

A hybrid system for condition based maintenance in nuclear power plants

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DECLARATION

I, Ronke Monica Ayo-Imoru, hereby declare that this thesis entitled:

“A hybrid system for condition based maintenance in nuclear power plants”

is my own work and has not been submitted to any other University before. Where publications involving co-authors were used, the necessary permission from these authors had been obtained in writing. Relative contributions by the different authors are acknowledged in the relevant chapters.

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PREFACE

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STATEMENT FROM CO-AUTHOR

The contributions from the co-author Prof. Anthonie C. Cilliers are recognised, and statements are as shown below:

Statement of consent: A. C. Cilliers

To whom it may concern

I, Anthonie C. Cilliers, give my consent to Ronke Ayo-Imoru, candidate for the degree Philosophiae Doctor in Nuclear Engineering at the North-West University, to include in her thesis articles as entitled in the following publications, of which I am a co-author:

1. Ronke M. Ayo-IMORU and A. C. Cilliers (2017). "Hybrid nuclear plant simulator design requirements to enable dynamic diagnostics of plant operations." *Annals of Nuclear Energy*, 101: 447-453.
2. Ronke M. Ayo-IMORU and A. C. Cilliers. "A survey of the state of condition-based maintenance (CBM) in the nuclear power industry." *Annals of Nuclear Energy*, 112: 177-188.
3. Ronke M. Ayo-IMORU and A. C. Cilliers. "Continuous machine learning for abnormality identification to aid condition-based maintenance in nuclear power plant." *Annals of Nuclear Energy*, 118: 61-70.
4. Ronke M. Ayo-IMORU and A. C. Cilliers. "A digital twin approach for condition-based maintenance in nuclear plants." *Progress in Nuclear Energy* (submitted).

The relative contributions to the paper by the different authors are given in Chapters 3, 4, 5 and 6. This statement serves to comply with academic rules 5.4.2.8 and 5.4.2.9 of the University.

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A. C. Cilliers

LIST OF PUBLICATIONS

1. Ronke M. Ayo-IMORU and A. C. Cilliers (2017). "Hybrid nuclear plant simulator design requirements to enable dynamic diagnostics of plant operations." *Annals of Nuclear Energy*, 101: 447-453
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3. Ronke M. Ayo-IMORU and A. C. Cilliers. "Continuous machine learning for abnormality identification to aid condition-based maintenance in nuclear power plant." *Annals of Nuclear Energy*: 118, 61-70.
4. Ronke M. Ayo-IMORU and A. C. Cilliers. "A Digital Twin Approach for Condition-based Maintenance in Nuclear Plants." *Progress in Nuclear Energy* (submitted).

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ABSTRACT

Condition-based maintenance (CBM) involves undertaking maintenance activities based on the health of the system. Establishing a CBM regime in an industry will result in eliminating unnecessary maintenance cost without jeopardising the safety of the plant. CBM has found useful applications in many industries like medicine, accounting, military, aeronautics, railway and many more. The nuclear power industry is also not completely left out. However, the nuclear power industry faces special challenges that make it more difficult to implement CBM, especially the unavailability of run-to-failure data. This thesis looked at the current practices of CBM in the nuclear industry and the ongoing research on the different methods and technologies being developed. Based on this, a hybrid system was developed to estimate the degradation level of a nuclear power plant (NPP) components. This should aid maintenance personnel in making useful decisions on the maintenance of NPP components. The hybrid system explored combining an NPP simulator and data-driven machine learning tools. The NPP simulator was used to generate the plant degradation data required for the machine learning tools. The machine learning tools of interest are the artificial neural network (ANN) and the neuro-fuzzy system.

The thesis also estimated the requirements the simulator must meet in order to allow it to be used for plant diagnostics and prognostics. These include the user requirement specification (URS), the simulator model requirements and the functional requirements. Using data-driven methods for fault diagnostics and prognostics in the nuclear industry has been problematic because of the unavailability of run-to-failure data. This thesis has addressed this problem by employing an NPP simulator to generate the required data.

The hybrid system used data from the simulator in training the ANN and the neuro-fuzzy system. The ANN was able to identify transients and faults while the neuro-fuzzy system was used in estimating the degradation level of the component. These results can be used by maintenance personnel in making informed decisions on whether or not to replace an NPP component.

Key terms: artificial neural network, condition-based maintenance, diagnostics, machine learning, neuro-fuzzy system, simulator, transients.

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ABBREVIATIONS

AE	Acoustic emission
ANN	Artificial Neural Network
ANFIS	Adaptive neuro fuzzy system
CBM	Condition based maintenance
DNNA	Dynamic neural network aggregation
DBA	Design basis accident
DBN	Deep belief network
DWT	Discrete wavelet transform
FDD	Fault detection and diagnosis
FDI	Fault detection and isolation
FDS	Fault diagnostic system
FL	Fuzzy Logic
FSS	Full scope simulator
HARDLIM	Hard Limit transfer function
HMI	Human machine interface
IAEA	International Atomic Energy Agency
I&C	Instrumentation & Control (sometimes referred to as C&I)
LOGSIG	Log-sigmoid transfer function
LPMS	The loose part monitoring system
ML	Machine learning
MPS	Main power system
MSE	Mean square error
NPP	Nuclear power plant
O&M	operations and maintenance
OLM	Online monitoring
PBIL	Population-Based Incremental Learning

PCA	Principal component analysis
PDS	Plant diagnostic system
PHM	Prognostic health management
PSD	Power spectral density
PURELIN	Linear transfer function
PWR	Pressurised water reactor
RUL	Remaining useful life
RCS	Reactor coolant system
RCP	Reactor coolant pumps
SWOT	Strength, weakness, opportunity and threat
SSC	Structures, systems and components
SVM	Support vector machine
TEDE	Total effective dose equivalent
TMI	Three Mile Island
TANSIG	Hyperbolic tangent transfer function
URS	User requirement specification

CHAPTER 1: INTRODUCTION

The energy sector is becoming more competitive. Specifically, the costs of wind power, photovoltaic (PV) solar power and gas power have plummeted. Where a combination of cheap wind and solar power is backed up by gas power and power storage, it might be possible to produce reliable load-following power at costs that are similar or even lower than that of new coal or new nuclear plants (Kåberger, 2018; Pfeifer *et al.*, 2019; Tulloch, 2018). Therefore, in order for the nuclear industry to be able to compete with other energy sources, it might need to look for a means of reducing its cost of production. This gives rise to the need for an intelligent maintenance system that is able to reduce the cost of maintenance. This need has informed the research on condition-based maintenance.

The implementation of CBM in the nuclear industry is not without its own challenges. The nuclear industry is a highly regulated industry which limits the introduction and acceptance of any new/improved system in the sense that the safety of the new system must be proved rigorously before its implementation will be allowed (Pelo, 2013). There is thus a need to develop a system to aid CBM that will not impinge negatively on the nuclear plant safety performance.

All parts of the NPP undergo continuous material degradation as a result of operating conditions, which include normal operation and transient conditions (Bond *et al.*, 2007). There is thus a need to employ methods that can be used both in normal operation and during transients. Proper implementation of CBM requires timely and accurate monitoring, fault detection, diagnosis and prognostics for proper analysis of the plant condition. No one tool can be used for every one of these needs. There is thus a need to select the right approach from the various methods developed in literature in order to aid CBM for the nuclear plant.

This research work consists of seven chapters which contain four articles which are already published or have been submitted for review in accredited journals. This chapter introduces this work, comprising the problem statement, research objectives, introduction to the hybrid system developed and a breakdown of the remaining six (6) chapters.

1.1. Problem statement

1.1.1 The need for reducing nuclear maintenance costs and component failures

A nuclear power plant is a critical facility that can suffer potentially catastrophic radioactive nuclear accidents, such as those at Chernobyl and Fukushima, and thus the nuclear regulators require that these plants must be operated safely at all times, regardless of the cost of that safety.

On the other hand, nuclear power faces stiff price competition from a variety of other power sources. Sustained low natural gas prices, which suppress prices in power markets, are one of the reasons contributing to the premature closure of nuclear power plants in the United States (NEI, 2018). Therefore, there is also a need for nuclear plants to be operated cost-effectively. However, their cost effectiveness is negatively impacted by the fact that operations and maintenance cost for nuclear plants all over the world is estimated to contribute as much as 40-70% of the overall generating cost (Bond *et al.*, 2007).

From a purely mechanical perspective, the maintenance requirements for nuclear power plants are similar to that for e.g. coal-fired power plants. However, nuclear maintenance requirements are uniquely strict and thus more expensive because nuclear regulators require much higher safety standards than for e.g. coal plants. Nuclear maintenance regimes thus need to produce much lower risks of component failure, especially for those components for which their failure could induce radioactive nuclear accidents. This includes that the risk of failures that would expose personnel to substantial radiation doses must be reduced to extremely low probabilities. On top of this regulators require that components for all nuclear safety related systems must be manufactured and maintained to extremely high standards. This drastically increases the production costs of these components.

Load factors for nuclear plants are typically substantially higher than for e.g. coal plants, which could create the impression that component failures and the resulting unplanned outages do not contribute substantially to the cost of nuclear power. However, in practice the cost of fractional plant unavailability is exceptionally high for nuclear plants (IAEA, 2002). The reasons for this include the following:

- When a plant is out of service, due to component failure, the cost of capital continues to accumulate, while the cost of fuel ceases. Both gas-fired and coal-fired power plants have costs of capital that are much lower than for nuclear plants, while their respective fuel costs are much higher than for nuclear plants. Therefore, the cost of capital incurred while a gas or coal plant is unavailable is relatively low, while their fuel savings are substantial. However, the opposite applies for nuclear plants: their capital costs are very high, while their fuel costs are low. For instance, it is well known that the capital cost of a new nuclear plant is roughly double that of a new coal plant, while its fuel cost is roughly half that of a coal plant. Similarly, the capital cost of a gas plant is substantially lower than that of a coal plant and its fuel cost substantially higher than coal fuel cost. Therefore, the cost of a percentage point of plant unavailability is much higher for a nuclear plant than for a coal or gas plant. Therefore, although fractional plant unavailability is relatively low for nuclear

plants, the financial implications of an additional percentage point of unavailability is exceptionally high.

- Furthermore, nuclear plants often come in larger unit sizes than other power plants, e.g. 900 MW_e per unit for Koeberg nuclear plant, versus 600 MW per unit for many coal plants in South Africa. Therefore, **the impact on the stability of the grid of losing a nuclear unit is particularly high** and therefore there is a particularly large strategic incentive to reduce nuclear plant unavailability, i.e. to increase nuclear load factors.
- **Nuclear spare parts are also particularly scarce and thus more difficult and expensive to obtain in a hurry.**
 - Although the Rankine steam cycles of nuclear plants are very similar to that of coal plants, some subtle differences make nuclear components largely unique and thus much scarcer and thus more difficult and more expensive to replace in a hurry. To begin with, the steam generators of pressurised water reactor (PWR) nuclear plants differ completely from the steam generating components in coal boilers. It is also well-known that PWR steam is of a substantially lower temperature and thus lower quality than coal steam and therefore the nuclear turbine blades are designed differently than for coal plants. Nuclear turbine power capacities are also normally substantially larger than for coal turbines.
 - Since there are globally many less nuclear steam turbines than coal turbines, nuclear turbines are much scarcer. For instance, South Africa have only the two 900 MW nuclear turbines at Koeberg, compared to a fleet of roughly 65 coal turbines of roughly 600 MW. Therefore, it is much less viable to keep a spare nuclear turbine in stock than a spare coal turbine. When you thus do need a spare nuclear turbine in a hurry, as happened during the infamous “loose bolt” accident that destroyed one of Koeberg’s steam turbines a couple of years ago, you often have only one supplier you can buy the spare turbine from and if they are out of stock, due to lack of mass production, you would have a crisis. In that particular incident, South Africa had to send one of its war ships racing to France to fetch the spare turbine and the result was many weeks of power cuts in the Western Cape province of South Africa (Van Wyk *et al.*, 2008). By contrast, outages on single coal turbines happen regularly in South Africa but are normally not viewed as very newsworthy.
- **Nuclear outage durations are often also particularly long:** once a nuclear plant has been shut down for refuelling or any other maintenance inside the fuel core, one must wait relatively long for the radiation levels inside the fuel core to drop to levels that are low enough to allow workers to safely enter the area. Therefore, component failures that

involve the nuclear fuel core normally result in plant unavailability for three to six weeks, which is much longer than the period of unavailability that would have resulted if a similar component would have failed inside a coal boiler.

- Simple nuclear plant component failures can and in fact have led to radioactive nuclear accidents that had strategic and international ramifications that are unheard of for coal plants: It is well-known that the Three Mile Island nuclear accident was largely caused by a pressure relief valve in the primary pressurised steam loop of that PWR that failed to close again tightly, after it opened to relieve the pressure. The reason was that as some of the water in this primary loop boiled off when it was released through this valve, the boric acid in the water crystallised on the valve stem and thus prevented it from closing tightly afterwards. Therefore, the primary coolant water leaked out and boiled off and thus the fuel overheated which led to the infamous core meltdown. Similarly, the Fukushima nuclear disaster was caused by a tsunami wave that swept away the diesel tanks for the backup power generators that drove the emergency coolant water pumps, after the nuclear plants tripped at the onset of the earthquake at Fukushima. For a coal plant, similar losses of coolant water flow through its boilers would have destroyed the boiler tubes, resulting in the boiler being shut down until these tubes could be replaced, which would hardly have been a newsworthy incident. However, at Fukushima this failure of coolant water flow triggered an international crisis: It is well known that the evacuation of people and the ensuing radioactivity clean-up effort already cost Japan roughly \$200 billion. On top of this their nuclear safety regulator shut down their entire fleet of nuclear plants for several years, until the whole nuclear safety system and culture could be overhauled. This resulted in power shortages that forced Japan to import large quantities of liquefied natural gas (LNG) to fuel its gas turbines. It is well-known in economic circles that this gas importation alone caused Japan's strong international trade surplus to turn into a trade shortage for several years. On top of this the Fukushima accident turned world opinion largely against nuclear power and led to more strict nuclear safety rules, which resulted in further increases in the cost of new nuclear plants, which contributed to halting the so-called Nuclear Renaissance, resulting in huge financial losses in the international nuclear construction industry (Cooper, 2011).

All these factors show that although the likelihood of component failures and thus plant unavailability is relatively low for nuclear plants compared to e.g. coal plants, the negative consequences of such incidents are sometimes uniquely high and thus there is a more serious imperative to reduce the occurrence of such nuclear component failures and the associated unplanned outages, compared to coal or gas plants.

1.1.2 Worsening condition of the current nuclear fleet

There are presently about 450 reactors in the world and about two-thirds of them are more than 20 years old, as shown in Figure 1-1 (IAEA-PRIS, 2019). About half of them are already considering lifetime extension.

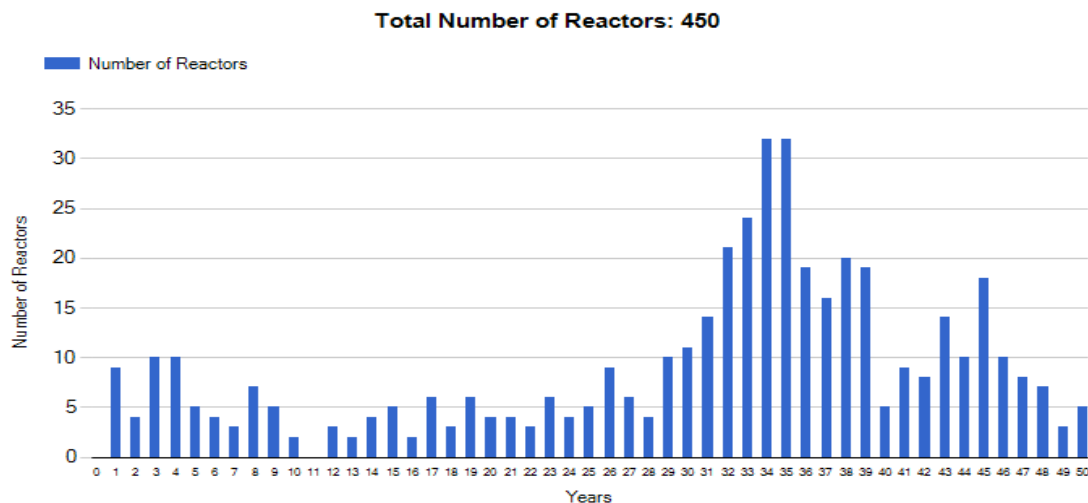


Figure 1-1: Total reactors in the world and their ages (IAEA-PRIS, 2019)

Due to the ageing of these plants, it would be normal to get surprises during routine planned maintenance outages, thereby increasing downtime, the associated costs of unavailability and maintenance cost.

1.1.3 Shortcomings of the traditional maintenance regime

The traditional maintenance system in a nuclear plant involves periodic inspection of plant components. Maintenance is usually scheduled based on a specified timeline, rather than on the condition of these components. The problem is that while the remaining useful lifespan of each component can be estimated roughly from experience and from the manufacturer's specifications, the remaining useful life for each critical component in a specific plant is normally not known accurately. This uncertainty in the remaining useful life often results in one of the following two types of additional and unnecessary operating costs:

- Components are replaced too early and thus the value of its remaining useful life is lost.
- A critical component is scheduled to be replaced too late, so it fails before it can be replaced, resulting in an unplanned outage, with all the associated negative consequences discussed above.

Therefore, there is a need for the nuclear industry to employ maintenance regimes that will reduce operating costs by:

- reducing unnecessary maintenance, while simultaneously
- reducing component failures and thus unplanned outages.

It is therefore important to be aware of the condition of components that are critical to the safety and operability of nuclear plants, especially as they age and are exposed to harsh conditions. Condition-based maintenance (CBM) is an obvious possible tool to achieve these maintenance goals. However, CBM normally relies on comparing, on a regular basis, measured data about the current condition of critical components in the power plant to historical data for each of these components, for the case where they were allowed to run to failure. From this the current time to failure, and thus the remaining useful life, for the critical components can be estimated and maintenance decisions can then be optimised, based on these estimates. However, for reasons of safety and economics, critical nuclear components are normally not allowed to run to failure and, therefore, such historical data are often not available for nuclear plants. This makes the implementation of CBM in nuclear plants particularly challenging, compared to other power plant types.

1.1.4 The problem to be solved

Therefore, the problem to be solved in this study is to reduce nuclear operating costs by developing a condition-based maintenance methodology that will reduce both unnecessary maintenance and unplanned outages:

- Due to the absence of measured run-to-failure data for critical components in nuclear plants, run-to-failure data will be simulated using the full-scope simulators, mainly developed for operator training, that must be present in all nuclear plants. These full-scope simulators will thus function as a digital twin for the physical components under consideration. The hybrid system proposed, using the existing full-scope simulators will save industry the cost and effort of developing dedicated digital twin simulators, which should greatly enhance the attractiveness of this methodology to industry.
- In this study the focus will be limited to developing and demonstrating the viability of this full-scope simulator-based version of the digital twin condition-based maintenance methodology, as opposed to implementing and testing it for every critical component. Therefore, the method will be tested on only a few important components/cases. Once the viability of the method is demonstrated, detailed implementation will be deferred to follow-up studies.

- Since simulated component condition data can be expected to deviate from data that would have been obtained through actual measurement, the simulation-based version of CBM can be expected to be less accurate than CBM based on actual measured data. Therefore, accurately estimating the level of deterioration of critical components and then making optimal maintenance decisions based on these estimations can be expected to be particularly difficult. A steep learning curve can thus be expected. The problem to be solved thus includes developing a component condition diagnostic system that is aided by machine learning tools such as artificial neural networks (ANN) and neuro-fuzzy systems.

1.2. Research aim and objectives

The aim of this research is to develop a CBM methodology in order to reduce unnecessary maintenance and unnecessary shutdown in a nuclear power plant. In this methodology, current data on the condition of critical components will be compared to simulated data, generated by a full-scope engineering simulator. In these simulations, the condition data will be simulated for these critical components, for the case where they are allowed to run to failure. This novel hybrid system will be aided by machine learning tools such as artificial neural networks (ANN) and neuro-fuzzy systems.

In order to achieve this aim, the following are the **objectives** of the proposed research work:

- Employ a full-scope engineering simulator to generate plant degradation data;
- Develop a neural networks model for identification of abnormalities in the NPP;
- Determine the level of degradation of nuclear plant components using the neuro-fuzzy method; and
- Propose a strategy to optimise maintenance decisions, based on the results of this CBM methodology.

1.3. Hybrid system implementation approach

Cilliers and Mulder (2011) in their research established the possibility of using a nuclear power plant simulator in fault diagnostics; This work is aimed at further exploring the use of the NPP simulator alongside machine learning tools in predicting faults and determining the degradation level of components. This research seeks to achieve this by using the nuclear power plant simulator in real-time condition monitoring, thereby obtaining useful data in identifying anomalies and estimating the degradation level of nuclear plant components. In order to develop a novel system, the approach taken involves the review of existing concepts and principles that relate to the research work. The areas of interest to accomplish this task include a study on the existing

condition-based maintenance methods, machine learning tools, and the NPP simulator technology. A review of these areas is presented in Chapter 2.

1.4. Thesis layout

The remaining part of this thesis contains five (5) chapters.

Chapter 2 is a comprehensive literature review of this thesis. A review is carried out on the major blocks of the research work which is condition-based maintenance, simulation technology, machine learning tool and a summary of the lessons learnt from literature.

Chapter 3 contains an article which is a survey of the state of condition-based maintenance in the nuclear industry. This chapter explores the length of work that has gone into the different aspects of condition-based maintenance in the nuclear industry. The different aspects considered include state of condition monitoring, detection, diagnostics and prognostics in the nuclear industry. It also explored the CBM data processing methods which are the data-driven, model-based and hybrid methods by performing a strengths, weaknesses, opportunities and threats analysis of these methods and CBM in the nuclear industry.

In Chapter 4, the second article titled “Hybrid nuclear plant simulator design requirements to enable dynamic diagnostics of plant operations” is presented. This article explains the necessary requirements for a nuclear plant simulator to be able to perform fault diagnostics. It covers simulator classifications based on their uses; the simulator and the real-world system; the hybrid full-scope engineering simulator requirements; simulator model requirements and simulator functional requirements.

Chapter 5 is the third article titled “Continuous machine learning for abnormality identification to aid condition-based maintenance in a nuclear power plant”. This article contains a description of a neural network system developed and combined with the nuclear plant simulator. The system was able to identify transients and detect a faulty valve.

Chapter 6 contains the fourth article titled “Implementation of a Neuro-Fuzzy System for Enhanced Abnormality Identification in Nuclear Plants”. The neuro-fuzzy system was developed. The system identified the fault and also gave the degradation level of the fault. The results were compared by using the machine learning tool independently.

Chapter 7 contains the conclusions.

Then the references and appendix follow.

CHAPTER 2: LITERATURE REVIEW

This chapter contains a review of this research work. The major themes of this literature review are condition-based maintenance, simulation technology and neuro-fuzzy systems as shown in Figure 2-1. The other sections of this chapter contain a review of these areas.

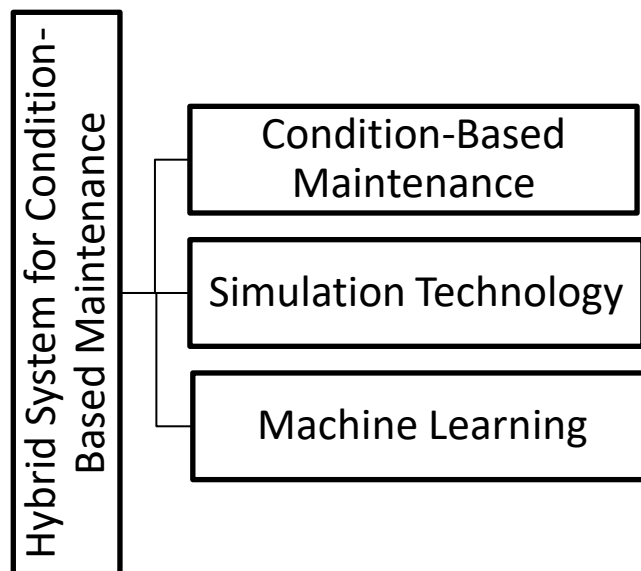


Figure 2-1: Major themes in this research.

2.1 Condition-based maintenance

The role of maintenance in the running cost of a nuclear power plant (NPP) cannot be overemphasised. This is because the operating and maintenance (O&M) cost contributes approximately 40 to 70% of the plant's generating cost (Bond *et al.*, 2007). Until now, the impact of maintenance on production, quality and cost has partly been ignored. Industries saw maintenance as a grey area and with the general mindset that 'maintenance is a necessary evil' (IAEA, 2007). With the recent growth in diagnostic technologies, things are beginning to take a different turn. Now industries are beginning to research and implement ways of optimising maintenance in order to reduce maintenance cost while improving equipment performance.

Maintenance has gone through several stages of development over the decades. It has moved from the "fix it when it fails approach" to an improved "planned and monitored approach". The different maintenance approaches can be classified into three categories, namely, time based/periodic maintenance, corrective maintenance and condition-based maintenance. Condition-based maintenance and time-based maintenance are also called preventive maintenance. Time-

based (periodic) maintenance involves carrying out maintenance actions based on a fixed time, rather than based on the condition of the components/equipment, and it does not require collection of data; while, on the contrary, condition-based (predictive) maintenance entails performing maintenance action based on monitoring the state of the plant, which involves collecting data and analysing the data before a decision can be reached. This approach can eliminate unnecessary maintenance (Davies *et al.*, 2000).

Our focus in this research is condition-based maintenance. CBM was first introduced by the Rio Grande Railway Company in the late 1940s and, initially, it was called “predictive maintenance.” Introducing CBM enabled the company to detect coolant, oil, and fuel leaks in the engine by trending changes in temperature and pressure readings. These helped them reduce the number of unplanned outages and unnecessary maintenance (Prajapati *et al.*, 2012).

From the early '50s till date the application of CBM has continued to grow, as several industries have started focussing on reducing their maintenance cost and downtimes. They have come to embrace this maintenance approach and tremendous growth has been experienced in the implementation of CBM. The nuclear industry was not completely left out. For the NPPs to survive the competition with other energy sources, it had to look for ways to reduce both its capital costs and its production cost. The nuclear industry has now focussed on ways to optimise maintenance to improve both reliability and competitiveness of nuclear power plant operation. This has resulted in the consideration of CBM in the nuclear plant maintenance strategy (IAEA, 2007). With a properly implemented CBM regime, the maintenance objective of maintenance in NPPs can be achieved in order to improve the probability that structures, systems and components (SSCs) will always operate safely, reliably and in an economic manner. Thus providing society with safe, good quality and clean power at a competitive price (Huang *et al.*, 2014).

2.1.1 Definition of CBM

Different definitions of CBM can be found in literature. Five of these definitions that will give insight into the concept of this research work are highlighted below:

- “[CBM] involves monitoring the condition of mission-critical and safety-critical parts in carrying out maintenance whenever necessary to avoid hazards rather than following a fixed schedule” (Nickerson & Hall, 1995).
- “[CBM] is a maintenance strategy that collects and assesses real-time information, and recommends maintenance decisions based on the current condition of the system” (Alaswad & Xiang, 2017).

- “CBM is a maintenance program that recommends maintenance actions (decisions) based on the information collected through condition monitoring process” (Jardine *et al.*, 2006)
- The US Air Force defines CBM as “a set of maintenance processes and capabilities derived from the real-time assessment of weapon system condition obtained from embedded sensors and/or external test and measurements using portable equipment. The goal of CBM is to perform maintenance only upon evidence of need” (Prajapati *et al.*, 2012).
- “The condition-based maintenance (CBM) process requires technologies, people skills, and communication to integrate all available equipment condition data, such as diagnostic and performance data; maintenance histories; operator logs; and design data, to make timely decisions about the maintenance requirements of major/critical equipment” (IAEA, 2007).

From these definitions, it can be deduced that CBM involves the process of collecting data of the system condition and analysing the data to know the condition of the plant. Lastly, based on these steps as shown in Figure 2-2, maintenance decisions can be made.

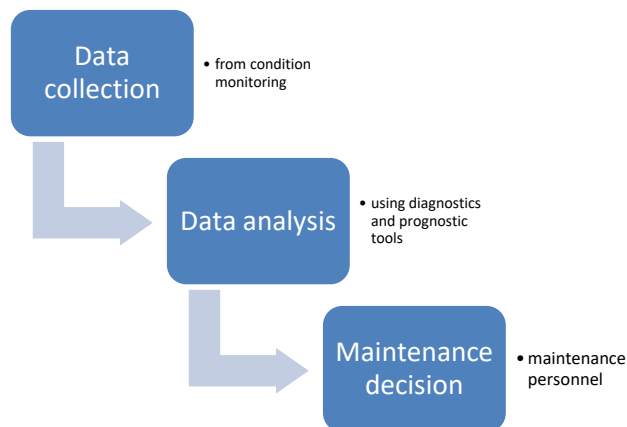


Figure 2-2: Stages involved in condition-based maintenance

This research is focused on the first two stages. The condition monitoring data will be obtained from the nuclear plant and simulator, while a machine learning tool will be used in data analysis. The results will aid the maintenance decision on when to schedule maintenance.

2.1.2 Advantages of CBM

Introducing CBM into the maintenance strategy has numerous benefits. Some of the benefits are:

1. Improving the general safety of the unit (Huang *et al.*, 2014).

2. Reducing uncertainty involved in maintenance (Rastegari *et al.*, 2017).
3. Optimising resource allocation, and improving the cost-effectiveness of maintenance (Huang *et al.*, 2014).
4. Improving the reliability of equipment (Alaswad & Xiang, 2017).
5. Making full use of the effective service life of equipment (Huang *et al.*, 2014).
6. Increasing the plant machinery useful operating life (IAEA, 2007).
7. Reducing maintenance costs, leading to cost savings of 20% to 40% or more (Huang *et al.*, 2014).
8. Reducing overhaul burden and shortening overhaul period (Huang *et al.*, 2014).
9. Reducing total life cycle cost (Akindele, 2010).
10. Helping in enhancing the relationship between the operations and maintenance departments as well as among other maintenance personnel of different backgrounds and skills (Davies *et al.*, 2000).
11. Significantly enhancing availability, reliability and operating costs of the nuclear plant (IAEA, 2007).
12. Helping in the verification of the condition of new equipment, verification of repairs and rebuilding of work and product quality improvement (IAEA, 2007).

2.1.3 Implementation of CBM

CBM is developed based on the premise that components/equipment failure is a process and is usually not a sudden event (Huang *et al.*, 2014). Therefore, a careful study and analysis of the equipment failure process will aid CBM. Studying an equipment failure pattern will help in monitoring the plant condition, detecting anomalies, identifying fault characteristics and also in estimating the remaining useful life of the equipment. CBM entails monitoring, detection, diagnosis and prognosis; this is depicted in Figure 2-3. The result from these four steps in CBM helps the maintenance team in making reasonable decisions about maintenance scheduling and equipment replacement.

Monitoring	Detection	Diagnosis	Prognosis
•entails monitoring the condition of the plant through: •vibration monitoring •acoustic emission •thermography •tribology •visual inspection •process parameter monitoring	•entails fault detection using a data analysis tool which could be: •model based methods •data driven methods •hybrid methods	•entails fault characterisation using a data analysis tool which could be: •model based methods •data driven methods •hybrid methods	•entails estimating the remaining useful life (RUL) with the aid of a data analysis tool which could be: •model based methods •data driven methods •hybrid methods

Figure 2-3: Stages involved in condition-based maintenance

2.1.4 Application of CBM

Since 1950, the introduction of CBM into the maintenance strategy has continued to increase. In a similar trend, industries that use CBM are not limited to the military, navy, aerospace, IT infrastructure, manufacturing, food processing and automotive. There are also other industries that are considering the use of CBM applications (Prajapati *et al.*, 2012). However, in the nuclear industry, CBM is gradually being introduced into the maintenance regime (IAEA, 2007). More details on the application of CBM in the nuclear industry is discussed in Chapter 3.

2.1.5 Challenges of CBM

The introduction of CBM is not without challenges and these include:

1. The ability to do real-time prognostics (Davies *et al.*, 2000).
2. The availability of data (Ahmad & Kamaruddin, 2012).
3. Data quality preparation/selection and data collection/transmission (Davies *et al.*, 2000).
4. The use of different techniques for on-line and off-line condition monitoring and diagnostics, as well as techniques for non-destructive inspection and surveillance (IAEA, 2007).
5. The effectiveness of CBM is usually affected by issues like parameter selection for monitoring condition, component selection for CBM, and evaluation of condition monitoring results (IAEA, 2007).

2.2 Simulation technology

The nuclear industry can be seen as one of the first industries to apply the use of simulators. In the 1970s, the nuclear industry had already developed 3D models for safety analyses, 3D models for neutron power distributions, analytical models for safety analysis, transient analysis codes for plant dynamics and two-phase models for DBA blowdown. The Three Mile Island accident in 1979 also further enhanced the development of nuclear plant simulators, in which a wider scope of accident conditions was added to the safety codes. The improvement of computer technology further enhanced the growth of simulator technology in the nuclear industry; in the 1980s the simulator was able to be used for real-time process simulation. In 1986, the Chernobyl accident also brought about improvements in the core neutronics. The tremendous increase in computer speed in the 2000s has made the nuclear industry to greatly advance simulator technology. Aside

from simulating process behaviour, the simulators could also be used in validating new instrumentation and control (I&C) components (Miettinen, 2008).

2.2.1 Applications of NPP simulators

NPP simulators were primarily designed for training but with time they have been applied in other areas. For example, nuclear plant simulators are used in testing new designs, designing operator support systems (Vilim *et al.*, 2017), severe accident analysis (Osborn *et al.*, 2015), research, human performance evaluation, industrial process studies while many other applications are being developed (Ayo-Imoru & Cilliers, 2017).

One of the notable applications of the nuclear plant simulator is the development of a plant diagnostic system in which the NPP simulator and the nuclear plant operating under the same conditions have their data combined in real-time for fault diagnosis (Cilliers & Mulder, 2012). With this approach, incipient faults can be detected faster than with the NPP safety system. This method was validated using the Three Mile Island accident. This research was carried out with the PCTTRAN simulator. The work was further verified using data from the Koeberg NPP which helped in validating the approach and the PCTTRAN data used (Pelo, 2013).

This research aims to further explore the use of simulators in combination with machine learning tools for fault diagnosis in nuclear power plants. The next section describes the machine learning tool of interest.

2.2.2 The concept of using a simulator as an NPP digital twin

The digital twin concept was first developed by the aerospace industry and was defined in 2010 by NASA as “an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. The digital twin is ultra-realistic and may consider one or more important and interdependent vehicle systems.” (Liu *et al.*, 2018)

The digital twin (DT) can be described as a virtual system that has been created to represent a physical system or equipment for the purpose of improving product design, monitoring equipment health to identify potential degradation and simulating manufacturing operations. This is achieved by making the digital system to continually learn until it correctly mirrors the physical system. This digital twin concept has found successful application in the aerospace industry and is being considered in manufacturing industries. It is useful in situations where physically accessing the real asset is a challenge. The data stream from the twin might feed into data analytics and machine learning stacks for pattern recognition and decision support (Erikstad, 2017).

Considering the success of the digital twin concept in the aerospace industry and the aerospace similarity with the uniqueness of the nuclear industry, the digital twin can also be adopted in the nuclear power plant. The nuclear plant is unique in that the nuclear plant has mandatorily in almost every facility a full-scope simulator which is a replica of the NPP with high fidelity. Although the full-scope simulator (FSS) was primarily designed for training, with the DT concept the use of the FSS as the NPP digital twin can now also be explored.

2.3 Machine learning tools for condition-based maintenance in NPP

Machine learning is one of the data-driven tools used in modelling a system by means of understanding the system behaviour using historical data for the purpose of detecting and predicting patterns and faults in the system. Machine learning has found very wide application in almost every field in all facets of life ranging from medicine to accounting, geography, engineering, astronomy, etc. The nuclear industry which is not an exception has also seen lots of research employing different machine learning tools in solving different challenges in the industry. Some notable applications in the nuclear industry using machine learning include the following examples:

- The use of a support vector machine (SVM) is a machine learning tool for the classification of transients in nuclear power plants. This involved the combination of a single- and multiclass SVM into a hierarchical structure for distinguishing among transients in nuclear systems using measured data. It was able to classify faults that occurred in the boiling water reactor's (BWR) feed-water system data from the HAMBO simulator of the Halden Reactor Project (Zio, 2007).
- Another machine learning tool – the Deep Belief Network (DBN) technique – was developed for detection and classification of faults for thermocouples used in NPPs. The DBN method can be used online and is very sensitive to small data variations. This method was tested and validated using data from thermocouple sensors used in a fast breeder test reactor (Mandal *et al.*, 2017). Trace gas releases from an NPP was observed and estimated using a machine learning tool. This was done through a combination of Bayesian inversion, machine-learning algorithms and simulations. The research was carried out on a coastal California nuclear power plant by quantifying the probability distribution functions (PDFs) of model inputs that affect the transport and dispersion of a trace gas released from the NPP (Lucas *et al.*, 2017). An artificial neural network (ANN) was used to investigate the impact of seismic activities on NPP structures by computing the fragility curve and estimating the probability of failure of the structure output using the seismic intensity measures as inputs to the ANN (Wang *et al.*, 2018).
- A probabilistic kernel approach was developed for intelligent online monitoring of mechanical components. The learning ability of the Gaussian processes (GPs) was employed and used

in predicting the component failure trend. This approach was tried and validated using degradation data from an actual turbine blade (Alamaniotis *et al.*, 2012).

- A machine learning technique was developed for postures recognition of NPP operators by a supervised learning method. Several image processing techniques were combined to detect the operators' silhouettes in the images. Their postures were recognised by a machine learning technique. Their operations were summarised and visualised with human body computer graphics. Operators usually take various postures during NPP operation; therefore, posture recognition is really a challenging task. To recognise the detected operator silhouettes, the four postures that have been classified by the cognitive scientists engaged in human factors research of NPP operations were used. Over twenty thousand images were used in this experiment. They were able to classify operator postures successfully (Nakajima, 2004).
- A genetic algorithms method was investigated and employed in the proposed Population-Based Incremental Learning (PBIL) algorithm. The PBIL is a stochastic optimisation technique which is based on Darwin's biological metaphor of the survival of the fittest. This approach was used to optimise the nuclear reload process of the seventh operation cycle of the Brazilian PWR Angra 1 (Da Silva *et al.*, 2018).
- Leakages in pipelines were investigated using several learning algorithms for classification and finding the key predictors that affect leaking in pipelines. The different features of the acoustic signals from microphone sensor nodes around a laboratory-scale NPP coolant system were monitored in order to diagnose high-pressure steam leakages. This method was able to accurately classify leakages in pipes even in the presence of nearby loud machine-driven noises (Oh *et al.*, 2018).
- Neural networks and principal component analysis (PCA) methods were used in developing a comprehensive knowledge base for the operator support system of the Chinese Qinshan II NPP. The PCA method was used for noise filtering in the pre-diagnostic stage, and two different recurrent neural networks were used for prediction and diagnosis of faults (Ayodeji *et al.*, 2018).
- Machine learning was also employed in site selection for a nuclear power plant. This was achieved by developing a method based on fuzzy logic. It was also possible to employ this method for existing nuclear power plants location selection policy for Turkey. A sensitivity analysis was conducted to analyse the effects of changes in the decision's parameters (Erdoğan & Kaya, 2016).

The machine learning tool of interest is the hybridised neural network and fuzzy logic: this is because it combines the strength of neural networks and fuzzy logic. The subsequent sections will further explain these machine learning tools individually and in the hybrid form.

2.3.1 Artificial neural network (ANN)

The ANN is a machine learning tool that is patterned after the human brain. The computer is made to function like the human brain by learning statistical data and creating patterns. ANN can be called a virtual brain as it tries to emulate how the brain works. ANNs are structured after the brain to perform operations like pattern classification, perception and motor control (Demuth & Beale, 1993). The ANN consist of a collection of neurons, which are interconnected to form a network. The neurons' interconnection strength called synaptic weight is used in storing knowledge (Haykin, 1998).

ANN are typically defined by three major parameters, which include structure (i.e. the interconnection pattern between the different layers of neutrons); learning algorithm (which is the learning process for updating the weights of the interconnections); and the activation function (which converts the neurons' weighted input to its output function). Different architectures exist which include the multilayer perceptron, radial basis function, and general regression neural network. Learning methods include error correction method, memory-based learning, Hebbian learning, competitive learning, and Boltzmann learning activation function.

A neural network has the ability to learn and generalise so that it can produce output from inputs it did not encounter during training. The other strengths of a neural network are: it can work well in non-linear systems; it can do an input-output mapping; it can adapt to changes in the environment; it can give a confidence level on the decision made; and it can deal with information that is noisy, inconsistent, vague or probabilistic (Leondes, 1998).

The ANN is nonlinear, distributed, parallel, and adaptable and has local processing capability which makes it suitable for application in a complex system like the NPP. ANN is a data-driven modelling technique in which the system physics of failure is not required; rather, the network is trained to understand how the systems work, but large amounts of data is required for accuracy. This makes it applicable in the NPP because of the availability of historical data and because of the large amounts of data being produced in the plant during operation. In the nuclear industry, ANN has been applied in different research areas like loose part monitoring (Kim *et al.*, 2002), transient diagnosis (Mo *et al.*, 2007), nuclear plant condition monitoring (Şeker *et al.*, 2003), monitoring check valves (Seong *et al.*, 2005), fault diagnosis (Leger *et al.*, 1998; Simani & Fantuzzi, 2000) and sensor validation (Xu *et al.*, 1999).

2.3.2 Fuzzy systems

Fuzzy logic was introduced in 1965 by Lotfi Zadeh, he presented this ground-breaking idea in a continuous-valued logic that he called fuzzy set theory (Ross, 2005). This approach deals with

linguistic vague information based on fuzzy sets and fuzzy logic. Fuzzy logic has been widely applied in different fields like meteorology, medicine, engineering, management, computer science, etc. (Leondes, 1999). A fuzzy system is similar to the algebraic function which maps an input variable to an output variable. A fuzzy logic system also maps a set of inputs to a set of outputs. Fuzzy logic mimics the human reasoning skill of interpreting incomplete and imprecise information by solving problems in the form of IF-THEN rules. Fuzzy logic is able to perform numerical computation by using linguistic labels specified by membership functions (MFs). The degree of membership between 0 and 1 are assigned based on fuzzy rules. Membership in a fuzzy set is usually represented graphically and different approaches are used in estimating the membership function. A fuzzy logic system incorporates human knowledge in decision making and inferencing. Fuzzy logic, in summary, is an approach for computing with words instead of numbers. Fuzzy logic has the advantage of allowing imprecision which reduces the cost of the solution.

2.3.3 The hybrid system

The combination of neural network and fuzzy logic (FL) approach is aimed at harnessing the strength and diminishing the weakness of both tools. For instance, the neural network can easily do pattern recognition and make a decision without showing the reason behind it, while fuzzy logic can explain the reasons for its decision but is not able to automatically get the rules needed for it. The hybrid system can be combined in different ways which include fuzzy rule-based systems with learning ability, fuzzy rule-based systems represented by network architectures, neural networks for fuzzy reasoning, fuzzified neural networks and other approaches (Leondes, 1999). Combining these two methods helps give a stronger data-driven approach. The advantages of having this hybrid method are numerous, including:

1. Ability to incorporate human knowledge effectively;
2. Ability to handle different types of input data (numeric, linguistic, logical, etc.);
3. Ability to use data that are vague, imprecise, partial and imperfect,
4. Ability to adapt to an unknown or changing environment;
5. Being fault-tolerant;
6. Model-free learning;
7. Ability to be trained, and ability for self-learning, self-organising and self-tuning; and
8. Not needing prior knowledge of how data relates.

This hybrid method of combining ANN and FL has been used in different areas which include streamflow forecasting in a river watershed tributary using the adaptive neuro-fuzzy inference system (ANFIS) and Bayesian regression. In this work, the ANFIS models performed satisfactorily

(Hamaamin *et al.*, 2016); and prediction of tool conditions under high-speed machining conditions by employing a method called Evolving eXtended Takagi-Sugeno (exTS) based neuro-fuzzy algorithm (Massol *et al.*, 2010). The neuro-fuzzy approach was employed in the prognosis of crack propagation problems (Di Maio & Zio, 2013). The neuro-fuzzy method was also employed in estimating the remaining useful life (RUL) of lithium-ion batteries. This was accomplished by making use of the past and current batteries' data to predict the upcoming values of the battery capacity. This approach was able to estimate the remaining useful life of the battery. The experimental results showed the brilliant performance of the neuro-fuzzy technique compared to other methods (Razavi-Far *et al.*, 2016).

The neuro-fuzzy method has also been used for estimating remaining useful life (RUL) using just a few learning data that starts from the basics, without any prior knowledge. This method was tried on the commercial modular aero-propulsion system simulation (C-MAPPS) turbofan dataset and the RUL estimates were very close to actual values (Massol *et al.*, 2010). The adaptive neuro-fuzzy inference system has been used in combination with discrete wavelet transform (DWT) for fault gear identification and classification based on vibration signal. Their approach was used to classify the fault gear positions and the gear fault conditions. Their results showed that ANFIS outperformed the traditional vision inspection methods (Wu & Hsu, 2009).

Other applications of the neuro-fuzzy approach are in the design of a fault classification system in an induction motor (Alexandru, 2003), and condition monitoring in the railway industry, which involved detection and diagnosis of the most commonly occurring track problems (Chen *et al.*, 2008). A combination of the neuro-fuzzy approach and a support vector machine was developed for detection and diagnosis of incipient steam turbine faults (Salahshoor *et al.*, 2010).

2.4 Summary and conclusions

From the current literature studied, it can be seen that CBM has enormous benefits which include:

- Increased production availability;
- Less emergency work being performed;
- Improvement of product quality;
- Enhanced safety;
- Substantial energy savings;
- Reduction of inventory cost;
- Extended life of plant time;
- Reduction of maintenance cost; and
- Extended useful life of critical systems.

CBM has been successfully employed in many industries and some areas in the nuclear industry, but not without some challenges, including:

- Intensive regulatory scrutiny;
- Need for strong management commitment;
- Need for special training for operators, technicians and maintenance engineers; and
- Selecting the right approach in estimating the condition of the structures, system, and component.

Several approaches have been developed for the four stages of CBM which can be summarised as model-based, data-driven and hybrid methods. The model-based method requires an understanding of system physics of failure, the data-driven method is easier but requires a large amount of historical data, while the hybrid method combines one or more of either model-based, data-driven or both methods to give a better result than using any individual approach separately.

The nuclear industry has the advantage of a large amount of historical data which is of great benefit in employing a data-driven approach. The nuclear industry has also been employing simulators although primarily for operator training. The full-scope simulator, which is the simulator of interest, has high fidelity and is able to work in real-time and even faster than real-time.

This has brought about the possibility of employing this data-driven approach, and the nuclear plant simulator for fault diagnosis. The neuro-fuzzy method, which is the tool of interest, can be used for complex systems and has the advantage of being able to adapt to an unknown or changing environment. Since it is fault-tolerant, it requires model-free learning, can be trained and has the ability for self-learning, self-organising and self-tuning. It also does not need prior knowledge of how data relates.

In the following chapter, a more in-depth survey is carried out to explore the state of condition-based maintenance in the nuclear industry.

CHAPTER 3 - ARTICLE 1: A SURVEY OF THE STATE OF CONDITION-BASED MAINTENANCE (CBM) IN THE NUCLEAR POWER INDUSTRY

Condition-based maintenance (CBM) involves undertaking maintenance activities based on the health of the system. CBM has found useful applications in many industries. This paper presents a survey of the state of condition-based maintenance in the nuclear industry. This is achieved by systematically looking at the major phases of CBM, which are monitoring, diagnostics and prognostics. A methodical review has been done on these aspects of CBM. This includes the current practices in the nuclear industry and the ongoing research on the different methods and technologies being developed. This will give maintenance stakeholders and researchers an overview of the current practices and extent of research undertaken on condition-based maintenance in the nuclear industry.

Keywords: condition-based maintenance, monitoring, diagnostics, prognostic, maintenance stakeholders.

3.1 Introduction

Maintenance has evolved over time as advancement in technology and fast-growing research has been used to build 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 termed corrective maintenance. In the period after World War II, the world began to experience great advancement in technology and industries had more complex machines, demand for products and services increased and downtimes could mean being out of business. As a result, the maintenance approach has evolved from a corrective approach to a new approach to preventive maintenance. The preventive type of maintenance from the 1970s, consisting of periodic maintenance, involved scheduling maintenance at regular intervals to avoid failure. Over time as technology kept advancing, interest shifted from an “avoiding failure” type of maintenance to more cost-effective maintenance. This has brought about another type of preventive maintenance, which is condition-based maintenance (CBM). CBM involves undertaking maintenance activities based on the health/condition/level of degradation of the system/equipment. In Table 3-1 a summary of how maintenance has evolved over time and the characteristics of the different types of maintenance are portrayed (IAEA, 2007; Moubray, 1995).

Table 3-1: Types of maintenance systems and their characteristics

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

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 nine (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 sections discuss the different modelling methods used in CBM, and also strengths, weaknesses, opportunities and threats (SWOT) analyses of these modelling methods. The last section is the conclusion.

3.2 Condition-based maintenance (CBM) in the nuclear industry

The nuclear industry is a major contributor to 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 in 1999 was 17% (Davies *et al.*, 2000). Davies *et. al* also mentioned that this percentage will most likely reduce in the coming decades due to challenges faced in the nuclear industry. Figure 3-1 shows the nuclear power contribution to world's electricity in terawatt hour which shows an increase in nuclear power production over the decade but Figure

3-2 (IEA, 2017), shows the percentage contribution which is declining; this implies the growing world energy need and the need for the nuclear industry to increase her production to meet the world’s energy need.

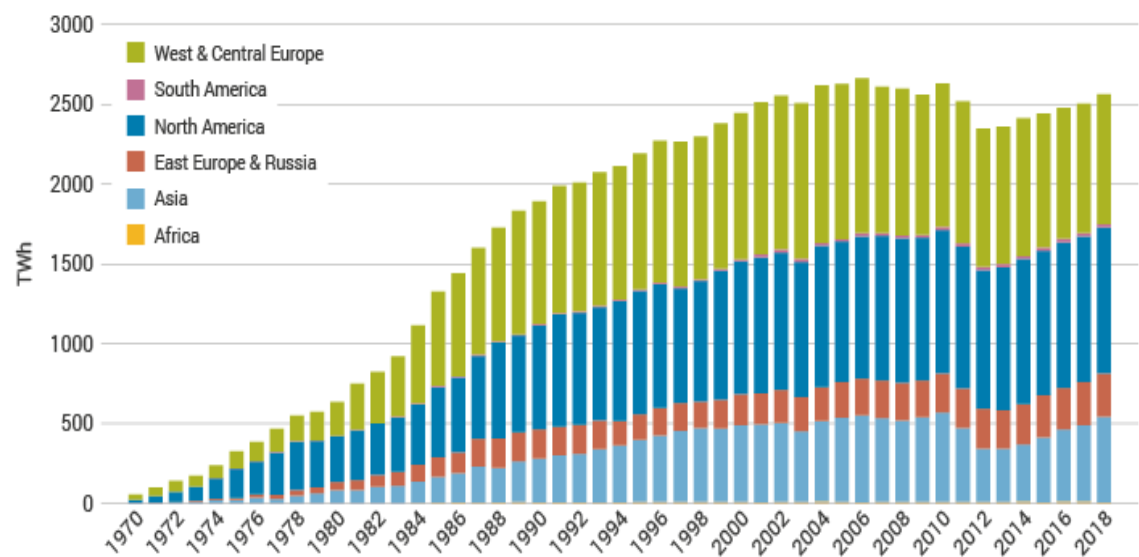


Figure 3-1: Nuclear power contribution (TWh) to world electricity from 1999-2018. (IAEA-PRIS, 2019):

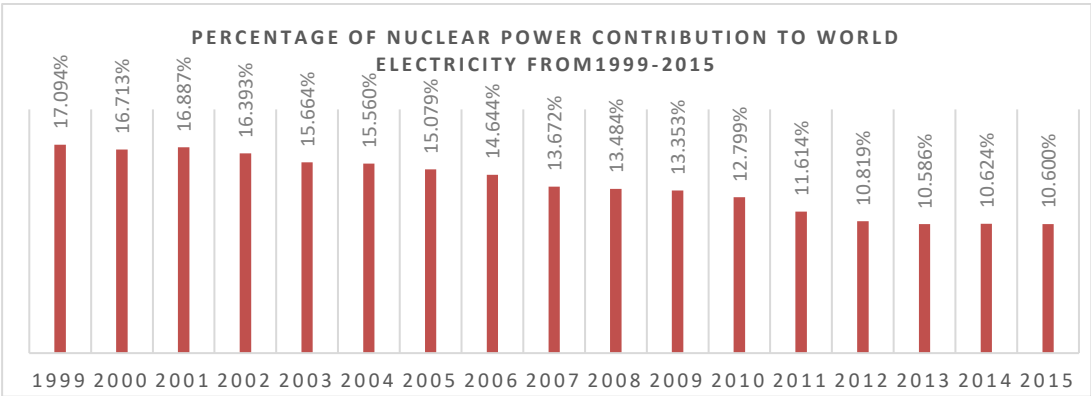


Figure 3-2: Percentage of nuclear power contribution to world electricity from 1999-2015.

One major factor affecting the nuclear power plant (NPP) is producing electricity in a cost-effective manner without jeopardising safety, which is of the highest priority in the nuclear industry. In NPPs, the cost of operations and maintenance (O&M) is about 60-70% of the total cost of

generation (Coble *et al.*, 2012). Therefore, to reduce the cost of producing electricity, one important aspect is to reduce maintenance cost. For the NPP to compete successfully with other energy sources, the nuclear industry must reduce the cost of generating electricity, which can partly be achieved through a condition-based maintenance strategy.

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

NPP equipment is divided into three categories, namely structures, systems and components (SSC). These SSCs are further classified as active and passive. The active SSCs are the ones that contain moving parts and the passive SSCs are the stationary ones. Maintenance is carried out based on these categories in line with their design and functions. Maintenance programmes in the nuclear industry are 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 effective maintenance. Maintenance in the NPP entails different activities which include surveillance, inspection, testing, service, overhaul, repairs and part replacement.

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. Some 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 in 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 scrutinised to such an extent that many systems never get implemented (IAEA, 1999). This particularly has caused damaging delays in adopting CBM in the nuclear industry. However, this can be overcome by introducing CBM systematically by starting with components that are of less concern to the regulators. This could have made the technology 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 are no longer produced and the stringent regulatory process of the nuclear industry does not allow the use of just any off-the-shelf components in their place (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 characterising the detected abnormality, i.e. locating and knowing the magnitude of the fault. The results of monitoring, detection and diagnostics can be analysed through different methods to project and determine the possible time to failure of the equipment which is the estimation of the remaining useful life. The results from all these stages of CBM can help the maintenance personnel to make a useful decision about the type and time of maintenance to be done. Figure 3-3 below shows the different stages of CBM. The state of each of the stages in the nuclear industry is discussed in the following sections.

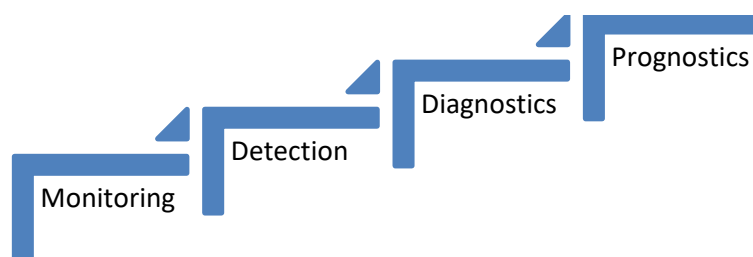


Figure 3-3: Stages in condition-based maintenance.

3.3 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. 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. However, nuclear plants in the US and Europe have started adopting condition-based monitoring which is referred to as online 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 a non-intrusive, non-destructive and in-situ manner, 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 information to the nuclear plant operator on the state of the plant and maintenance personnel, and data for the necessary action to take. IAEA (2013) explains in detail the different online monitoring techniques in the nuclear industry.

Hines and Davis (2005) conducted a 'lessons learned' exercise on NPP online monitoring systems. They investigated the state of the 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 the 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.

Mainly, data from on-line monitoring in nuclear plants, are used in checking vibrations in reactor internals, measuring core stability margins, leak detection, verifying plant thermal performance, anticipating failures of rotating equipment, verifying proper operation of valves, and identifying and locating loose parts within the reactor system (IAEA, 2013). The recent research on the different types of monitoring techniques used in the NPP is discussed below.

3.3.1 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 involves 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 the literature for monitoring these vibration signals in different parts of the NPP. Many of the methods have been compared with conventional monitoring techniques and have yielded desirable results.

Some areas of application include the monitoring of vibrations in the reactor coolant pump carried out by Liu *et al.* (2015). In their work, they developed a technique on flywheels in main coolant pumps using the Hilbert-Huang transform (HHT) algorithm. Their results showed that the proposed method would be effective in condition-based maintenance of reactor main coolant pumps. Koo & Kim (2000) also worked on vibration monitoring within reactor coolant pumps. Their 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 transforms. Their study showed that vibration signals using WD are easier to analyse. There are other notable research efforts in monitoring vibrations in RCP (Lebold *et al.* 2005; Prasad *et al.*, 2002; Qinghu *et al.*, 2009; Ko & Kim, 2013).

Vibration monitoring is also used in monitoring turbine blade conditions. Rao & Dutta (2010) described a method based on a 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 a more economical method. De Pauw *et al.* (2013) in their research carried out an estimation of the performance of the different vibration monitoring methods used for measuring flow-induced vibrations on a fuel pin mock-up. Maekawa *et al.* (2016) presented a non-contact measurement technique for vibration stress in piping. Kong *et al.* (2014) also studied vibrations in piping systems. Czibók *et al.* (2003) monitored control rod vibration signals for degradation. A review of vibration signal techniques used in the nuclear industry can be seen in Sinha (2008).

3.3.2 Acoustic monitoring

Acoustic monitoring involves the different methods used in measuring the acoustic emissions (AEs) of different processes and components in a nuclear facility (IAEA, 2008). Acoustic emissions (AEs) are transient elastic waves that originate from a speedy release of strain energy which is due to 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 includes investigation using an acoustic monitoring system for timely detection of check valves (Lee *et al.*, 2006a). They concluded that their approach was able to correctly predict failures like disc wear failure and the 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 densities are estimated with an auto-regressive model. They were able to prove that the AE based technique was good for detecting check valve failures without the need for disassembling.

Al-Ghamd & 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 have more enhanced identification capability than the vibration analysis techniques. There are other AE based monitoring techniques developed for nuclear plants (Kaewwaewnoi *et al.*, 2010; Shimanskiy *et al.*, 2004; Ai *et al.*, 2010; Lu *et al.*, 2005).

3.3.3 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's internal structures (Choi *et al.*, 2011).

A typical LPMS comprises sets of accelerometers mounted on the reactor vessel, steam generators and reactor coolant pumps (Figedy & Oksa, 2005). LPMS makes use of audio signals and noise data records. When any part of the system is loose beyond a given set point the audio signal produces alarms. The alarm setpoints are based on the plant and the sensitivity of the loose parts monitoring equipment. When the alarm is raised, the next step is determining the location and size of the loose part; this is achieved by analysing the accelerometer output data (IAEA, 2008; KIMa *et al.*, 2012). One major factor in building an LPMS is reducing the false alarm rates.

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 & Oksa (2005) further enhanced the use of neural networks in LPMS by combining artificial neural networks and the wavelet in signal processing and enhancing the loose part monitoring system performance. Their method outperformed 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 the research of Cao *et al.* (2012) 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 a support vector machine (SVM). This they actualised in two stages: first, they detected weak burst signals at the initial stage which in the second stage were used in reducing the rate of false alarms by identifying the detected burst signal.

3.3.4 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 (IAEA, 2008). Reactor noise analysis is useful in monitoring, investigating and diagnosing the internal core vibrations; determining and trending in detail 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 that of Ontario Power Generation in Canada (Ma & Jiang, 2011). The reactor noise analysis system was also installed in the upgrading of the monitoring system of the Borssele NPP in the Netherlands. The system was used for measuring the reactor coolant pump vibrations and the core-barrel motions. The newly installed system satisfied the nuclear plant's maintenance needs (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 noise analysis can effectively test sensor response times while the nuclear plant is operating (Hashemian & Jiang, 2010). Noise analysis was employed in measuring the time response of the reactor protection system's sensors and in the ANGRA-I nuclear power plant. 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 a vibrating control rod from the measured power spectral density of neutron noise.

3.3.5 Motor electrical signal analysis

Motor electrical signal analysis is used in monitoring the state of the nuclear plant electrical systems, which comprise motors, actuators, generators, instruments channels, cables and

electric circuits. Monitoring the electrical components is very important in nuclear plant maintenance (IAEA, 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) and Mehala (2010) in his work extensively described the use of MCSA in condition monitoring.

Jung & Seong (2006) monitored the condition of the 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 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 predicted future defects and estimated the cables' remaining useful life.

3.3.6 Instrumentation calibration monitoring

Instrumentation calibration monitoring is used in ensuring that 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 a publication by the IAEA (2008). Extensive research in the area of sensor validation are available in the literature and different techniques have been used. The work of Gribok *et al.* (2000) where they developed techniques in regularising statistical approaches to sensor validation is one of such. Hines *et al.* (1996), Xu *et al.* (1999) and Dorr *et al.* (1996) also used neural network-based methods in instrumentation calibration monitoring. One of the common causes of sensor failure has been identified as inaccurate calibration due to human error. Employing online calibration monitoring will not only reduce such miscalibration it will also minimise exposure of personnel to radiation. This will lead to both increased safety and reduced false alarms and maintenance cost (IAEA, 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 online 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.

3.4 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 analysed. This section explores the state of fault detection envisioned and implemented in the nuclear industry. Many of the monitoring systems 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 the 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 diagnosis were accomplished in a conventional way. Parisini recognised 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 networks. 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 was 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 robust to faults in the main sensors of a multi-loop control system is proposed with the aim of improving the safety and reliability of plant operations. A state variable transformation was carried out in 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 estimation 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 a 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 generalisation performance for the detection and isolation of a number of security-related faults. They presented their results by making a qualitative representation of symptoms and diagnostics using coloured shades, which changed with time making a friendly interface for efficient communication with operators in charge of 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 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 pressurised 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 digitalised system where they replaced the integrated circuit components with C++ based hardware. Their evaluation involved getting error detection coverage and 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 recognised statistical modelling method. Their fault detection system was able to detect and isolate a single sensor fault and this could be done while the plant was in operation. The PCA was also combined with data reconciliation by Amand *et al.* (2001). In developing a fault detection system with increased efficiency, they introduced data reconciliation in the first stage of the PCA projection matrix. The method was applied to raw process data. Its efficiency depended on the number of components monitored. Baraldi *et al.* (2010) also developed a PCA-based early fault

detection system used for identifying faulty sensors and correcting their measured values. The technique developed was based on the sequential probability ratio test. They demonstrated this method, using a simulated case study of the pressuriser pressure and level control of a PWR.

3.5 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 characterising the fault. Diagnostics is focused on determining the location and magnitude of the existing fault. Upadhyaya *et al.* (2003) addressed economic and reliability concerns in existing and new generation NPPs. They pointed out that 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 diagnostics methods in NPPs was carried out by Ma & Jiang (2011) in which they showed 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 NPPs tightens.

Patton (1997) investigated the robustness in model-based diagnostics with the aim of providing 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 human error, thereby preventing 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 & Howell (2001) proposed an FDD method based 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) emphasised 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 localisation.

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 pressurised water reactor (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 nuclear power plant digital systems. They employed a simulated fault injection method in evaluating the faults coverage on the digital systems. They used their methods on the fifth and sixth units of the Ulchin NPP local coincidence logic processor for a digital plant protection system. Their experiments showed that their method could effectively quantify faults coverage for critical digital systems.

Rocco and Zio (2007) developed a method for classifying transients in NPPs using the support vector machine approach. The method was used in differentiating the transients in nuclear systems. This they achieved by applying different classes of support vector machines (SVM) in a hierarchical 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 actualised 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 actual plant 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 system malfunctions can be correctly classified with the h–s 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 was developed to detect, classify and predict transients in NPPs. The system tries to overcome the problem of the limited reliability of the single general-purpose neural networks by adopting and utilising 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 a 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-tube steam generator NPP. They applied two types of neuro-fuzzy networks. The neural network's training was done using data collected from a full-scale U-tube steam generator simulator and used for generating residuals in the fault detection step. A locally linear neuro-fuzzy model was used in the identification of the steam generator. With their approach, they were able to make a qualitative characterisation 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 in the closed-loop acts to compensate for the fault by actuating a system that overrides the fault. This action makes the system continue to operate without shutting down. In their research, they analysed the actions of the control system based on this characteristic of the system, 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. They also worked on detecting faults during transients when operating point references are usually unavailable and detecting 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 plant's 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

characterise faults that occur in the system. They also proposed the use of the NPP simulator in providing a dynamic reference, 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.

3.6 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 the literature include that of Pham *et al.* (2012) that defined prognosis as the estimation of the expected remaining useful life (RUL) and the associated uncertainties. The ISO (2004) defined prognosis as the estimation of time to failure and risk for one or more existing and future failure modes. Wheeler *et al.* (2009) defined 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) describe prognostics as predicting the remaining useful life of a system from the inception of a fault based on a continuous health assessment made by direct or indirect observation from the ailing system. Suhir (2011) also defines prognostics as the ability to predict the remaining useful life after a certain malfunction is detected or anticipated. Daigle and Goebel (2011) say 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, that it is an estimation of time, and that there is a 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 of a component.

Prognostics is a very important aspect of CBM as it could help the operator and maintenance personnel to better understand how to schedule maintenance and also could result 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 as 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 about prognosis. This shows that in condition-based maintenance prognosis takes fault diagnosis a step further than diagnostics. 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 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 being applied in some nuclear power and related systems. They discussed also areas where PHM is still under development. They explained the present needs of applying prognostics. They also highlighted the challenges, technical gaps and areas of research 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 & Hines, 2008). This is also supported in the work of Barbieri *et al.* (2015) where they combined several degradation parameters using an optimisation process to obtain a prognostic parameter which was trended to estimate the RUL. They used genetic algorithm and ordinary least square in the optimisation process and estimated RUL using a general path model. Their method was validated using steady-state data from electric motor accelerated degradation testing. With their method, they were able to achieve good RUL estimates 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 general 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 extrapolating 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 method was introduced which allowed for the inclusion of prior information. Their method was applied to the prognostics challenge problem posed at PHM 2008.

The results showed that their proposed method performed better than the conventional regression used in RUL estimation.

Welz *et al.* (2014) 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 test-bed setup at the University of Tennessee. They relied on how the system residuals progressed and how the residuals related to the overall system condition. This was used in estimating 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 technique. In their study, they explored and analysed different methods 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 outperformed 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 on a percentile calculation on several levels. The profiles are modelled by a gamma process. They used simulation in illustrating their method, and also compared their method with other filtering methods based on discrete wavelet transform (DWT) and empirical mode decomposition (EMD) algorithms, which showed the effectiveness and applicability to data with noisy trends. This allows one to have a probability density function (PDF) of RUL with a confidence 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 patterns that serve as the reference is taken using the different failure scenarios of the plant. The condition of the system is then monitored and compared with the library of the reference patterns. The RUL is then estimated using fuzzy similarity analysis and aggregating their times to failure in a weighted sum. This accounted for their similarity to the developing pattern. The prediction 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 possible. 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 in the computing speed.

McCarter *et al.* explored an RUL estimation technique for 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 conditions. The IM technique can be used online, 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 testbed in which several types of measurement parameters were obtained for ageing cables. They further explained practical techniques in which simple IM measurements can take advantage of condition monitoring and RUL estimation. Their result from the error analysis showed that the 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 turbine of an NPP. An appropriate model for the deterioration understudy was selected. Results show that the accuracy of the technique varied due to the nature of the data that was utilised to estimate the model parameters.

3.7 Modelling techniques for CBM

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

3.7.1 Physical modelling

Physical modelling methods are sometimes also referred to as model-based or physics of failure or behavioural model methods. They involve the use of mathematical relationships of the physical behaviour between process parameters to detect the process or sensor anomalies. This method incorporates the physical understanding 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 the residual. When the plant is operating normally, the residual should be approximately zero, but large residuals signify a fault in the system. The physical model usually gives a result with minimal uncertainties when accurate models are used. However, the major setback with obtaining good models is that they are often over-complicated. A complete model is usually not available for complex systems and they often also require detailed technical knowledge of the relevant failure mechanisms.

Reviews of model-based methods available in the literature were done by Venkatasubramanian *et al.* (2003), and 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) and a control-based diagnostics model by Cilliers (2013), and Cilliers & Mulder (2012). Examples of model-based techniques in literature are just a handful compared to the other modelling techniques. Their strengths, weaknesses, opportunities and threats (SWOT) analysis are shown in Figure 3-4.

Strengths

- Gives result with minimal uncertainties.
- Ability to incorporate the understanding of physics of the processes involved.
- Outputs are more easily understood.

Weaknesses

- Models must be derived from first principles.
- Obtaining a good model is complicated.
- A complete model is not available because of the complexity of the system.
- Requires detailed technical knowledge of failure mechanisms.

Opportunities

- Nuclear plants are equipped with simulators which are designed from first principles which can be modified for online monitoring, diagnostics and prognostics purposes .

Threats

- Unavailable first-principles models describing the complex degradation mechanisms in nuclear components.
- Developing a physical model is both costly and time-consuming for complex systems.
- Applicability of the models are often limited.

Figure 3-4: SWOT analysis of the physical modelling techniques

3.7.2 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 categorised into three: artificial intelligent methods, statistical-based methods, and similarity-based methods.

The artificial intelligent method uses machine learning tools which transform raw data into relevant information and behaviour models – examples are neural networks (Atiya *et al.*, 1999; Simani & Fantuzzi, 2000; Şeker *et al.*, 2003), Bayesian networks (Pingfeng & Byeng Dong, 2008), Markov processes (Fleming, 2004; Bechhoefer *et al.*, 2006; Kacprzyński *et al.*, 2004). The artificial intelligent methods mostly depend on previous patterns of abnormalities of systems that are alike and, based on these data, the future condition of the system is projected.

The quality and quantity of system historical data required for a 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) (Amand *et al.*, 2001; Du & Jin, 2007; Baraldi *et al.*, 2010), proportional covariate model (PCM) and 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 – examples are fuzzy systems (Zio *et al.*, 2010) and expert systems.

The major setback with the data-driven approach is that it cannot handle unanticipated failures. Data-driven methods also require a high quality and quantity of data for its computation. These data are mostly difficult to obtain. The strengths, weaknesses, opportunities and threats (SWOT) analysis of the empirical modelling technique is shown in Figure 3-5.

Strengths

- There is no need to understand the systems physics of failure.
- Does not require detailed technical knowledge of failure mechanisms.
- Mostly easier to understand.
- Mostly simpler to develop.

Weaknesses

- Large collection of data required.
- Methods are mostly brittle i.e can only be applied to the same, or similar, operating conditions.
- Not very reliable.
- Prone to instabilities and inconsistencies.

Opportunities

- In nuclear power plants, conditions, systems and components are being monitored from the onset of commissioning. Therefore the availability of large amounts of system and component condition data can be explored in developing empirical models, thereby removing the complexity of the physical model methods.

Threats

- Not enough data available to train models to recognise the wide range of different sensor failure patterns.
- Might not be able to simulate all possible faults.

Figure 3-5: SWOT analysis of the empirical modelling technique

3.7.3 Hybrid models

Hybrid approaches are developed to obtain the best of multiple worlds by combining the strengths of one or more approaches and limiting their weaknesses. This approach integrates the strengths of an ensemble of methods, thereby giving estimations that are more reliable. Some applications of hybrid approaches are the combination of Kalman filters and neural methods for fault diagnostics of industrial processes by Simani and Fantuzzi (2000), and a neuro-fuzzy method used by Wang *et al.* (2004) for the prognosis of machine health conditions and giving better RUL estimations 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 a 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 a Bayesian updating method and an expectation maximisation algorithm in RUL estimation. The strengths, weaknesses, opportunities and threats (SWOT) analysis of the hybrid modelling technique is shown in Figure 3-6.

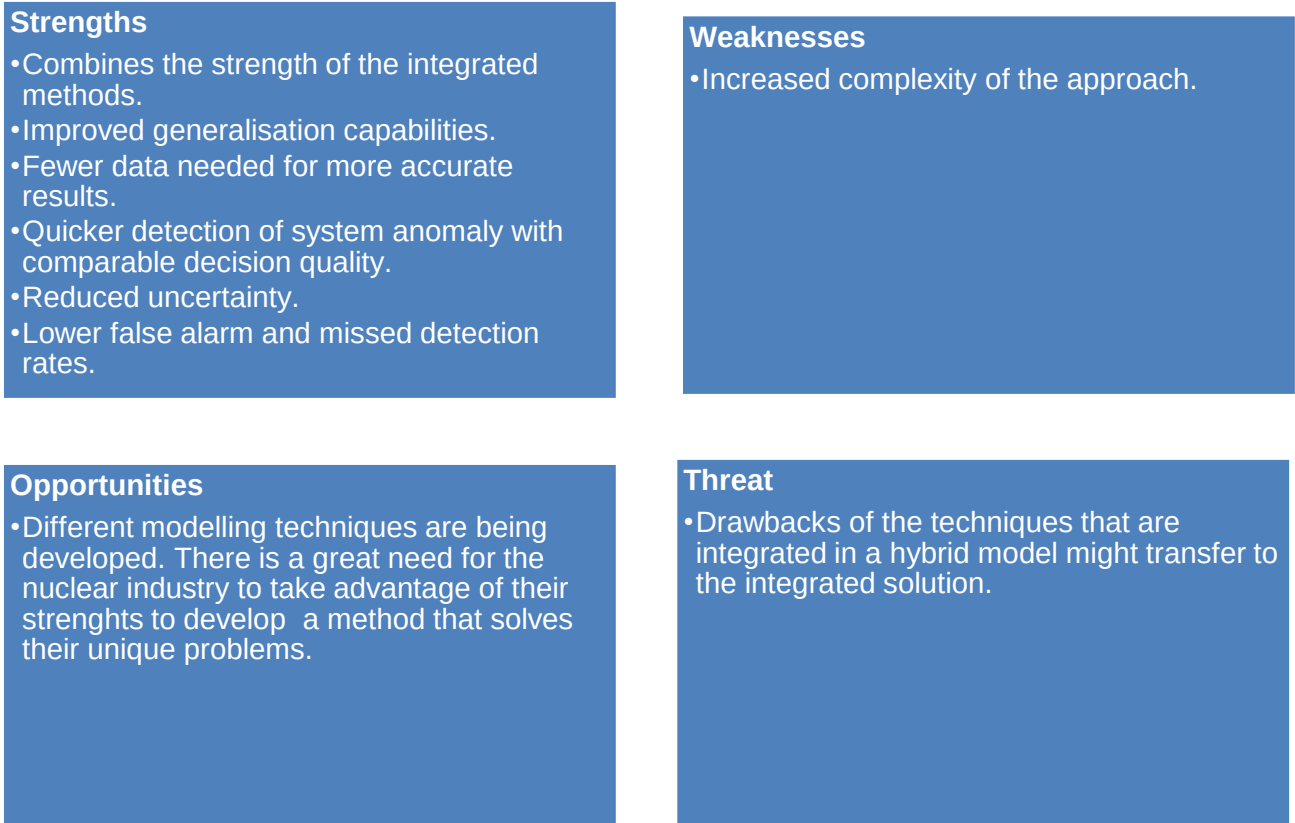


Figure 3-6: SWOT analysis of the hybrid modelling technique

3.8 SWOT analysis of CBM applications 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 challenges. This section highlights the possible strengths, weaknesses, opportunities, and threats in applying CBM in the nuclear power plant considering the uniqueness of nuclear plants. The strengths, weaknesses, opportunities and threats (SWOT) analysis of condition-based maintenance is shown in Figure 3-7.

Strengths

- Reduced downtimes.
- Planned maintenance.
- Cost-effective maintenance.
- Lower cost of operation.
- Replacement of only bad component parts.
- Increased production.
- Plant life extension.
- Fewer emergency activities.
- Satisfied customer.

Weaknesses

- Networks of expertise is needed to provide technical support to operators.
- Lack of harmonised procedures for the selection of monitoring/diagnostics/prognostics techniques and equipment.
- Requires detailed technical knowledge of failure mechanisms.
- A cultural change is required to implement in NPPs.
- Development of long-lived, radiation resistant sensors needed.
- There is need to develop strategies for optimal sensor placements for monitoring passive component condition.

Opportunities

- Many utilities are aiming to keep their NPPs operating for 60 or more years.
- New NPPs can imbibe CBM for cost effective maintenance and operations.
- Will lead to a better rapport and closer relationship between the operation and maintenance personnel.
- Improves NPP reliability and cost-effectiveness in the energy sector.

Threats

- Intensive regulatory scrutiny.
- Need for strong management commitment.
- Need for special training for operators, technicians and maintenance engineers.
- A potential future problem may arise due to regulatory capacity being stretched.
- Uncertainty quantification for sensor measurements.
- Verification and validation of CBM methods.
- Cost of implementation.

Figure 3-7: SWOT Analysis of CBM application in NPPs

3.9 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 taken into consideration before fully adopting a different maintenance strategy. Therefore, CBM should be systematically adopted in nuclear plants starting with components and systems that are of lesser safety concern. This paper has explored the different stages of CBM and highlighted 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 analysis of the different techniques of CBM in the nuclear power plant. This paper gives

maintenance stakeholders and researchers an overview of the current practices and extent of research undertaken on condition-based maintenance in the nuclear industry.

Based on this review the authors aim to further research the development of a hybrid system to enhance CBM in NPPs. 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 approach is favoured because it combines the strength of the control-based fault diagnostic with the simplicity of the data-driven approach, which does not require the understanding of the plant's physics of failure. This hybrid system is expected to give a more accurate plant diagnosis for CBM.

CHAPTER 4 - ARTICLE 2: HYBRID NUCLEAR PLANT SIMULATOR DESIGN REQUIREMENTS TO ENABLE DYNAMIC DIAGNOSTICS OF PLANT OPERATIONS

With nuclear plant full-scope simulator technology reaching maturity, the possibility of using its capabilities in expert systems such as online plant diagnostics has become a reality. The effectiveness of plant diagnostics using real-time simulated measurements as a plant reference has been shown in previous papers. However, in order to implement these systems, the full-scope plant simulator needs to be designed specifically with this application in mind. This will help in maximising the effectiveness and scope of use of the system. This paper investigates the various simulator technologies available as well as the development strategies and focus areas to establish the design requirements of a single full-scope engineering and training nuclear plant simulator. This can be implemented to provide a real-time dynamic reference to the plant diagnostic system.

Keywords: full-scope simulator, plant diagnostics, real-time, dynamic reference

4.1 Introduction

Owing to the risks involved with the training of operating personnel on a live nuclear plant, all plants are equipped with a full-scope simulator that is designed to provide an accurate representation of all plant operations for training purposes; in fact, all nuclear plants are required to be equipped with a plant simulator and a simulated control room for training purposes. Accurate simulator codes for engineering, maintenance planning and analysing postulated accidents have been in use in the nuclear industry since the 1980s (IAEA, 2004).

With developments in data-processing system speed and improved accuracy of real-time calculations, these simulators can now be combined to provide a single full-scope training and engineering simulator as well as a maintenance planning function. The accurate, real-time simulator can also be used to provide a dynamic reference for plant operations during steady-state and transient conditions.

The advancements in processor speeds, parallel processing, and the development of more sophisticated numerical algorithms enable the simulation of plant processes in real-time. This has long been anticipated, but it has only been very recently that the possibility has been put into practice (IAEA, 1999) by combining the training and engineering simulator to develop an accurate real-time simulator.

The benefits of real-time simulation of systems have not been fully exploited, as these would only be realised if real-time simulations could continuously be compared to all measured information, and decisions based on the expected behaviour of the plant could then be made. This plant diagnostic system was developed and established in the previous work (Cilliers *et al.*, 2011; Cilliers and Mulder, 2012; Cilliers, 2013a; Cilliers, 2013b). The principle of combining real-time plant data and data from a plant simulator operating under the same conditions not only aids detecting faulty plant behaviour while the operating point is still within the structural safe boundaries of the plant, but it also allows for the description of the fault condition up to a certain level. For this process to be successful a modern nuclear plant simulator needs to provide specific functionality and adhere to a number of requirements related to modelling methods, interfacing and fidelity.

The ultimate goal of this research is the implementation of the full-scope engineering simulator for fault identification system to be implemented as a supervisory system in the Koeberg NPP as well as including it into the control and instrumentation systems to be implemented in South Africa and other proposed new-build programmes in Africa and beyond.

This paper is organised into five sections. The first part is the introduction; then the second section describes the existing simulation technology and uses. The reason for the hybrid full-scope simulator is discussed in the third section. The fourth section is an overview of the integrated simulator. The fifth section contains the hybrid full-scope engineering simulator requirements and lastly, the conclusion.

4.2 Existing simulation technology and uses

Simulation technology has advanced with time as the data processing speed keeps increasing which was about 0.5 Mflops in the 1980s and has risen to 1000Mflop in the 21st century (Miettinen, 2008). This increase has tremendously affected the advancement and the applications of the simulation systems in the nuclear industry. The different types of simulators presently in the nuclear industry according to the IAEA (2004) are:

- **Full-scope simulators (FSS):** They are also known as full replica simulators. The FSS is a physical representation of the control room that fully replicates the control room for the purpose of training. The FSS completely models systems of the referenced plant with which the operator interfaces in the actual control room environment. Most nuclear power plants are equipped with an FSS.

- **Basic principle simulators:** These simulators, unlike FSS, do not fully replicate the control room, but only provide a simulation of general concepts relevant to the operation of the nuclear plant. They can be used in training at the system operation level.
- **Partial scope simulators:** This type of simulator only represents specific systems or part of the actual plant and are used for training on only specific aspects of the plant's operation.
- **Other-than-full-scope control room simulators:** These simulators closely mimic plants, but unlike the other categories of simulators they have a different human-machine interface as does the referenced plant. Generally, for a simulator of this type, the human-machine interface is provided through computer-driven displays and either touch screens or mouse control of on-screen buttons.

4.3 Simulator classifications based on their uses

The dedicated nuclear power plant training simulators have limitations which include its limited availability, limited flexibility, limited data collection, limited human-machine interface (Boring *et al.*, 2012). These factors result in the development of simulators which can be used for other specific purposes. These simulation systems have been developed with various uses in mind; these uses often dictate the focus being put on speed, accuracy, human-machine interface, realism, or a combination of these. The most common types are listed below:

- **Engineering:** Engineering simulators are usually focused on the development of detailed studies of industrial processes. The aim of engineering simulators is to evaluate and compare alternative process and control solutions. The engineering simulator relies on a plant model that is a complete, integrated, dynamic representation of the behaviour of all the plant systems controlled by the digital control system in their various states of operation. The mathematical models are the most important part of the simulator, and they are usually very accurate. The human-machine interface is of less importance than in other simulators (L3 MAPPS, 2013b).
- **Training and demonstration:** Training and demonstration simulators are aimed at training of the operating personnel of the nuclear plant. This is usually a continuous process as operators require to be trained constantly. Training and demonstration scenarios are designed to instruct individuals and team operation and control of unit systems and equipment during normal, abnormal and emergency conditions. The human-machine interface is crucial, while the accuracy of the mathematical models can be lower. When the simulator is used in other disciplines (for example, maintenance), the accuracy can be even lower (IAEA, 2004).

- **Testing:** Test simulators are applied in the design and implementation of process and automation to test its performance in normal operating and transient conditions. The accuracy requirements vary depending on the test case. In automation tuning, the process model needs to give a realistic dynamic response. In testing the automation implementation, qualitative behaviour is often enough (Carrasco & Paljakka, 2004).
- **Operation support:** Simulators are used in supporting operative tasks. By using predictive simulators, operators can estimate the consequences of alternative actions, and production management teams can test and optimise production plans. As the simulation speed must be faster than real-time, the accuracy requirements cannot be very strict. It is sufficient if the simulation model can predict potential problems and estimate production measures.
- **Severe Accidents:** Simulators are used in training nuclear power reactor operators on how to respond to severe accident situations. Before the Fukushima Daiichi accident, simulating severe accidents was regarded as optional but after the accident, interest has been renewed in the severe accident simulator and a lot of work has gone into it. The Modular Accident Analysis Program (MAAP) is one example of a widely accepted model used for severe accident analysis. These simulators are designed to be used in an off-line, stand-alone, non-continuous and non-real-time application (L3 MAPPS, 2016). The Sandia National Laboratory also developed the MELCOR for severe accidents simulations (Osborn *et al.*, 2015).
- **Human performance:** Control room simulators are used in assessing human performance by evaluating operators and crews. This simulator allows for help in conducting research in areas of human factors and human reliability – for this simulator the human-machine interface is crucial (Le Blanc *et al.*, 2001). The OECD Halden Reactor Project (HRP) has extensively used the nuclear power plant simulator in the research of simulation for human performance research for over 25 years (Skjerve & Bye, 2011).
- **Research reactors:** Notable work by world-known laboratories have been done in the development of research simulators. One of such is the Idaho National Laboratory in which there is currently an LWRS (Light Water Reactor Sustainability) project which has involved the development of the Human Systems Simulation Laboratory (HSSL) used to conduct research in the design and evaluation of advanced reactor control rooms, integration of intelligent support systems to assist operators, development and assessment of advanced human performance models, and visualisations to assess advanced operational concepts across various infrastructures (Boring *et al.*, 2012). The Sandia National Laboratory

conducted research on severe accidents and the Halden research project on human performance.

- **Real-time control and protection:** Simulators are used in predicting plant behaviour in parallel to the actual plant, and faulty plant behaviour can be recognised by measured values and simulated values drifting outside predefined limits. As the simulation speed must be synchronised with the actual plant, and control variables in the plant and the simulator have the same source, the accuracy of simulations may vary during transients. Although accuracy may vary, a very specific minimum accuracy must be adhered to in order to enable high protection reliability.

In the following sections, the requirements for a full-scope engineering simulator that can be used in real-time control and protection are developed further and its limitations and specifications are also provided.

4.4 Reason for hybrid full-scope engineering simulator

This section describes the need for this research and reasons why it is necessary to develop a hybrid full-scope engineering simulator.

4.4.1 Modelling and simulation needs for advanced nuclear energy systems

In 2006, the “Workshop on Simulation and Modelling for Advanced Nuclear Energy Systems” identified a number of shortcomings in the current state of the simulations industry. The workshop also identified a number of research and development fields that should be pursued in order to address the shortcomings and enable better utilisation of simulators throughout the nuclear industry (Finc, 2006).

These themes are:

- Uncertainty quantification and error estimation in simulations.
- Methods for systems that couple multiple models, i.e. moving away from empirical models toward physics-based first-principles models.
- Methods for systems with multiple scales.
- Algorithms and software that scale well on high-capability computational platforms.
- Simulation workflow management, including data archiving and automated discovery.

The following are some of the high-level findings of the workshop:

- i. The code-base currently used for advanced nuclear systems is insufficiently predictive to guarantee the attainment of the ambitious technology stretch goals of the Global Nuclear Energy Partnership.
- ii. A significant opportunity exists to apply advanced modelling and simulation and high-performance computing to improve designs of future reactors, reduce uncertainty in facilities development and construction costs, improve safety, and reduce development times of new fuel types needed to close the nuclear fuel cycle.
- iii. Significant research challenges remain in developing and scaling multi-scale and multi-physics codes to the performance levels on advanced high-performance computers needed for fundamental studies, as well as for design and engineering use. These research challenges are similar (but not identical) to those faced in other science and engineering domains; thus, many methods can be leveraged from other disciplines.
- iv. The creation of new physics-based high-fidelity simulation codes offers the possibility of accelerating the licensing process if the regulatory process can be modified to incorporate first-principles simulations as a basis for risk analysis and design approvals.

From these findings, it can be deduced that a common belief exists that processing speed and parallel processing technology have advanced to such a stage that new simulation paradigms can be formed. The investment in these research areas promises to add much value to the current state of nuclear plant design, safety, and control. This research sets goalposts for simulator development that new simulator technologies need to attain to enable them to be used in the control and protection process of the nuclear plant.

4.4.2 The simulator and the real-world system

Since the simulation of any system is designed to mimic the real system as closely as possible, a certain number of measurable variables should always be available from the simulator as well as from measurements found on the real system. It should, in theory, be impossible for the controller sitting in front of the control system to distinguish between the source of the values for these variables, be it the simulator or the real plant. For this concept, we introduce a 'black box' to indicate the source of data to the control system. This concept is depicted in Figure 4-1. The control system should not be able to distinguish between data coming from the measurement instruments or from the simulator.

In practice, this concept will not be realistic, since a number of differences between the simulator and the real plant measurements exist. In order to use the simulator, a lengthy set-up procedure is often required to simulate the plant under specific conditions. Many simulators cannot calculate data in real-time. It is, therefore, required to set a number of constraints and requirements on a simulator that enable it to truly mimic the real-world system.

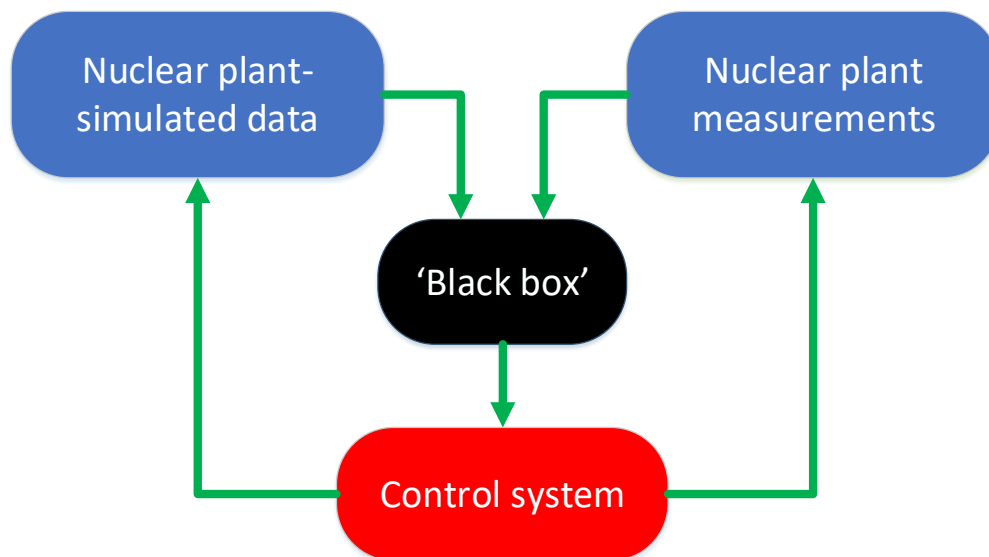


Figure 4-1: The 'black box' as a source of data to the control system

The full-scope engineering simulator will have the following functionality:

- Plant licensing: the simulators will be used in design base verification as well as simulating contamination dose dispersions in the case of severe accident scenarios.
- Equipment specification optimisation: this will be aimed at optimising equipment specifications.
- Plant modification validation: the simulator should be capable of simulating plant response to intended modifications.
- Training: a training platform for engineers will also be available.

Real-time system simulator requirements – User Specific Requirements (USRs) – are:

- i. The simulator should be able to calculate values for all discrete measurement points that the real plant would provide to the control system.

- ii. The simulator should be able to deliver these calculated values at the same frequency as the real plant would provide the measured values.
- iii. The simulator should be able to calculate values at the same or better resolution than the measurement equipment is capable of.

Following the above simulator requirements, the following comments seem in order:

1. Since the simulator uses first principles to calculate values, the simulator will be able to calculate values at specific discrete points in the system. The simulator will consequently be able to provide calculated values from positions in the system where no measurement instrumentation is installed. This is one of the major benefits of having a simulator running alongside the real system.
2. Delivering calculated values at the same frequency as the real plant is referred to as real-time data. This real-time data is one of the most difficult requirements to adhere to, as complex calculations would require more iterations to produce the required accuracy. This can be overcome by increasing the processor speed or by optimising the calculation algorithms to make use of advances in parallel processing technology, including the use of dedicated mathematical and physics co-processors that are becoming more available. It should, however, be noted that the purpose of this study is not to develop a new simulator.
3. The accuracy of the simulator is linked to the speed of the simulator as well as the quality of the plant model used. Using numerical methods to calculate values remains a trade-off between speed and accuracy. This study implemented a fault identification system that improves effectiveness for cases of simulation where accuracies are being reduced. In doing so it reduces false fault identification.

The online plant verification simulator will have the following functionality:

The simulator will be implemented together with an expert diagnostic system running in real-time, in parallel with the nuclear power plant. This is used to verify correct plant operation and detect and identify faulty plant behaviour as it occurs.

4.5 Integrated simulator overview

The full-scope engineering simulator consists of a software-based first-principles physics calculation module that calculates expected plant measurements and passes it onto the simulated control system which calculates control actions to maintain the plant state or transient as shown in Figure 4-2. The simulated plant measurements are provided to the engineering staff via a

human-machine interface (HMI).

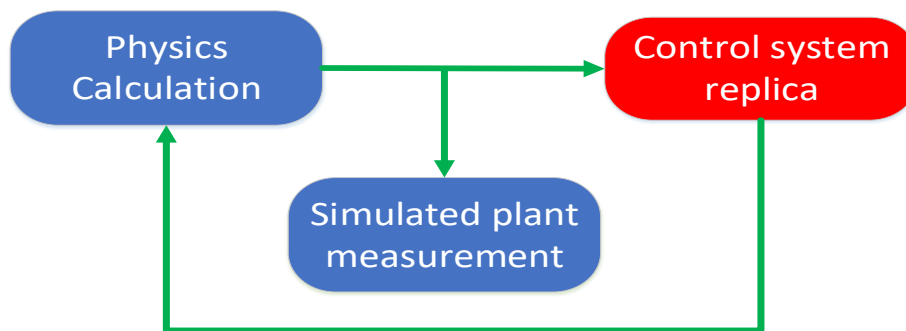


Figure 4-2: Full-scope engineering simulator

4.5.1 Reactor response simulation

The full-scope simulator uses physics models of plant operations to generate plant measurements and information based on operational inputs. The system is designed to make use of a number of physics models to provide boundary conditions to other physics models in order to realistically simulate the nuclear plant in all aspects.

Figure 4-3 provides a functional flow block diagram (FFBD) indicating the sequence of the functionality of the full-scope simulator. The FFBD is a high-level demonstration of the functional interfaces of the plant to attain primary objectives depicted in the hierarchy in Figure 4-3 .

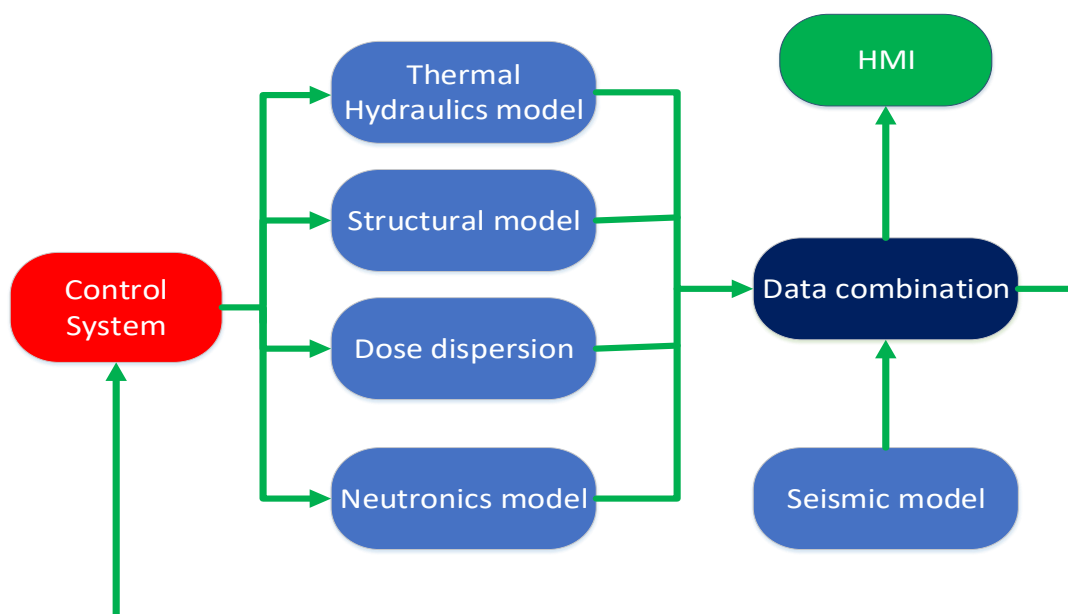


Figure 4-3: Full-scope simulator functional flow block diagram

The objective of reactor core simulations is to predict a series of plant parameters (fluxes, temperatures, stresses, damages, etc.) during normal and abnormal events, during static and transient events, for short-term operational times, up to and including plant end of life. These parameters are important for the plant efficiency and safety for single components, system reliability and system lifetime.

4.5.1.1 Neutronics

A model allowing simulation and modelling of nuclear reactor physics shall be included. Most industrial modelling is specific to current reactor designs. Departures from these designs, such as using reprocessed fuel, will require higher-fidelity simulation tools, based more on first principles than on normalisation to current designs.

4.5.1.2 Thermal-hydraulics

A model simulating fluid flow and heat transfer shall be included for core modelling, as well as for the rest of the plant, including steam generators, pipes, pumps, and condensers. Because of the complexity of the phenomena and geometries involved, current codes often rely on empirical correlations. It is often not clear whether these correlations can be readily extrapolated to new situations. The scientific challenges are in physical modelling, numerical methods, and computer science. The physical modelling must rely more on first-principles methods for single-phase and two-phase multi-fluid flows, for steady and unsteady flows, and with or without heat transfer. Numerical methods must be more robust and must provide the optimal mix between accuracy and stability. Codes must deal with a large number of mesh elements and enable easy multi-scale and multi-physics coupling.

4.5.1.3 Dose dispersion

A puff and plume model for projection of thyroid and total effective dose equivalent (TEDE) in 16 km should be included. The model should take into account geographic information of the site and allow for wind speed and direction changes.

4.5.1.4 Control and instrumentation

The control and instrumentation of the plant should be modelled based on the exact control philosophy and configurations of the plant design. It should also include the protection systems as described in the plant design.

4.5.1.5 Seismic analysis and design

Enabled by modern solution algorithms and high-performance computing, more rigorous and realistic seismic simulation models should be included. These models will significantly increase the understanding of seismic events, enable performance-based design for significant cost savings, and increase design efficiency. Also included in the model should be the philosophy behind the earthquake events, which spans from energy release at the causative fault to energy transport through seismic wave propagation in a highly heterogeneous media, to ultimate shaking and response of the structure. The phenomenon is inherently three-dimensional, and the response occurs in two distinctly different, but closely coupled, domains: the earth and a structural system.

4.5.1.6 Structural mechanics

Modelling of advanced material constitutive models that can accurately represent the time-dependent behaviour of materials in extreme environments should be possible. These models should address the effects of high irradiation levels, extreme temperatures, and chemical interactions on material behaviour. Advanced materials models should account for fully 3D, multi-axial states of stress both at low strain rates (normal operations) and at high strain rates (accident scenarios). Graphical information on structural damage due to accidents should be shown.

3D models should also allow for the design of the following:

- Radiation shielding: areas of high radiation should be indicated on the 3D model and allow for the insertion of proper shielding for use in engineering analysis and specifications.
- Provide real-time navigation through the 3D-rendered environment.
- Allow highlighting components and seamlessly provide information on components from the simulator platform database. It should also update changes to the simulator database.

4.6 The hybrid full-scope engineering simulator requirements

In this section, the requirements for the hybrid full-scope engineering simulator are given. They include the simulator design base requirements, modern plant simulator requirements, the simulator model requirements and the functional requirements.

4.6.1 Simulator design base requirements

When developing the nuclear simulator, some of the challenging problems are nucleate boiling, critical heat flux (with mixing grids effect), pressurised thermal shock, re-flooding, and fluid-

structure interaction. This calls for better physical modelling, better-applied mathematics algorithms, multi-resolution and adaptability for multi-resolution of multi-physics multi-scale problems. An innovative approach for integration level of solvers (e.g., writing the integrated governing equations for the coupled problem) is required. As a consequence, the solving of problems related to the parallelisation of the solvers, the software architecture for efficient integration, and some intractable number of unknowns (e.g., deterministic neutronics 10^{15} , DNS fluid and heat transfer 10^{16} , for static problems) is required.

The simulator should adopt a first-principles approach utilising advances in both hardware and software tools which will open the possibility to a new simulation system with advanced capabilities. An integrated high-fidelity system of software tools would describe the overall nuclear plant behaviour taking into account coupling among the different systems and physical phenomena during reactor operations and transients. This coupling would link neutronics, fuel behaviour, fluids and heat transfer, and structural mechanics as well as radiation dose dispersion models during severe accident simulations. The system must also be coupled with the structural mechanics' software model. The new system should perform sensitivity and uncertainty analyses to assess margins, qualify, validate, and optimise designs.

The plant fidelity should be scalable to enable high-resolution high accuracy calculations used for design and specification applications, or lower resolution, lower accuracy calculations optimised for real-time and faster than real-time simulations used for transient analysis and training.

Verification and validation of simulation software, although very challenging because of the difficulties associated with uncertainty propagation through multi-physics multi-scale simulators and lack of integral experiments, remains a very important requirement for implementing as a full-scale engineering and training simulator.

4.6.2 Modern plant simulator requirements

As the trends in simulation technology are known, additional requirements are defined to specify a state-of-the-art simulator, allowing for not only online monitoring and plant diagnostics, but also improved design tools and safety verification tools.

We have developed a user requirement specification (URS) that includes all requirements to which a modern plant simulator should adhere, based on the findings of this research. This will enable traditional tasks associated with plant simulators as well as allow the simulator to be implemented in new tasks, such as the plant diagnostic system (PDS) discussed in previous papers. The main requirements from the URS are described in the following paragraphs. It is important to note that not all requirements are essential for enabling the implementation of a PDS

but are deemed important since they form part of the envisioned set of tasks for which simulators will be used in future.

During the development of a nuclear engineering simulator, some of the challenging problems are simulating nucleate boiling, critical heat-flux-pressurised thermal shock, flooding, and fluid-structure interaction. This calls for continually improved applied mathematical algorithms and physical modelling.

4.6.3 Simulator model requirements

To achieve the described improvements an original approach to the integration level of solvers is required, as shown in Figure 4-4. These requirements are:

- i. The simulator should adopt a first-principles approach, utilising advances in both hardware and software platforms, which will open the possibility of a new simulation system with advanced capabilities. This is very crucial for the online plant diagnostic system as it is needed for a dynamic reference that can help in detecting unanticipated faults. This requirement is not only limited to a PDS but will be beneficial for other functions of the simulator like engineering, testing, training, etc.
- ii. An integrated high-fidelity system of software tools should describe the overall nuclear plant behaviour, taking into account coupling amongst the different systems and physical phenomena during reactor operations and transients. The coupling should link neutronics, fuel behaviour, fluids and heat transfer, and structural mechanics, as well as radiation dose dispersion models during severe accident simulations. The system should also be coupled with the structural mechanics' software model. This is because the online monitoring system characterises the detected fault by combining fault diagnostics information from a number of systems, each reacting differently to the same fault. Therefore the coupling of all the different systems will help in the effectiveness of the fault detection system.
- iii. The new system should be able to perform sensitivity and uncertainty analyses to assess margins and be able to qualify, validate, and optimise designs (IAEA, 1999). This is not only important for the PDS, but it is also useful for other simulator applications as it will help in verifications and validations.
- iv. The plant fidelity should be scalable to enable high-resolution, high-accuracy calculations used for engineering design and specification applications or lower-resolution, lower-accuracy calculations optimised for real-time and faster than real-time simulations used

for transient analysis and training. With this requirement, the simulator can be used to carry out useful analysis for fault detection and characterisation. This is because the PDS system depends largely on the system sensitivity, speed and security. This requirement is also important in other simulation applications like the engineering simulator that is used in assessing and comparing alternative processes and control.

- v. The simulator should be benchmarked to be able to quantify the accuracy of the plant model and mathematical solver combination in real-time during the simulation process. The simulation accuracy should be available to plant diagnostic systems at all times. This is required to enable uncertainty quantification and error estimation in simulations, thereby having a more reliable system.

These requirements are summarised in Figure 4-4. The verification and validation (V&V) of simulation software is very challenging because of the difficulties associated with uncertainty propagation through multi-physics multi-scale simulators and lack of integral experiments. It remains a very important requirement before implementation as a full-scale engineering and training simulator (WENRA, 2007).

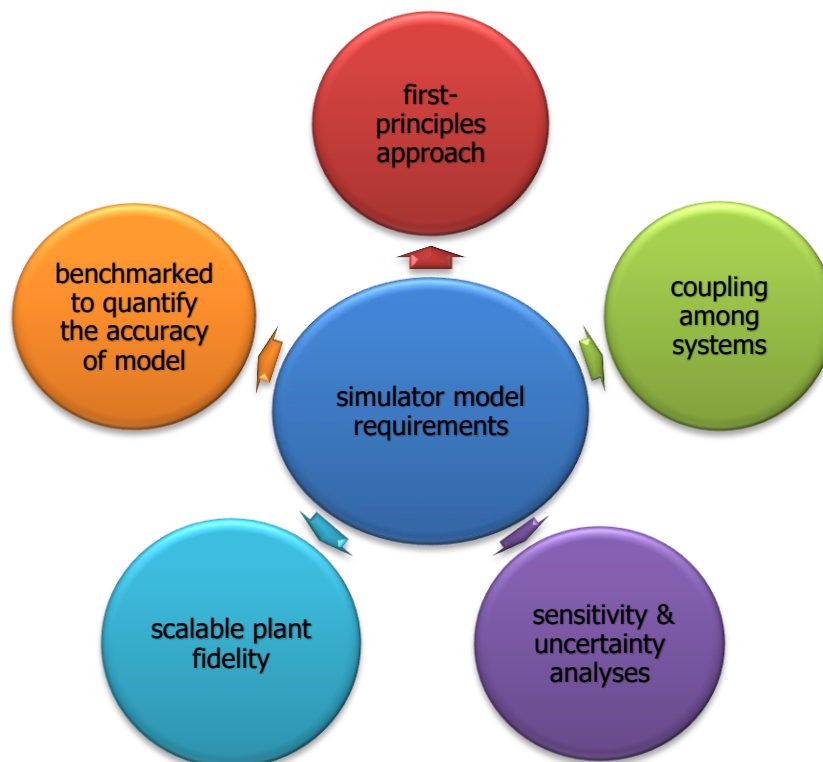


Figure 4-4: The full-scope engineering and training simulator model requirement

4.6.4 Simulator functional requirements

The full-scope NPP simulators shall incorporate detailed first-principles modelling of systems and components of the NPP as the base architecture for both control room simulated environment and the engineering simulator. The simulator will be used to interface with the operator in the simulated control room, as well as with the design engineer in the office environment.

- i. The simulator shall calculate and demonstrate expected plant responses to normal and abnormal operating conditions, including malfunctions.
- ii. The simulator shall contain all systems and components necessary for complying with ANSI/ANS-3.5-(2009), including, but not limited to:
 - a. Plant simulator hardware and software;
 - b. A comprehensive virtual model of the NPP;
 - c. Plant control software from the DCS vendors, where the controller algorithms can be compiled and executed on the simulator platform under the control of the simulator real-time executive;
 - d. Software modelling tools required to maintain and modify the simulator software models;
 - e. A graphical interface allowing the configuration of operation scenarios; and
 - f. A system for the recording, archiving, and playback of simulator operations and simulated transients.
- iii. In addition to the dynamic capabilities, the simulator tool shall have the capability to solve all models in steady-state to provide a steady-state solution. This will be used for mass/energy/heat balance calculations as well as real-time synchronisation with the actual nuclear plant. An overview of the full-scope engineering and training simulator requirements for PDS is shown in Figure 4-5.

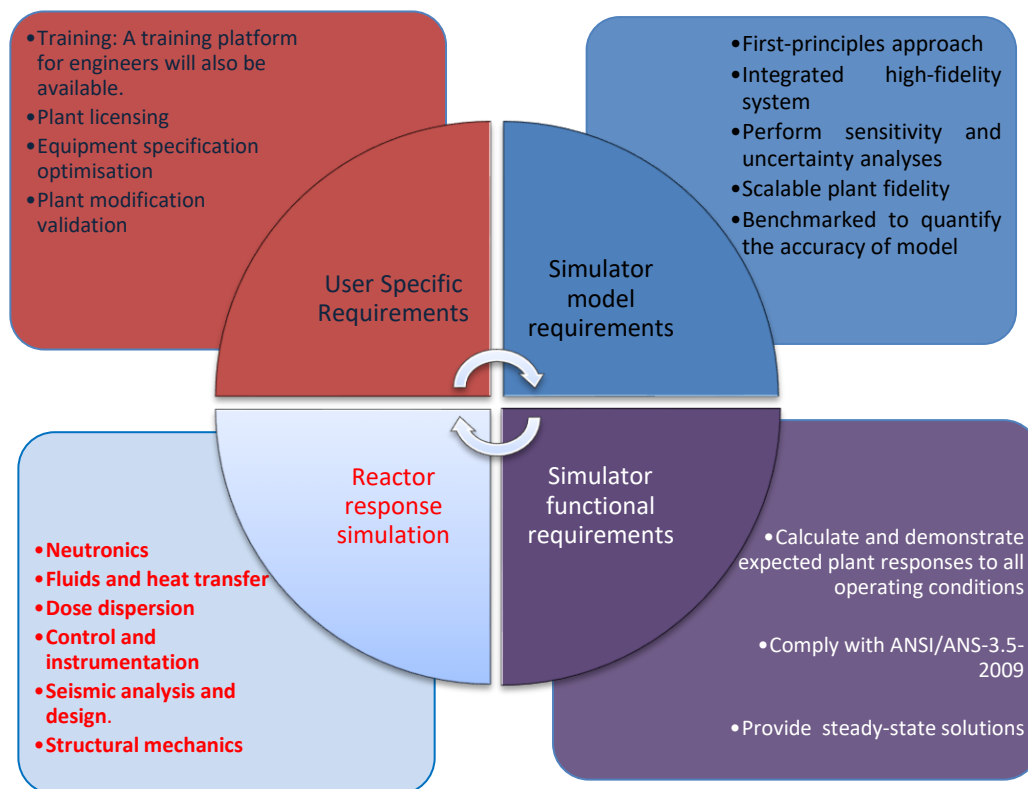


Figure 4-5: An overview of the full-scope engineering and training simulator requirements for PDS.

4.7 Conclusion

The use of simulation technology has greatly advanced with the increase in data processing speed like in the nuclear industry where most of its power plant is equipped with a full-scope simulator (FSS). The FSS has now gained wider applications aside from its primary purpose of training operators. One of such applications is the use of the FSS in an online plant diagnostic system, in which the real-time simulated measurements are compared continuously with the actual plant measurements so as to allow for early fault detection in the operation of the NPP.

For an effective plant diagnostic system, there is a need to have this function in mind while designing the full-scope simulator. In this work we have developed the user requirement specification (URS), the simulator model requirements, functional requirements and also the reactor response simulation.

Based on the discussion above, it can be concluded that the requirements are not only essential for the implementation of a plant diagnostic system they will also enhance the simulator's

performance for future applications. The financial and manpower restraints are vital requirements which can also be considered for future work.

4.8 Additional note

This chapter presented an article that described the use of the NPP simulator for diagnostics. This research is focussed on implementing a hybrid system for condition-based maintenance in NPPs. One of the objectives of this work is to implement this system using the simulator and other data-driven approaches.

This article emphasised the possibility of using an NPP simulator. For the simulator to carry out fault diagnostics some requirements are to be met. These requirements are also essential and needed for a successful prognostic system. A good prognostic system depends largely on successful fault diagnostics. This article has established these requirements for the nuclear plant simulator to be useful for diagnostic and prognostic purposes.

In the next chapter, we will be combining the plant data and simulator data with machine learning tools to develop a hybrid system that can identify transients and faults in the plant.

CHAPTER 5 - ARTICLE 3: HYBRID NUCLEAR PLANT SIMULATOR DESIGN REQUIREMENTS TO ENABLE DYNAMIC DIAGNOSTICS OF PLANT OPERATIONS

A condition-based maintenance (CBM) regime in a nuclear plant will result in eliminating unnecessary maintenance cost without jeopardising the safety of the plant. The foundation of a good CBM regime is accurate and timely fault detection. A method has been developed to identify transients and detect a fault in a nuclear power plant in transients. This is to aid condition-based maintenance in a nuclear power plant. This method was achieved by using the nuclear plant simulator as a dynamic reference. At steady-state, a fault is easily detected but in transients, it is difficult. This gives rise to the introduction of machine-learning tools like artificial neural networks (ANN) in order to train both the simulator and plant parameters. The neural network outputs of the plant and simulator are then compared, and this results in better identification of faults in transients.

Keywords: artificial neural network (ANN), condition-based maintenance (CBM), dynamic reference, fault, machine learning, transient.

5.1 Introduction

Identifying anomalies in nuclear power plants are crucial for proper diagnosis and condition-based maintenance (CBM). The nuclear plant is a critical facility whose operation must not only be kept safe but also economically viable for proper competition with other energy sources. This, therefore, requires a proper maintenance strategy that will not tamper with the safety systems and will simultaneously reduce expenses. With a CBM regime, unnecessary maintenance is eradicated, thereby reducing maintenance cost. A good CBM regime is aided by early and accurate detection of faults. In a nuclear power plant, safety is ensured by the plant protection system, which initiates a SCRAM when certain safety limits are exceeded. This is achieved by the control system which constantly compares plant parameters with given set-points and the difference in values is used to adjust plant operations. These two systems help in keeping the plant safe.

A fault can be defined as an unanticipated change in a system due to malfunctions or an unexpected change in operating conditions that degrades the overall system performance (Genovesi *et al.*, 1999). Faults in the nuclear plant can be abrupt, in which safety set points are exceeded and SCRAM is initiated. There is also the incipient fault, which does not initiate a SCRAM and easily goes undetected. Incipient faults are too small to actuate a SCRAM because

the plant control system compensates for the faults and they go unnoticed by the system operators until the faults become large enough to cause a SCRAM. Cilliers (2013) and Cilliers & Mulder (2012) in their work proposed the use of an NPP simulator as a dynamic reference to enable identification of these types of faults by comparing control system behaviours of this plant. They were able to diagnose faults in transients. This paper is focussed on identifying these incipient faults in nuclear plants using the simulator as a dynamic reference and using a machine learning tool to continuously monitor the system behaviour to identify anomalies in the nuclear plant.

There are different methods for fault identification in nuclear plants that have been developed in literature. They are categorised into three groups, namely the model-based, data-driven and hybrid approaches. The authors, in a previous paper, did a review of these different approaches used in fault diagnosis in a nuclear plant (Ayo-Imoru & Cilliers, 2018). They highlighted that data-driven approaches are easier to implement but require large amounts of data. This paper seeks to adopt the uniqueness of the nuclear plant, which is the availability of historic operations data, and the availability of the full-scope simulator in virtually all nuclear plants, which is able to closely mimic the nuclear plant. With this capability, it is possible to use the nuclear plant simulator as a dynamic reference working in real-time with the nuclear plant so that the nuclear plant data can be continuously compared with that of the simulator and anomalies can be identified. The paper is organized into five sections. The first section is the introduction, which is then followed by the methodology in the second section. The third section describes the use of a simulator as a reference model. The fourth section explains how the neural network is used alongside the simulator in transient identification while the fifth section contains the conclusion.

5.2 Methodology

The methodology developed in this research is illustrated in a block diagram in Figure 5-1 . The simulator is operated with the same initial conditions as the plant (this is expected/usually the case with all nuclear plant full-scope simulators). At the first stage of this work, the nuclear plant outputs are compared with the simulator outputs in steady-state. Based on the results from the first stage, the plant and simulator outputs are passed through an ANN, in the second stage, which are then compared for better fault identification in transients.

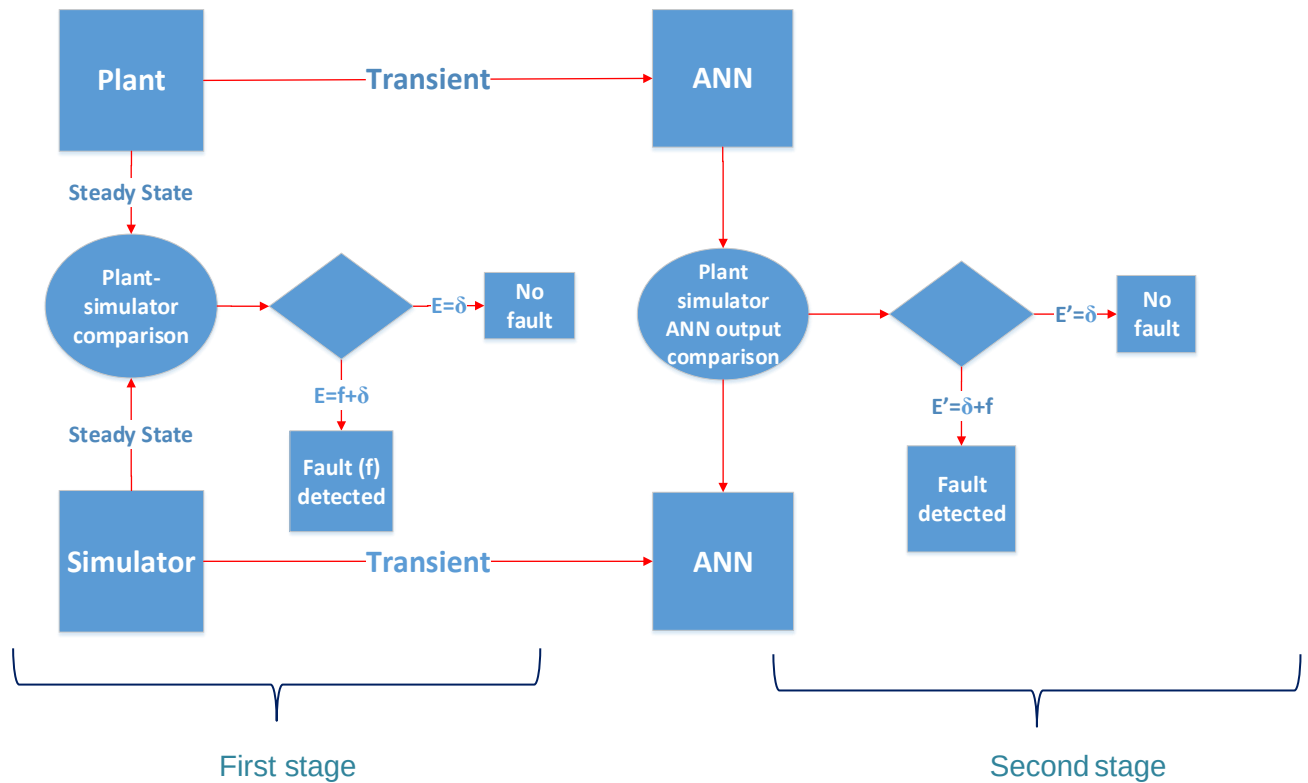


Figure 5-1: Methodology for anomaly identification in nuclear plant

In Figure 5-1:

- ' δ ' represents the error between plant and simulator, which measures how much the simulator deviates from accurately mimicking the plant. This deviation is due to simulator inaccuracy. The simulator is expected to closely mimic the plant, having a high fidelity. The ' δ ' must be negligible for this method to be applicable.
- ' E ' represents the difference between plant output and the simulator output which is due to a fault in the plant. The assumption in this research is that, when ' E ' is smaller than or equal to ' δ ', it means there is no fault. In the case where ' E ' is larger than ' δ ', then there is a fault.
- ' f ' represents the presence of a fault in the plant.
- 'ANN' is the artificial neural network: this is a machine-learning tool, which has been trained with the plant and simulator parameters for better identification of faults.

5.3 Nuclear plant simulator as a reference model

In order to maintain the NPP in a safe and normal operating condition, certain parameters are controlled within specified set points. These parameters include the reactor power, pressuriser pressure, pressuriser water level, steam generator header pressure and steam generator water level. The nuclear power plant uses a negative feedback control system, which ensures the plant will work within the reference set points. A simple block diagram of the closed-loop control system is depicted in Figure 5-2.

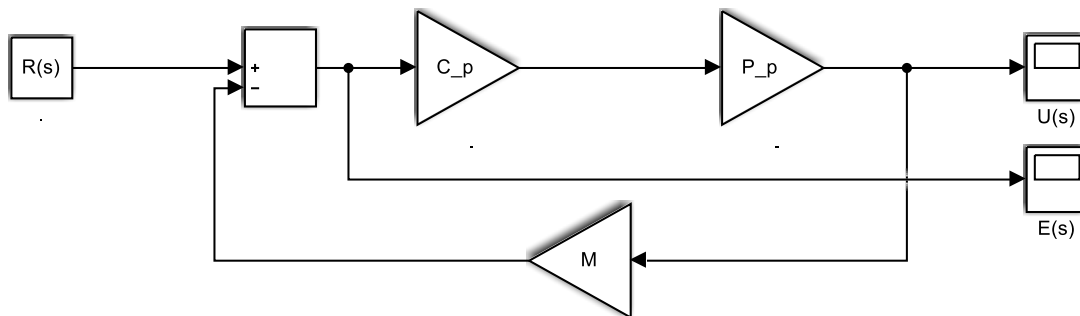


Figure 5-2: A typical closed-loop control system

In Figure 5-2:

- $R(s)$: Static reference (plant's operating setpoints)
- C_p : Plant control system
- P_p : Plant
- M : Measuring sensors
- $E(s)$: Error between measured parameter and the reference
- $U(s)$: Plant output

The benefits of the closed-loop control system are numerous, one of which is, that the plant parameters are measured and compared continuously with given setpoints (static references) and in the presence of discrepancies the control system is activated to compensate for these discrepancies. This enables the reactor to operate within the safety limits, but it also allows little faults to go undetected except if they are large enough to initiate a SCRAM. This research is focussed on further exploring the use of a dynamic reference in detecting these incipient faults.

In previous research by Cilliers and Mulder (2012), a diagnostic system was developed using the nuclear plant as a dynamic reference. The authors in their previous work explained the requirements for simulators to be used as a dynamic reference. This principle of using the simulator as a dynamic reference involves combining plant data and data from a plant simulator operating under the same conditions. This will not only help in detecting incipient faults, but it will also give an insight into the fault condition up to a certain level. For this process to be successful a modern nuclear plant simulator needs to provide specific functionality and adhere to a number of requirements related to modelling methods, interfacing and fidelity (Ayo-Imoru & Cilliers, 2017). Figure 5-3 shows the control system block diagram of the plant and simulator that have been compared.

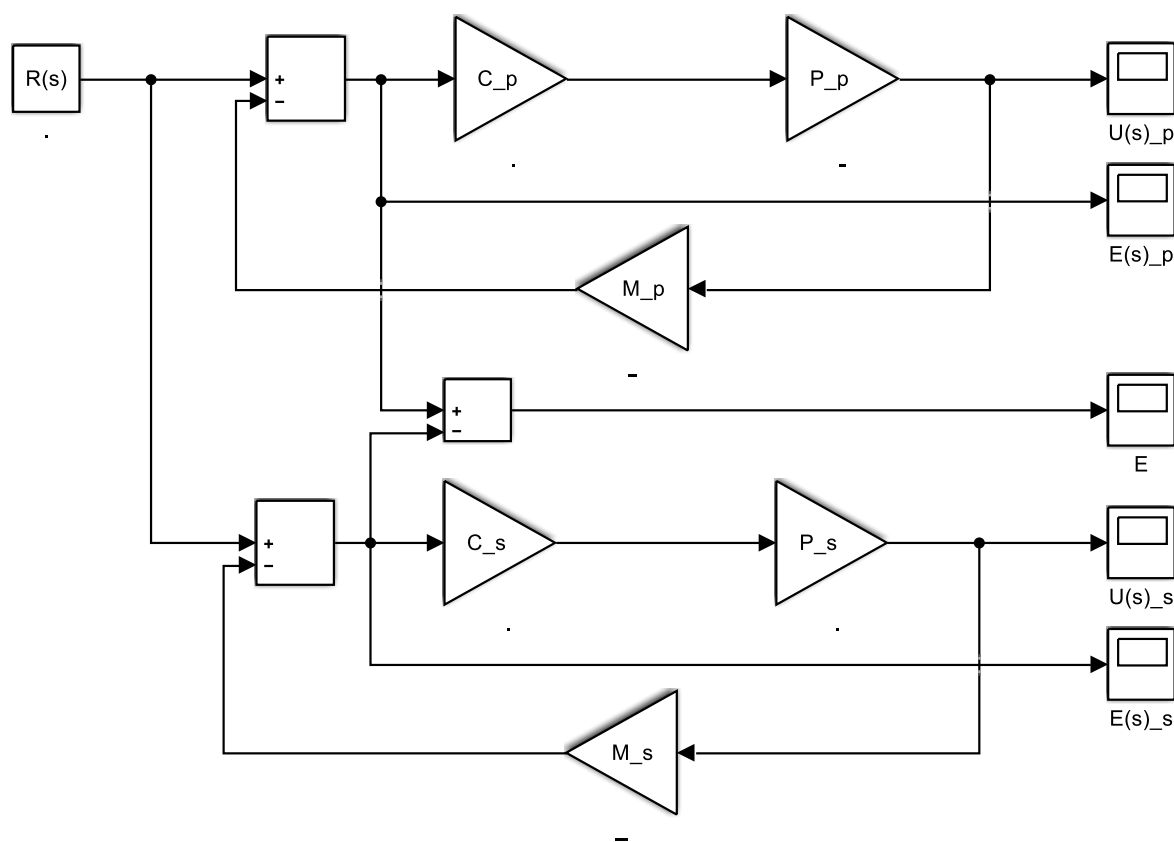


Figure 5-3: Simulator as a dynamic reference

When the plant and simulator outputs are compared as shown in Figure 5-3, it is observed that at steady-state the control system equation is given by Equations (5-1) and (5-2) for plant and simulator where E is the control parameter, and P is the input parameter:

$$E_p = U_p * M_p - R \quad (5-1)$$

$$E_s = U_s * M_s - R \quad (5-2)$$

Since the simulator input parameters are the same as that of the plant, the difference between plant and simulator output will be δ . δ represents the error between plant and simulator which must be negligible in a high-fidelity plant simulator to allow for fault detection.

Therefore

$$E = E_p - E_s \quad (5-3)$$

$$E = U_p * M_p - R - (U_s * M_s - R) \quad (5-4)$$

$$E = U_p * M_p - U_s * M_s \quad (5-5)$$

$$E = \delta \quad (5-6)$$

If the difference between plant and simulator (E) output is not smaller than δ , then a fault is present.

During a transient, the plant goes through a form of disturbance, represented as 'D'. The outputs of plant and simulator under the same transient condition are compared giving rise to Equations (5-7) and (5-8).

$$E_p = U_p * M_p + D - R \quad (5-7)$$

$$E_s = U_s * M_s + D - R \quad (5-8)$$

$$E = E_p - E_s \quad (5-9)$$

$$E = U_p * M_p + D - R - (U_s * M_s + D - R) \quad (5-10)$$

$$E = U_p * M_p - U_s * M_s \quad (5-11)$$

$$E = \delta \quad (5-12)$$

Also, in plant transients, if the difference between plant and simulator (E) output is not smaller than δ , then a fault is present.

The technique used in this research is developed on the premise that transients are known disturbances introduced into the plant, while faults are unknown disturbances in the plant. The

failure mode of most components is mostly gradual degradation and, therefore, faults in the early stage might not be discovered because of the compensatory action of the NPP control system.

To demonstrate these assumptions, an experiment was set up using two PC based plant simulators: PC-A represents the plant and PC-B represents the simulator. Since PC-A and PC-B have the same initial conditions, δ is negligible. A small fault of a leaking valve was introduced into the plant and the fault was gradually increased until it was fully leaking (this is done considering the failure mode of valves, which is usually slow). When the valve was fully open it did not cause the reactor to SCRAM as, due to the compensatory effect of the reactor control system, it would only initiate a SCRAM when safety limits are exceeded.

The valve leakage in the plant was gradually increased from 10% to 100% while the plant operated in steady-state. The plant output was compared with the simulator output and the results are shown in Figure 5-4a.

Then the experiment was repeated again with the same leakage but now the plant was made to experience different power transients (from 90% to 50% power change). The same transient was also introduced into the simulator. The results comparing the plant and simulator are shown in Figures 5-4b to Figure 5-4f.

The core thermal power percentage is considered in this research as our target and was used in our analysis. Figure 5-4 shows the results of the plant and simulator when a fault was introduced into the plant in steady-state (100% i.e. full power) as well as in transient (from 50% to 90% power change).

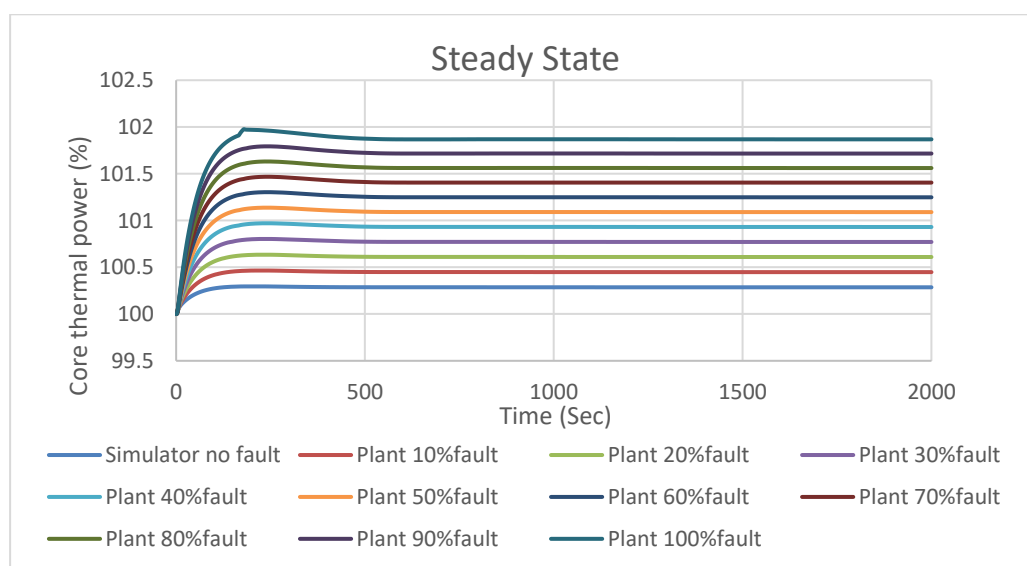


Figure 5-4a: Simulator – Plant outputs in steady-state for different valve leakages

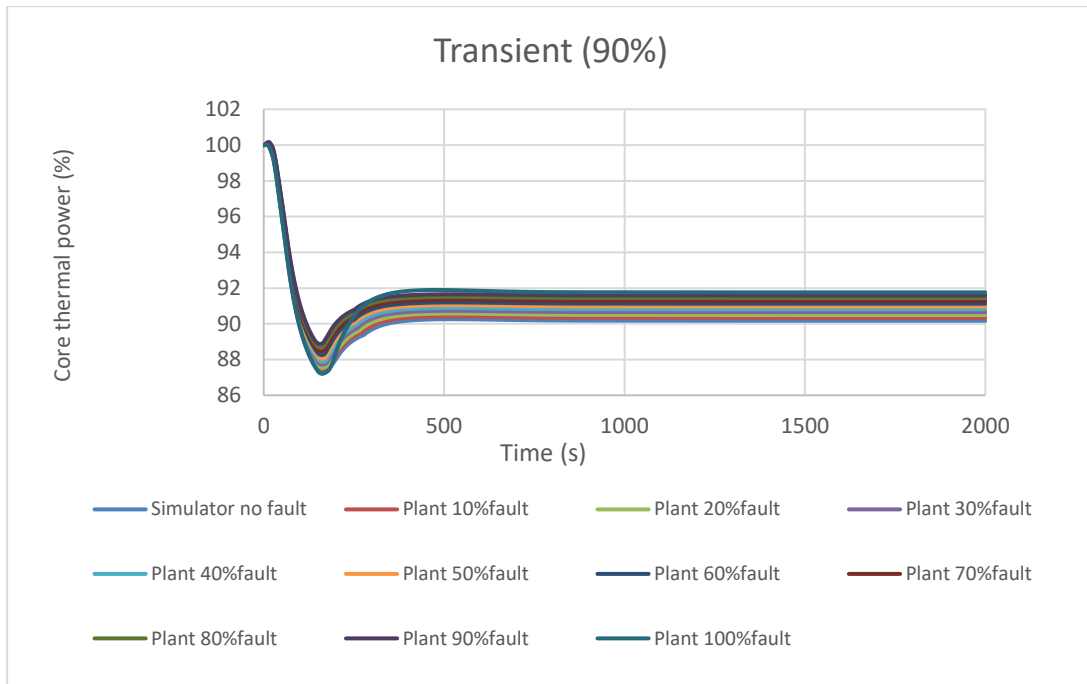


Figure 5-4b: Simulator – Plant outputs in 100-90% power change transient for different valve leakages

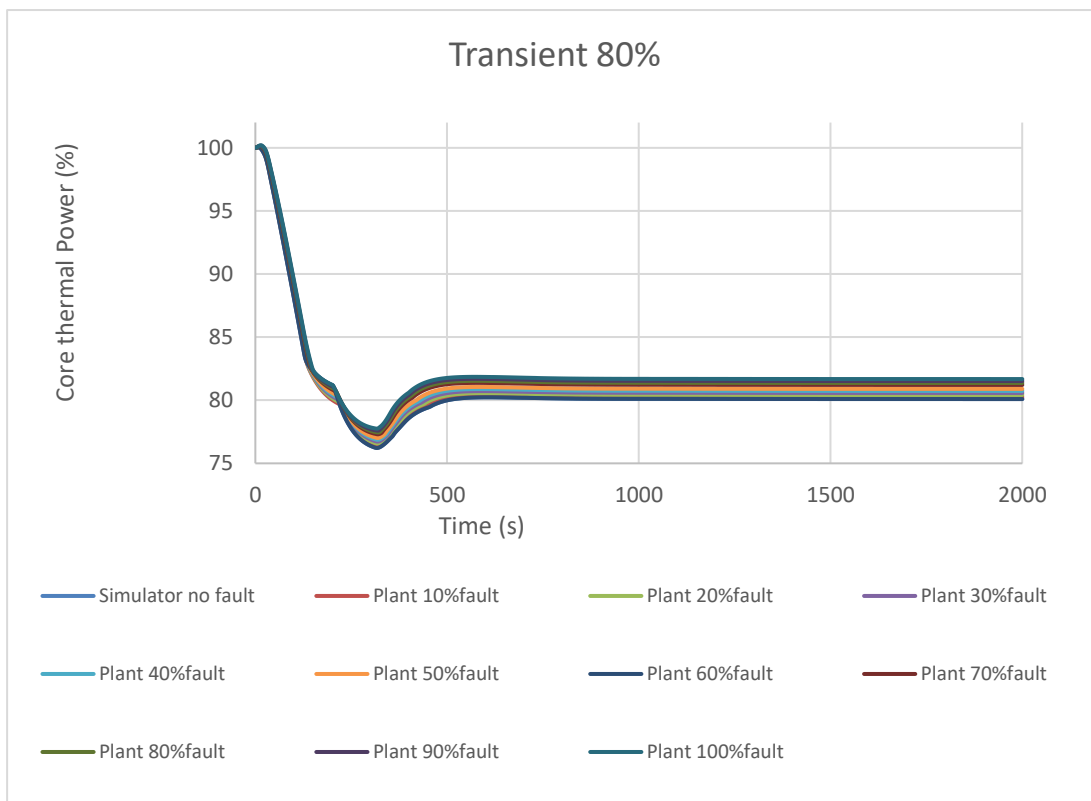


Figure 5-4c: Simulator – Plant outputs in 100-80% power change transient for different valve leakages

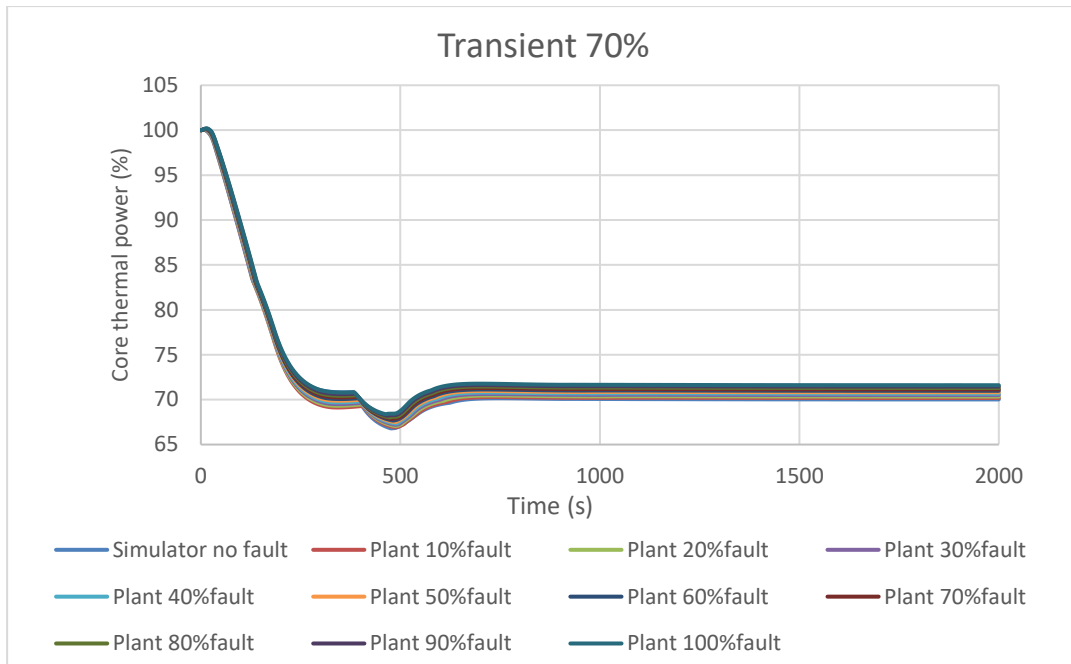


Figure 5-4d: Simulator – Plant outputs in 100-70% power change transient for different valve leakages

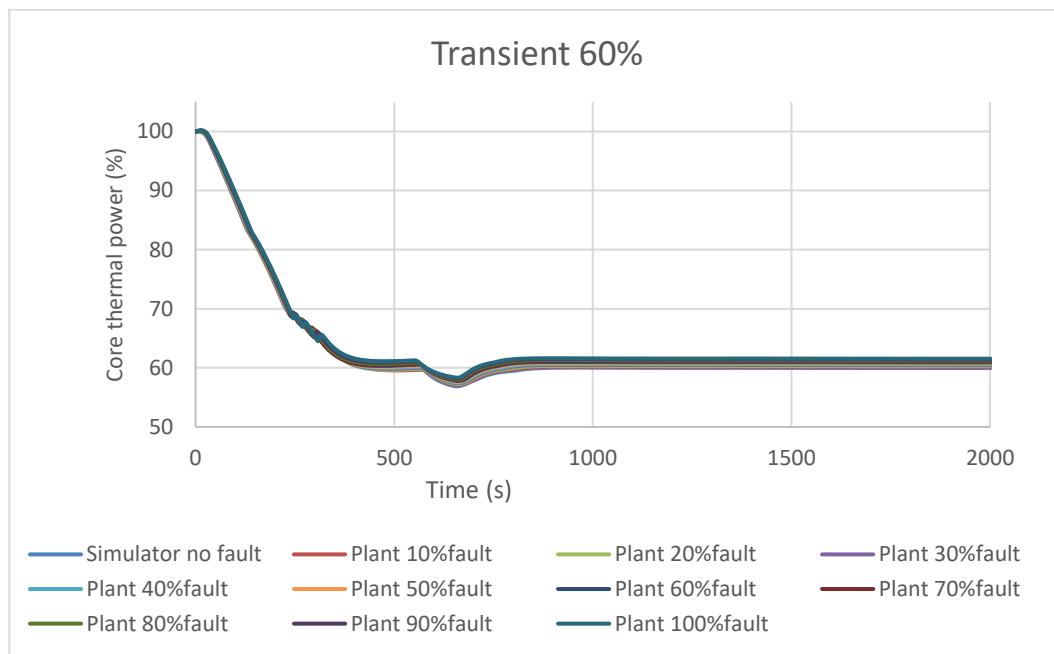


Figure 5-4e: Simulator – Plant outputs in 100-60% power change transient for different valve leakages

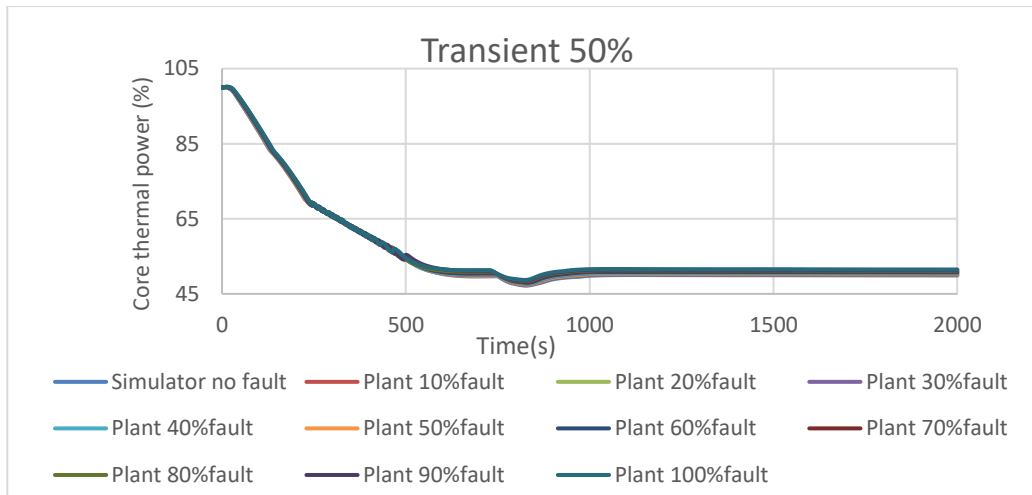


Figure 5-4f: Simulator – Plant outputs in 100-50% power change transient for different valve leakages

Figure 5-4: Simulator – Plant outputs in steady-state and power change transients for different valve leakages

It can be seen from Figure 5-4 that at steady-state, comparing the outputs of the simulator and plant, the results clearly indicate faults. When it is introduced into the plant during transients, faults are not explicitly identified. This is due to the compensatory action of the plant control system. This inability to identify faults in transients has brought about the initiative of training a neural network with the plant parameters and simulator parameters working under the same conditions. The neural network will be trained with these parameters and will continually monitor the plant condition in real-time.

Thus, introducing the machine-learning tool in the system helps to show how the plant and the simulator are meant to behave so that in transient the output from the plant neural network should be the same as that of the simulator. When there is a difference, it indicates the presence of a fault. This approach is further explained in the subsequent sections.

5.4 A neural network, a machine-learning tool for anomaly identification

Machine learning has been widely used in nearly every field and the nuclear industry is not an exception. The advancement in machine learning and its wide application has been due to its ability to be applied to many problems in almost all fields. The tool of interest for this research is the artificial neural network (ANN). ANN can be called a virtual brain as it tries to emulate how the brain works. ANNs are structured after the brain; the concept is based on making machines operate like the brain to perform operations like pattern classification, perception and motor control (Demuth & Beale, 1993). The ANN consist of a collection of neurons, which are interconnected to form a network. The neuron's interconnection strength, called synaptic weight,

is used in storing knowledge (Haykin, 1998). The ANN is nonlinear, distributed, parallel and adaptable and has local processing capability which makes it suitable for application in a complex system like the NPP.

The ANN is a data-driven modelling technique in which the system physics of failure is not required. Rather the network is trained to understand how the systems work. However, large amounts of data are required for accuracy. This makes it applicable to the NPP because of the availability of historical data and because of the large amounts of data being produced in the plant during operation. It has been used in the nuclear industry in some research areas like loose part monitoring (Kim *et al.*, 2002), transient diagnosis (Mo *et al.*, 2007), nuclear plant condition monitoring (Şeker *et al.*, 2003), monitoring check valves (Seong *et al.*, 2005), fault diagnosis (Simani & Fantuzzi, 2000; Leger *et al.*, 1998) and sensor validation (Xu *et al.*, 1999).

A simple neural network connection containing three inputs, one neuron and one output is shown in Figure 5-5.

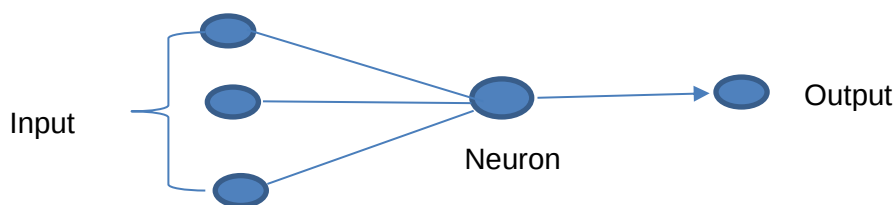


Figure 5-5: A simple neural network

Artificial neural networks are mathematical models representing a function $F : X \rightarrow Y$, or distribution over X or over both X and Y . They can compute inputs that are non-linear. The mathematical operations of the artificial networks involve varying the network's parameters like the connection weights or specifics of the architecture such as the neurons or their connectivity. This mathematical operation can be depicted in a block diagram, shown in Figure 5-6.

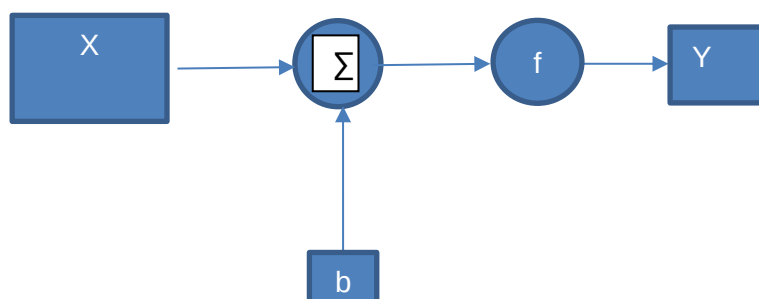


Figure 5-6: Block diagram of an ANN mathematical operation

The equation can be written as (5-13)

$$Y = f(WX + B) \quad (5-13)$$

Where X represents input, which could be either scalar or vector; B is the bias, which is mostly a constant value of '1'.

n is the net input, which is the net function of the input, and is given by:

$$n = (WX + B) \quad (5-14)$$

Y is the output, which could be scalar or vector, depending on the input.

W is the weight function and is an adjustable parameter, which is continually adjusted during training until learning has been accomplished in the network.

f is the transfer function, which is a mathematical representation, in terms of spatial or temporal frequency, of the relation between the input and output. The transfer function could be linear or nonlinear. The transfer functions mostly used in ANN are the log-sigmoid transfer function (LOGSIG), hyperbolic tangent transfer function (TANSIG), linear transfer function (PURELIN) and the hard limit transfer function (HARDLIM) (Dorofki *et al.*, 2012). These transfer functions' graphs and equations are shown in Figure 5-7.

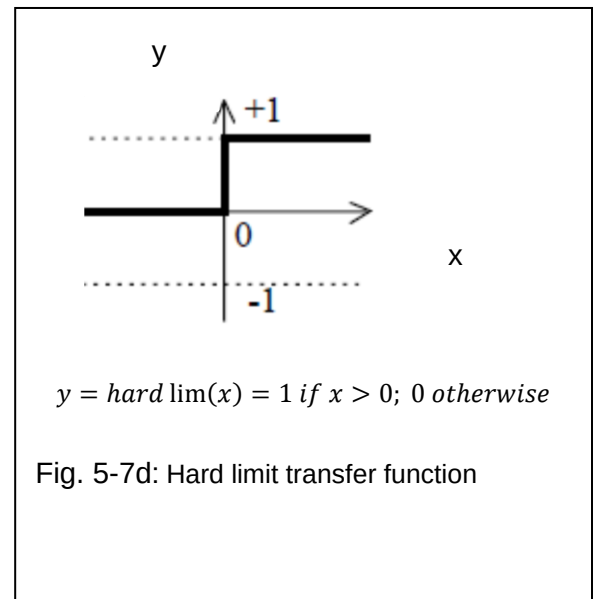
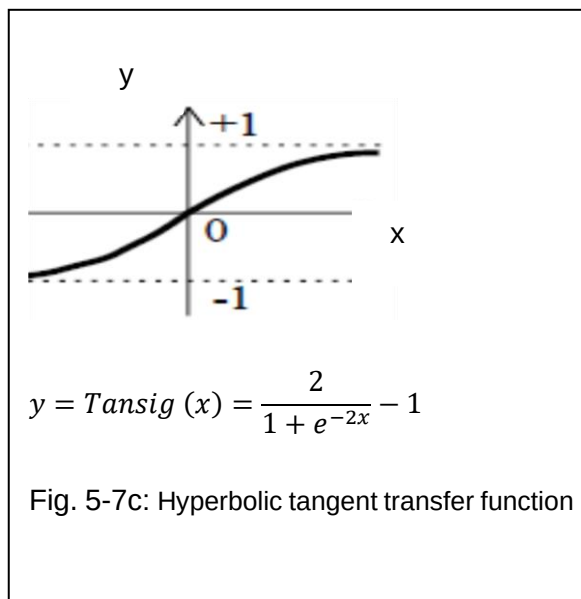
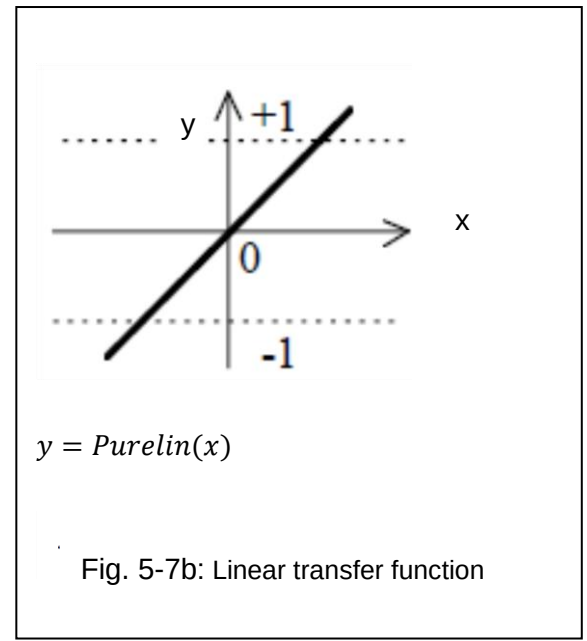
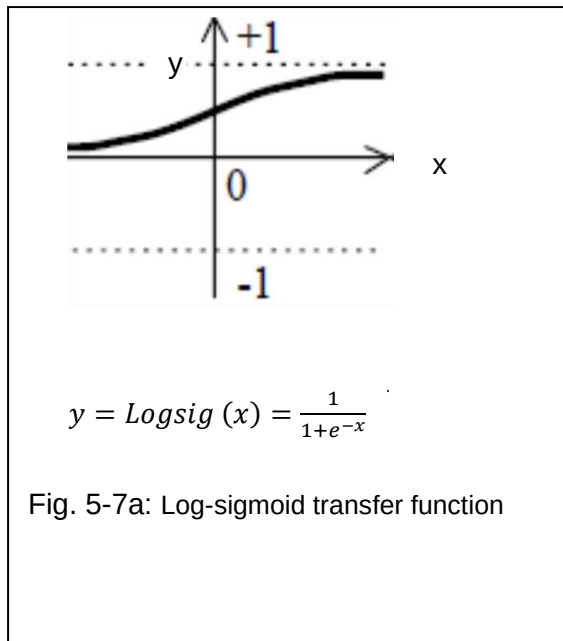


Figure 5-7: Transfer functions' graphs and equations

An ANN is typically defined by three major parameters, namely the structure (i.e. the interconnection pattern between the different layers of neurons), learning algorithm (which is the learning process for updating the weights of the interconnections) and the activation function (which converts the neuron's weighted input to its output function). Different architectures exist which include the multilayer perceptron, radial basis function, and general regression neural network. Learning methods include the error correction method, memory-based learning, Hebbian

learning, competitive learning, and Boltzmann learning activation function. For the purpose of this research, the feed-forward back-propagation neural network was used. The structure is shown in the block diagram in Figure 5-8.

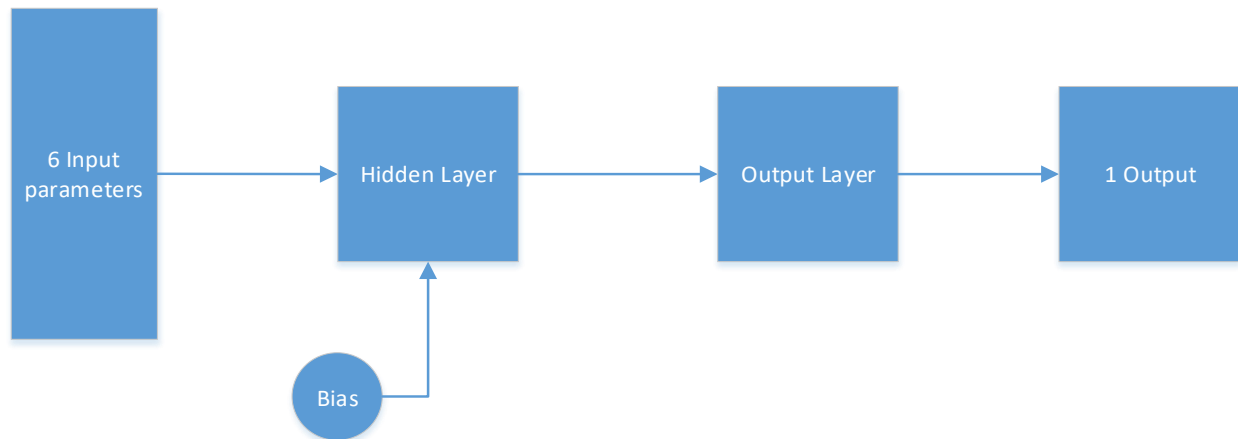


Figure 5-8: Feed-forward back-propagation neural network block diagram.

This ANN consists of six inputs, two layers and one output. The neural network was trained using six plant parameters as inputs for both steady-state and transient conditions. The input parameters used are given in Table 5-1.

Table 5-1: ANN input parameters

Nuclear plant variables	Label	Units
RCS pressure	P	(kg/cm ²)
RCS average temperature (°C)	TAVG	°C
SG feedwater flow (t/hr)	WFW	(t/hr)
Pressuriser level (%)	LVPZ	%
Charging flow (t/hr)	WCHG	(t/hr)
Pressuriser heater power (KW)	HTR	KW

The output parameter used is the reactor core thermal power percentage. Five (5) different power change transients were used in the training. The network had two layers, one hidden layer with ten neurons, which used the LOGSIG transfer function while the second layer, which is the output layer used the TANSIG transfer function. The feed-forward back-propagation architecture was used because it performed better than other architectures evaluated in the course of this research.

One very useful attribute of the ANN is generalisation. For generalisation to be achieved a method called “early stopping” is used. This involves dividing the available data into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error on the validation set is monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to over-fit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The test set error is not used during the training, but it is used to compare different models. It is also useful to plot the test set error during the training (Demuth & Beale, 1993).

The ANN is trained using a set of examples of proper network behaviour. The training process involves iteratively adjusting the weights and biases of the network to minimise the network performance function. The default performance function for feed-forward networks is mean squared error (MSE), which is the average squared error between the network outputs and the target outputs. The performance of a trained network is usually measured using the errors on the training, validation and test sets. The best performance is obtained at the lowest mean squared error (MSE). Very often, performing a regression analysis gives a more useful investigation of the network response (Demuth & Beale, 1993). The result of the performance is shown in Figure 5-9 and Figure 5-10.

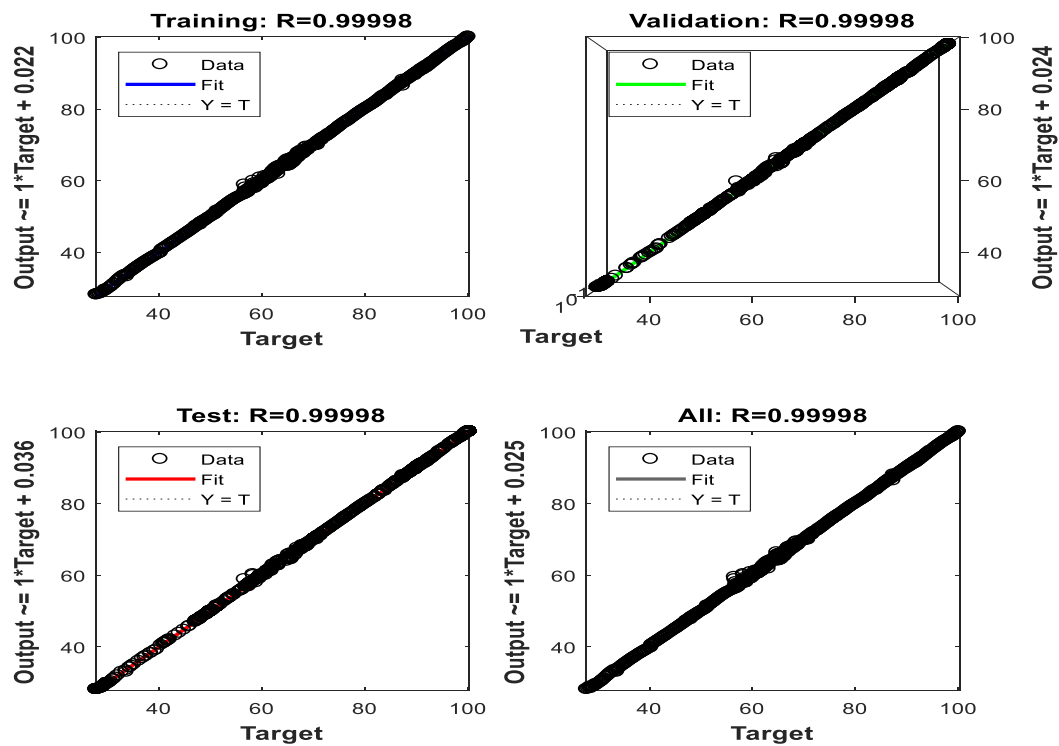


Figure 5-9: Regression analysis for the ANN

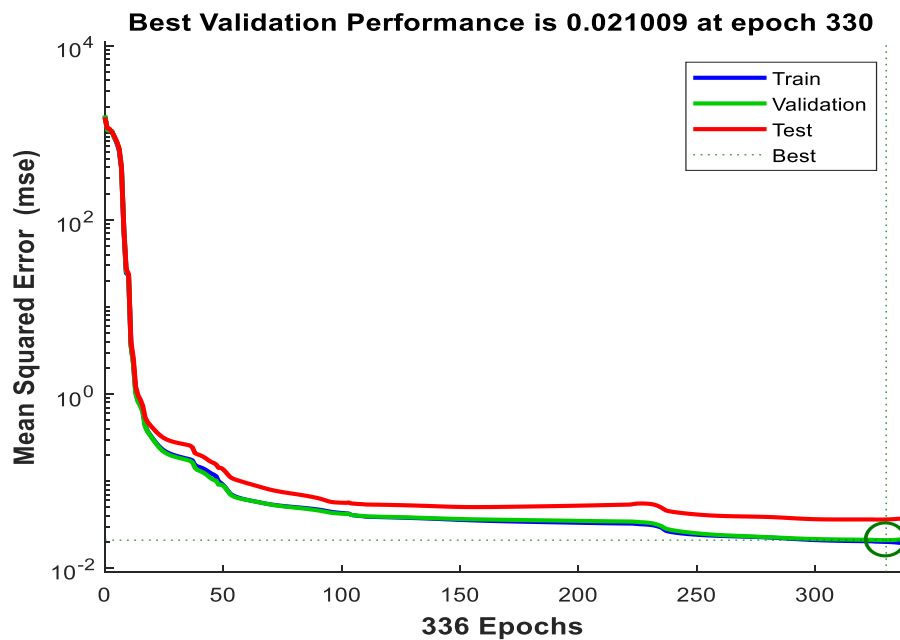


Figure 5-10: Performance plot for ANN

5.5 Transient identification with neural network

First, the neural network was trained with power change transients of 90%, 80%, 70%, 60%, 50% and 30%. There were six input parameters used which were pressuriser pressure, average temperature, pressuriser level, feed flow, charge flow and pressuriser heater capacity. Core thermal power percentage was used as the output. The network was then tested using 95%, 85%, 75%, 65%, 55% and 45% transients. The ANN was able to identify each of these transients successfully. Figure 5-11 shows the plant output and the ANN output.

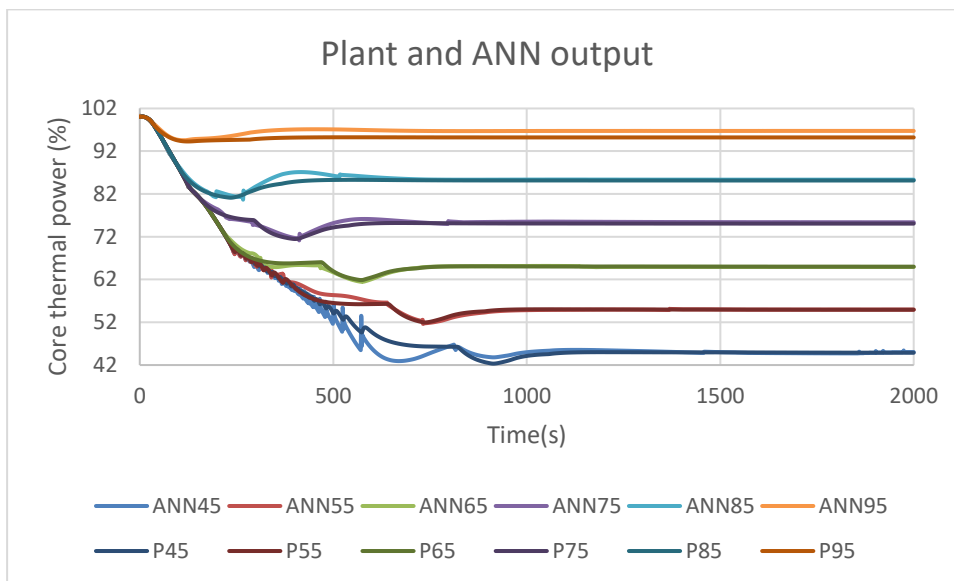


Figure 5-11: Transient identification with ANN

Using the neural network output of both the plant and the simulator takes care of the neural network error. The only error to take into consideration is the accuracy of the simulator. Before this method can be used, the error between the plant and simulator must be minimal. For the purpose of this work, the PCTTRAN simulator was used. The PCTTRAN source code is developed in FORTRAN, verified against final safety analysis reports, and validated with respect to real plant data and computer analyses RETRAN, RELAP5, TRAC, MAAP, and SAFE (Micro-Simulation Technology, 2009). Pelo (2013) showed that it was possible to use the PCTTRAN simulator in fault diagnostics investigation. This was achieved by comparing the PCTTRAN data with data from the Koeberg NPP in South Africa, which gave good outcomes.

Instead of just comparing the plant and simulator outputs, plant data and simulator data were sent through the neural network. A valve leakage fault from 10% to 100% was introduced into the plant. The ANN output using the simulator parameters was compared to the ANN output using plant parameters with the fault introduced. At 90% power change transient, this approach clearly

detected the faults. Figure 5-12a to 5-12d show the results from 10%, 40%, 70% and 100% valve leakage in a 90 % power change transient.

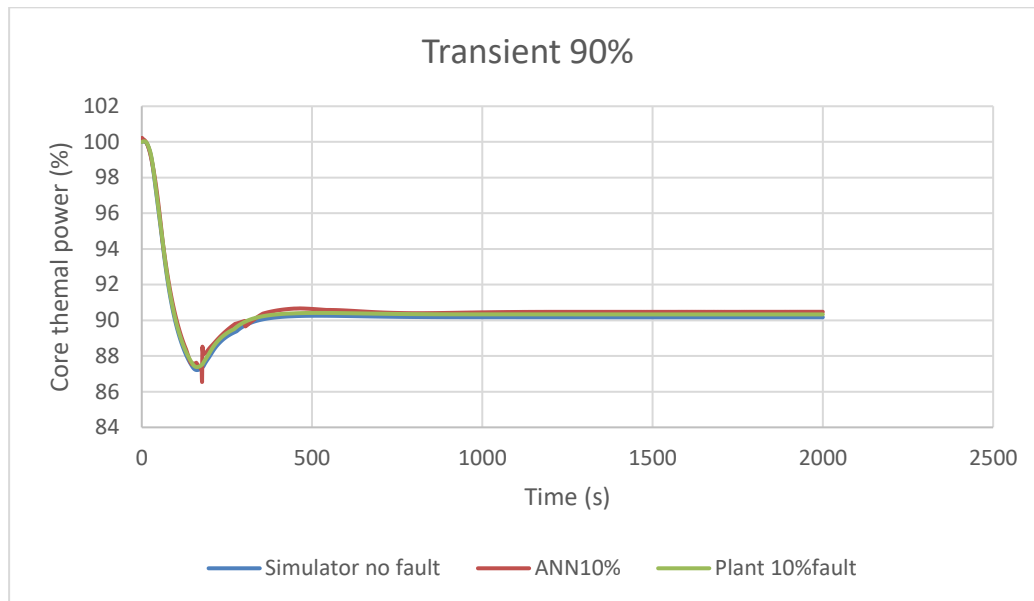


Figure 5-12a: 10% valve leakage identification

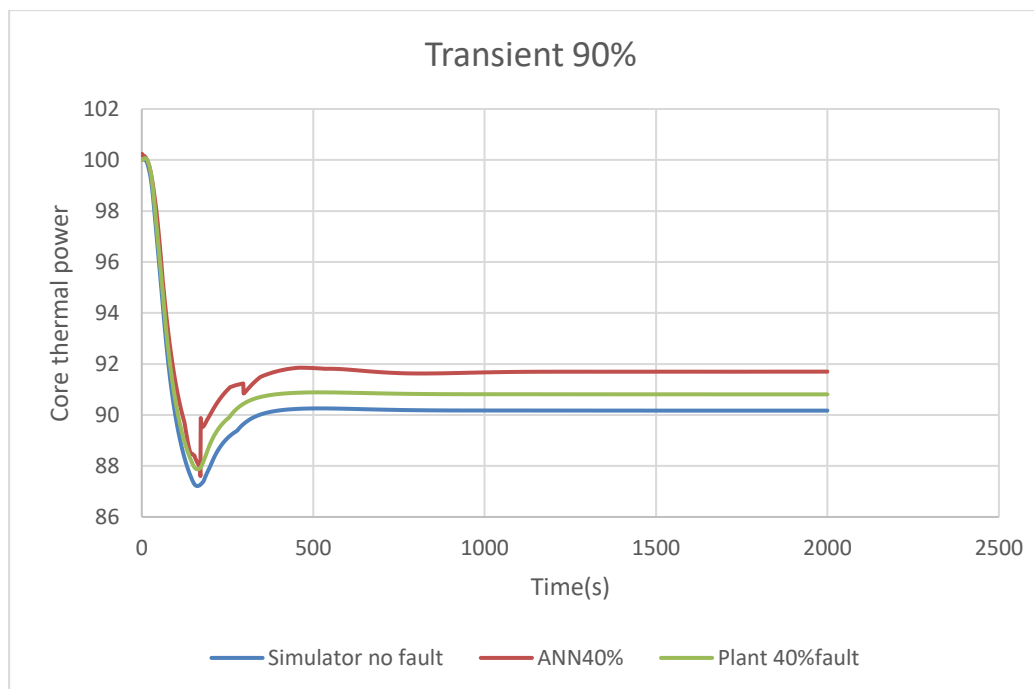


Figure 5-12b: 40% valve leakage identification

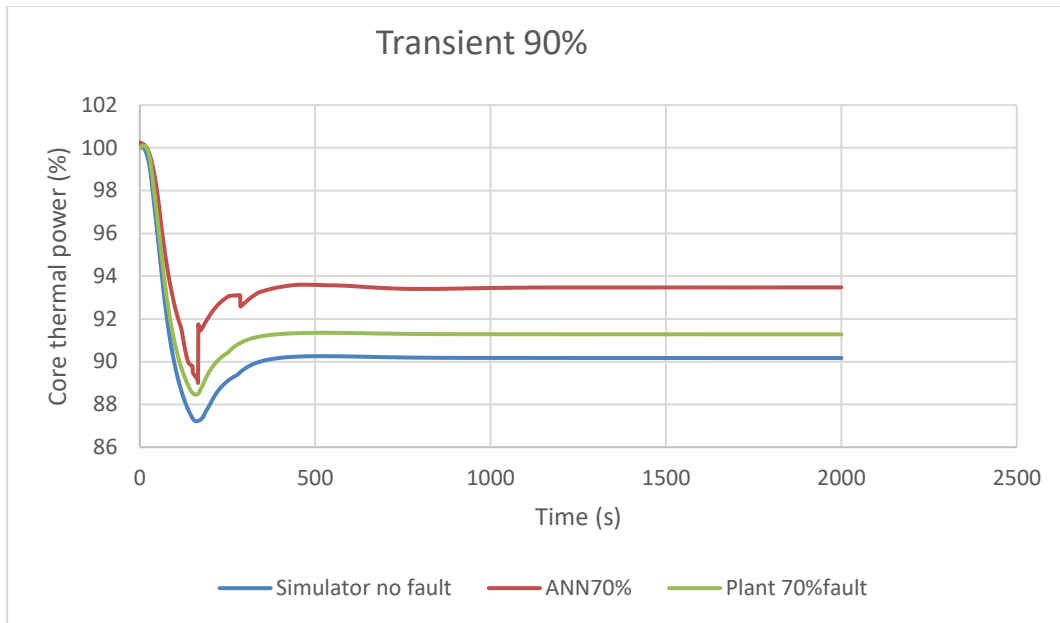


Figure 5-12c: 70% valve leakage identification

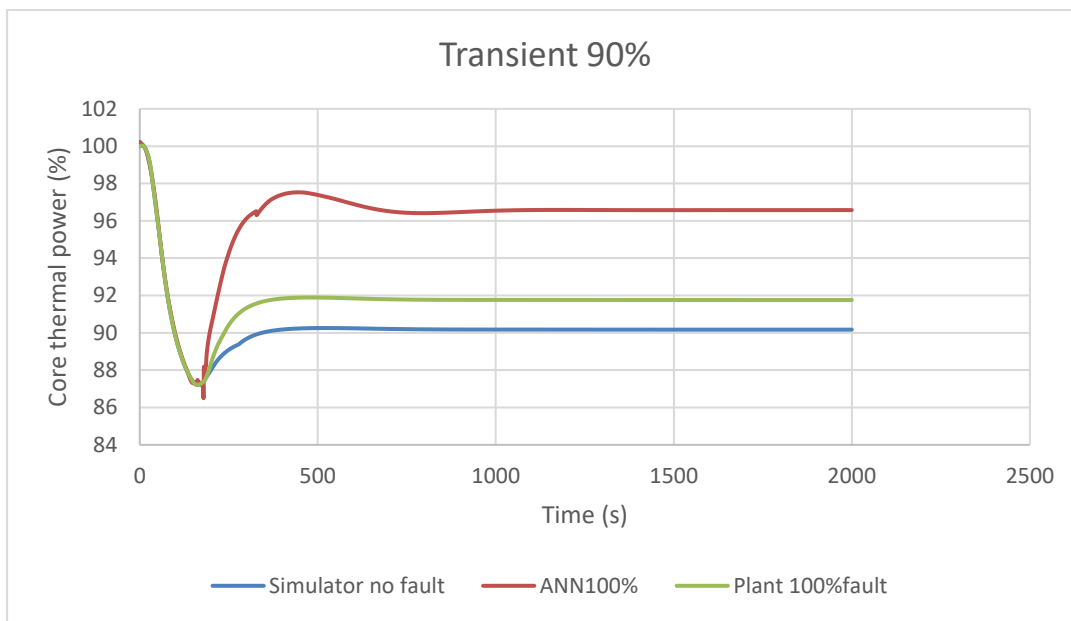


Figure 5-12d: 100% valve leakage identification

Figure 5-12: Percentage valve leakage identification

From Figures 5-12a to 5-12d, it is seen that, during transient conditions, using the neural network amplifies the fault compared to just comparing the plant and simulator output.

5.6 Conclusion

In this paper, the possibility of detecting operational anomalies using the simulator as a dynamic reference has been explored. This was implemented using the PCTTRAN simulator. From the

results, it was observed that comparing the simulator output with the plant output directly could only identify faults in steady-state but not during transients. A method has been developed to identify transients and detect the fault in a nuclear power plant during transients. This was achieved by using the nuclear plant simulator as a dynamic reference and a machine-learning tool, an artificial neural network, to train both the simulator and plant parameter. The neural network output of the plant and simulator were compared. The method resulted in better identification of faults in transients. The error in the ANN output is mitigated by passing the simulator and plant parameters through the neural networks before the comparison is made so that the error can be neglected.

To apply this method the accuracy of the simulator's mimicking of the real plant must be taken into consideration. Some requirements, like user requirement specification, the simulator model requirements, the functional requirements and the reactor response simulation, also need to match to enable the use of the full-scope simulator as a dynamic reference. These requirements are further explained in Ayo-Imoru and Cilliers (2017).

5.7 Additional note

In this chapter, we have been able to successfully combine the NPP and simulator data to identify transients and faults using a neural network. The aim of this research is to be able to identify faults and also to determine the degradation level to enable maintenance personnel to decide whether or not to replace the faulty component. Therefore, in the next chapter, we would be estimating the degradation level using another machine learning tool.

CHAPTER 6 - ARTICLE 4: A DIGITAL TWIN APPROACH FOR CONDITION-BASED MAINTENANCE IN NUCLEAR PLANTS

Condition-based maintenance regimes in nuclear plants should result in eliminating unnecessary maintenance cost by providing accurate and timely fault diagnosis, without jeopardising the safety of the plant. In this study, a method has been developed to identify transients and estimate faults in a nuclear power plant (NPP), in order to aid condition-based maintenance in the plant. This was achieved by using the digital twin concept which involved using the nuclear plant simulator data alongside the nuclear plant data. To this was added the adaptive neuro-fuzzy inference system (ANFIS) approach in fault estimation. This system was then able to identify a fault as well as the level of degradation in the component in the nuclear power plant.

Keywords: condition-based maintenance, degradation, diagnosis, digital twin, fault, neuro-fuzzy, transient.

6.1 Introduction

To meet the ever-increasing world energy demand there is a need for sustainable, reliable and safe energy sources. Nuclear power plants are one of the prominent candidates for meeting this need, provided that they can be operated safely and cost-effectively. Since the production cost of especially wind power, solar power and gas power has decreased rapidly in recent years, there is a need for reducing the cost of producing nuclear electricity. However, this should be done without tampering with safety, since safety is of the utmost importance in the nuclear industry. One of the methods for reducing the cost of operating an NPP is reducing maintenance costs. This could be achieved by introducing a condition-based maintenance regime for the nuclear plant operation, in order to supply timely and accurate abnormality identification.

Several methods have been employed in identifying abnormalities in nuclear plants. This can be classified into three approaches, namely the model-based, data-driven and hybrid approaches. The hybrid approach is the focus of this work as it combines the strengths of the model-based and data-driven approaches, in order to give better fault identification.

The digital twin concept was first introduced by Grieves in 2003 and was proposed to comprise of a physical product, a virtual product and their connections (Tao et al., 2018). The digital twin concept was later developed by the aerospace industry and was defined in 2012 by NASA as “[a]n integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying

twin. The digital twin is ultra-realistic and may consider one or more important and interdependent vehicle systems” (Liu et al., 2018).

The digital twin can be described as a virtual system that has been created to represent the physical system or equipment for the purpose of improving product design, monitor equipment health in order to identify potential degradation and simulate manufacturing operations. This is achieved by “coaching” the digital system to continually learn until it correctly mirrors the physical system. The digital twin concept has found successful application in the aerospace industry and is considered in the manufacturing industries. It is useful in situations where physically accessing the real asset is a challenge. The data stream from the twin might feed into data analytics and machine learning stacks for pattern recognition and decision support (Erikstad, 2017).

The digital twin concept in the industry is mainly based on two approaches namely the data-driven and the model-based approaches. The data-driven approaches rely on plant historical data for the digital twin applications, while the model-based approach is developed using first-principles models which rely on physics, engineering or chemical descriptions to represent the plant’s behaviour. One of the model-based approaches of interest in this work is the simulator-based digital twin which is also known as the online model-based approach. The simulator-based digital twin is implemented by making a simulator model run along with the plant, while being and kept in the same state as the plant (Martínez *et al.*, 2018). The simulator is then “coached” to continuously reduce the deviation between its simulation outputs and the actual measurement outputs from the plant. Setbacks with using the online model-based digital twin are the rigour and cost involved in developing models for complex systems (Pantelides & Renfro, 2013).

Considering the success of the digital twin concept in the aerospace industry and the similarities between the aerospace and nuclear industries, it seems logical that the digital twin concept can also be adopted in nuclear power plants. The nuclear plant is unique in that the nuclear plant mandatorily has in almost every facility a full-scope simulator, which is a replica of the nuclear power plant with reasonably high fidelity. Although the full-scope simulator was primarily designed for training, with the advent of the digital twin concept, the use of the full-scope simulator as the nuclear power plant’s digital twin can be explored (Ayo-Imoru & Cilliers, 2017). The required cost and rigour of model development of the simulator-based digital twin is reduced in the nuclear industry because the mandatorily available full-scope nuclear plant simulators can be used as the digital twin.

This research is based on the premise of operating a plant alongside a simulator with the possibility of using the simulator as a reference for fault diagnosis in a nuclear power plant. The simulator can be used in generating degradation data which can be used in machine learning.

The use of the simulator as a dynamic reference has been developed in previous research by Cilliers and Mulder (2012) where they explored control system behaviour of the nuclear plants. As faults start to develop, e.g. a valve that should be fully open starts to close, resulting in a reduction in the coolant flow rate and thus an increase in the fuel temperature, the control system will automatically adjust the plant's operational parameters, e.g. it might increase the pumping pressure in order to increase the coolant flow rate and thus reverse the fuel temperature increase. By monitoring these compensatory actions of the control system, they could identify faults. Ayo-Imoru and Cilliers (2018) used a simulator to train an artificial neural network for fault detection. The present article is focussed on using the neuro-fuzzy approach for transient identification and fault estimation of components in the plant by using both simulator and plant data as shown in Figure 6-1.

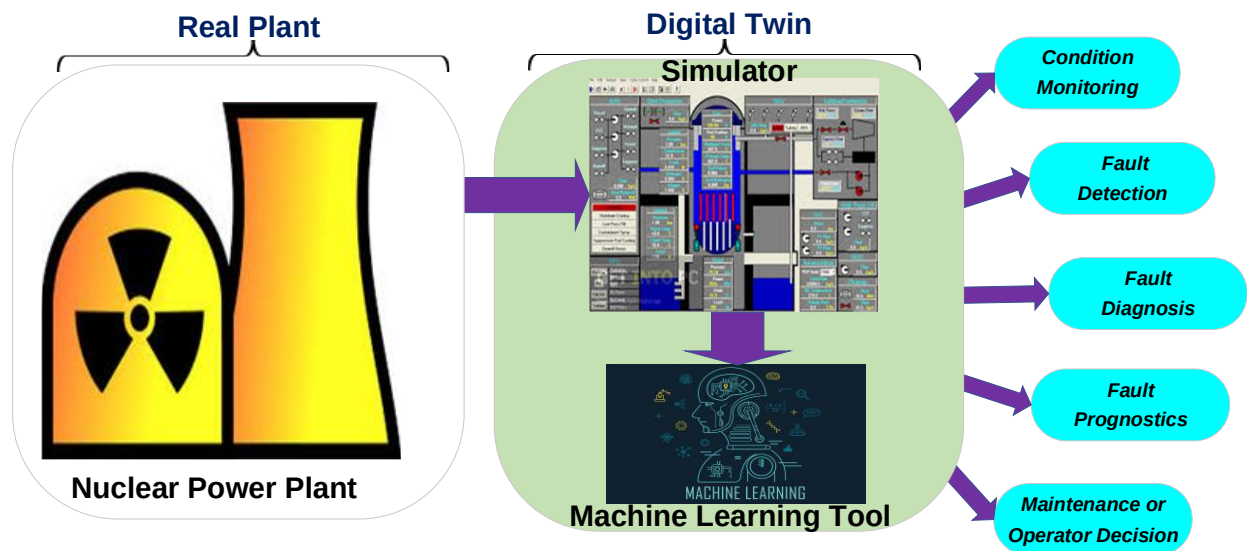


Figure 6-1 The digital twin concept

This work is organised in seven (7) sections. The first section is the introduction. The second section explains the research methodology. The third section explains the neuro-fuzzy approach. The fourth section shows the hybrid system implementation steps. The fifth section contains transient identification results. The sixth sections show the fault estimation examples and the seventh section contains the conclusion.

6.2 Research methodology

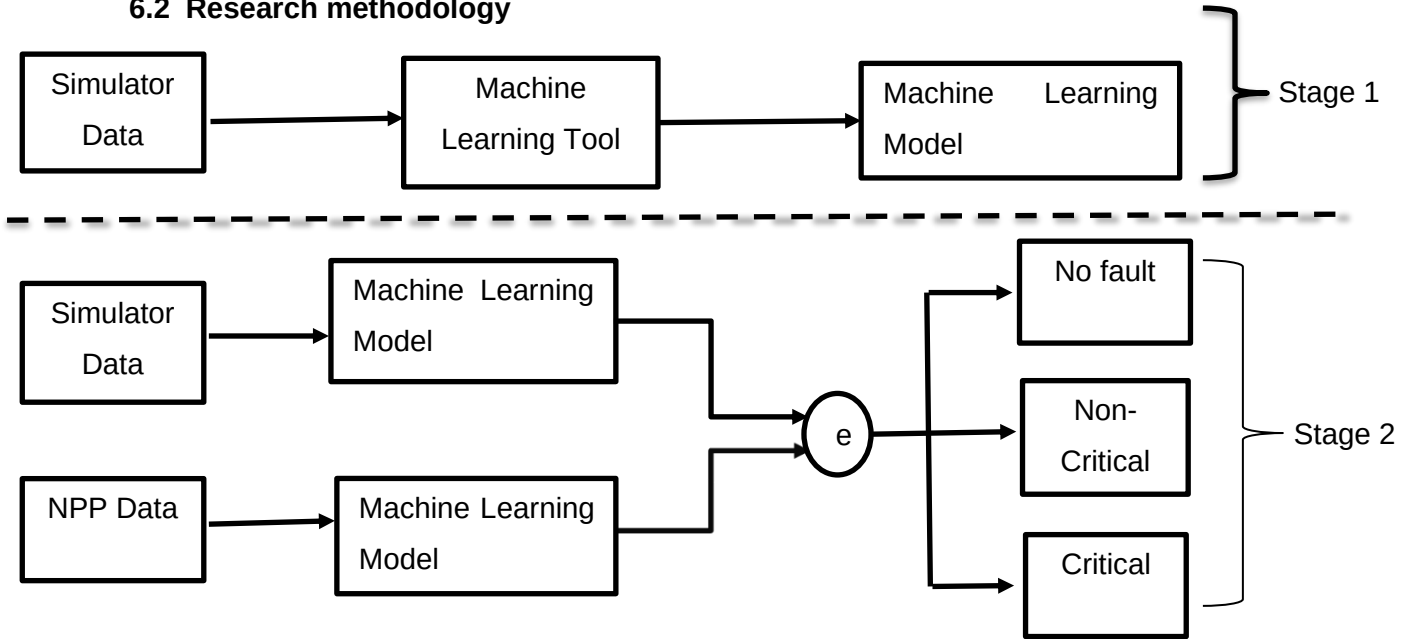


Figure 6-2: Research methodology

The method used in this paper is shown in Figure 6-2. The simulator is the nuclear plant twin and the data is used as a dynamic reference for the plant. The simulator is made to operate under the same condition as the NPP so that the data from the nuclear power plant and simulator can be analysed for diagnostic purposes.

The first stage of the research is to use the simulator data which is our reference to train a machine learning tool, which will produce a computer code. Then the nuclear plant data and simulator data are passed through the program and the difference is used to identify and evaluate the condition of the plant. The first requirement is that the simulator is able to correctly mimic the plant in real-time. So, the plant data and simulator data are continuously and directly fed into the machine learning program to identify the plant's condition. Secondly, the machine learning tool must be rightly selected and thirdly the data that best represents the plant must be rightly selected. For this research, the machine learning tool of interest is the neuro-fuzzy approach which is further explained in the next section.

6.3 The neuro-fuzzy approach

The neuro-fuzzy method is a computational method that combines both the artificial neural network (ANN) and fuzzy logic methods. This hybrid system is formed with the aim of diminishing the weakness of the individual methods and harnessing their strengths. For instance, the neural network can easily do pattern recognition and make a decision without showing the reason behind it, while fuzzy logic can explain the reasons for its decision but cannot automatically estimate the

rules needed for it (Ross, 2005). So, combining these two methods, helps give a stronger data-driven approach. The advantages of having this hybrid method are numerous, including:

- Ability to incorporate human knowledge effectively.
- Ability to handle different types of input data (numeric, linguistic, logical, etc.).
- Ability to use data that are vague, imprecise, partial and imperfect.
- It can adapt to an unknown or changing environment.
- It is fault-tolerant.
- Model-free learning.
- It can be trained and has the ability for self-learning, self-organising and self-tuning.
- It doesn't need prior knowledge of how data relates.

The neuro-fuzzy tool has found useful applications in different areas which include streamflow forecasting in a river watershed tributary using the adaptive neuro-fuzzy inference system (ANFIS) and Bayesian regression (Hamaamin *et al.*, 2016); predictive prognosis of a crack propagation problem (Di Maio & Zio, 2010); estimating the remaining useful life (RUL) of lithium-ion batteries (Razavi-Far *et al.*, 2016); design of fault classification systems in an induction motor (Alexandru, 2003); condition monitoring in railway industry which involved detection and diagnosis of the most commonly occurring track problems (Chen *et al.*, 2008). The neuro-fuzzy method has also been combined with other data-driven methods in fault diagnosis, including the development of an intelligent diagnosis for fault gear identification and classification based on vibration signal using discrete wavelet transform and an adaptive neuro-fuzzy inference system (Wu & Hsu, 2009).

A hybrid system of the neuro-fuzzy approach and a support vector machine was also employed for detection and diagnosis of incipient steam turbine faults (Salahshoor *et al.*, 2010). The neuro-fuzzy system combines the theory of neural networks and fuzzy logic which are further explained in the next section.

6.3.1 Artificial neural networks (ANN)

ANN is inspired by the operation of the human brain. It is patterned after how the brain works. The human brain is a highly complex, non-linear and parallel information processing system. It is able to perform functions like pattern recognition, perception and motor control faster than any

computer that ever existed (Demuth & Beale, 1993). ANN can be called a virtual brain – the ANN components are similar to that of the brain which includes a collection of neurons which are interconnected through synapses (Haykin, 1998). The neurons are simple processing units with the ability to store knowledge and making it available for later use by other components of the code. Neuron interconnections have strength called the synaptic weight, which is used to store the acquired knowledge. A simple ANN structure is shown in Figure 6-3:

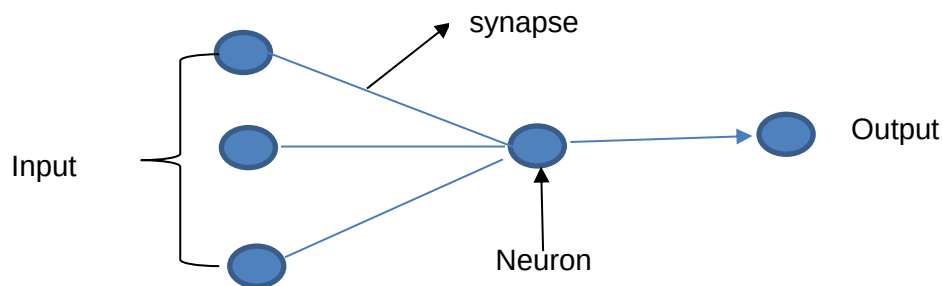


Figure 6-3: A simple neural network

ANN have different procedures for learning which are called learning algorithms. The learning algorithms modify the synaptic weight of the network in an orderly fashion to attain the desired design objective. A neural network has the ability to learn and generalise so that it can produce output from inputs it didn't encounter during training. The other strengths of the neural network are that it can:

- work well in non-linear systems;
- do input-output mapping;
- adapt to changes in the environment; and
- give confidence level on decisions that it made.

6.3.2 Fuzzy logic (FL)

Fuzzy logic uses human expertise in interpreting incomplete and imprecise information in the form of IF-THEN rules to solve problems. It performs numerical computation by using linguistic labels stipulated by membership functions. The fuzzy system incorporates human knowledge and performs inferencing and decision making (Demuth & Beale, 1993). Fuzzy logic may be viewed as a methodology for computing with words rather than numbers. Although words are inherently less precise than numbers, their use is closer to human intuition. Furthermore, computing with words exploits the tolerance for imprecision and thereby lowers the cost of the solution

(MathWorks, 1998). Fuzzy logic relies on age-old skills of human reasoning. The strengths of fuzzy logic are:

- Approximation capability;
- Ability to compute with words;
- Tolerance for imprecision; and
- Ability to model non-linear functions.

6.3.3 Adaptive neuro-fuzzy inference system (ANFIS)

The adaptive neuro-fuzzy inference system (ANFIS) is the neuro-fuzzy method of interest in this research. ANFIS was proposed by Jang (1993). ANFIS combines the strength of fuzzy logic approximation with the adaptive capability of the ANN. The membership functions are generated using a neural network approach and, therefore, it does not require expert knowledge, which is normally a prerequisite for a standard FL system. In ANFIS the membership function (MF) parameters change through a learning process. ANFIS uses either back-propagation or a combination of least squares estimation and back-propagation for MF parameter estimation. The ANFIS approach and applications are well described in Jang (1993), Jang (1996), Jang *et al.* (1997), Karaboga & Kaya (2018), Lu & Upadhyaya (2005), Salahshoor *et al.* (2010) and Zarei *et al.* (2014).

6.4 Hybrid system implementation steps

For this work, the PCTTRAN simulator is used to generate data (Micro-Simulation Technology, 2009). The research is based on the premise of operating a plant alongside a simulator, in which the simulator is the digital twin of the nuclear plant simulator. Data from the plant is monitored and compared with that of the NPP twin (the full-scope simulator). The data is then analysed using machine learning to understand the condition of the plant and diagnose a fault. The possibility of using the simulator as a dynamic reference for fault diagnosis in a nuclear power plant has been explored in previous research by the authors (Ayo-Imoru & Cilliers, 2018; Ayo-Imoru & Cilliers, 2017; Cilliers *et al.*, 2011; Cilliers, 2013; Cilliers & Mulder, 2012). Firstly, by using the nuclear plant control system behaviour, the neural network approach was used; this is further explored in this paper using a neuro-fuzzy approach. The objective of this work is to develop a hybrid system (combining simulator data, NPP data and machine learning) that uses the ANFIS approach to identify transients and estimate faults in the nuclear plant components. Figure 6-4 shows the steps followed in this research work:

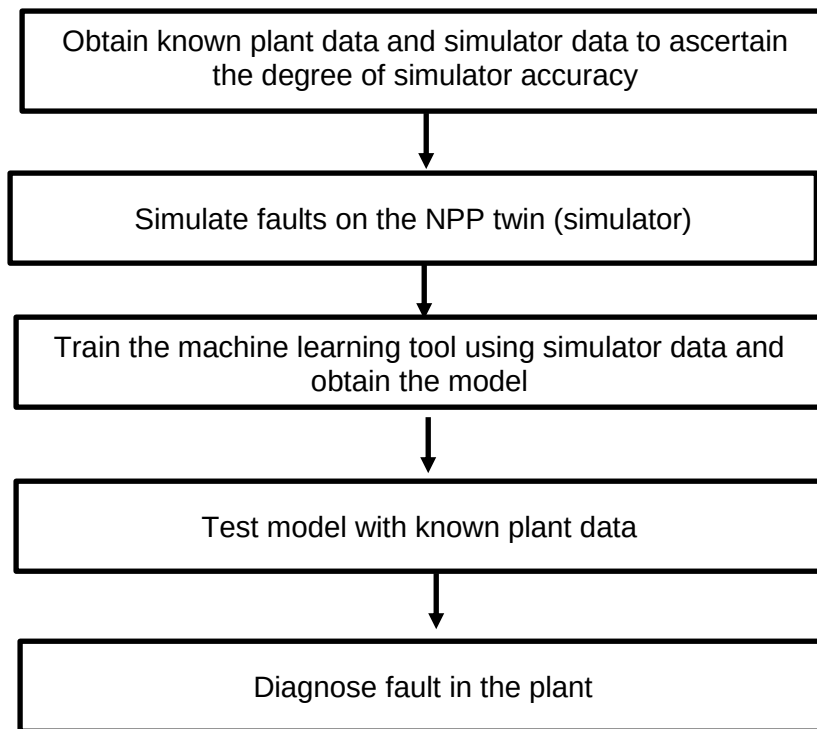


Figure 6-4: Hybrid system implementation steps.

6.5 Fault characterisation

6.5.1 Operational transient identification

The ANFIS was generated using six (6) data inputs and one output. The inputs are the pressuriser pressure, core average temperature, level pressuriser, heater capacity, feed-water flow and charge flow. The output is the core thermal power. The ANFIS was trained with the steady-state data and then with the data for power transients down from 100% to 50%, 60%, 70%, 80 and 90% power respectively. Then test data for 45%, 55% and 65% power transients were used in order to test whether the ANFIS was able to correctly identify these different power transients as shown in Figure 6-5a-c:

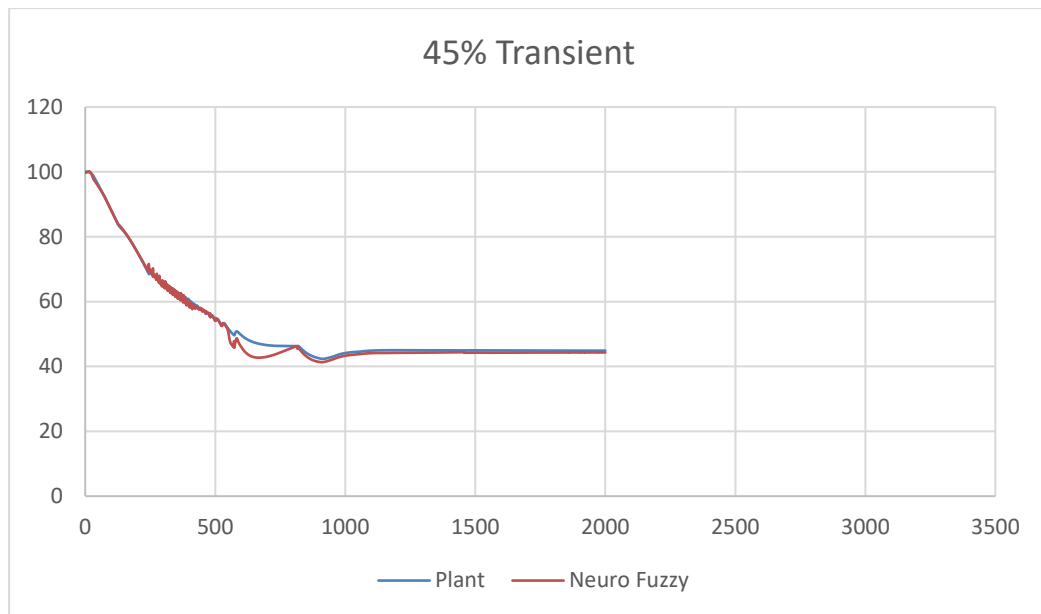


Figure 6-5a: ANFIS identification for 45 per cent transient

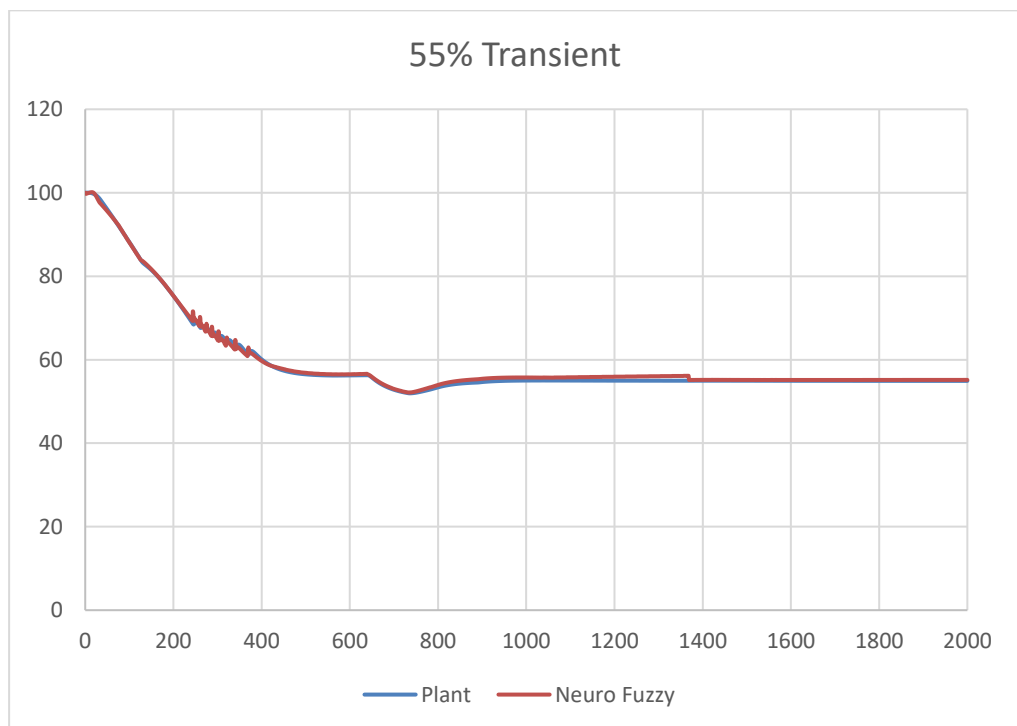


Figure 6-5b: ANFIS identification for 55 per cent transient

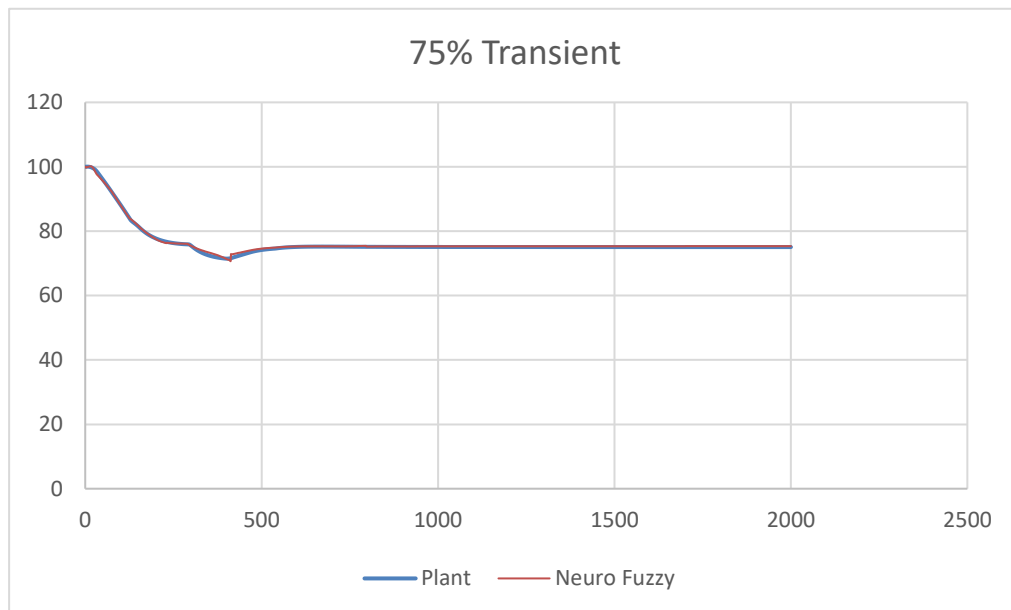


Figure 6-5c: ANFIS identification for 75 per cent transient

Figure 6-5: ANFIS identification for different per cent transient

Figure 6-5 shows that the ANFIS is able to predict the plant transients as we can see the similarity in the plant and ANFIS output from the graph. The result from the ANFIS flows into that of the plant and the difference is negligible. The ANFIS was trained with the simulator data for power change transients, and it was able to show a very close result to a different set of power change transients which it was not initially trained with.

6.5.2 Fault identification

Some faults can easily go undetected by the reactor protection system. This is because they are not large enough to initiate a SCRAM. Some of these kinds of faults were used in training the machine learning tool of interest. Two tools of interest were used: artificial neural network and adaptive neuro-fuzzy inference system methods. The faults considered were the steam generator tube rupture (SGTR), small loss of coolant accident (LOCA), moderator dilution, steam line break outside containment and steam line break inside the containment.

6.5.2.1 Steam generator tube rupture (SGTR)

This is one of the frequently occurring accidents in pressurised water reactors. In pressurised water reactors (PWRs), the steam generator is the heat exchanging component that is used for an efficient primary to secondary heat transfer and protection against the release of radioactive nuclides into the secondary loop. There are usually around 3000 to 16 000 tubes in a pressurised

water reactor's steam generator (Cilliers, 2013). Although steam generator tube ruptures are not the major contributors to total core damage frequency, they can result in the release of radionuclides outside the containment, which is a serious issue. It is possible to reduce the frequency of steam generator tube ruptures if they are timely and appropriately detected (Ayodeji & Liu, 2019). In this paper, a steam generator tube rupture with a small failure fracture, not large enough to actuate the emergency core cooling system (ECCS), was simulated.

6.5.2.2 Loss of coolant accident (LOCA)

This is a major fault in a typical pressurised water reactor. LOCAs are usually categorised into a small break LOCA and a large break LOCA. The large break LOCAs are breaks whose diameter is larger than 0.95 cm while the small break LOCAs are breaks whose diameter is between 0.25 and 0.95 cm. The large break LOCA can result in fuel cladding damage and release of radioactive products into the containment. The reactor protection systems actuate ECCS when there is a large break LOCA. The small break LOCA can easily be compensated for by the reactor control system and thus can easily go undetected by the reactor protection system because the pressuriser level is maintained (Cilliers, 2013). The small break LOCA does not result in fuel damage but can cause radionuclides to be released into the containment. To avoid the release of these radioactive products to the containment there is a need for timely detection of this fault.

6.5.2.3 Moderator dilution

Moderator dilution involves the addition of unborated water into the reactor (Claassen, 2016). This makes the concentrations of boron in the moderator lower than normal. Boron is a neutron absorber because of its high thermal neutron cross-section; therefore, boron is used for reactivity control in the pressurised water reactor. When the concentration of boron in the moderator is reduced, reactivity is injected into the nuclear plant. This accident is usually due to human error and is therefore an unplanned addition of reactivity to the plant. It does not usually result in actuation of the reactor protection system. Moderator dilution occurs when there is an inadvertent dilution of boron concentration in the reactor coolant system. It is an accident of interest in this research because it can easily go undetected as it does not actuate the reactor protection system.

6.5.2.4 Steam line break inside and outside the containment

Steam release due to a rupture of the main steam line could occur inside or outside the containment since the main steam line passes through the containment. It is expected that the initial increase in steam flow through the rupture will decrease as the steam pressure drops. Since the containment is pressurised at atmospheric pressure, an increase in the containment pressure is expected if the fault occurs inside the containment. When simulating the accident, the size of

the break is selected to be small enough for the control system to counter the changes due to the fault, so the fault would normally go undetected by the protection systems inside the reactor.

6.6 Fault identification result

The nuclear power plant simulator, PCTRAN, was used in simulating different faults. Steam generator tube rupture (SGTR), loss of coolant accident (LOCA), moderator dilution, steam line break inside and outside the containment were introduced into the plant while the plant was operating at an 80% power transient.

The outputs from the simulator were obtained when there was no fault and again when the faults listed above were introduced into the plant. These outputs from the simulator were used in training a feed-forward back-propagation network. Codes from 0 to 5 were used to represent the different faults. No-fault was given a Code 0, SGTR a Code 1, LOCA a Code 2, steam line break in container a Code 3, steam line break outside containment a Code 4 and moderator dilution a Code 5. After the network was trained it was used to identify faults of a different degree from what was used for the neural network training. The result obtained for three faults are given in Table 6-1:

Table 6-1: Fault type identification using ANN

Fault type	Given code	Neural network output
Steam Generator Tube Rupture	1	1.0094
Loss of Coolant Accident	2	1.6347
Moderator Dilution	5	4.9116

6.6.1 Artificial neural network performance plot

The artificial neural network performance can be measured by using the mean squared error, regression plot and the learning curve, which shows the prediction accuracy of the network on the test set as a function of the training set or the desired output as a function of the input vectors. The mean squared error (MSE) plot is shown in Figure 6-6 and the learning curve is shown in Figure 6-7. These plots showing a low MSE validate the ANN algorithm used.

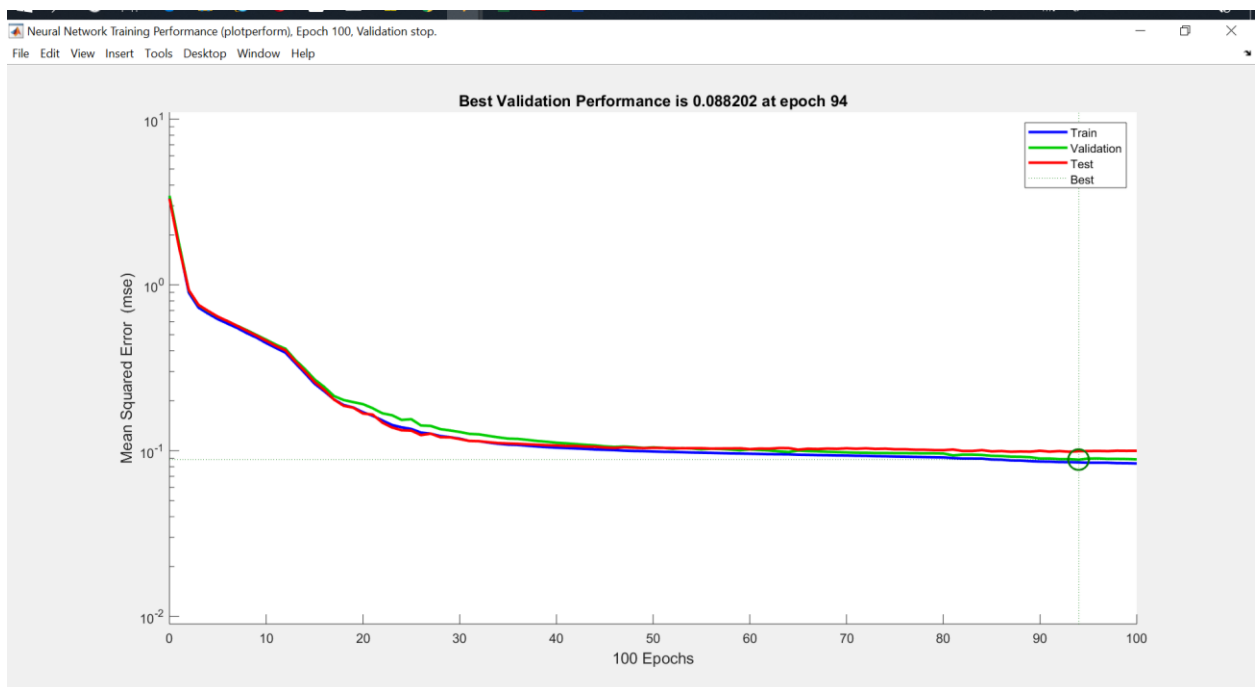


Figure 6-6: Neural network training performance (mean squared error plot)

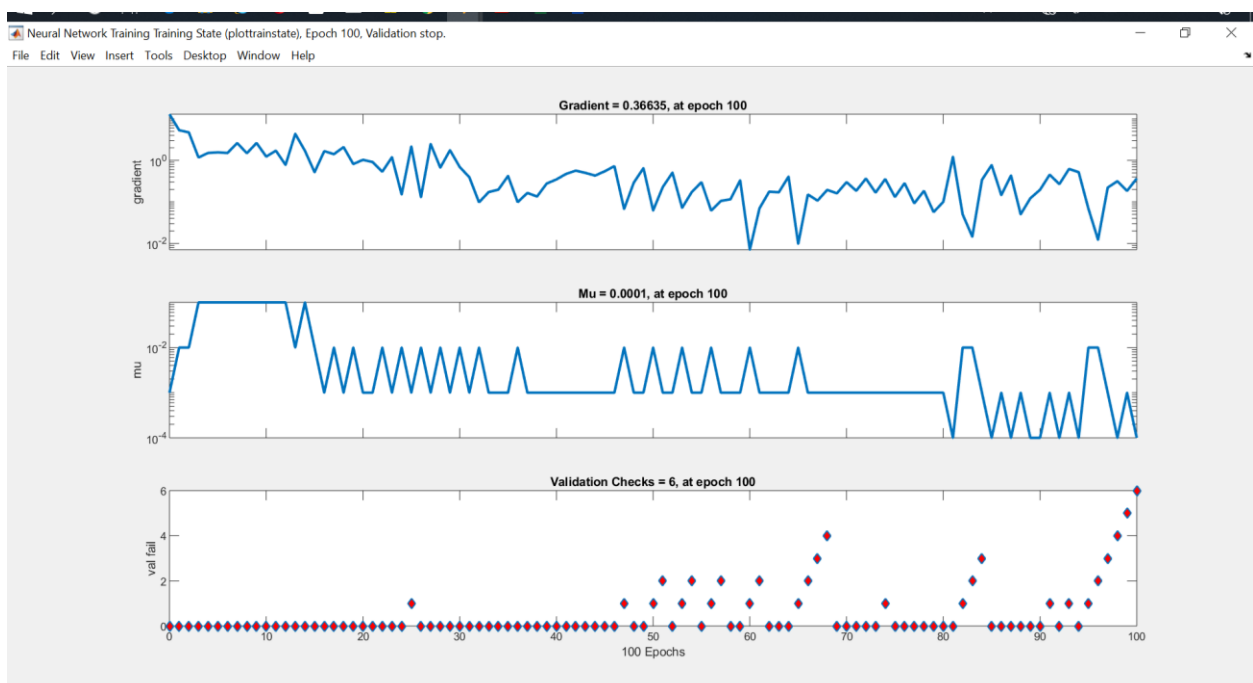


Figure 6-7: Neural network training performance (learning curve)

6.6.2 Fault estimation of steam generator tube rupture

Steam generator tube rupture is one of the major causes of downtimes in a pressurised water reactor (PWR). In a PWR, when the steam generator ruptures, a path is created between the primary coolant and secondary coolant system, in which the coolant flows out of the reactor coolant system into the steam generator secondary loop because the primary loop is at a higher pressure. This, therefore, breaks the barrier that is designed to prevent the release of radiation into the environment. It is therefore very important for operators to prevent this by early diagnosis of an SGTR. The system developed in the paper, after locating the fault, goes on to quantify the size of the fault. Different sizes of SGTRs were simulated on the PCTTRAN. The data from the simulator had 82 variables. From the 82 variables, 11 variables were selected to train the ANFIS. The 11 variables are the parameters that had significant change when the degree of fault increased. The 11 variables that showed significant changes as the size of tube rupture increased are shown in Table 6-2. These variables are used for training the ANFIS fault.

Table 6-2: NPP variables for ANFIS training

No.	Variables	Name
1	P	Reactor coolant system pressure (kg/cm ²)
2	PSG	Steam generator pressure (kg/cm ²)
3	WFW	Steam generator feedwater flow (t/hr)
4	WECS	ECCS total flow (t/hr)
5	WRC	Reactor coolant flow (kt/hr)
6	STSG	Radiation release rate SG valves (GBq/s)
7	LSG	Steam generator level wide range (M)
8	VOL	Volume RCS liquid (M ³)
9	LVPZ	Pressuriser volume (%)
10	HTR	Power pressuriser heater (KW)
11	WCHG	Flow charging (t/hr)

The variables were selected by studying the parameters that changed as the size of the steam generator tube rupture changed. Some of the changes observed are seen in the different trends on the reactor coolant system pressure, pressuriser level, steam generator feed-water flow and RCS liquid volume which are shown in Figures 6-8, 6-9, 6-10 and 6-11

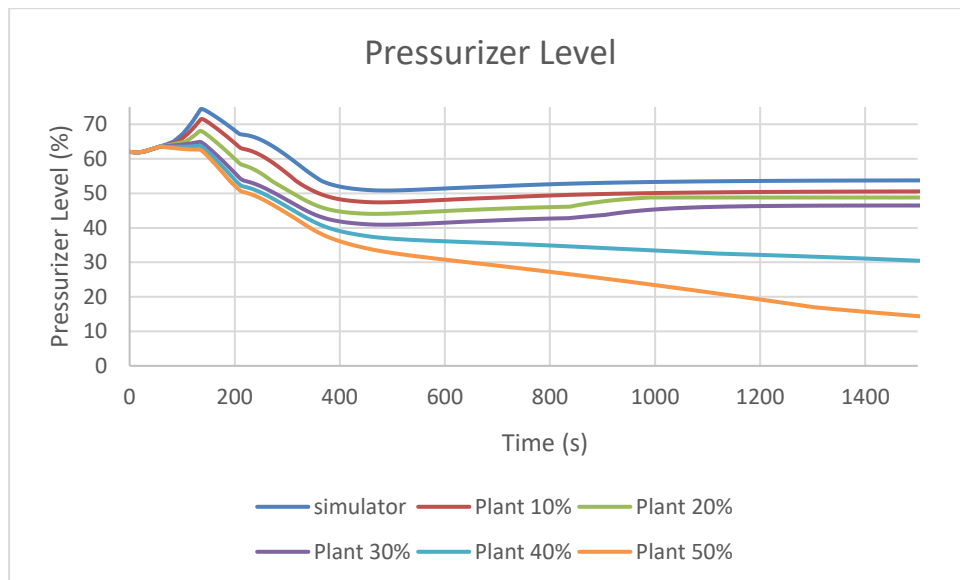


Figure 6-8: Pressuriser level for different SGTR sizes

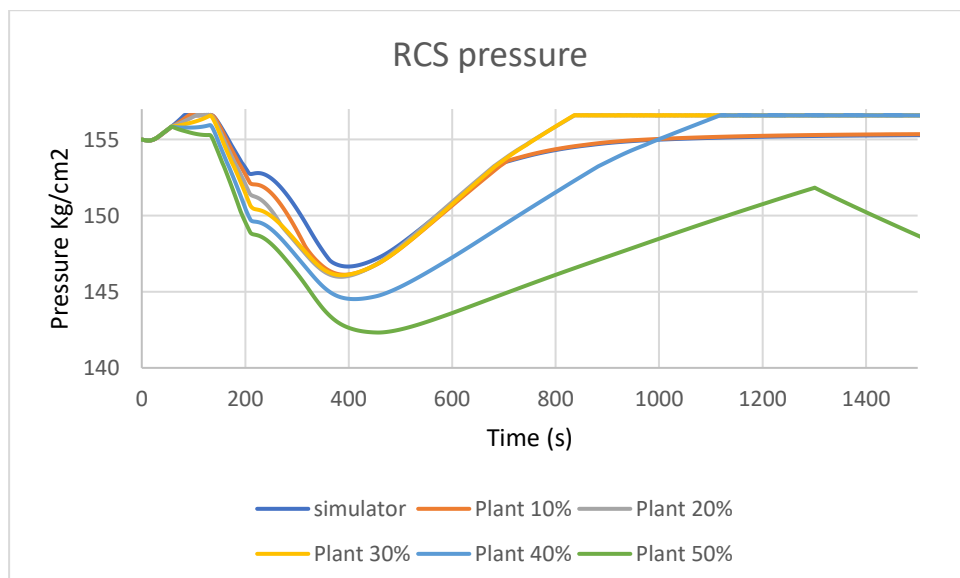


Figure 6-9: RCS pressure level for different SGTR sizes

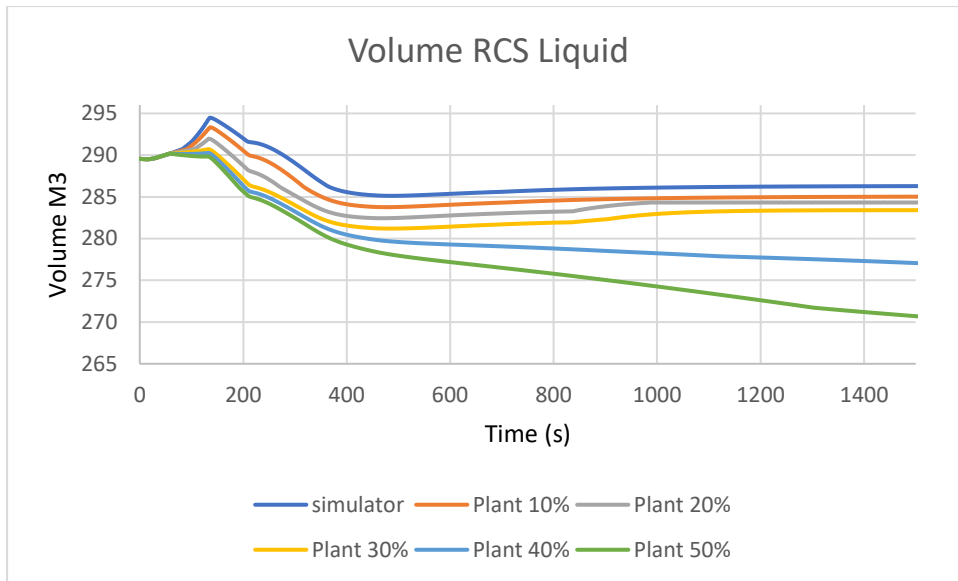


Figure 6-10: RCS liquid volume for different SGTR sizes

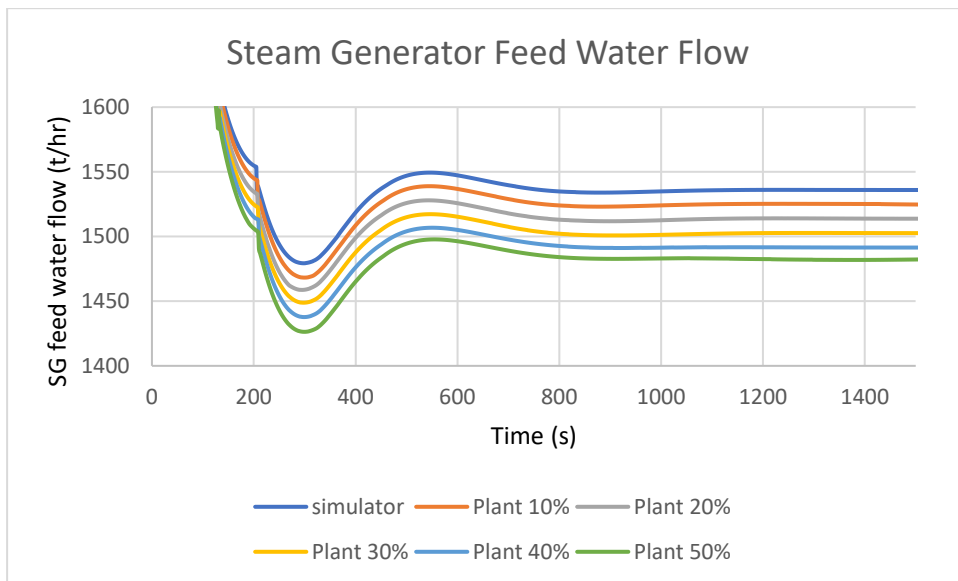


Figure 6-11: Steam generator feed water for different SGTR sizes

The eleven variables that were the input data were normalised and used to train the ANFIS. The selected data were a 12006 x 11 data point matrix for the input data and a 12006 x 1 data point matrix for the output. The tube rupture size is the output of the ANFIS model. The sub-clustering method was used in the fuzzy inference system (FIS) generation and hybrid propagation used in training the FIS. The FIS model generated after training was used in evaluating the different sizes of tube rupture which was not used in the training and the results are shown in Table 6-3.

Table 6-3: Estimation of steam generator tube rupture using ANFIS

SGT RUPTURE	ANFIS	% ERROR
15	16.5485	10.323
25	21.2414	15.0344
35	34.3581	1.834
45	43.4415	3.463

6.7 Discussions and conclusion

A digital twin approach for condition-based maintenance in the nuclear plant has been developed. The method was used for identifying and estimating the magnitude of faults in the nuclear plant simulator. The experiments were carried out using a PC based nuclear plant simulator, PCTRAN. A steam generator tube rupture of different sizes from 10% tube rupture to 50% tube rupture was introduced into the plant. Each rupture size percentage was selected such that it was not large enough to cause a reactor trip. The fault was identified, and its magnitude estimated. This approach can also be used to identify and estimate other faults. This result justifies the following points:

1. **The use of NPP simulator as a nuclear plant twin:** The nuclear plant simulators are generally designed for training nuclear plant operators. This research explored the use of the simulator as the plant's digital twin in which plant parameters on the simulator are continuously compared in real-time with the actual plant. The use of the already existing nuclear plant simulator as a digital twin has helped to reduce the required cost and rigour of having to build a new model-based simulator from scratch. This is possible because it is mandatory for every nuclear plant facility to be equipped with a full-scope simulator that replicates the actual control room.
2. **Use of data-driven method in fault estimation:** This research combines the use of the data-driven and model-based approaches (using the nuclear plant simulator) in fault diagnosis. One major setback in the use of the data-driven approach is getting quality data for analysis. This research has shown that with the digital twin concept, the nuclear plant simulator is able to continuously feed our data-driven tool with sufficient data for its analyses.

3. **Incipient fault diagnosis:** The faults analysed in this study were all faults which were too small or appeared too gradually to cause a reactor trip. The digital twin aided system was able to identify these faults and estimate their sizes. This implies that the digital twin system that was developed can diagnose faults even before the reactor protection system would be able to identify them. This will give plant operators ample time to detect and mitigate faults.
4. **Operator support system:** The use of the nuclear plant simulator as a digital twin does not impinge on the design of the plant's control room or affect licensing regulation of the plant, which is a big issue in the nuclear industry. However, this application could serve as an advisory tool to aid operators in detecting incipient faults. The results obtained can assist operators in locating and estimating each fault before the fault is large enough to cause a reactor trip. This will further reduce unscheduled downtimes and help operators in making more accurate and faster decisions.

The results obtained from the hybrid system which combined the nuclear plant data with the aid of machine learning tools could help maintenance personnel know levels of degradation of equipment and components and could greatly assist them in deciding on whether to replace the component or not.

It is important to note that the use of the simulator as the plant digital twin is limited by the level of instrumentation and sensor placement in the real plant. Therefore, the aim should be to maximise correspondence between the simulations and the plant measurements, as measurements for which no corresponding simulations are available would be useless to the task of fault identification and similarly simulations for which no corresponding measurements are available would also be useless. This limitation will be considered in detail in the authors' future work. The authors will also explore the use of other machine learning tools like support vector machines, genetic algorithms, auto-encoders and deep neural networks in fault diagnosis to enhance condition-based maintenance (CBM) in the nuclear power plant (NPP) in their subsequent articles.

6.8 Additional notes

6.8.1 Simulator accuracy

The direct comparison of the current measured plant data to the simulated run-to-failure data does not directly lead to successful identification of faults. The reason is that the simulations are not always very accurate. Therefore, even when no fault is present, the difference between the actual measured plant data and the simulated data can incorrectly suggest that a fault is present

or is busy developing. Therefore the function of the neural networks and the fuzzy logic is to learn from a large number of datasets when the difference between the measured plant data and the simulated data is merely due to inaccuracies in the simulated data and when it is due to a fault that is busy developing.

When no fault is present, the simulated data will differ from the measured plant data both during steady state and transient operations, although the extent of these inaccuracies will differ between different modes of operation. Therefore, the neural networks and fuzzy logic is required for correct fault identification, both during steady state and transient operations. The function of the neural networks and fuzzy logic is to learn from large datasets of normal data; and for known fault conditions, how the differences between the simulated and measured data look for all conditions where faults are not present and for the same conditions where faults are present. From this experience it will then be able to correctly identify the faults as they develop, both during steady state and transient operations.

It is true that the inaccuracies of the simulator will change as the rate of change varies. Therefore, it is important that the neural networks and fuzzy logic should be exposed to datasets over the widest possible range, including from very low to very high rates of change. As this learning process can be continued indefinitely, it is indeed possible to, over time, expose the learning process to almost all possible plant conditions.

6.8.2 Non-physicality of the neural networks and fuzzy logic data

The issue of non-physicality of neural networks and fuzzy logic data is not problematic: since a neural network does not generate its own input data, but only uses data that it receives from the measured plant data and the simulated data, all the data that it works with is already physically meaningful and bound by the conservation laws. The task of neural networks is only to interpret the differences between these two datasets.

Regarding the physicality and non-physicality of results, the following logic seems applicable:

The measured physical plant data obviously always obeys the laws of nature and are thus fully physical.

The simulated data = the actual plant data + the modelling error + the deviation due to the fault in the plant.

Assuming that the modelling error is relatively small, the simulated data will thus also be physical, except that the simulator will not be aware of the fault and will thus ignore the deviation due to the fault.

However, the ANN and ANFIS assess only the magnitude of the difference between the measured plant data and the simulated data. For cases where there is no fault, by definition:

Plant data - simulated data = modelling error of the simulator

Since the modelling error is an “error”, it by definition does not correctly follow any rules, i.e. the error will be completely non-physical and will not obey any of the laws of nature and will thus be completely meaningless. However, this does not mean that the error will have a random nature. If the simulator, e.g., always changes slower than the actual data, the simulated data will always be above the plant data when the plant data is falling rapidly and will always be below the plant data when the plant data is increasing rapidly. This means that this non-physical error will still behave in an orderly and thus predictable pattern. The task of the ANN and ANFIS is only to figure out this orderly pattern of the error and to then use this to determine when the difference between the plant and simulator data deviates from this normal error pattern, which will then indicate that a fault is busy developing.

CHAPTER 7 – SUMMARY OF THESIS, CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH WORK

7.1 Summary of thesis

This research has developed a hybrid system for fault identification and estimation to aid condition-based maintenance in the nuclear plant. This system will help to reduce unnecessary maintenance and shutdown, thereby reducing overall NPP operation cost.

This work has employed the strength of the nuclear industry which is the presence of a high-fidelity simulator on every NPP that is able to simulate real-time and even faster than real-time data. Therefore, enabling the generation of sufficient run-to-failure data which cannot be necessarily done on a real NPP, because a real plant cannot be left to run to failure. The research has combined the use of machine learning, nuclear power plant data and simulator data for condition-based maintenance. This has helped eliminate the problem of using machine learning in the nuclear industry (i.e. lack of run-to-failure data).

Machine learning tools like neural networks and neuro-fuzzy logic were used in this research; these are data-driven tools that require a large amount of historical data to model plant behaviour. These tools are easy to use as they mostly do not require an understanding of the physics of the system which is usually complex to handle. The approach used in this research is summarised in Figure 7-1.

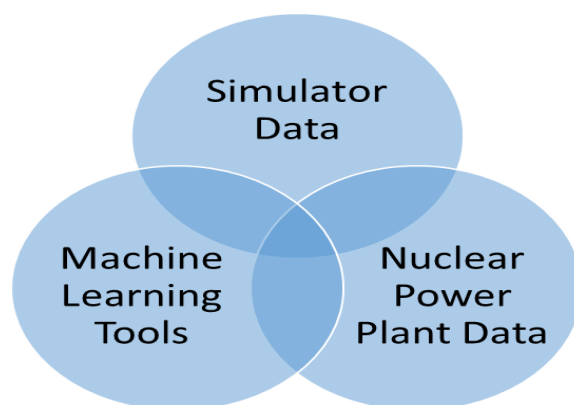


Figure 7-1: The hybrid system chart

Chapter 1 of this work gave an introduction to the research, the concept, the aim and the implementation process to be taken. Chapter 2 covered different ideas from the literature that were found in this research. A further survey on the state of condition-based maintenance was done in chapter 3. Chapter 4 established the requirements of simulators to enable them to carry out diagnostics and prognostics in the NPP. Chapter 5 contains the development of the first part of the hybrid system using a neural network to identify transients and faults in the plant. In chapter 6 the second part of the hybrid system was developed using ANFIS to identify transients and further estimate the fault level of the plant. In summary, the hybrid prognostic method was able to identify transients, identify faults and estimate the level of degradation in the NPP component. This will help the maintenance personnel make a decision on whether or not to replace the component of interest.

7.2 Summary of literature review and original contributions of research

To achieve the aim of this research a thorough literature review was done in Chapter 2 and also in the four articles contained in Chapters 3, 4, 5 and 6 of this thesis. The literature review covered four major bodies of knowledge:

1. **Condition-based maintenance (CBM) in the nuclear industry:** In this review it was shown that CBM has been applied in other industries and has resulted in better optimisation of their maintenance regime. This section explains the need for the nuclear industry to also adopt the CBM as its maintenance strategy. A review paper on the CBM in the nuclear industry is article 1 found in Chapter 3 that has been published. This work is original and published in a peer reviewed journal in which originality is a criterion for publication.
2. **NPP Simulator:** The nuclear plant simulator has been in existence since the 70s primarily for training plant operators. This work explores the possibility of expanding the use of the simulator to include plant condition monitoring and diagnostics. The use of a plant simulator in fault diagnostics is not the authors' original idea; the idea stems from the work of Cilliers and Mulder (2013) which has been reviewed in Chapters 2 and 3. However this work is different from that of Cilliers and Mulder (2013), in that the author added the use of machine learning tools like the ANN and the ANFIS to form a hybrid system for diagnosis. The introduction of ANN and ANFIS takes care of the issues of simulator inaccuracies, as is explained in Par. 6.8.1. In addition, the simulator-based plant diagnostics in this work can be easily implemented without the need for special expertise in nuclear plant instrumentation and control systems.
3. **Digital twin:** The digital twin concept is a newly developing research area which has been well adopted in the aerospace industry and has gradually been explored in the

manufacturing industry. The digital twin as it has been used in the aerospace industry required the development of a very accurate dedicated digital twin simulation model, which is very costly and time consuming to create. The digital twin concept is not an original idea of the author; however, the novelty of my work is twofold:

- I. For economic and safety reasons, critical nuclear components are normally not allowed to run to failure, or even to closely approach run-to-failure. Therefore, the lack of run-to-failure data in the nuclear industry is substantially greater than for, e.g. coal plants.
 - II. While run-to-failure data is similarly lacking for the aerospace industry, they had the luxury of designing digital twin codes from scratch for the purpose of modelling the physical system in such a way as to simulate the required run-to-failure data, in order to facilitate condition-based maintenance. However, I purposely tried to show that it is possible to successfully implement condition-based maintenance using the already existing full-scope nuclear plant simulator to fulfil the function of a digital twin. On the one hand, this complicated the study as I had to make do with the shortcomings of the existing full-scope simulators, which were primarily designed for purposes such as training operators and thus focussed more on high simulation speed and ease of use, rather than on accuracy. On the other hand, this greatly enhanced the usefulness of my study to the nuclear industry as I could prove to industry that they could take their existing full-scope simulators and expand its use to plant monitoring and diagnostic purposes, thus saving industry the time, effort and cost to redesign a purpose-built digital twin. It is likely that this saving will greatly enhance the probability that industry will adopt the method which I started to develop here.
4. **Machine learning:** From the review in Par. 2.3, the major issues noted with the use of these machine learning tools for fault diagnosis, are
- I. Your result is as good as the quality of data used.
 - II. These methods cannot diagnose faults which have not been included in the training set.
 - III. The machine learning tools will give better results when used in combination with other methods.
 - IV. No single machine learning tool can solve all fault diagnostic problems. Effort must be put into finding the best approach for the problem of interest.

The approach devised in surmounting these issues makes this work novel. This approach involves the development of a hybrid system that combines the use of the nuclear plant simulator and machine learning tools. Nuclear full scope simulators are of reasonably high

fidelity and modelled based on first principles, thereby providing quality data for training the neural networks and neuro-fuzzy system. This full-scope simulator is capable of providing large amounts of data to cover every critical component in the plant. However, in this study the focus will be limited to developing and demonstrating the viability of this full-scope simulator-based version of the digital twin condition-based maintenance methodology. Therefore, the method will be tested on only a few important components/cases. Thus the aim of this study was not to train the neural networks and fuzzy logic to be able to handle every possible scenario for every important plant component, but rather to determine whether these methods have the ability to be easily trained to accurately identify faults, despite known inaccuracies in the simulator data. Once this ability, as well as its limitations, have been established, it will be easy to train the neural networks and fuzzy logic for very large numbers of scenarios in very large numbers of plant components.

7.3 Assessment of the original contributions of this study

The hybrid system developed in this research is based on the use of the NPP simulator as a mirror of the real NPP, combined with the use of machine learning for condition-based maintenance. In line with one of the North-West University's criteria for original works, this in fact is the combination of two existing methods in a new way to achieve a new method. From literature some of the notable research with these existing methods are:

i. **Use of nuclear plant simulator for plant diagnosis**

Cilliers and Mulder (2013) studied the control system behaviour of the nuclear plant and based on their findings, compared the control system parameters of the plant and the simulator for plant diagnosis. The great stride of this research was its ability to diagnose faults before the reactor protection system picked them up. The originality of this research is in the difference between the work of Cilliers and Mulder and the present study. In this work machine learning is combined with simulator-based diagnosis to form a hybrid system for diagnosis. The addition of the machine learning tool helps surmount the problems with simulator accuracy further explained in Par.6.8.1. In addition, our method, unlike Cilliers and Mulder's, does not require special expertise in plant control systems. Once the model is developed with the machine learning tool, the faults are detected in seconds, well before the reactor protection system.

ii. **Use of the digital twin concept**

The digital twin concept involves the development of a virtual system to monitor the condition of a real asset. This has been used in the aerospace industry; the review is

in Par. 6.1. The novelty of this present study is that rather than build another model as a digital twin, the author has adapted the nuclear plant full-scope simulator aided by machine learning tools (ANN and ANFIS). This removes the rigour of modelling from scratch and cost involved. In addition, the regulatory issues of introducing a new concept in the nuclear industry have been addressed by employing the full-scope simulator aided with machine learning. This is because in the nuclear industry, the existing nuclear plant simulators have already been approved through the licensing procedure and is of reasonable high fidelity.

iii. Use of machine learning tool (artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS)):

Machine learning is another major concept applied in this work, it has been reviewed and can be found in Par. 2.3. The difference of this research from that done in literature is the method of surmounting the problems associated with machine learning approaches pointed out in Par. 7.2. The novelty of this work is in the introduction of the nuclear plant simulator which are of reasonably high fidelity and modelled based on first principles.

7.4 Assessment of the research outcomes for the PhD degree

The author claims to have attained the North-West University's stated outcomes for obtaining a PhD degree in that the following have been achieved:

1. An original research problem was formulated in Par. 1.1. The research problem is found in Par 1.1.4
2. A critical literature survey was presented. From this literature survey, the originality of the research aim and objectives were shown. The literature survey is covered in Chapters 2 and 3 and summarised in Par. 7.21.
3. The originality of the research aims has already been motivated in Par. 7.2. The original aims achieved are now summarised:

The aim of this research was to develop a condition-based maintenance methodology using the nuclear plant simulator and machine learning tools such as artificial neural network (ANN) and:

- i. Employ a full-scope engineering simulator to generate plant degradation data. This research displayed the use of the NPP simulator in generating run-to-failure data for specific plant components. This has been covered in Chapters 4, 5 and 6. The novelty of this work is in developing a hybrid

system that combines the use of the nuclear plant simulator and machine learning tools for fault diagnosis. The application of this hybrid system is covered in the author's published article in Chapter 5 and submitted article in Chapter 6 of this work and claimed to be original by the author (originality is one of the criteria for publication in the journal).

- ii. Develop a neural networks model for identification of abnormalities in the NPP: a neural network model has been developed using the feed-forward back-propagation method with the simulator data. The plant data and the trained simulator data were then compared for transient identification. Different power change transients were run on the simulator. This was identified using a neural network. Then faults were introduced into the plant and the faults were also identified. This is covered in a published article by the author in section 5 of this work and claimed to be original by the author.
- iii. Determine the level of degradation of nuclear plant components using the neuro-fuzzy method. A neuro-fuzzy system (ANFIS) was developed. Different faults like steam generator tube rupture (SGTR), loss of coolant accident (LOCA), moderator dilution, steam line break inside and outside the containment were identified using the hybrid system. Also steam generator tube rupture size was estimated. The fault diagnosis and estimation were done using the digital twin concept already covered in Chapter 6 of this work that has been submitted to a reputable peer reviewed journal.
- iv. Propose a strategy to optimise maintenance decisions, based on the results of this CBM methodology: the results obtained from this work are shown and discussed in Par. 5.6 and Par. 6.7 and will enable operators and maintenance personnel to make quality decisions for plant operations and maintenance (O&M).

4. Verification of results

The simulator parameters were obtained and used in training the machine learning tools. The results obtained were with very minimal error; the network performance was obtained using the mean squared error (MSE) plot and the training set learning curve and shown in section 6.6.1.

5. Validation of results

The approach has been used to identify transients, and different faults which include valve leakage in Section 5, steam generator tube rupture (SGTR), loss of coolant accident (LOCA), moderator dilution (MD), and steam line break inside the containment (SLBIC) in

Section 6. This shows that the approach can be used to identify more than one fault. Another issue that can affect the validity of this approach is that of simulator accuracy. The research has also addressed the issue of simulator accuracy in Section 6.8.1. The validity of this approach can further be established when actual plant data is used, and this is considered for future work.

7.5 Conclusion of the thesis

In order to develop a hybrid system that can aid condition-based maintenance, the following specific objectives were highlighted and implemented. Conclusions drawn based on these objectives are as follows:

i. Employ the full-scope engineering simulator to generate plant degradation data:

This work displayed the use of the NPP simulator in generating run-to-failure data for the machine learning tool. These data are not readily available in a real plant because the NPP is not expected to run to failure. Due to the traditional maintenance regime, most components are not allowed to fail before they are being replaced. This is because most components are replaced periodically and not necessarily because they are bad. In this research we have highlighted the requirements that will enable the NPP full-scope simulator to be used to generate this data that can help in diagnostics. As most NPPs are equipped with full-scope simulators, this can aid its implementation in these plants. It will not affect normal system safety systems. Due to the fact that NPP in most countries is considered security-critical systems, thereby limiting access of the public to the data, this is the reason a PCTRAN simulator has been used to generate the data for this work. The PCTRAN has been validated against the Koeberg NPP by Pelo (2013) and qualified using RELAP codes and MAAP codes. This work proposes that the simulator data is used in training the machine learning tool and then the model obtained is used in evaluating the NPP data for faults.

ii. Develop a neural networks model for identification of abnormalities in the NPP:

Accurate identification of abnormalities in the NPP is important for a good condition-based maintenance regime. Therefore, a neural network model was developed using feed-forward back-propagation method with the simulator data. The plant data and the trained simulator data were then compared for transient identification. Different power change transients were run on the simulator. They were identified using a neural network. Then faults were introduced into the plant and the faults were also identified.

iii. Determine the level of degradation of nuclear plant component using the neuro-fuzzy method:

A neuro-fuzzy system (ANFIS) was developed. Different faults like steam generator tube rupture (SGTR), loss of coolant accident (LOCA), moderator dilution, and steam line break inside and outside the containment were identified using the hybrid system. Also steam generator tube rupture size was estimated. This is discussed in section 6 of this work.

7.6 Suggestions for future work

To further improve the hybrid system developed in this research more can still be done, and suggestions for future work include:

- i. Other machine learning tools apart from neural networks and neural-fuzzy logic can be explored which might give better degradation estimation.
- ii. Prognostics which involves time to failure estimation can be further investigated.
- iii. Due to restrictions in acquiring real plant data, it has not been used in this research; therefore it is recommended that real plant data be used in further validating the hybrid system.

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APPENDIX

Appendix A: A survey of the state of condition-based maintenance (CBM) in the nuclear power Industry by RM Ayo-IMORU and AC Cilliers (2018).

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Review

A survey of the state of condition-based maintenance (CBM) in the nuclear power industry

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ABSTRACT

Condition-based maintenance (CBM) involves undertaking maintenance activities based on the health of the system. CBM has found useful applications in many industries. This paper presents a survey on the state of condition-based maintenance in the nuclear industry. This is achieved by systematically looking at the major phases of CBM, which are monitoring, diagnostics and prognostics. A methodical review has been done on these aspects of CBM. This includes the current practices in the nuclear industry and the ongoing research on the different methods and technologies being developed. This will give maintenance stakeholders and researchers an overview of the current practices and extent of research undertaken on condition-based maintenance in the nuclear industry.

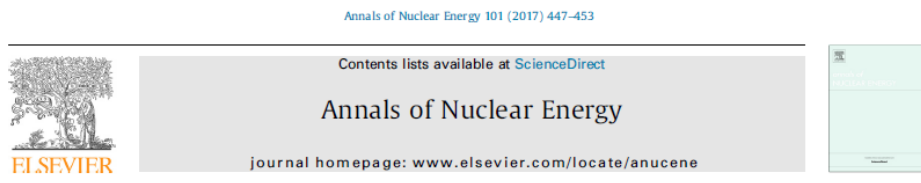
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Appendix B: Hybrid nuclear plant simulator design requirements to enable dynamic diagnostics of plant operations by RM Ayo-IMORU and AC Cilliers (2017).



Hybrid nuclear plant simulator design requirements to enable dynamic diagnostics of plant operations



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ABSTRACT

With nuclear plant full scope simulator technology reaching maturity, the possibility of using its capabilities in expert systems such as online plant diagnostics has become a reality. The effectiveness of plant diagnostics using real-time simulated measurements as a plant reference has been shown in previous papers. However, in order to implement these systems, the full scope plant simulator needs to be designed specifically with this application in mind. This will help in maximising the effectiveness and scope of use of the system. This paper investigates the various simulator technologies available as well as the development strategies and focus areas to establish the design requirements of a single, full scope engineering and training nuclear plant simulator. This can be implemented to provide a real-time dynamic reference to the plant diagnostic system.

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1. Introduction

Owing to the risks involved with the training of operating personnel on a live nuclear plant, all plants are equipped with a full scope simulator that is designed to provide an accurate representation of all plant operations for training purposes. In fact, all nuclear plants are required to be equipped with a plant simulator and a simulated control room for training purposes. Accurate simulator codes for engineering, maintenance planning and analysing postulated accidents have been in use in the nuclear industry since the 1980s (IAEA-TECDOC, 2004).

With developments in data-processing system speed and improved accuracy of real-time calculations, these simulators can now be combined to provide a single full scope training and engineering simulator as well as a maintenance planning function. The accurate, real-time simulator can also be used to provide a dynamic reference for plant operations during steady state and transient conditions.

The advancements in processor speeds, parallel processing, and the development of more sophisticated numerical algorithms enable the simulation of plant processes in real time. This has long been anticipated, but it has only been very recently that the possibility has been put into practice (AC02591847, 1999) by combining the training and engineering simulator to develop an accurate real-time simulator.

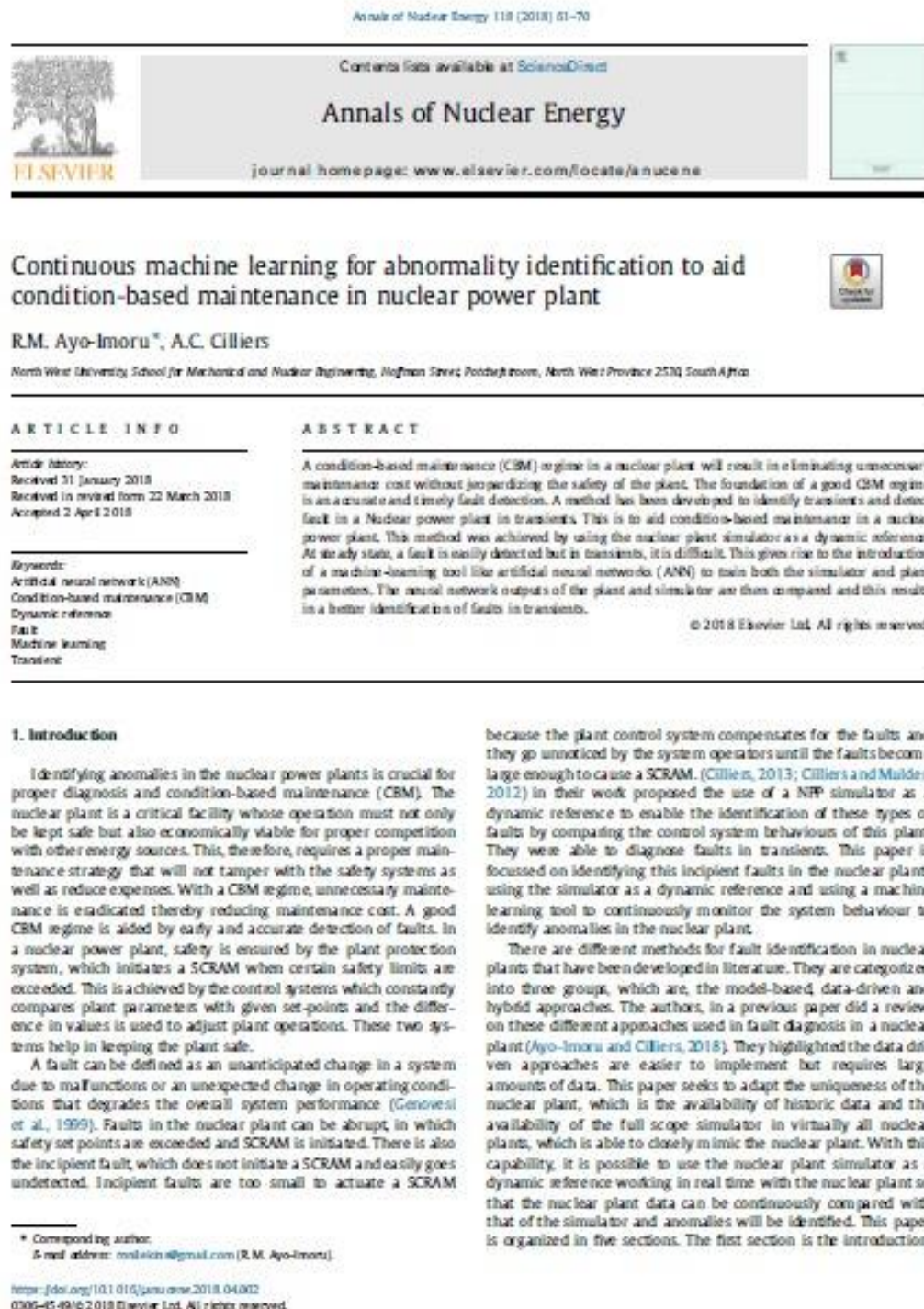
The benefits of real-time simulation of systems have not yet been fully exploited, as these would only be realised if real-time simulations could continuously be compared to all measured information, and decisions based on the expected behaviour of the plant could then be made. This plant diagnostic system was developed and established in previous work (Cilliers et al., 2011; Cilliers and Mulder, 2012; Cilliers, 2013a,b). The principles of combining real-time plant data and data from a plant simulator operating under the same conditions not only aids the detecting of faulty plant behaviour while the operating point is still within the structural safe boundaries of the plant, but it also allows the description of the fault condition up to a certain level. For this process to be successful, a modern nuclear plant simulator needs to provide specific functionality and adhere to a number of requirements related to modelling methods, interfacing and fidelity.

The ultimate goal of this research is the implementation of the full scope engineering simulator for a fault identification system to be implemented as a supervisory system in the Koeberg Nuclear Power Plant (NPP) as well as including it into the control and instrumentation systems to be implemented in South Africa and other proposed new building programmes in Africa and beyond.

This paper is organised into five sections. The first part is the introduction, followed by the second section which describes the existing simulation technology and uses. The reason for hybrid full scope is discussed in the third section. The fourth section is an overview of the integrated simulator. The fifth section contains the hybrid full scope engineering simulator requirements, followed lastly by the conclusion.

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Appendix C: Continuous machine learning for abnormality identification to aid condition-based maintenance in nuclear power plants by RM Ayo-IMORU and AC Cilliers (2018).



Appendix D: A hybrid system based on a machine learning tool for condition-based maintenance by RM Ayo-IMORU et al (2018).

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A hybrid system based on a machine learning tool for condition based maintenance in a nuclear power plant

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Abstract

An effective maintenance regime in a nuclear power plant will improve the competition of the NPP amongst other energy sources. Condition based maintenance (CBM) entails carrying out maintenance based on the health of the system. An effective CBM regime can only be achieved with timely and accurate condition monitoring and abnormality detection. This paper proposes a hybrid system that will enhance CBM in the nuclear plant by employing the use of the nuclear plant simulator as a dynamic reference, thereby combining the artificial neural network (ANN) and fuzzy Logic to estimate fault which will aid condition based maintenance in the nuclear plant. The ANN and Adaptive neuro-fuzzy inference system (ANFIS) were investigated and we were able to establish that combination of more than one machine learning tool can yield better results.

Keywords: artificial neural network(ANN), condition based maintenance(CBM), fuzzy logic(FL), machine learning, nuclear power plant(NPP);

1. Introduction

The Nuclear Power Plant is a critical facility that needs to be operated safely and cost-effectively. To achieve these; there is the need to solve the problem of costly and unnecessary maintenance and shutdown which are mostly due to the unknown time to failure of components.

The role of maintenance in the running cost of an NPP cannot be overemphasized. It contributes to approximately 30 to 35% of this cost. Not until now the impact of maintenance on production quality and cost has been ignored, industries saw maintenance as a grey area and with the general mindset that "maintenance is a necessary evil"[1]. With the recent growth in diagnostic technologies, things are beginning to take a different turn and now industries are beginning to research as well as implement ways of optimizing maintenance (i.e. reducing maintenance cost).

Maintenance has evolved over time as an 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." 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 termed 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, demands got higher and downtimes could mean being out of business, and brought about a new approach to maintenance

Appendix E: Fault detection and characterisation in Pressurised Water Reactors using real-time simulations by AC Cilliers et al (2011).

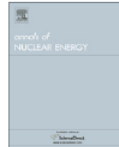
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Fault detection and characterisation in Pressurised Water Reactors using real-time simulations

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ABSTRACT

The use of real-time plant simulators running in parallel with a nuclear plant to predict the control system behaviour and highlighting unexpected plant behaviour is presented. The study is performed on a 910 MW Generation II Framatome Pressurised Water Reactor model and simulator. By simulating the plant behaviour in real-time whilst comparing it with the real-time transient the plant is following, a complete second set of expected control operations and simulated plant measurements is generated. This enables the calculation of the unknown set of variables introduced into the plant as a fault condition. The benefit of such a system is that plant faults that are too small to detect (especially during transients when the plant operating point is moving around) can be identified as unexpected or faulty plant behaviour. The behaviour of the control system is also continually predicted so the effect of the control system compensating for fault symptoms (which in most cases hides the fault condition) is used to characterise the fault as a control variable acting on the plant. The approach is illustrated by simulating a specific fault, small enough to go undetected for an extended period of time, during a typical transient. This is continually compared with a plant simulation, simulating the same transient without the fault. Using the described methodology, the fault is detected and characterised long before the plant safety is jeopardised or the fault is detected by the conventional protection system.

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1. Introduction

With the advances of microprocessor technology and the development of integrated simulation codes over recent years, it has become possible to simulate large parts of a nuclear power plant as an integrated system in real-time with an astonishing level of accuracy. This has long been a focus area in plant simulator development (Finc et al., 2006) and is resulting in the unification of the traditional training simulator and the various simulation codes used for engineering purposes, with a complete simulation model based on first principle calculations, able to simulate a nuclear power plant in real-time and so enabling real-time online monitoring of the plant.

The effectiveness of such an online monitoring system is largely dependent on the accuracy of the simulation model being used. This is problematic since it would be very difficult to build and maintain a simulator at the accuracy required for the application. To overcome this problem, the implementation illustrated in this study focuses on the operations of the control system, which require a lower degree of accuracy since the control system follows

the trend of various measurements inside the plant and interacts with the plant to control these variables. The implementation of an exact replica of the control system and logic in a software environment is fairly simple.

For a fault detection system to be effective it needs to improve the system dependability. A dependable operation requires that the fault be detected (sensitivity), that the detection process is quick enough to be of value (speed) and that the decision taken is the correct one (security). A completely dependable protection system will always operate correctly for a detected fault (Wall, 2005).

- Sensitivity is critical to being able to detect actual faults as they occur. The three measurement components measurement, being accuracy, precision and resolution are independent qualities of a measurement.
- Speed is important for limiting exposure and potential damage. The time to clear a fault is mainly determined by the time it takes the system to make the decision. This decision time is based on the extent to which a value should drift from the norm before it is flagged as a fault.
- Security reflects the sureness of the protection system decision. In plant protection, it refers to the ability of not operating for false alarms, but acting fast for true faults.

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Appendix F: A description of the pressurised water reactor (PWR) and the plant simulator.

The pressurised water reactor is the nuclear power plant of interest in this work and it is being described in this section.

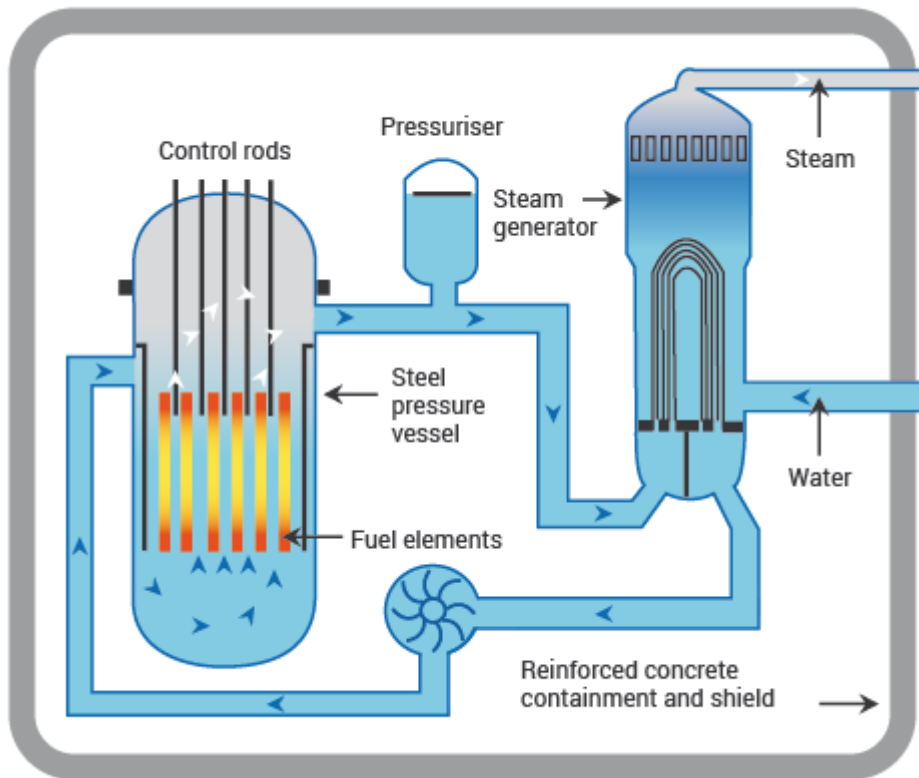


Figure F-1: A typical pressurised water reactor (World Nuclear Association, 2020)

A typical pressurised water reactor (PWR) is shown in Figure F-1. A pressurised water reactor is a nuclear power plant that is characterised by having pressurised water as its primary coolant and as its moderator. Electricity in a typical PWR is generated through four (4) stages which are:

1. Stage 1, which involves heat generation in the reactor core. The core is housed in a reactor vessel. The reactor core has the fuel elements which generate heat through a nuclear fission process.
2. Stage 2 entails a transfer of heat in the reactor core to water which makes the primary coolant loop. The primary coolant loop contains pressurised water which carries the heat from the core to the steam generator.
3. In the third stage, we have the steam generator which is made up of the primary coolant loop and the secondary coolant loop. The heat from the primary coolant loop is transferred to the secondary coolant loop in the steam generator to produce steam.

4. In the fourth stage, the steam from the steam generator is transferred via steam lines to the steam turbines which turns the main turbine that generates electricity

F-1 PWR Structures

PWRs are made of structures systems and components that enable the plant to function properly. Some of the structures in a typical PWR are

- The containment building: This is the structure that encloses the reactor. The containment serves as a final barrier for the release of radioactivity to the environment. The primary purposes of the containment are for shielding the environment from radiation both during normal and accident condition. Protecting the reactor from external intrusion and to contain radioactivity in case of an accident.
- Nuclear Auxiliary building: This structure houses most of the auxiliary and safety systems related with the reactor, such as the chemical and volume control systems, emergency cooling water systems, ventilation systems and the radioactive waste systems.
- Electrical building: this building houses all electrical gadgets used for plant control and instrumentation. It also contains the control room

F-2 PWR- systems

This process of generating electricity is from the PWR driven by different systems that ensure productivity and safety. These systems include:

- The nuclear plant control system: This is the system in the PWR that maintains a constant flow rate and heat evacuation at a constant rate. The control system mainly controls the reactor power, steam flow and feedwater flow. In the PWR there are seven control systems which are the power control, pressuriser control, steam pressure control, steam generator level control, condenser level control, turbine speed and load control and generator voltage control. (Cilliers, 2013)
- Nuclear steam supply system: This comprises of the reactor and the reactor coolant pumps, steam generators and associated piping in a nuclear power plant that is used to generate the steam needed to drive the turbine-generator unit. The main function of the nuclear steam supply systems (NSSS) is to convert the energy released by the fission nuclear reaction into thermal energy
- Reactor protection system: The protection systems ensure the reactor shuts down automatically Whenever the reactor's operating parameters exceed certain defined safety limits. The reactor protection system prevents the three (3) radiation barriers from being compromised. The main functions of the reactor protection system are: safety injection; emergency feedwater supply; and component cooling. In nuclear engineering terms, the

automatic shutdown of a nuclear reactor is called a reactor trip or scram. A reactor trip causes all the control rods to insert into the reactor core and shut down the plant in a very short time. Key operating parameters of a nuclear power plant, such as coolant temperature, reactor power level, and pressure are continuously monitored, to detect conditions that could lead to exceeding the plant's known safe operating limits, and possibly, to damaging the reactor core and releasing radiation to the environment. A reactor protection system (RPS) is a set of nuclear safety and security components in a nuclear power plant designed to safely shut down the reactor and prevent the release of radioactive materials. The system can "trip" automatically (initiating a scram), or it can be tripped by the operators. Trips occur when the parameters meet or exceed the limit setpoint. A trip of the RPS results in full insertion (by gravity in pressurised water reactors or high-speed injection in boiling water reactors) of all control rods and shutdown of the reactor.

- Auxiliary systems: this includes chemical and volume control systems, emergency cooling water systems, ventilation systems and the radioactive waste systems.

F-3: PWR components and Possible faults

The PWR systems are made up of components that ensure their proper functioning. The components require proper monitoring and maintenance in order to reduce unnecessary shutdowns and cost. These components and possible faults are further explained.

F-3.1 Steam generator

The steam generator is the heat exchanging component of the reactor that transfers heat from the primary loop (reactor core) to the secondary loop. The feed water in the secondary loop is converted into steam which is used to drive the turbine. The steam generator serves the purpose of an efficient primary to secondary heat transfer and protection against the release of radioactive nuclides into the secondary loop. The steam generator is maximised by using tubes. The PWR steam generators have around 3000 to 16000 tubes each about 19mm diameter (Cilliers, 2013). The use of tubes in the steam generator allows for increased amount of heat generated thereby increasing power.

The steam generators are of two designs, the once through type of steam generator and the U-tubes steam generator type. In a typical PWR, the primary coolant which is water is pumped into the primary inlet of the steam generator at a temperature of 330°C and pressure of 16Mpa. The hot liquid flows through the many tubes at high pressure. The heat is transferred to the secondary loop in the steam generator through the walls of the tubes. The secondary coolant is heated from about 260°C to 280°C at 6.5Mpa. Thus, the secondary coolant which is at lower pressure is converted to steam, which is then transferred to drive the steam turbine.

Since nuclear power began to be widely used for commercial purposes in the 1960s, unit operators have experienced a variety of problems with major components. Although many of the problems have diminished considerably, those associated with pressurised water reactor (PWR) steam generators persist. Steam generator problems rank second, behind refuelling outages, as the most significant contributor to lost electricity generation.

The major faults that develop in the steam generator are denting, intergranular attack (IGA), a vibration of tubes which cause wear and fatigue, wastage of tubes, pitting, erosion-corrosion, water hammer and circumferential cracks. Any of these can lead to a breach of the integrity of the tubes and to leakage of primary (contaminated) coolant into the secondary fluid. Since the secondary fluid is leaving the containment vessel to the turbines, it must not be radioactive, and must not be contaminated by primary fluid. Therefore, when leaking tubes are detected, the plant must be shut down for repairs, and replacement of SGs, at great costs and loss of revenue.

F-3.2 Reactor coolant pumps

The reactor coolant pumps are large motor-driven single-stage centrifugal pumps that serve the purpose of providing forced primary coolant flow in the reactor's primary loop. They ensure the removal and transfer of heat generated in the reactor core. Reactor coolant pumps are powerful, they can consume up to 6MW each and therefore they can be used for heating the primary coolant before a reactor start-up. Therefore, the functions of the reactor coolant pumps are primarily to:

1. provide the forced circulation of reactor coolant for the removal of core heat;
2. improve departure from nucleate boiling ratio during the loss of all reactor coolant pump motor power; and
3. provide energy to heat up the RCS from ambient temperature to greater than the minimum temperature for criticality prior to reactor start-up. (USNRC HRTD, 2008?).

The loss of RCPs results in the immediate shutdown of the plant. Natural circulation flow then ensures a sufficient and safe residual heat removal through the reactor. However, natural circulation is not sufficient to remove the heat being generated when the reactor is at power. The main components of the reactor coolant pump are the pump case assembly, electric motor, the impeller, shaft (rotor) and the shaft seal package, pump cover and the heat exchanger assembly, flywheel, bearings and the auxiliary system. (reactor coolant pump)

The possible faults in the reactor coolant pump are:

- The single pump shaft seizure: a pump shaft seizure provides the most potential for core damage; and
- The four-pump loss of flow incident (due to loss of off-site power).

F-3.3 Pressuriser

The pressuriser is a cylindrical tank that is connected to the reactor coolant system piping by a surge line. The pressuriser main functions are to maintain the pressure of the primary coolant system within a given range such that no boiling occurs in the primary system under normal and transient operations. The pressure is normally controlled using heaters and a spray valve to maintain the pressure range. A balance of water and steam exist in the pressuriser space (Belles, 2015). The water level in the pressuriser provides an indication of water inventory in the reactor coolant system. The pressuriser level is controlled by changing the flow from the charging pumps. A continuous small release of coolant occurs via the let-down valve. For decreasing pressuriser levels, the charging flow is increased such that charging flow exceeds let-down flow. For increasing pressuriser levels, charging flow is decreased such that let-down flow exceeds charging flow (Weaver, 1976). The main degradation mechanisms which can occur in pressuriser nozzles are thermal fatigue, vibratory fatigue, and boric acid corrosion (Jeong and Hwang, 2013)

Large PWR designs also use a power-operated relief valve (PORV) connected to a pressuriser relief tank to assist in controlling pressure. The PORVs will open to reduce pressure prior to the system reaching the RCS safety valve relief set point.

In large PWR designs that utilize a PORV, a stuck open PORV is a potential small-break LOCA initiating event

F-3.4 Control rods:

The control rod maintains the desired state of fission reactions within a nuclear reactor. is a device that is used to absorb neutrons so that the nuclear chain reaction taking place within the reactor core can be slowed down or stopped completely by inserting the rods further or accelerated by removing them slightly. Essentially, control rods provide real-time control of the fission process, ensuring that it remains active while preventing it from accelerating out of control. The fundamental safety function of the power reactor is to control reactivity, to remove heat from the reactor, and to confine radioactive material. documents. The possible control rods faults include:

- uncontrolled rod bank withdrawal at low power or full power;
- misalignment of control rod withdrawal;
- ejection of control rod; and
- control rods failed to completely insert upon the scram signal.

F-4: THE NUCLEAR PLANT SIMULATOR

For this research, the PCTran simulator was used. This simulator is briefly described in this section.

The PCTran simulator is a reactor transient and accident simulation software program that is designed based on a Westinghouse 3 loop pressurised water reactor (Micro-Simulation Technology, 2009)

Operation of all PCTran systems is based on a user-friendly concept using point-and-click mouse control in pull-down menus. The PCTran windows mimic is shown in Figure F-2.

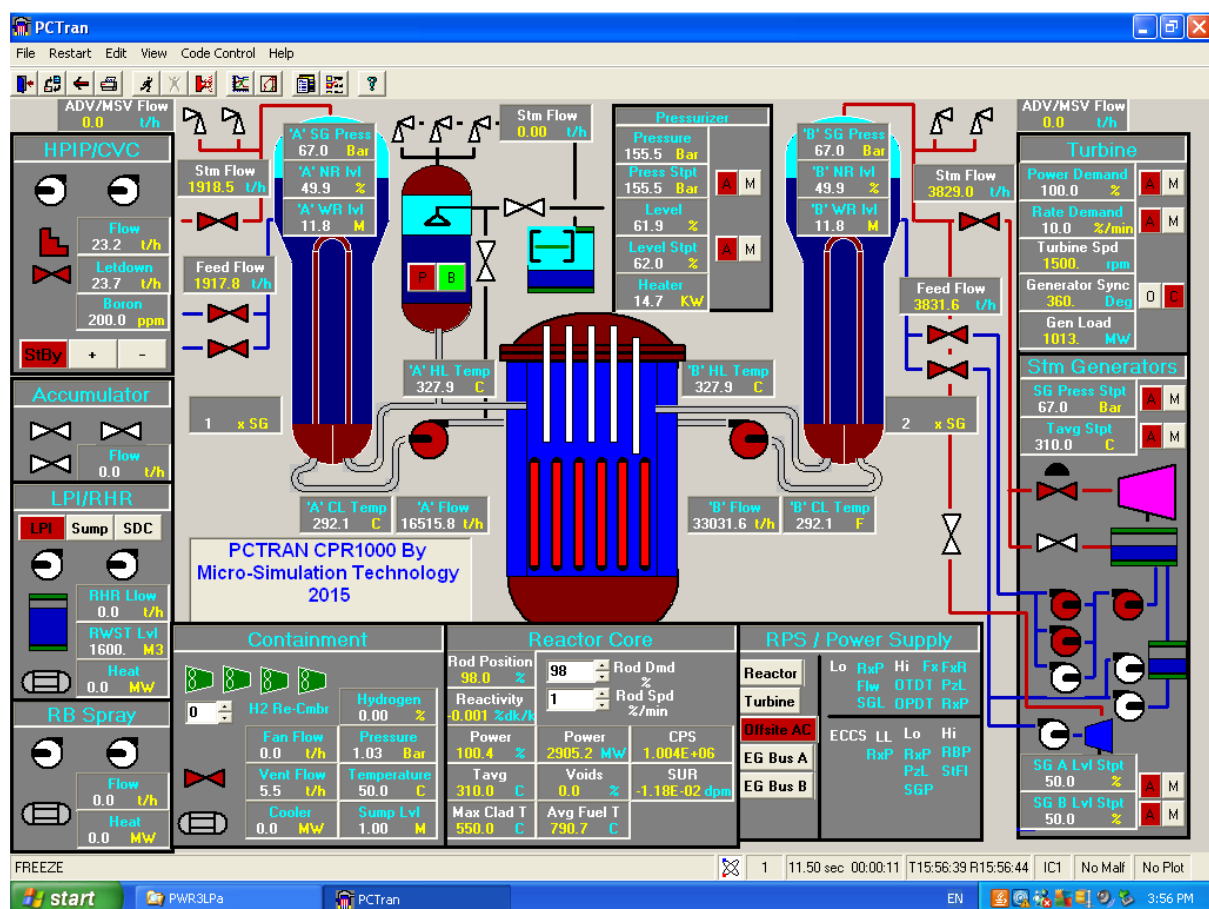


Figure F-2: PCTran windows mimic (Micro-Simulation Technology, 2009)

Shown in Figure F-2 is the mimic of the PWR model for a three-loop PWR of 2900 MWt. Its net electric output is about 1000 MW electric. A single loop designated as "A" is at the left side and the other two loops are combined as "B" at the right side. The main features of the PCTran simulator are Important components such as the Power-Operated-Relief-Valves (PORV) and safety valves of the pressuriser and the steam lines, pressuriser spray valve and heaters, Main Steam Isolation Valves (MSIVs), Turbine Bypass (Steam Dump) Valves, feedwater valves, Reactor Coolant Pumps, etc which are displayed locally (Micro-Simulation Technology, 2009).

The PCTRAN can be used for normal operations and accidents.

The Parameters, settings and ratings for normal operations are given in Table F-1 :

Table F-1: PCTRAN parameters for normal operations (Micro-Simulation Technology, 2009)

Parameter Code	Ratings	Description(unit)
POWER	2895	Rated Thermal Power (MW)
P0	155.5	RCS initial pressure (Bar)
T0	310	RCS initial average temperature (°C)
WRC0	49547.45	Total core flow rate (t/hr)
TCST	15	RCP coastdown time (sec)
RCP	18	Total RCP heat input (MWt)
APORV	10	Area of PORV (cm ²) per valve
ASAFT	33	Area of pressuriser safeties (cm ²) valves combined
PORV1	165.2	PORV open setpoint (bar)
PORV2	163.2	PORV reseal setpoint (bar)
SAFT1	176	Safety valve open setpoint (bar)
SAFT2	175	Safety valve reseal setpoint (bar)
PHIGH	165.7	High pressure reactor scram setpoint (bar)
TEFW0	10	EFW initiation delay time (sec) after initiation signal (sec)
AL0	0.62	Initial pressuriser level (fraction of full)
PHPI	118.1	HPI auto start setpoint (bar)

PSCRAM	132	Low pressure reactor scram setpoint (bar)
TEMP	25	HPI and EFW temperature (°C)
PADV	77.8	SG relief valves (atmospheric dump valve) opening pressure (bar)
ADV	300	SG relief valves total capacity (t/hr)
WLD0	23.7	Letdown flow for Chemical & Volume Control System (CVCC) during normal operation (t/hr)
CHG	45	Charging flow (t/hr)
TRIN	5	Rod insertion minimum time (sec)
TROT	2	Rod withdrawal minimum time (sec)
AKRD	1.333	Reactivity worth of one rod (\$)
AKCHG	-10	Accumulator/RWST boron activity (pcm/ppm)
GFW	0.5	Feedwater controller constant
VSG	516	VPRZ 39.75 pressuriser volume (M3)
TBV	0.4	total TBV flow capacity in fraction of full power steam
HMFWD	950	feedwater enthalpy at full power (kJ/kg)
TRXT	9999	reactor trip delay time after turbine trip (sec)
TER1	9.18	maximum Tavg error for steam dump control (°C)
EFW	180	EFW capacity (t/hr) for turbine driven pump
VPRZ	39.75.	pressuriser volume (M3)

VRCS	265	total RCS volume excluding pressuriser (M3)
MSG0	159000	total SG water inventory including steam mass (kg)
TSG0	290	no-load steam generator temperature or RC Tavg (°C)
SSMS	350	reactor vessel stainless steel mass (ton) no-load steam generator temperature or RC Tavg (°C)
UO2MS	82.1	fuel UO2 mass (ton)
WTR0	114.5	SG tube rupture flow per tube break (t/hr)
PCFT	43.267	pressure set point for core flood tank initiation (bar)
CFT	90	CFT tank (accumulator) total water capacity (M3)
WCF0	35.3	nominal CFT flow rate at initiation (t/hr)
PLPI	11.36	LPI system initiation pressure (bar)
TAVGL	281	Low Tavg set point for SG isolation (°C)
ULSG	8.535	height of SG U-tubes (M)
HRLV	0.17	pressuriser low level set point for heater shutoff
SPRY	136.2	PRZ spray flow capacity (t/hr)
PSP1	1.6	PRZ spray initiation error (bar)
PSP2	5	PRZ spray maximum error (bar)
HTR1	315	PRZ proportional heater capacity (KW)

PHTR1	0	proportional heater initiation error (bar)
PHTR2	-1.1	proportional heater error for full capacity (bar)
PHTRB	-1.5	set point for pressure error to turn on backup heater capacity (bar)
VTAF	181	RCS volume to top of active fuel (M3)
ATAF	10	RCS or core cross section area at top of fuel (M2)
LSG0	11.83	SG wide range level at full power (M)
PSG100	67	Steam generator pressure at 100% power (bar)
HTRB	862	backup heater capacity (KW)
LPSG	3	Number of steam generator loops
GSTM	2	turbine control valve and bypass valve gain constant
TER2	2.78	deadband for Tav _g steam dump control for load rejection (°C)
SGHH	82	high-high SG level for turbine trip (%)
ASG1	2.954	SG lower section cross section area (M2)
RLSG	5.1	range for SG narrow range level instrument (M)
SGLL	17	low SG narrow range scram set point (%)
CFTN2	38.227	total nitrogen volume in Core Flood Tanks or accumulators (M3)

PH(1)	0	The head curve for SI pump pressures 1st data point (bar)
PH(2)	34	The head curve for SI pump pressures 2nd data point (bar) total SGPH(1) 0 The head curve for SI pump pressures 1st data point (bar)
PH(3)	83	The head curve for SI pump pressures 3rd data point (bar)
PH(4)	125	The head curve for SI pump pressures 4th data point (bar)
PH(5)	165	The head curve for SI pump pressures 5th data point (bar)
PH(6)	185	The head curve for SI pump pressures 6th data point (bar)
PH(7)	280	The head curve for SI pump pressures 7th data point (bar) volume (M3)
WH(1)	70.9	The head curve for SI pump flow 1st data point (t/hr)
WH(2)	65.5	The head curve for SI pump flow 2nd data point (t/hr)
WH(3)	54.5	The head curve for SI pump flow 3rd data point (t/hr)
WH(4)	43.6	The head curve for SI pump flow 4th data point (t/hr)
WH(5)	27.3	The head curve for SI pump flow 5th data point (t/hr)
WH(6)	0	The head curve for SI pump flow 6th data point (t/hr)

WH(7)	0	The head curve for SI pump flow 7th data point (t/hr)
PL(1)	0	The head curve for RHR pump pressures 1st data point (bar)
PL(2)	7	The head curve for RHR pump pressures 2nd data point (bar)
PL(3)	8	The head curve for RHR pump pressures 3rd data point (bar)
PL(4)	8.5	The head curve for RHR pump pressures 4th data point (bar)
PL(5)	8.8	The head curve for RHR pump pressures 5th data point (bar)
PL(6)	9	The head curve for RHR pump pressures 6th data point (bar)
PL(7)	155	The head curve for RHR pump pressures 7th data point (bar)
WL(1)	900	The head curve for RHR pump flow 1st data point (t/hr)
WL(2)	852	The head curve for RHR pump flow 2nd data point (t/hr)
WL(3)	800	The head curve for RHR pump flow 3rd data point (t/hr)
WL(4)	500	The head curve for RHR pump flow 4th data point (t/hr)
WL(5)	300	The head curve for RHR pump flow 5th data point (t/hr)

WL(6)	40	The head curve for RHR pump flow 6th data point (t/hr)
WL(7)	0	The head curve for RHR pump flow 7th data point (t/hr)
PCSP	1.3	containment spray initiation pressure (bar)
GCSP	850	containment spray capacity (t/hr)
USTC	0.05	core uncover steam cooling effectiveness as fraction of water cooling
TF0	788.9	average fuel temperature at full power (°C)
PDSN	5.2	containment design pressure (bar)
WSV	3240	main steam safety valve total capacity (t/hr)
PSV	85	main steam safety valve opening pressure (bar)
TRB0	50	initial containment temperature (°C)
PRB0	1.034	initial containment pressure (bar)
LWRB0	1	initial sump water level (M)
ARB	860	sump or containment cross section area (M2)
VRB	49400	containment volume (M3)
PFCL	9.9	High containment pressure set point to start fan cooler (bar)
QCSP0	15	Emergency SI heat exchanger rated capacity (MW)
QCLO	38	Fan cooler capacity (MW)

TDSN	145	containment design temperature (°C)
CRTM	10	containment heat sink concrete mass (ton)
STLM	5	containment heat sink steel mass (ton)
RLK0	0.3	containment leak rate (%/day) at design pressure
PCRT	6.895	RC pressure for break flow changed to non-critical (bar)
RDSP	0.001	Rod speed constant
QRHR0	12	RHR heat exchanger rate (MW)
TANK0	1600	RWST initial water volume M3
TKMIN	600	RWST water volume to switch to sump M3
PRBH	1.3	High RB press for SI initiation (bar)
LPZL	0.1	Simultaneous low PRZR level with RC press for SI initiation
PSGL	38	Low SG press for SI initiation (bar)
PHPL	128	Simultaneous low RC press with PZR level for SI initiation (bar)
HCOR	3.68	Fuel length (M)
AFUT	4500	Total core heat transfer area M2
MZRKT	3500	Total mass of fuel channel (Zr) Kg
MZRST	27000	Total mass of fuel cladding (Zr) Kg
MCRT	24000	Total mass of control rods Kg
MVES	5800	Mass of vessel bottom

CNH2B	5	Concentration of H2 in ctmt to start burn (%)
FH2O	0.0533	Fraction of H2O in concrete
FCO2	0.1939	Fraction of CO2 in concrete
FDEC	0.1	Fraction of decomposed concrete gas reacts with corium
WVNT0	10	Containment vent flow at 1 psid (kg/s)
PPMEC	2000	ACC & RWST boron concentration (ppm)
QPAR	0.01	Passive Auto-catalytic Recombiners strength factor

The accidents that can be simulated using PCTTRAN include:

1. Loss of Coolant Accident (Hot Leg);
2. Loss of Coolant Accident (Cold Leg);
3. Steam Line Break Inside Containment;
4. Steam Line Break Outside Containment;
5. Loss of Feedwater Accident;
6. Main Steam Isolation Valve Closure;
7. Loss of Flow (Locked Rotor);
8. Anticipated Transient Without Scram;
9. Turbine Trip (Loss of Load);
10. Steam Generator A Tube Rupture;
11. Steam Generator B Tube Rupture;
12. Inadvertent Rod Withdrawal;
13. Inadvertent Rod Insertion;
14. Moderator Dilution;
15. Load Rejection;
16. Containment Failure;
17. Fuel Failure at Power; and
18. Let down Line Break in Auxiliary Building