al. (2006a). They concluded that their approach was ableto predict correctly failures like disc wear failure and presence of foreign objects from flow characteristics and check valve leakage behaviours. Seong et al., (2005) also used AE signals in monitoring failures in check valves, which was achieved by developing a method based on the AE sensors. These AE sensors detected the sound waves of the leakage flow and then the power spectral den- sities are estimated with an auto-regressive model. They were ableto prove that the AE based technique was good for detecting check valve failures without the need for disassembling.

Al-Ghamd and Mba (2006) performed a comparative investigation on vibration monitoring and acoustic emission monitoring for bearing diagnosis. They found out that AE techniques were able to detect fault earlier and has more enhanced identification capability than the vibration analysis techniques. Other AE based monitoring techniques developed for nuclear plants can be seen in Kaewwaewnoi et al. (2010), Shimanskiy et al. (2004), Ai et al. (2010) and Lu et al. (2005).

3.3. Loose part monitoring

Loose parts monitoring is very vital for monitoring structural integrity. The loose part monitoring system (LPMS) is used to detect detached objects in the nuclear plant. Loose parts in the plant would cause flow blockage in the fuel channel, damage the pump impeller, and result in cracks in the steam generator's tube sheet. Detecting loose parts will prevent damage to the plant'sinternal structures (Choi et al., 2011).

A typical LPMS comprises of sets of accelerometers mounted on the reactor vessel, steam generators and reactor coolant pumps (Figedy and Oksa, 2005). LPMS makes use of audio signals and noise data records. When any part of the system is loose beyonda given set point the audio signal produces alarms. The alarm set points are based on the plant and the sensitivity of the loose parts monitoring equipment. When the alarm goes up, the next step is determining the location and size of the loose part, this is achieved by analysing the accelerometer output data. (Series, 2013; kimaet al., 2012). One major factor in building an LPMS is reducingthe false alarm rate.

Kim et al. (2002) designed LPMS applying the back propagation neural network. Their algorithm was used to estimate the mass of loose parts. The result showed that the neural network can be applied to LPMS. Their system also resulted in reduced false alarms.

Figedy and Oksa (2005) further enhanced the use of the neural networks in LPMS by combing the artificial neural networks and the wavelet in signal processing and enhancing the loose part monitoring system performance. Their method outdid the traditional methods of assessing the mass of loose parts by using the spectral index. Their method also resulted in suppressing false alarms.

The focus of Cao et al. (2012) research was also to reduce false alarms in LPMS which they achieved by developing a hybrid method for NPPs in which they combined linear predictive coding (LPC) and support vector machine (SVM). This they actualised in two stages; first, they detected weak burst signals at the initial stage then in the second stage was used in reducing the rate offalse alarms by identifying the detected burst signal.

3.4. Reactor noise analysis

Reactor noise analysis techniques make use of fluctuations in process signals (referred to as reactor noise) to get useful information on the system condition (Series, 2013). Reactor noise analysis

Copyright @ 2019 Authors

is useful in monitoring, investigating and diagnosing the internal core vibrations; determining and trending in details the coolant flow velocity distribution; monitoring of core-barrel motion; and in qualifying sensors (Czibók et al., 2004). Condition monitoring techniques based on noise analysis have been successfully employed in In-situ instrumentation channel dynamic performance monitoring in plants like the Ontario Power Generation in Canada (Ma and Jiang, 2011) Reactor noise analysis system was also installed in the upgrading of the monitoring system the Bors- sele NPP in Netherlands. The system was used measuring the reac-tor coolant pump vibrations and the core-barrel motions. The newly installed system satisfied the nuclear plant's maintenance need (Barutçu et al., 2003)

Reactor noise analysis is very useful in testing sensors response time. The speed of response in sensing lines that connect pressure, level and flow transmitters are reduced largely because of blockages, voids, and leaks. Amongst other techniques only the noise analysis can effectively test sensor response time while the nuclear plant is operating (Hashemian and Jiang, 2010) Noise analysis was employed in measuring the time response of the RPS's sensors and in ANGRA-I NPP. In their results, they observed that for systems whose power spectral density PSD showed a first-order behaviour, simple or not, the values of the time constant are easily determined, and the results are very coherent with the expected values. Even for quadratic systems, in cases where it was possible to identify the low frequencies asymptotes, the determination of the time constant was immediate and showed coherent values. But in cases where the low frequencies asymptotes were not accurately determined, the classification of the system was not possible, so the time constant associated with the break frequency has not shown a coherent value, but a much higher value than it would be expected as a true value for those sensors (Perillo et al., 2014).

Ansari et al. (2008) validated the application of neutron noise technique for detection of flow-induced vibrations of in-core components. They were able to calculate the magnitude of the displacement of vibrating control rod from the measured power spectral density of neutron noise.

3.5. Motor electrical signal analysis

The motor electrical signal analysis is used in monitoring the state of the nuclear plant electrical systems, which comprise of motors, actuators, generators, instruments channels, cables and electric circuits. Monitoring the electrical components is very important in nuclear plant maintenance (Series, 2013). The variation in current drawn by induction motor during load variation is used in monitoring. This approach is called the motor current signal analysis MCSA. (Mehala, 2010) in his work described extensively the use of MCSA in condition monitoring.

Jung and Seong (2006) monitored the condition of reactor coolant pump using power line signal analysis in which they combined Wigner–Ville Distribution (WVD) and feature area matrix comparison method in abnormality diagnosis. They validated their approach by comparing it with an RCP vibration monitoring technique. They were able to detect cracks on the pump shaft keyway and thermal sleeve. Their approach was carried out without the use of any intrusive sensors.

Wang et al. (2008) worked on detecting cable degradation in nuclear plants. They proposed the joint time-frequency domain reflectometry (JTFDR). The method was verified on a cross-linked polyethylene (XLPE) cable. This cable is used in critical instrumentation and control operations in nuclear power plants. Their method successfully and effectively monitored the cables ageing process and even predict future defects and estimate the cables remaining useful life.

3.6. Instrumentation calibration monitoring

Instrumentation calibration monitoring is used in ensuring the sensors are transmitting accurately within acceptable limits. This is usually done through a process called inference. Inference involves comparing the sensor value with a calculated value from the process equations. The processes involved in instrumentation calibration are explained in NP-T (20080 extensive research in the areas of sensor validation are available in literature and different techniques have been used such as in the work of Gribok et al. (2000) where they developed techniques in regularizing statistical approaches to sensor validation. Hines et al. (1996), Xu et al. (1999) and Dorr et al. (1996) also used neural network based methods in Instrument Calibration Monitoring. One of the common cause of sensor failure has been identified to be because of miscalibration due to human error. Employing on-line calibration monitoring will not only reduce miscalibration it will also minimise exposure of personnel to radiation. This will lead to both increased safety, reduced false alarms and maintenance cost reduction (NP-T, 2008)

The different condition monitoring techniques when compared with the traditional approaches gave better performances. Most of these techniques are automated non-destructive and performed on-line while the plant is still in operation, which brings about more effective plant monitoring, reduced human errors and human exposure to radiation. This ultimately enhances safety and cost-effective maintenance.

4. State of fault detection in the nuclear industry

In CBM after monitoring the condition of the plant, the next stage is fault detection. Fault detection is based on the output of the monitored condition of the plant. Anomalies are detected when data from the different monitoring techniques are analyzed. This section explores the state of fault detection envisioned and implemented in the nuclear industry. Many of the monitoring system discussed in the previous section are able to detect faults and many others are being discussed in this section. Since the early 1990s, a lot of work has been done with the aim of improving protection system dependability and improving plant uptime and economics.

Parisini (1997) presented a simulation-based fault identification method. Parisini first developed an accurate nonlinear model of a section of a real 320 MW power plant. They modelled the most frequent faults that may occur in plants within the framework of that global method. The fault identification method worked in real-time and provided the plant technicians with crucial information on the plant behaviour. Fault detection and the diagnosis were accomplished in a conventional way. Parisini recognized the effect of the control system acting on the fault and created signatures of the secondary effect of these control responses.

Leger et al. (1998) developed a fault detection system combining cumulative summation (CUSUM) control charts and artificial neural. They tested their method on a model of the heat transport system of a CANDU nuclear reactor. Their result showed that their method was feasible. They were able to eliminate false alarms at steady state. They were able to detect six (6) fault conditions promptly.

Muñoz and Sanz-Bobi (1998) proposed a fault detection system that based on the probabilistic radial basis function network. The probabilistic radial basis function network is a neural network model, which is able to estimate I/O mappings and probability density functions. The fault detection system was able to prevent false alarms by detecting unknown operating conditions.

Afonso et al. (1998) conducted an experimental evaluation of an automatic procedure for sensor fault detection and identification in a real process under closed-loop control. A scheme that is very

Copyright @ 2019 Authors

robust to faults in the main sensors of a multi-loop control system is proposed with the aim of improving safety and reliability ofplant operations. A state variable transformation was carried outin order to derive a model suitable for recursive least squares identification valid for all regimes of operation. The fault detection method was based on a moving window statistical analysis of the estimated model parameters. At the same time, a state estima- tion scheme, based on the extended Kalman filter, enabled the fault identification, reduced false alarms and provided redundant measurements for alternative control purposes. Experimental runs were carried out in an industrial-scale pilot plant. Despite the large number of uncertainties and nonlinearities in the process, the system exhibited a good performance when faults occurred in the sensors of the control loops.

Evsukoff and Gentil (2005) in their work presented recurrent neuro-fuzzy systems for fault detection and isolation in nuclear reactors. Their results showed that the recurrent topology showed better generalization performance for the detection and isolation of a number of security-related faults. They presented their resultsby making a qualitative representation of symptoms and diagnos- tics using coloured shades, which changed with time making afriendly interface for efficient communication with operators in charge of the process safety.

Zhao and Upadhyaya (2005) presented an integrated fault detection and isolation technique which used an adaptive fuzzy inference causal graph. This technique was for field devices, which comprised of controllers, sensors and actuators in NPPs. Fault detection and isolation was achieved by monitoring the residuals and cause-effect reasoning conducted. They demonstrated their method on the steam generator system of a pressurized water reactor (PWR). They were able to isolate both simple and complex faults even at the early fault stages irrespective of fault magnitudes and initial power level.

The replacement of the traditional analogue-based safety-related control and instrumentation (C&I) systems in NPPs with modern digital-based systems has prompted (Lee et al., 2006b) to develop a safety assessment system for a digitalized system where they replaced the integrated circuit components with a C++ based hardware. Their evaluation involved getting the error detection coverage and the fault tolerance. Their focus was primarily on the NPP digital plant protection system. From experiments carried out, they confirmed their safety assessment system was able to evaluate the error detection coverage and the fault-tolerance in NPPs.

Du and Jin (2007) developed a fault detection system using principal component analysis (PCA) to detect single sensor faults in heating, air-conditioning and ventilation systems. The PCA is a recognized statistical modelling method. Their fault detection system was able to detect and isolate a single sensor fault and this can be done while the plant is in operation. The PCA was also combined with data reconciliation by Amand et al., (2001) in developing a fault detection system with increased efficiency, he introduced data reconciliation in the first stage of the PCA projection matrix. The method was applied on raw process data. Its efficiency depended on the on the number of components monitored. Baraldi et al. (2010) also developed a PCA based early fault detec- tion system used for identifying faulty sensors and correcting theirmeasured values. The technique developed was based on the sequential probability ratio test. They demonstrated this method using a simulated case study of the pressurizer pressure and level control of PWR.

5. State of fault diagnostics in the nuclear industry

Diagnostics is the next stage in CBM after detection. Fault diagnostics is aimed at not just detecting a fault but characterizing the fault. Diagnostics is focused on determining the location and mag- nitude of the existing fault. Upadhyaya et al. (2003) addressed eco-nomic and reliability concerns in existing and new generation NPPs. They pointed out they needed to overcome the problem of unscheduled downtime, improve the overall plant performance, and work on the long-term management of critical assets. This can be achieved by developing and adopting an integrated approach for control, monitoring, detection and diagnosis of plant components such as sensors, actuators, control devices and other equipment. Over the years a lot of work has gone into developing diagnostic methods and tools in the nuclear industry, an overview of this research is presented in this section.

A review of applications of fault detection and diagnosis methods in NPPs was carried out by Ma and Jiang (2011) in which that the nuclear plant industry has a strong interest in employing fault detection and diagnostics (FDD) methods for improving their plant's safety, reliability, and availability. They described the various modelling techniques applied in fault diagnosis, which they classified into model-based methods, data-driven methods, and signal-based methods. They investigated the principles behind the different approaches used and examined their various applications in the nuclear plant industry. They believe that the application of FDD in nuclear applications will continue to increase as new advanced FDD techniques continue to emerge and the safety and reliability requirement for NPP tightens.

Patton (1997) investigated the robustness in model-based diagnostics with aim of providing a rapid and reliable detection and isolation of system faults when the plant under control is disturbed, and when the mathematical model upon which the diagnosis is based cannot effectively reproduce the full dynamic operation of the plant.

Later, Kim and Seong (2000) proposed a fault diagnostic system (FDS) that could act as an operator decision support system. The system was designed to increase the efficiency of the NPP and reduce the human error, which results to NPP accidents.

Simani and Fantuzzi (2000) combined the neural networks and the model–based Kalman filter in developing an FDS. During the same time (Chen and Howell, 2001) proposed an FDD methodbased on control system theories in identifying steady-state errors in NPPs. The approach can be implemented on virtually all types of process plants, open loop stable or not. Based on this method they were able to derive cause-effect knowledge and fault isolation procedures that considered factors like the interactions between control systems, and the availability of non-control-loop-based sensors.

Power and Bahri (2004) emphasized an FDD approach based on dynamic fault data and a two-step fault detection and diagnosis framework for early fault detection. This method outperformed other alternative methods because it can be applied to large- scale systems without the need for excessive computing; the approach also gave early fault detection and localization.

In the same year (Lu and Upadhyaya, 2005) developed an advanced fault detection and isolation (FDI) technique using a principal component analysis algorithm for the steam generator system of a typical (PWR) plant. The results demonstrated the implementation of the FDI algorithm for both instrument and actuator monitoring.

Kim et al. (2006) developed a fault diagnostic system for the NPP digital systems. They employed a simulated fault injectionmethod in evaluating the faults coverage on the digital systems. They used their methods on the 5 th and 6 th Units of the Ulchin NPP local coincidence logic processor for a digital plant protection system. Their experiments showed that their method could effec- tively quantify faults coverage for critical digital systems.

Rocco S and Zio (2007) developed a method for classifying transients in NPPs using the support vector machine approach. This

Copyright @ 2019 Authors

method was used in differentiating the transients in nuclear systems. This they achieved by applying different classes of support vector machine (SVM) in a hierarchal structure. One-class SVM was used to classify unknown anomalies and the multi-class SVM was used to classify unknown anomalies. They applied their method to the feed water system of a boiling water reactor using measured data from the HAMBO simulator of the Forsmark-3 nuclear power plant in Sweden. Using this method in transient classification will help in the interpretation of events in the plant and reduce the risk of misclassification.

Berton and Hodouin (2007) completed a model-based FDI system to evaluate plant measurements. The method is also used for control, optimisation, process observation and data reconciliation. The technique was illustrated for a mineral separation plant. The method resulted in efficiently detecting faults during process transitions, even when the dynamic model is not exactly known.

Du Rand et al. (2009) from the North West University in South Africa developed an enthalpy–entropy (h-s) graph approach in fault detection. This approach was actualized for the main power system (MPS) of a pebble bed modular reactor (PBMR). This approach involved classifying faults in the main power system from fault patterns by applying the comparison between the actualplant and reference graphs. Their method was demonstrated for four single and two multiple fault conditions during normal power operation of the plant. Their result showed that all examined sys- tem malfunctions can be correctly classified with the hAs graph approach, using only single reference fault signatures.

To diagnose transients in NPPs, Mo et al. (2007) proposed a dynamic neural network aggregation (DNNA) model which developed to detect, classify and predict transients in NPPs. The system tries to overcome the problem of limited reliability of the single general- purpose neural networks by adopting a two-level classifier architecture with a DNNA model. The system, when compared with the conventional ANN methods, gave better diagnostic results.

Razavi-Far et al. (2009) also used neuro-fuzzy networks based scheme but did not use fault classification in their approach. Their study was implemented for fault diagnostics in an NPP U-tubesteam generator NPP. The applied two types of neuro-fuzzy net- works. The neural network's training was done using data collectedfrom a full-scale U-tube steam generator simulator and used for generating residuals in the fault detection step. A locally linear neuro-fuzzy model is used in the identification of the steam gener- ator. With their approach, they were able to make a qualitative characterization of the fault.

Cilliers (2013) and Cilliers and Mulder (2012) developed a fault diagnostic system (FDS), which was based on the behaviour of the nuclear power plant control system. They developed this control system based method by taking into consideration how the PWR closed loop control system operates. They noticed that when a small fault is introduced into the system the control system inthe closed loop acts to compensate for the fault by actuating a sys- tem that overrides the fault. This action makes the system continue to operate without shutting down. In their research, they analyzed the actions of the control system based on this characteristic of the control system acting, and by so doing; they were able to detect faults. This approach focused on improving the existing fault detection methods and plant dependability by detecting faults that are of such a small magnitude that they would go undetected when comparing plant measurements to a reference such as expected operating points or even a simulator predicting the expected operating point. This FDS method can detect faults during transients when operating point references are usually unavailable. It can also detect faults that have not been preconceived and simulated to provide a reference fault signature. This they achieved by introducing a plant diagnostic system (PDS) between the plant and the simulator. The PDS continuously compared the plants parameter measured values with the simulator pre-determined values. The system made use of the information provided by the model reference adaptive control system that is used in nuclear plants to maintain the operating point of the desired reference to detect and characterize faults that occur in the system. They also pro- posed the use of the NPP simulator in providing a dynamic refer- ence, which is very important for their FDS. Ayo-Imoru and Cilliers (2017) further discussed the requirements to enable the NPP simulator to be used effectively as a dynamic reference for fault diagnostics.

6. State of prognostics in the nuclear industry

One basic step in prognostics, is understanding the process involved, which begins with the proper definition of prognostics. The absence of a unified definition of prognostics is one of the challenges in prognostics (Coble, 2010). Some notable definitions from literature include that of Pham et al. (2012) that defines Prognosis as the estimation of the expected remaining useful life (RUL) and the associated uncertainties while (ISO-13381-1, 2004) defined prognosis as estimation of time to failure and risk for one or more existing and future failure modes. Wheeler et al. (2009) defines it as the ability to detect, isolate and diagnose faults in components as well as predict and trend the accurate remaining useful life of those components degradation before eventual failure occurs. Saxena et al. (2010) describes prognostics as predicting the remaining useful life of a system from the inception of a fault basedon a continuous health assessment made by direct or indirect observation from the ailing system. Suhir (2011) also, defines prog-nostics as the ability to predict the remaining useful life after a cer-tain malfunction is detected or anticipated. Daigle and Goebel (2011) says prognostics is concerned with determining the health of system components and making an end of life and remaining useful life predictions. The underlying factors in these definitions are that prognosis is used for prediction, is an estimation of time, and there is common event "failure". These factors have given rise to the definition of prognostics for the purpose of this research as the prediction of the time to failure and associated uncertainties ofa component.

Prognostics is a very important aspect of CBM as it will help the operator and maintenance personnel to better understand how to schedule maintenance and also results in cost-effective maintenance. Prognostics depends largely on the stages of CBM (monitoring, detection and diagnostics) as the accuracy of the monitoring technique will affect RUL estimation. Prognostics cannot be done in isolation and that it relies on the output of diagnostics(Sikorska et al., 2011). Bechhoefer and He (2012) highlighted four processes required for successful prognostics which are:Estimation of damage by feature extraction of measured data; Setting a set-point for the feature, which, when exceeded, shows the need for maintenance;

- Development of a model that can estimate the RUL of the component based on the current state of degradation and the future load profile; and
- An estimation of the confidence level of the prognostic method used.

Looking at these steps required for a successful prognostic, it is noticed that the first two steps involve diagnosis and the other two steps are mainly prognosis. This shows that prognosis takes fault diagnosis a step further in condition-based maintenance. Unlike diagnostics, prognostics is just beginning to gain attention compared to other components of CBM and most of its application in the nuclear industry are still mainly at the research level and found

Copyright @ 2019 Authors

only little practical applications. Coble et al. (2012) worked on a comprehensive review of the technologies and application of prognostics and Health Management in Nuclear Power Plants. In their review, they discussed how prognostics and health management (PHM) are been applied in some nuclear power and related sys- tems. They discussed also areas where PHM is still under develop- ment. They explained the present needs in applying prognostics, the challenges, the technical gaps and also highlighted areas ofresearch needs for the increased application of PHM in the nuclear industry. Other notable research on prognostics on different parts of the nuclear plants is further discussed.

One important step in prognostics is, knowing the parameters that are needed for the best RUL estimation. Prognostics involves analysing degradation data from the monitored condition of the plant, which is then trended for RUL estimation. For better RUL estimation, it is good to combine different degradation parameters (Coble and Hines, 2008). This is also supported in the work of Barbieri et al., where they combined several degradation parame- ters using an optimization process to obtain a prognostic parame- ter which was trended to estimate the RUL. They used Genetic Algorithm and ordinary least square in the optimization process and estimated RUL using a using general path model. Their methodwas validated using steady-state data from electric motor acceler- ated degradation testing. With their method, they were able to achieve good RUL estimate with a percentage error of 5%.

Coble and Hines (2011) proposed a prognostic method that can be applied to components and systems. They combined the Gen- eral Path Model (GPM) with dynamic Bayesian updating as one effects-based prognostic algorithm. The general path model was used for the remaining useful life estimation (RUL) by extrapolat- ing of the prognostic parameter curve to a critical failure set- point, then for cases where there were only a few data points or where the data was contaminated with noise, the Bayesian methodwas introduced which allowed for the inclusion of prior informa- tion. Their method was applied to the prognostics challenge prob- lem posed at PHM '08. The results showed that their proposed method performed better than the conventional regression used in RUL estimation.

Welz et al. developed a prognostic system which was based on Bayesian and Bootstrap Aggregation modelling methods. Their method relied on the predicting of the progression of systems residual. This method was illustrated using data collected from a heat exchanger testbed setup at the University of Tennessee. They relied on how the system residuals progressed and how the resid- uals relate with the overall system condition. This was used in esti-mating the RUL. As a result of restrictions on available data, they employed the use of a Leave One Out Cross Validation (LOOCV) method to evaluate and validate the effectiveness of their tech- nique. In their study, they explored and analyzed different meth- ods that gave an RUL estimation with reduced variance and improved accuracy. The results of this analysis showed that across all test cases the Bayesian transition using Type I priors outper- formed the GPM with no Bayesian updating, and resulted in up to a 99% reduction in regression parameter standard deviation.

Another method to tackle the problem of noise in data used in RUL estimation was developed by Djeziri et al. (2015). They developed a noise filtering method to extract profiles of trends based ona percentile calculation on several levels. The profiles are modelledby a gamma process. They used simulation in illustrating theirmethod, they also compared their method with other filtering methods based on discrete wavelet transform (DWT) and empirical mode decomposition (EMD) algorithms, which showed the effec- tiveness and applicability to data with noisy trends. This allows one to have a probability density function (pdf) of RUL with a con- fidence interval (CI) that ensures the safety margins for industrial applications.

Di Maio and Zio (2010) presented a similarity-based approach for prognostics of the Remaining Useful Life (RUL) of a system. In the similarity- based method a collection of different failure pat- terns that serves as the reference is taken using the different failure scenarios of the plant. The condition of the system is then being monitored and compared with the library of the reference patterns. The RUL is then been estimated using the fuzzy similarity analysis and aggregating their times to failure in a weighted sum. This accounted for their similarity to the developing pattern. The pre- diction on the failure time was dynamically updated as time goes by and measurements of signals representative of the system state were collected. With this method, on-line RUL estimation is possi- ble. They demonstrated this technique on failure scenarios of the Lead-Bismuth Eutectic eXperimental Accelerator Driven System (LBE-XADS). Their approach gave satisfactory results in the RUL accuracy and also in the computing speed.

McCarter et al. explored an RUL estimation technique for of I&C cables in the nuclear plant. They employed the indenter modulus (IM) approach in predicting the remaining useful life (RUL). This IM technique is a technique that has been accepted by industries for monitoring cable condition. The IM technique can be used on-line i.e. while the plant is in operation and it is a non- destructive technique, which makes it a useful tool for CBM. This method was used in an accelerated ageing cable test bed in which they obtained several types of measurement parameters for ageingcables. They further explained practical techniques in which sim- ple IM measurements can be taken advantage of for condition monitoring and RUL estimation. Their result from the error analy- sis showed that IM technique can give a better RUL estimation compared to the conventional methods like simple trending and curve fitting for cables.

Panni et al. (2016) used the Bayesian linear regression model in estimating the RUL using the data from an operational steam tur- bine of an NPP. An appropriate model for the deterioration under study is selected. Results show that the accuracy of the technique varies due to the nature of the data that is utilized to estimate the model parameters.

7. Modelling techniques for CBM

In the different parts of the CBM discussed one recurring step inthe methods used in condition monitoring, detection, diagnostics, and prognostics are modelling. This section looks at the different modelling techniques applied in these processes. The modelling techniques generally adopted in CBM can be categorized into three; the physical modelling, empirical modelling and the hybrid modelling. These modelling techniques are further described and their strengths weaknesses opportunities and threats (SWOT) anal- ysis are shown below;

7.1. Physical modelling

Physical modelling methods are also referred to as model-based or physics of failure or behavioural model methods in some litera- ture. They involve the use of mathematical relationships of the physical behaviour between process parameters to detect process or sensor anomalies. This method incorporates the physical under- standing of the system into the estimation of the system state. In this approach, mathematical equations representing the monitored system are derived from first principles. The output of the actual process is usually compared with that of the physical model, the difference is called residual. When the plant is operating normally, the residual should be approximately zero but large residuals sig- nify a fault in the system. The physical model usually gives a result with minimal uncertainties when accurate models are used but the

Copyright @ 2019 Authors

major setback is obtaining a good model is complicated, a complete model is usually not available in complex systems and also detailed technical knowledge of failure mechanisms is required. Reviews on model-based available in the literature are (Venkatasubramanian et al., 2003; Chen and Patton, 2012), other examples of the physical model applied are the use of particle filtering for parameter estimation of damage (An et al., 2013). Particle filters were also used by Daigle and Goebel (2011) to develop a general model based prognostics methodology within a robust probabilistic framework. Other works on model-based modelling are that of Patton (1997), Simani et al. (2003) also control based diagnostics model by Cilliers (2013) and Cilliers and Mulder (2012). Examples of model-based techniques in literature are justa handful compared to the other modelling techniques. Fig. 3 shows the S.W.O.T analysis of the physical modelling method.

7.2. Empirical modelling

They are also known as data-driven or data-based models. They depend on past patterns of the system to determine the state of the plant or predict the future state of the plant. Unlike the physical models, Data-based models try to define relationships between variables by means of data fitting and do not need an understanding of the physical properties of the variables being compared.They can be further categorized into three, artificial intelligent methods, statistical based methods, and similarity-based methods. The artificial intelligent method uses machine learning tools which transforms raw data into relevant information and behaviour models examples are neural networks (Atiya et al., 1999; Simani and Fantuzzi, 2000; Şeker et al., 2003), Bayesian networks (Pingfeng and Byeng Dong, 2008), Markov processes (Fleming, 2004; Kacprzynski et al., 2004; Bechhoefer et al., 2006). The artificial intelligent methods mostly depend on previous patterns of abnormalities of systems that are alike and based on these data thefuture condition of the system is projected. The quality and quan- tity of system history data required for data-driven method make it a challenging task in real applications (Liu et al., 2012).

The statistical-based methods rely on available data based on past observations examples are proportional hazard modelling PHM (Vlok et al., 2002), Autoregressive moving average (ARMA) (Yan et al., 2004), principal component analysis PCA (Amandet al., 2001; Du and Jin, 2007; Baraldi et al., 2010), proportional

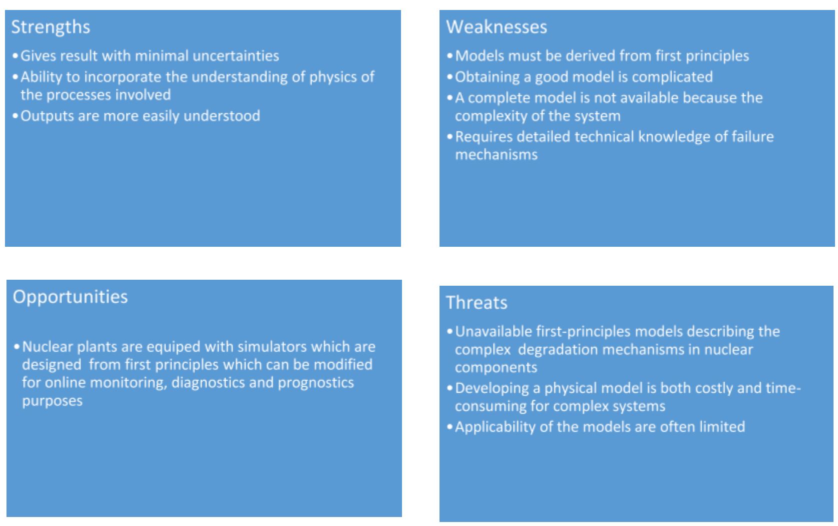

Fig. 3. SWOT analysis of the physical modelling technique.

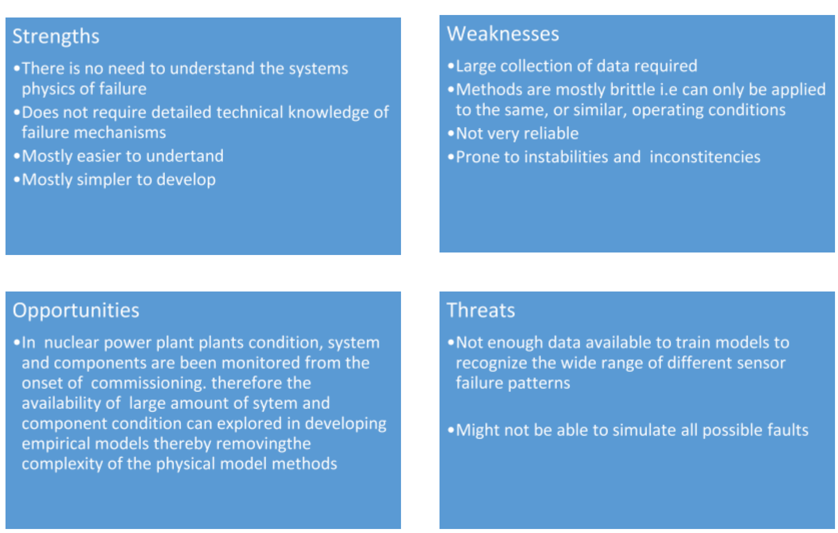

Fig. 4. SWOT analysis of the empirical modelling technique.

Copyright @ 2019 Authors

covariate model PCM, support vector regression SVR (Agarwal et al., 2015).

Similarity-based methods weigh the comparison between an observed present situation and a library of failure patterns example are fuzzy systems (Zio et al., 2010) and expert systems.

The major setback with the data-driven approach is that they cannot handle unanticipated failures and because of the quality and quantity of data required in computation, which might be dif- ficult to obtain. Fig. 4 shows the SWOT analysis of the empirical modelling approach.

7.3. Hybrid models

Hybrid approaches are developed to combine the strength of one or more approaches and to limit their weaknesses. This approach integrates the strength of the ensemble methods thereby giving estimations that are more reliable. Some application of hybrid approaches are the combination of Kalman filters and neu- ral methods for fault diagnostics of industrial processes by Simani and Fantuzzi (2000), Neuro-fuzzy method used by Wang et al. (2004) for prognosis of machine health conditions and gave better RUL estimation than the time-delayed neural network. Liu et al. (2012) developed a hybrid method to improve the accuracy of system state long-horizon forecasting by combining model-based particle filtering approach and a data-driven predictor based on Bayesian learning. This approach was used to predict the RUL of lithium-ion batteries. Si et al. (2013) combined Bayesian updating method and expectation maximisation algorithm in RUL estimation. Fig. 5 shows the SWOT analysis of the hybrid modelling approach.

8. SWOT analysis of CBM application in nuclear power plants

CBM has found wider application in other industries like aerospace, naval, electronics, chemical, and medicine, compared to the nuclear industry. CBM has various advantages and also chal- lenges. This section highlights the possible strengths, weaknesses, opportunities, and threats in applying CBM in the nuclear power plant considering the uniqueness of the nuclear plant. Fig. 6 shows the SWOT analysis of the application of CBM in the nuclear industry.

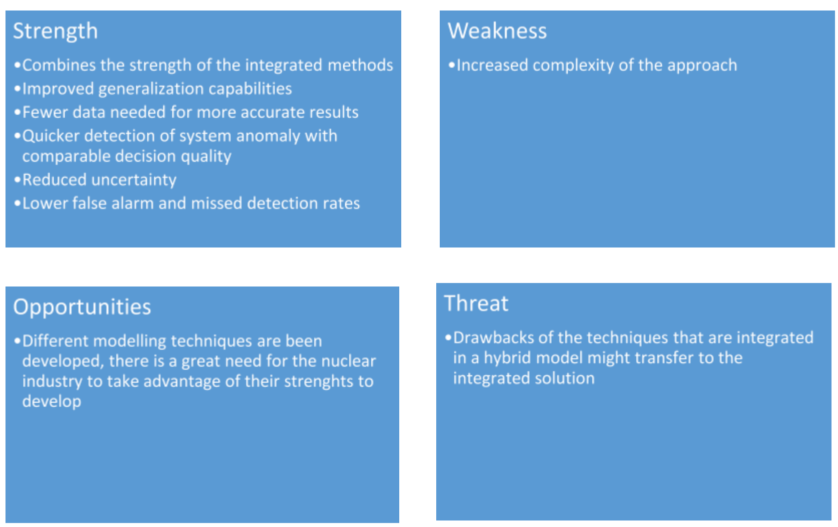

Fig. 5. SWOT analysis of the hybrid modelling technique.

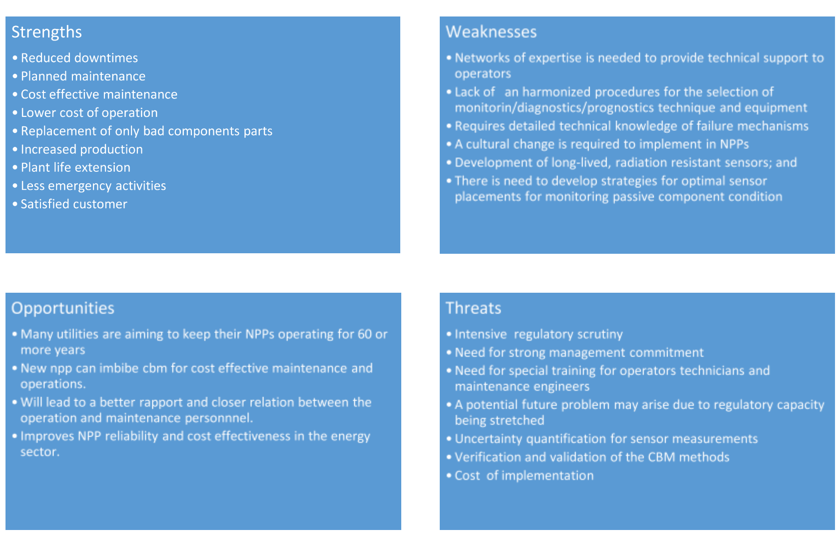

Fig. 6. SWOT Analysis of CBM application in NPPs.

Copyright @ 2019 Authors

9. Conclusion

This paper has presented a survey on the state of condition-based maintenance (CBM) in the nuclear industry. From this survey, it is seen that CBM has been widely used and successfully applied in other industries. The nuclear industry is unique due to safety-related issues and this must be put in consideration before completely adopting a different maintenance strategy. Therefore, CBM should be systematically adopted in the nuclear plant startingwith components and systems that are of lesser safety concern. This paper has explored the different stages of CBM and high- lighted recent research that has been done. From these studies, several opportunities exist that the nuclear plant can explore in implementing CBM these have been summarised in a SWOT anal- ysis of the different techniques of CBM in the nuclear power plant. This paper gives maintenance stakeholders and researchers anoverview of the current practices and extent of research under- taken on condition-based maintenance in the nuclear industry.

Based on this review the authors aim to research further on developing a hybrid prognostic system to enhance CBM in NPP. This they hope to achieve by harnessing and combining the control- based fault diagnostic system developed by Cilliers and Mulder (2012), with other data-driven approaches. This is because of the strength of the control-based fault diagnostic system which is, early,accurate fault detection and it can used in transients combined with the simplicity of the data-driven approach which does not require the understanding of the plant's physics of failure. This hybrid sys-tem is expected to give a more accurate plant prognosis for CBM.

Reference

Afonso, P., Ferreira, J., Castro, J., 1998. Sensor fault detection and identification in a pilot plant under process control. Chem. Eng. Res. Des. 76, 490–498.

Agarwal, V., Alamaniotis, M., Tsoukalas, L.H., 2015. Predictive Based Monitoring of Nuclear Plant Component Degradation Using Support Vector Regression. Idaho National Laboratory (INL), Idaho Falls, ID (United States).

Agency, I.A.E., 1999. Modern Instrumentation and Control for Nuclear Power Plants. International Atomic Energy Agency, Vienna.

Agency, I.A.E., 2007. Implementation Strategies and Tools for Condition-Based Maintenance at Nuclear Power Plants. International Atomic Energy Agency, Vienna.

Ai, Q., Liu, C.-X., Chen, X.-R., He, P., Wang, Y., 2010. Acoustic emission of fatigue crack in pressure pipe under cyclic pressure. Nucl. Eng. Des. 240, 3616–3620.

Al-Ghamd, A.M., Mba, D., 2006. A comparative experimental study on the use of acoustic emission and vibration analysis for bearing defect identification and estimation of defect size. Mech. Syst. Signal Process. 20, 1537–1571.

Amand, T., Heyen, G., Kalitventzeff, B., 2001. Plant monitoring and fault detection: synergy between data reconciliation and principal component analysis. Comput. Chem. Eng. 25, 501–507.

An, D., Choi, J.-H., Kim, N.H., 2013. Prognostics 101: a tutorial for particle filter-based prognostics algorithm using Matlab. Reliab.Eng. Syst. Saf. 115, 161–169.

Ansari, S.A., Haroon, M., Sheikh, Z., Kazmi, Z., 2008. Detection of flow-induced vibration of reactor internals by neutron noise analysis. IEEE Trans. Nucl. Sci. 55, 1670–1677.

Atiya, A.F., El-Shoura, S.M., Shaheen, S.I., El-Sherif, M.S., 1999. A comparison between neural-network forecasting techniques-case study: river flow forecasting. IEEE Trans. Neural Networks 10, 402–409.

Ayo-Imoru, R.M., Cilliers, A.C., 2017. Hybrid nuclear plant simulator design requirements to enable dynamic diagnostics of plant operations. Ann. Nucl. Energy 101, 447–453.

Baraldi, P., Cammi, A., Mangili, F., Zio, E., 2010. An ensemble approach to sensor fault detection and signal reconstruction for nuclear system control. Ann. Nucl. Energy 37, 778–790.

Barbieri, F., Hines, J.W., Sharp, M., Venturini, M., Sensor-based degradation prediction and prognostics for remaining useful life estimation: validation on experimental data of electric motors.

Barutçu, B., Şeker, S., Ayaz, E., Türkcan, E., 2003. Real time reactor noise diagnostics for the Borssele (PWR) nuclear power plant. Prog. Nucl. Energy 43, 137–143.

Bechhoefer, E., Bernhard, A., He, D., Banerjee, P., 2006. Use of hidden semimarkov models in the prognostics of shaft failure. HIP 1, 3.

Bechhoefer, E., He, D.W., 2012. A process for data driven prognostics. Prognostics and Health Management Solutions Conference-PHM: Driving Efficient Operations and Maintenance, MFPT 2012.

Berton, A., Hodouin, D., 2007. Synchronized node imbalances for fault detection and isolation in plant networks involving material circulation. Comput. Chem. Eng.31, 815–832.

Bond, L.J., Ramuhalli, P., Tawfik, M.S., Lybeck, N.J., 2011. Prognostics and life beyond 60 years for nuclear power plants. Prognostics and Health Management (PHM). In: 2011 IEEE Conference on. IEEE, 1–7.

Cao, Y., He, Y., Zheng, H., Yang, J., 2012. An alarm method for a loose parts monitoring system. Shock Vibr. 19, 753–761.

Chapin, D.M., Strawson, D.G., Stone, J.T., Lubnow, T.S., 1999. Application of condition-based maintenance in Japanese nuclear power plants. In: 7th International Conference on Nuclear Engineering, April 1999.

Chen, J., Howell, J., 2001. A self-validating control system based approach to plant fault detection and diagnosis. Comput. Chem. Eng. 25, 337–358.

Chen, J., Patton, R.J., 2012. Robust Model-based Fault Diagnosis for Dynamic Systems. Springer Science & Business Media.

Choi, Y.-C., Park, J.-H., Choi, K.-S., 2011. An impact source localization technique fora nuclear power plant by using sensors of different types. ISA Trans. 50, 111– 118.

Cilliers, A.C., 2013. Correlating hardware fault detection information from distributed control systems to isolate and diagnose a fault in pressurised water reactors. Ann. Nucl. Energy 54, 91–103.

Cilliers, A.C., Mulder, E.J., 2012. Adapting plant measurement data to improve hardware fault detection performance in pressurised water reactors. Ann. Nucl. Energy 49, 81–87.

Coble, J., Hines, J.W., 2011. Applying the general path model to estimation of remaining useful life. Int. J. Prognostics Health Manage. 2, 71–82.

Coble, J.B., 2010. Merging data sources to predict remaining useful life–an automated method to identify prognostic parameters.

Coble, J.B., Hines, J.W., 2008. Prognostic algorithm categorization with PHM challenge application. Prognostics and Health Management, 2008. PHM 2008. In: International Conference on, 2008. IEEE, 1–11.

Coble, J.B., Ramuhalli, P., Bond, L.J., Hines, J., Upadhyaya, B.R. 2012. Prognostics and Health Management in Nuclear Power Plants: a Review of Technologies and Applications. National Technical Information Service.

Czibók, T., Kiss, G., Kiss, S., Krinizs, K., Végh, J., 2003. Regular neutron noise diagnostics measurements at the Hungarian Paks NPP. Prog. Nucl. Energy 43, 67–74.

Czibók, T., Kiss, S., Lipcsei, S., 2004. Reactor noise analysis with simultaneous acquisition of 512 signals for improved process monitoring. In: Proc. of the IAEA–OECD NEA Technical Meeting on Increasing Instrument Calibration Interval Through on-line Monitoring Technologies, 2004. Citeseer, 27–29.

Daigle, M.J., Goebel, K., 2011. A model-based prognostics approach applied to pneumatic valves. Int. J. Prognostics Health Manage. 2, 84–99.

Davies, L., Gueorguiev, B., Trampus, P., 2000. Role of NDT in condition-based maintenance of nuclear power plant components. In: Proc. 15th World Conference on NDT (Rome, 2000). Accessed on-line at www.ndt.net/article/ wcndt00/papers/idn078/idn078.htm.

de Pauw, B., Vanlanduit, S., van Tichelen, K., Geernaert, T., Chah, K., Berghmans, F., 2013. Benchmarking of deformation and vibration measurement techniques for nuclear fuel pins. Measurement 46, 3647–3653.

di Maio, F., Zio, E., 2010. A data-driven fuzzy approach for predicting the remaining useful life in dynamic failure scenarios of a nuclear power plant. Reliab. Eng.Syst. Saf. 95, 49–57.

Djeziri, M., Ananou, B., Ouladsine, M., Pinaton, J., 2015. Remaining Useful Life estimation for noisy degradation trends. IFAC-PapersOnLine 48, 85–90.

Dorr, R., Kratz, F., Ragot, J., Loisy, F., Germain, J.-L., 1996. Detection, isolation, and identification of sensor faults in nuclear power plants. IEEE Trans. Control Syst. Technol. 5, 42–60.

du Rand, C.P., van Schoor, G., Nieuwoudt, C., 2009. Enthalpy–entropy graph approach for the classification of faults in the main power system of a closed Brayton cycle HTGR. Ann. Nucl. Energy 36, 703–711.

Du, Z., Jin, X., 2007. Detection and diagnosis for sensor fault in HVAC systems. Energy Convers. Manage. 48, 693–702.

Evsukoff, A., Gentil, S., 2005. Recurrent neuro-fuzzy system for fault detection and isolation in nuclear reactors. Adv. Eng. Inform. 19, 55–66.

Figedy, S., Oksa, G., 2005. Modern methods of signal processing in the loose part monitoring system. Prog. Nucl. Energy 46, 253–267.

Fleming, K.N., 2004. Markov models for evaluating risk-informed in-service inspection strategies for nuclear power plant piping systems. Reliab. Eng. Syst. Saf. 83, 27–45.

Gribok, A.V., Hines, J.W., Uhrig, R.E., 2000. Use of kernel based techniques for sensor validation in nuclear power plants. American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Controls, and Human- Machine Interface Technologies (NPIC&HMIT 2000), Washington, DC, November 2000.

Hashemian, H., Jiang, J., 2010. Using the noise analysis technique to detect response time problems in the sensing lines of nuclear plant pressure transmitters. Prog. Nucl. Energy 52, 367–373.

Hines, J.W., Davis, E., 2005. Lessons learned from the US nuclear power plant on-line monitoring programs. Prog. Nucl. Energy 46, 176–189.

Hines, J.W., Wrest, D.J., Uhrig, R.E., 1996. Plant wide sensor calibration monitoring. Intelligent Control, 1996. In: Proceedings of the 1996 IEEE International Symposium on, 1996. IEEE, 378–383.

IEA, 2017. Electricity Information 2017, IEA.

ISO-13381-1, 2004. Condition monitoring and diagnostics of machines – Prognostics – Part 1: General Guidelines.

Jung, J.C., Seong, P.H., 2006. An improved method for reactor coolant pump abnormality monitoring using power line signal analysis. Nucl. Eng. Des. 236, 57–62. Kacprzynski, G.J., Sarlashkar, A., Roemer, M.J., Hess, A., Hardman, B., 2004. Predicting remaining life by fusing the physics of failure modelling with diagnostics. JOM56, 29–35.

Kaewwaewnoi, W., Prateepasen, A., Kaewtrakulpong, P., 2010. Investigation of the relationship between internal fluid leakage through a valve and the acousticemission generated from the leakage. Measurement 43, 274–282.

Kim, J.-S., Hwang, I.-K., Kim, J.-T., Moon, B.-S., Lyou, J., 2002. A study on loose part monitoring system in nuclear power plant based on neural network. Int. J. Fuzzy Logic Intell. Syst. 2, 95–

 Copyright @ 2019 Authors

99.

Kim, J.H., Seong, P.H., 2000. A methodology for the quantitative evaluation of NPP fault diagnostic systems' dynamic aspects. Ann. Nucl. Energy 27, 1459–1481.

Kim, S.J., Seong, P.H., Lee, J.S., Kim, M.C., Kang, H.G., Jang, S.C., 2006. A method for evaluating fault coverage using simulated fault injection for digitalized systems in nuclear power plants. Reliab. Eng. Syst. Saf. 91, 614–623.

Kima, S., Leeb, Y.-G., Jhunga, M.J., Kima, Y.-B., 2012. Development of mass estimation tools based on pre-operation test for the Loose part monitoring system of OPR-1000.

Ko, D.-Y., Kim, K.-H., 2013. Design of a vibration and stress measurement system for an advanced power reactor 1400 reactor vessel internals comprehensive vibration assessment program. Nucl. Eng. Technol. 45, 249–256.

Kong, K.K., Noroozi, S., Rahman, A.G.A., Dupac, M., Eng, H.C., Ong, Z.C., Khoo, S.Y., Vinney, J.E., 2014. Non-destructive testing and assessment of dynamic incompatibility between third-party piping and drain valve systems: an industrial case study. Nondestr. Test. Eval. 29, 154–163.

Koo, I.S., Kim, W.W., 2000. The development of reactor coolant pump vibration monitoring and a diagnostic system in the nuclear power plant. ISA Trans. 39, 309–316.

Lebold, M.S., Maynard, K., Reichard, K., Trethewey, M., Lissenden, C., Dobbins, D.,2005. A non-intrusive technique for on-line shaft crack detection and tracking.In: 2005 IEEE Aerospace Conference, 5–12 March 2005 2005. 1–11.

Lee, J.-H., Lee, M.-R., Kim, J.-T., Luk, V., Jung, Y.-H., 2006a. A study of the characteristics of the acoustic emission signals for condition monitoring of check valves in nuclear power plants. Nucl. Eng. Des. 236, 1411–1421.

Lee, J.S., Kim, M.C., Seong, P.H., Kang, H.G., Jang, S.C., 2006b. Evaluation of error detection coverage and fault-tolerance of digital plant protection system in nuclear power plants. Ann. Nucl. Energy 33, 544–554.

Leger, R.P., Garland, W.J., Poehlman, W.S., 1998. Fault detection and diagnosis using statistical control charts and artificial neural networks. Artif. Intell. Eng. 12, 35– 47.

Liu, J., Wang, W., Ma, F., Yang, Y.B., Yang, C.S., 2012. A data-model-fusion prognostic framework for dynamic system state forecasting. Eng. Appl. Artif. Intell. 25, 814–823.

Liu, M., Xia, H., Sun, L., Li, B., Yang, Y., 2015. Vibration signal analysis of main coolantpump flywheel based on Hilbert-Huang transform. Nucl. Eng. Technol. 47, 219–225.

Lu, B., Upadhyaya, B.R., 2005. Monitoring and fault diagnosis of the steam generator system of a nuclear power plant using data-driven modelling and residual space analysis. Ann. Nucl. Energy 32, 897–912.

Lu, B., Upadhyaya, B.R., Perez, R.B., 2005. Structural integrity monitoring of steam generator tubing using transient acoustic signal analysis. IEEE Trans. Nucl. Sci. 52, 484–493.

Ma, J., Jiang, J., 2011. Applications of fault detection and diagnosis methods in nuclear power plants: a review. Prog. Nucl. Energy 53, 255–266.

Maekawa, A., Noda, M., Shintani, M., 2016. Experimental study on a noncontact method using laser displacement sensors to measure vibration stress in piping systems. Measurement 79, 101–111.

Matthews, J.R., 1983. Acoustic Emission. CRC Press.

Mccarter, D., Shumaker, B., Mcconkey, B., Hashemian, H. Nuclear power plant instrumentation and control cable prognostics using indenter modulus measurements.

Mehala, N., 2010. Condition Monitoring and Fault Diagnosis of Induction Motor Using Motor Current Signature Analysis. National Institute Of Technology Kurukshetra, India.

Mo, K., Lee, S.J., Seong, P.H., 2007. A dynamic neural network aggregation model for transient diagnosis in nuclear power plants. Prog. Nucl. Energy 49, 262–272.

Moubray, J., 1995. Reliability-centred maintenance. Fuel Energy Abstracts, 304.

Muñoz, A., Sanz-Bobi, M.A., 1998. An incipient fault detection system based on the probabilistic radial basis function network: application to the diagnosis of the condenser of a coal power plant. Neurocomputing 23, 177–194.

NP-T, I. 2008. 1.1, On-line monitoring for improving performance of nuclear power plants part 1: Instrument channel monitoring. International Atomic Energy Agency, Vienna.

Panni, O., West, G., Catterson, V., Mcarthur, S., Shi, D., Mogridge, 2016. I. Implementation of a bayesian linear regression framework for nuclear prognostics. In: Third European Conference of the Prognostics and Health Management Society 2016.

Parisini, T., 1997. Physically accurate nonlinear models for fault detection and diagnosis: the case of a power plant. J. Process Control 7, 97–109.

Patton, R.J., 1997. Robustness in model-based fault diagnosis: the 1995 situation. Ann. Rev. Control 21, 103–123.

Pelo, H.L. 2013. Evaluation of an advanced fault detection system using Koeberg nuclear power plant data. Citeseer.

Perillo, S.R.P., Gonçalves, I.M.P., Dos Santos, R.C., Ting, D.K.S., 2014. Time response measurement of temperature and pressure sensors of Angra-I Nuclear Power Plant using noise analysis technique.

Pham, B., Agarwal, V., Lybeck, N., Tawfik, M., 2012. Prognostic Health Management System: Component Selection Based on Risk Criteria and Economic Benefit Assessment. Funding organisation. US Department of Energy.

Pingfeng, W., Byeng Dong, Y., 2008. A generic bayesian approach to real-time structural health prognostics. In: 12th AIAA/ISSMO Multidisciplinary Analysisand Optimization Conference. American Institute of Aeronautics and Astronautics.

Power, Y., Bahri, P.A., 2004. A two-step supervisory fault diagnosis framework. Comput. Chem. Eng. 28, 2131–2140.

Prasad, V., Satheesh, C., Acharya, V., Tikku, A., Mishra, S., 2002. Condition monitoring of main coolant pumps, Dhruva. In: Proceedings of the Second International Conference on Vibration Engineering and Technology of maChinery.

Qinghu, M., Qingfeng, M., Wuwei, F., 2009. Forecasting Conditions of Reactor Coolant Pump Based on Support Vector Machine. Computer Science andInformation Engineering, 2009 WRI World Congress on, 2009. IEEE, 293–297.

Rao, A.R., Dutta, B., 2010. Non-intrusive method of detecting turbine blade vibration in an operating power plant. In: Proc. ISMA 2010 Katholieke Universiteit Leuven (Belgium) 20–22 September, 2937.

Razavi-Far, R., Davilu, H., Palade, V., Lucas, C., 2009. Model-based fault detection and isolation of a steam generator using neuro-fuzzy networks. Neurocomputing 72, 2939–2951.

Rocco S, C.M., Zio, E., 2007. A support vector machine integrated system for theclassification of operation anomalies in nuclear components and systems. Reliab. Eng. Syst. Saf. 92, 593–600.

Saxena, A., Celaya, J., Saha, B., Saha, S., Goebel, K., 2010. Metrics for offline evaluation of prognostic performance. Int. J. Prognostics Health Manage. 1, 4–23.

Seker, S., Ayaz, E., Türkcan, E., 2003. Elman's recurrent neural network applications to condition monitoring in nuclear power plant and rotating machinery. Eng. Appl. Artif. Intell. 16, 647–656.

Seong, S.-H., Hur, S., Kim, J.-S., Kim, J.-T., Park, W.-M., Lee, U.-C., Lee, S.-K., 2005. Development of diagnosis algorithm for the check valve with spectral estimations and neural network models using acoustic signals. Ann. Nucl. Energy 32, 479–492.

Series, I.N.E., 2013. On line Monitoring for improving Performance of Nuclear power plants, Part 2: Process and component condition monitoring and diagnostics.No. NP.

Shimanskiy, S., Iijima, T., Naoi, Y., 2004. Development of acoustic leak detection and localization methods for inlet piping of Fugen nuclear power plant. J. Nucl. Sci. Technol. 41, 183–195.

Si, X.-S., Wang, W., Chen, M.-Y., Hu, C.-H., Zhou, D.-H., 2013. A degradation path- dependent approach for remaining useful life estimation with an exact and closed-form solution. Eur. J. Oper. Res. 226, 53–66.

Sikorska, J., Hodkiewicz, M., Ma, L., 2011. Prognostic modelling options for remaining useful life estimation by industry. Mech. Syst. Signal Process. 25, 1803–1836.

Simani, S., Fantuzzi, C., 2000. Fault diagnosis in power plant using neural networks. Inf. Sci. 127, 125–136.

Simani, S., Fantuzzi, C., Patton, R.J., 2003. Model-Based Fault Diagnosis Techniques. Model-based Fault Diagnosis in Dynamic Systems Using Identification Techniques. Springer.

Sinha, J.K., 2008. Vibration-based diagnosis techniques used in nuclear power plants: an overview of experiences. Nucl. Eng. Des. 238, 2439–2452.

Suhir, E. 2011. Remaining useful lifetime (rul): Probabilistic predictive model. Int. J. of Prognostics Health Manage. Volume 2 (color), 140.

Upadhyaya, B.R., Zhao, K., Lu, B., 2003. Fault monitoring of nuclear power plantsensors and field devices. Prog. Nucl. Energy 43, 337–342.

Venkatasubramanian, V., Rengaswamy, R., Yin, K., Kavuri, S.N., 2003. A review of process fault detection and diagnosis: Part I: quantitative model-based methods. Comput. Chem. Eng. 27, 293–311.

Vlok, P., Coetzee, J., Banjevic, D., Jardine, A., Makis, V., 2002. Optimal componentreplacement decisions using vibration monitoring and the proportional-hazards model. J. Oper. Res. Soc. 53, 193–202.

Wang, J., Crapse, P., Shin, Y.-J., Dougal, R., 2008. Diagnostics and prognostics of electric cables in nuclear power plants via joint time-frequency domain reflectometry. Electrical Insulation, 2008. ISEI 2008. In: Conference Record of the 2008 IEEE International Symposium on, 2008. IEEE, 24–27.

Wang, W.Q., Golnaraghi, M.F., Ismail, F., 2004. Prognosis of machine healthcondition using neuro-fuzzy systems. Mech. Syst. Signal Process. 18, 813–831.

Welz, Z., Nam, A., Sharp, M., Hines, J.W., Upadhyaya, B.R. Improved heat exchangerlifecycle prognostic methods for enhanced light water reactor sustainability.

Wheeler, K.R., Kurtoglu, T., Poll, S.D. A survey of health management user objectives related to diagnostic and prognostic metrics. In: ASME 2009 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 2009. American Society of Mechanical Engineers, 1287–1298.

Xu, X., Hines, J.W., Uhrig, R.E., 1999. Sensor validation and fault detection using neural networks. In: Proc. Maintenance and Reliability Conference (MARCON 99), 1999. 10–12.

Yan, J., Koç, M., Lee, J., 2004. A prognostic algorithm for machine performance assessment and its application. Prod. Planning Control 15, 796–801.

Zhao, K., Upadhyaya, B.R., 2005. Adaptive fuzzy inference causal graph approach to fault detection and isolation of field devices in nuclear power plants. Prog. Nucl. Energy 46, 226–240.

Zio, E., di Maio, F., Stasi, M., 2010. A data-driven approach for predicting failure scenarios in nuclear systems. Ann. Nucl. Energy 37, 482–491.

Copyright @ 2019 Authors