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Component Monitoring Strategies for iPWR Plant Systems during Operational Transients

Matthew S. Scott
mscott66@vols.utk.edu

To the Graduate Council:

I am submitting herewith a thesis written by Matthew S. Scott entitled "Component Monitoring Strategies for iPWR Plant Systems during Operational Transients." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Nuclear Engineering.

Jamie B. Coble, Major Professor

We have read this thesis and recommend its acceptance:

Richard T. Wood, Ivan Maldonado

Accepted for the Council:
Dixie L. Thompson

Vice Provost and Dean of the Graduate School

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Component Monitoring Strategies for iPWR Plant Systems during Operational Transients

A Thesis Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Matthew Stephen Scott

December 2022

To my loved ones who have been there since the beginning

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If you can't explain it simply, you don't understand it well enough. - Albert Einstein

Abstract

Small modular reactors (SMRs) are currently at the forefront of the nuclear industry as potential next stage in nuclear energy production. Implementing a new reactor technology in a commercial setting contains many challenges in terms of maintaining safety and regulatory standards since all of the regulatory framework is based on the traditional PWR design. One benefit of the SMR design is the increased ability to load-follow to meet the constant changes in grid demand. This type of operational strategy introduces changes into the system that impacts the operational lifespan of system components due to increased degradation. Since there are no current SMR plants in operation along with minimal operational experience for load maneuvering in the current reactor fleet, any type of system health analysis will have to rely heavily on simulation data to characterize how the plant systems respond to operational transients. This work proposes utilizing simulated operational data to assess which condition monitoring strategies would be suitable for a SMR plant with load following capabilities by simulating a fault in the feedwater pump. In this work, two of the three anomaly detection strategies introduced proved capable for identifying the simulated fault in the load following data.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Small Modular Reactor (SMR) is a new type of reactor design that offers many advantages in terms of overall cost, operability, and safety. The simplistic and modular design of the SMR makes it an attractive option for implementation to a grid especially when coupled with renewable energy sources such as wind and solar. There is great potential for SMRs to bring nuclear energy back to the forefront of the clean energy movement. As with all new reactor technologies however, concerns revolving around safety and reliability are always brought up to ensure that these reactors are capable of operating with minimal risk. Reliability and safety analyses generally rely on historical operational data but unfortunately there are no current SMR power plant facilities in operation.

The purpose of this work is to demonstrate the viability of using simulation data for assessing the health of system assets under various operational conditions (i.e. steady-state, load following) and investigate component monitoring strategies best suited for load following operation. A model of a SMR reactor module coupled with a Balance of Plant (BOP) is developed in the Dymola environment based on the NuScale SMR design. The objective behind this work is to utilize simulation data of the NuScale Power Module (NPM) to assess component health during steady-state and operational transients (e.g. load-following) through the utilization of anomaly detection routines.

1.1 Load Following Operations

Load following is an operational strategy where the electrical output of a nuclear power plant (NPP) is varied in order to meet the electrical demand of the grid. Typically, NPPs operate at steady-state conditions and other energy sources such as coal or natural gas help to meet the varying grid demand. However, countries such as France and Germany perform load following maneuvers with their NPPs to meet the variances in the electrical demand year round (Lokhov, 2011). This mode of operation with become essential for NPPs as more renewable energy sources come to market.

This concept is further elaborated by Lazarev et al. (2018) where details on the different forms of non-baseload operations for NPPs are given along with an analysis on the feasibility of this type of operational strategy. Ingersoll et al. (2015) describes the role nuclear power will need to take on as more renewables such as wind and solar are introduced. Specifically addressing the different strategies a multi-modular SMR power plant can utilize such as adjusting the reactor power for several units while the rest operate at steady-state or utilizing the steam bypass for more rapid changes in the power demand. In the work by Locatelli et al. (2015), a cogeneration strategy is proposed by pairing a SMR plant with a desalination plant as an economically feasible method for load following.

Regardless of the strategy implemented, load following will become an essential aspect of SMR plant operations especially when couple with other renewable energy sources. That is why this work focuses on this focuses on this mode of operation when assessing component health. By changing the operating conditions, increased degradation in system components is to be expected.

1.2 System Health Analysis

As mentioned previously, load following operations will likely lead to increased degradation for various components throughout the system. This is why assessing the system health will be an important consideration for utilities moving forward. This type of analysis generally relies on historical operational data to characterize the behavior of assets during operation. However, this presents a significant challenge without any current SMR based power plants currently in operation to collect data from. This work proposes the use of simulation data to perform this type of analysis.

In the work by McGhee et al. (2014), an approach is taken where valve degradation in a Combined Cycle Gas Turbine power station is simulated to develop remaining useful estimates (RUL) for various run-to-failure events. D'Amato and Patanian (2016) proposes a similar approach for assessing gas turbine valve degradation using a combination of physics based simulations and historical operational data to optimize the feature selection process to improve the overall detection accuracy. There is substantial work that can be done in this area of prognostics and health management which is why the purpose of work could be a potential first for adapting this type of analysis for iPWR plant systems.

1.3 Work Structure

This work provides two major contributions; the development of an iPWR plant system with load following capabilities and an investigation into anomaly detection methods suitable for load following operation. In terms of the model development, the iPWR plant model is developed in the Dymola modeling environment based on the NuScale SMR design. Data is collected using the model for the anomaly detection analysis for both steady-state and load following conditions to assess a simulated fault in the feedwater pump. The results demonstrate the validity of the model developed and which condition monitoring methods are suitable for load following data.

Chapter 2

Model Development

This chapter focuses on the development of the Dymola model based on the NuScale power module as specified in the DCA. The reactor model utilized in this work is based on the iPWR model developed in the nuclear hybrid energy system (NHES) Dymola library from Idaho National Laboratory (Frick and Bragg-Sitton, 2020). The design specifications of the INL reactor model are based on the NuScale design which allowed for an easier adaptation of the model for the purposes of this work. Further details on the model development are given in the following sections for both the reactor module and the BOP.

2.1 SMR Design Overview

The Nuclear Regulatory Commission (NRC) defines a SMR as a light water reactor design that produces less than or equal to 300 mega watts electric. What sets SMRs apart from other reactor designs is its integrated systems where the reactor core, pressurizer, and steam generator are all housed in a single reactor module. This integrated design offers inherent design features such as a decreased probability of a loss of coolant accident (LOCA) from occurring. Along with its overall reduced size, this allows for greater modularity in which multiple reactor modules can be implemented in a single site. For example, NuScale plans on implementing up to 12 reactor a plant site. Each reactor module is paired with its own balance of plant (BOP) and referred to as a NuScale Power Module (NPM).

Since NuScale is the only SMR design to receive NRC approval, this work focuses on their design specifications as described in the design certification application (DCA) NuScale submitted to the NRC (NuScale LLC, 2020). The following subsections give a detailed description of the NuScale design for both the reactor module and the Balance of Plant.

2.1.1 Reactor Module

The NuScale Reactor module contains all of the important components relevant to the primary coolant system are contained in a single reactor module. Components such as the steam generator and pressurizer which are traditionally external to the reactor containment vessel are housed in the reactor module with along with the reactor core (NuScale LLC, 2020). One key aspect of this design is that it utilizes natural circulation to transfer heat from the core to the steam generators. This helps to reduces the likelihood of a LOCA occurring the primary system. The coolant is heated in the core where it is then forced upward due to natural convection.

The heated coolant is then channeled into the the helical coil once-through steam generators (OTSG) on either side of the reactor module where it is generates super-heated steam in the secondary system. The pressurizer is housed above the reactor core and OTSGs where it maintains a constant pressure in the primary system. The design layout can be seen in Figure 2.1. Further details on the reactor module design specifications can be found in the NuScale DCA submitted to the NRC (NuScale LLC, 2020)

2.1.2 Balance of Plant

The steam and power conversion system, also referred to as the BOP, maintains the responsibility of channeling the super-heated steam for the OTSGs into the turbine

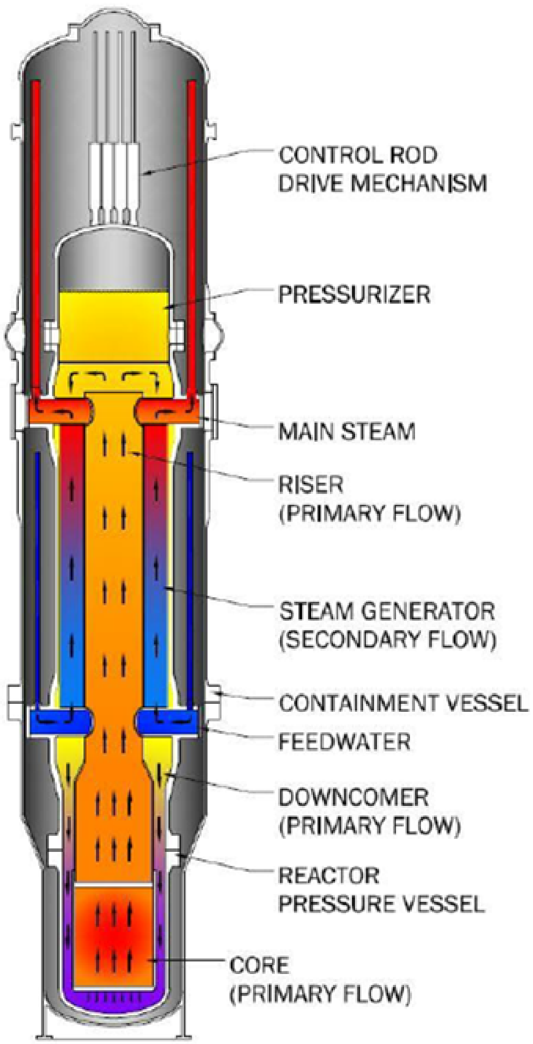

Figure 2.1: NuScale Power Module Overview

system for the purpose of electricity generation. For the NuScale plant design, each NPM will be coupled with a corresponding BOP which will be separate from the other NPMs. The BOP system consists on all the traditional components that are commonly found in current nuclear power plant steam and power conversion system. Figure 2.2 provides an overview of the NuScale BOP as described in the DCA (NuScale LLC, 2020). For the purposes of this work, not all of the components listed in the DCA are modeled in order to decrease the computational expense of the model. For example, the three feedwater pumps are represented by a single feedwater pump in the Dymola model.

2.2 Modelica/Dymola Model Development

Modelica is an object-oriented modeling language useful for modeling large scale complex systems such as a nuclear power plant. It utilizes a first principles approach to modeling where each component developed comprises of the physical governing equations that provide the necessary information for the behavior of that specific component. Dymola is a graphical user interface (GUI) for the modelica language where all of the models utilized in this work were developed. There are several advantages to using Dymola including the greater variety of solvers available that are not offered in the open source modelica GUI.

The following sections detail the development of both the reactor module and BOP in the Dymola environment and the control strategies utilized to obtain the operational parameters listed in the DCA.

2.2.1 SMR Model

The reactor model developed for this work is adapted from the iPWR model developed at Idaho National Laboratory (INL) from the Nuclear Hybrid Energy System (NHES) library (Frick and Bragg-Sitton, 2020). This SMR model is also based on the NuScale design parameters which allowed for a smooth transition for the purposes of this work. Only the physical components of the model were transferred over because the control structure the NHES model utilized would not be well suited for this work. The reactor model consists of the reactor core, pressurizer, and steam generator along with necessary piping to allow the coolant to flow based on natural circulation.

All of the initialization parameters set for this model are within the design criteria listed in the NuScale DCA. Reactor power is determined by simple point kinetics equations Additions made to this model include the average core temperature calculation based on the inlet and outlet temperatures of the coolant flow in the core model. The only input implemented on this level of the model is for reactivity control. The model connects to the BOP through ports a and b which are the exit steam piping and the inlet for the feedwater flow from the BOP side. Further information on the model structure can be found in the work by Frick and Bragg-Sitton (2020).

2.2.2 BOP Model

The BOP model developed in the Dymola environment is a simplified version of the NuScale BOP described in the DCA (NuScale LLC, 2020). This BOP is a simple regenerative reheat Rankine cycle consisting of all the important components needed to accurately represent the behavior of a real SMR plant. Figure 2.4 displays the BOP model layout in the Dymola environment.

This is based on the BOP model developed the work by Bisson (2021) where more detailed information on the model structure and equations utilized can be found. Each of these components were developed in the TRANSFORM library at Oak Ridge National Laboratory (ORNL). In order to increase the thermal efficiency in the cycle, an open feedwater heater is implemented via a volume model where a portion of the steam from the turbines is mixed with the condensate flow in order to increase the inlet temperature into the steam generator. This helps to increase the thermal efficiency in a manner that resembles a real plant setting.

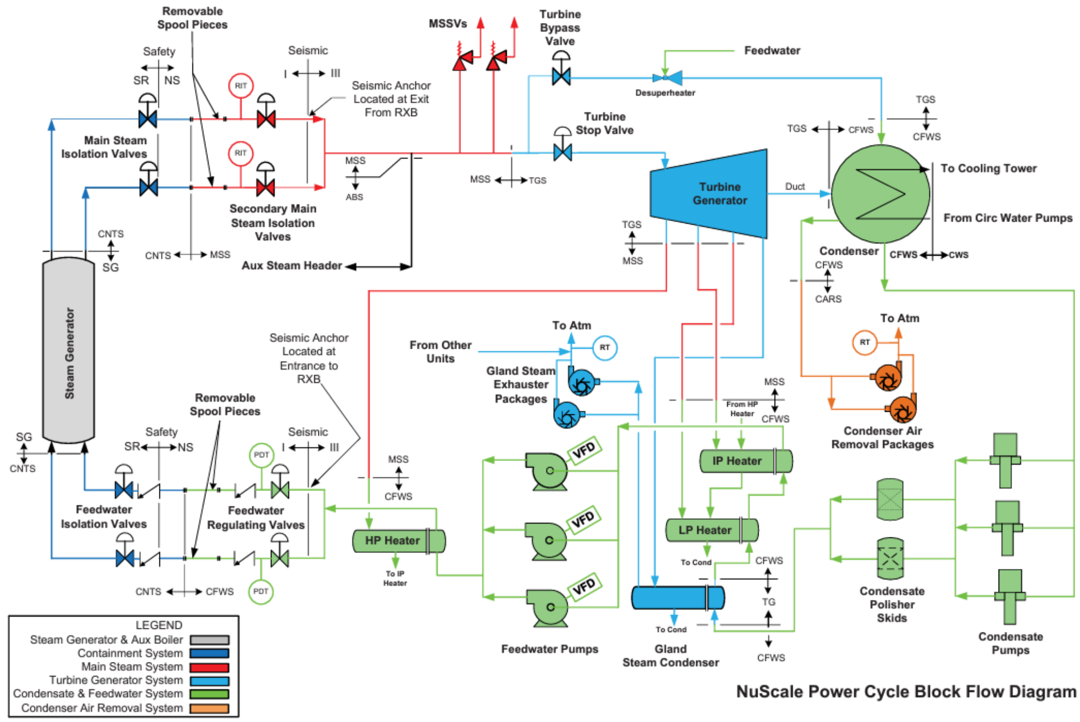

Figure 2.2: NuScale Balance of Plant Overview

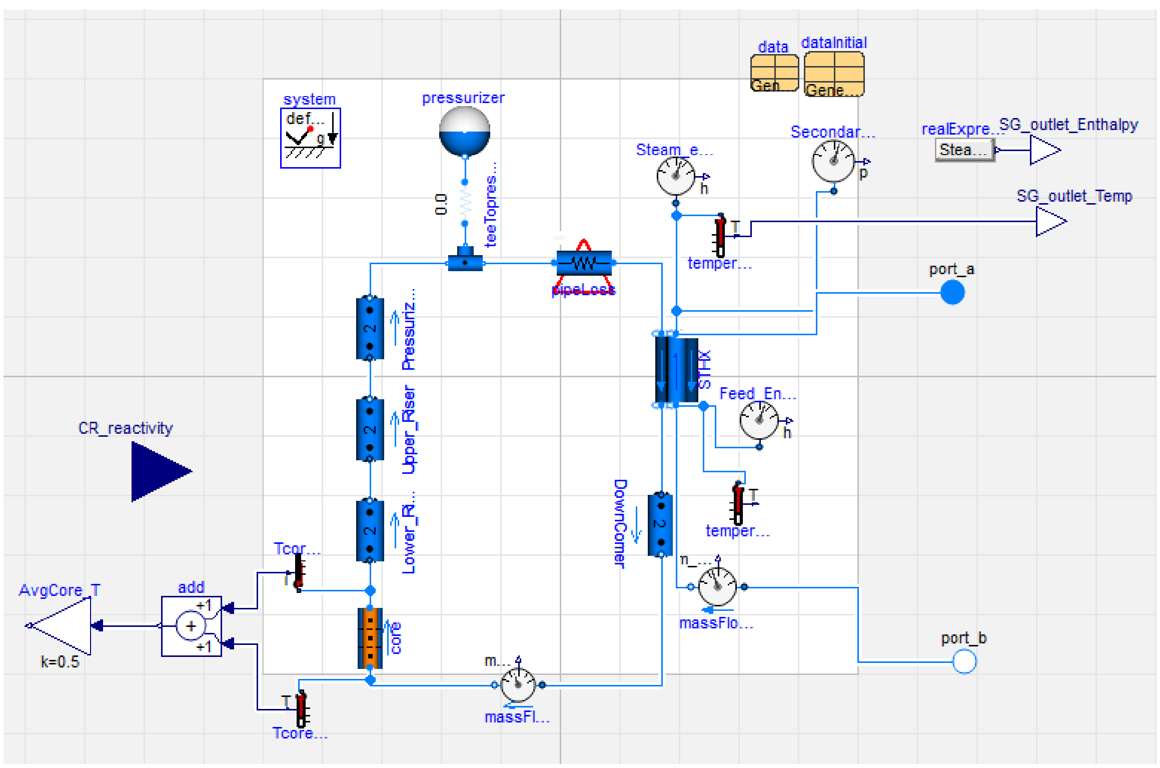

Figure 2.3: Reactor Model in Dymola Environment

The primary inputs for this model are for the feedwater pump and the turbine control valves. In terms of the feedwater pump, the input control the mass flow rate of the coolant into the steam generator. The input for the turbine control valves consists of a single input controlling all three valve positions simultaneously. The control strategies for both of these components are implemented at the top level of the model where both the reactor and BOP model are connected. Further details on the equations utilized in this model can be found in the work by Bisson (2021).

2.2.3 Power Plant Model

In order to be able to simulate full plant operations, the reactor module and the BOP models are combined in a separate model space with the control strategies in place in order to maintain the operational parameters listed in the DCA. The two models are connected via ports a and b which transfers the coolant flow information between the models for either the feedwater flow or the super-heated steam. Figure 2.5 displays the layout of the plant model along with the control elements in place.

The controllers that are implemented are focused on the reactivity, feedwater pump mass flow rate, and turbine control valve position inputs. A simple proportional controller is used for the reactivity input to maintain a constant average core temperature of 557 Kelvin. The turbine controls valves are controlled via a PID controller which is set to maintain a constant steam generator pressure of 34 bar. These two control strategies are meant to help maintain certain system parameters constant during operational transients.

As for the final control strategy, the primary purpose for controlling the feedwater pump mass flow rate is to control the reactor power. This is a feed-forward technique in which by changing the feedwater flow in the steam generator results in a direct change in the reactor power through the change in the heat transfer of the primary and secondary coolant. If the feedwater mass flow rate decreases, then the reactor power proportionally decreases. This strategy is implemented in the model via a

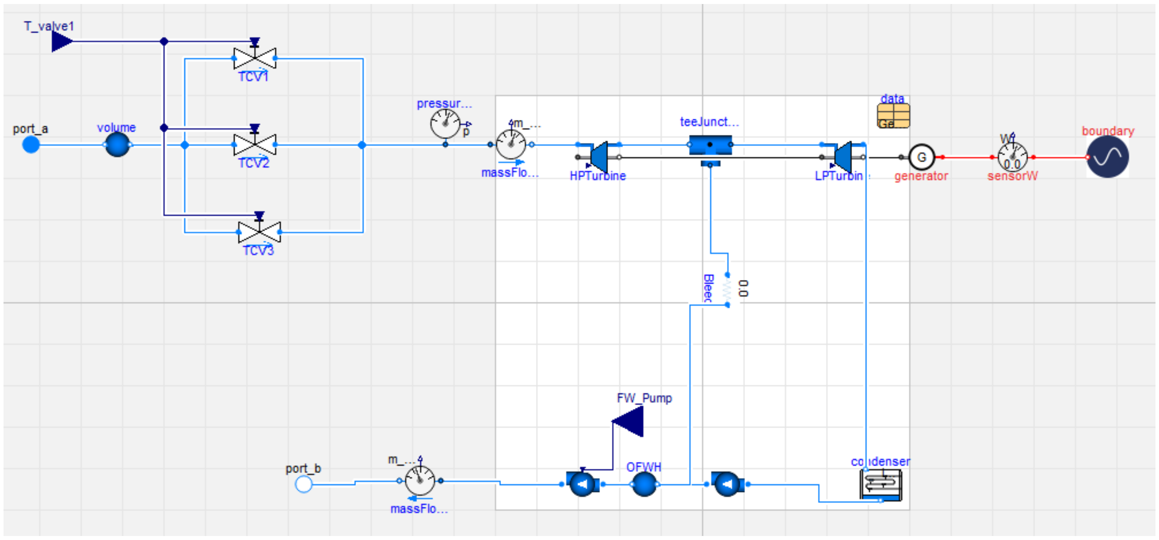

Figure 2.4: BOP Model in Dymola Environment

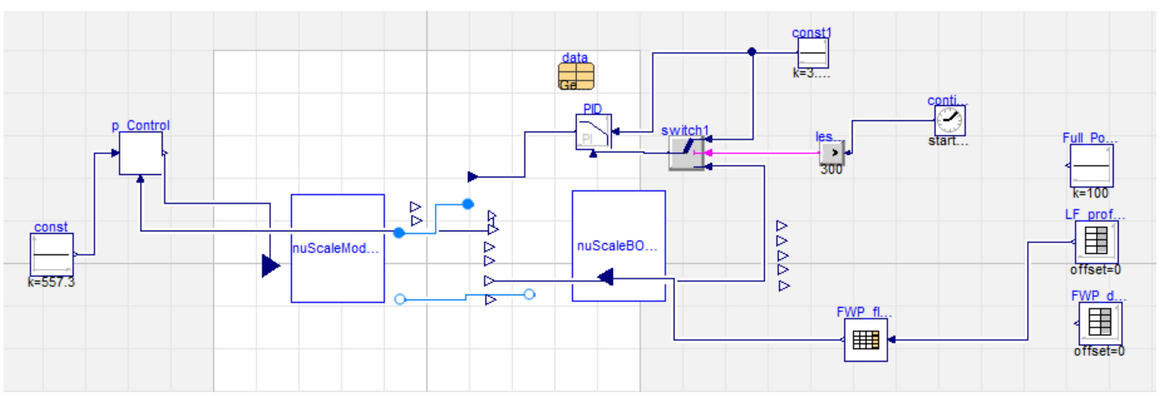

Figure 2.5: NPM model in Dymola Environment

lookup table. The desired power level can be specified through a user input and the lookup table with adjust the feedwater flow rate. Load following scenarios are predefined in a timetable for a specified time period, the following sections provide greater detail on this matter.

2.3 Model Validation

Now that the model has been fully developed in the Dymola environment, the next phase is to validate that the model can effectively simulate NuScale plant conditions at various power levels. The model was tested at each of the reactor power levels listed in the DCA and the results at each power level can be seen in table 2.1.

The results from table 2.1 can be compare with table 2.2 which contain the data from the NuScale DCA. These results demonstrate that the Dymola model is able to effectively simulate the NuScale plant conditions for power levels range from 100% to 15% of the reactor thermal power. All of the simulated temperatures and the primary coolant mass flow rate are within an agreeable range of 2% of the DCA data. The only major difference between the model and the DCA is that the thermal power is approximately 7% lower than what is described in the DCA. With these results, the model demonstrates its viability for analysis involving operational transients (e.g. load following).

2.4 Load Following Capabilities

With the model tested at various power level, load following scenarios can now be simulated with this model. By utilizing the feedwater mass flow rate control strategy, various load-following scenarios can be developed as an input for the model. This is done through the use of the timetable block in the Dymola environment where the load maneuvers are specified at designated time intervals during the simulation. For the purposes of this work, a two week simulation with various derates to either 90% or

80% of the reactor power occur. Figure 2.6 demonstrates the load following scenario used for the system health analysis portion of this work.

2.5 Model Development Summary

A model of the NuScale Power module was successfully developed in the Dymola environment. The reactor module is adapted from the INL iPWR model in the NHES library which is based on the NuScale design parameters. The BOP is based on a simple regenerative reheat Rankine cycle which is sufficient for simulating real plant conditions. The control strategies utilized in the model focus of the reactivity, turbine control valve position, and the feedwater pump mass flow rate which help maintain system parameters inline with the NuScale DCA. With these control strategies in place, the model is able to effectively simulate load following conditions for reactor power levels ranging from 100% to as low as 15%. The model can now be used for system health analysis involving operational transients.

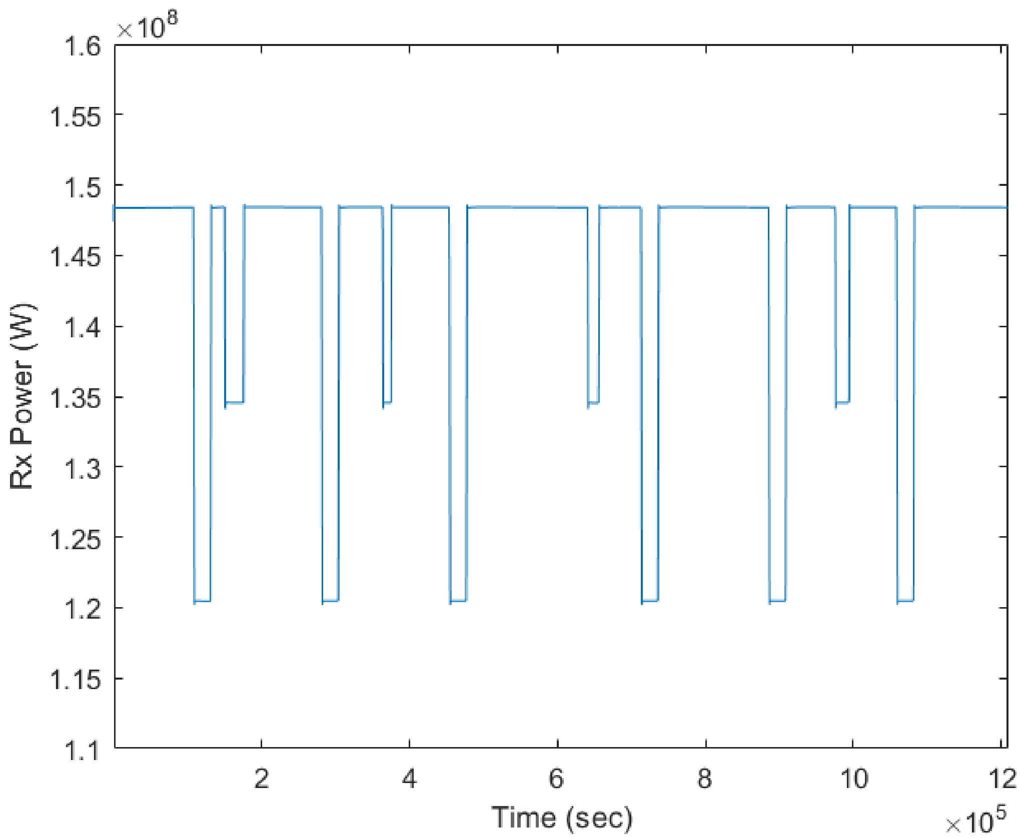

Figure 2.6: Simulated Load Following Scenario in the Dymola Environment

Table 2.1: Primary System Simulation Data

Percent	MWth	Percent	Flow-rate (kg/s)	Core ΔT (K)	CL Temp (K)	Avg. Temp (K)	HL Temp (K)
100%	1.48e+08	100%	573.1	49.3	533.1	557.1	582.4
75%	1.12e+08	90%	517.1	41.3	537.2	557.8	578.5
49%	7.25e+07	78%	446.3	31.1	542.4	557.9	573.5
15%	2.21e+07	51%	295.1	14.4	550.9	558.1	565.3

Table 2.2: Primary System DCA Data

Percent	MWth	Percent	Flow-rate (kg/s)	Core ΔT (K)	CL Temp (K)	Avg. Temp (K)	HL Temp (K)
100%	1.60e+08	100%	587.0	52.0	531.3	557.2	583.2
75%	1.20e+08	89%	521.6	44.0	535.3	557.2	579.2
50%	8.00e+07	76%	443.7	34.6	539.9	557.2	574.5
15%	2.40e+07	48%	280.2	16.5	549.0	557.2	565.5

Chapter 3

Condition Monitoring for the NPM

One strategy utilized in system health analysis is the condition monitoring of system components. Condition monitoring is a method for determining if an operating component is a healthy or unhealthy state based on historical operational data. This can be achieved through various methods either through threshold monitoring or machine learning algorithms. It allows for operators to determine when maintenance needs to be performed. There are various methods for performing condition monitoring which can involve machine learning methods such as auto-associative regression models or even support vector machines as demonstrated in the work by Agarwal et al. (2021).

3.1 Simulating Fault Modes

As previously mentioned, there is no historical operational data for an iPWR type power plant which means that further system health analysis will involve utilizing simulation data. This section describes the development of the simulated faults in the NPM model in the Dymola environment. These simulated fault modes represent the general impact of the faults on the entire system. There is no way to simulate an exact type of degradation mechanism occurring in the model component in the

Dymola environment but the behavior of the component can be adjusted to simulate the effect of degradation over the course of a simulation.

For the NPM model, fault modes are simulated in components such as the feedwater pump (FWP) and the turbine control valves (TCV). Both fault modes are simulated for both steady-state and load following conditions. In order to validate that the data generated in the model is suitable for further system health analysis, anomaly detection methods are utilized to determine if the faults are detectable using the data generated in the simulation.

3.1.1 Feed water Pump Fault Mode Description

Since there is no way to model the specific degradation mode in the component model, the strategy utilized in this work involves adjusting the output of the feedwater pump mass flow rate in order to simulate the degradation effect. This is done by adding in a gain past the feed water pump to cause the flow rate to gradually decrease over time starting at a specified time. Degradation is simulated for both steady-state and load following conditions.

Figures 3.1 and 3.2 demonstrate the rate of degradation the feed water pump experiences throughout the duration of the two week simulation. Since degradation in a component can occur over the course of days to months in a real plant setting, the degradation represented in the model describes a gradual degradation resulting in a steady decline in the flow rate of the FWP. The simulation demonstrating this fault mode is for two weeks of plant operation where the data is collected for both healthy and unhealthy conditions which can then be analyzed using the anomaly detection methods.

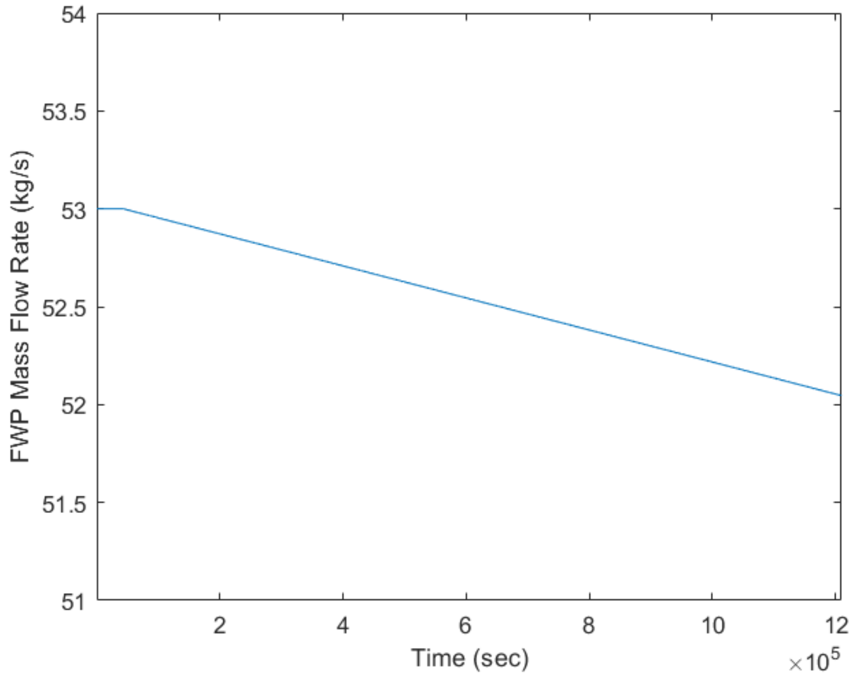

Figure 3.1: FWP Degradation in Steady-State Conditions

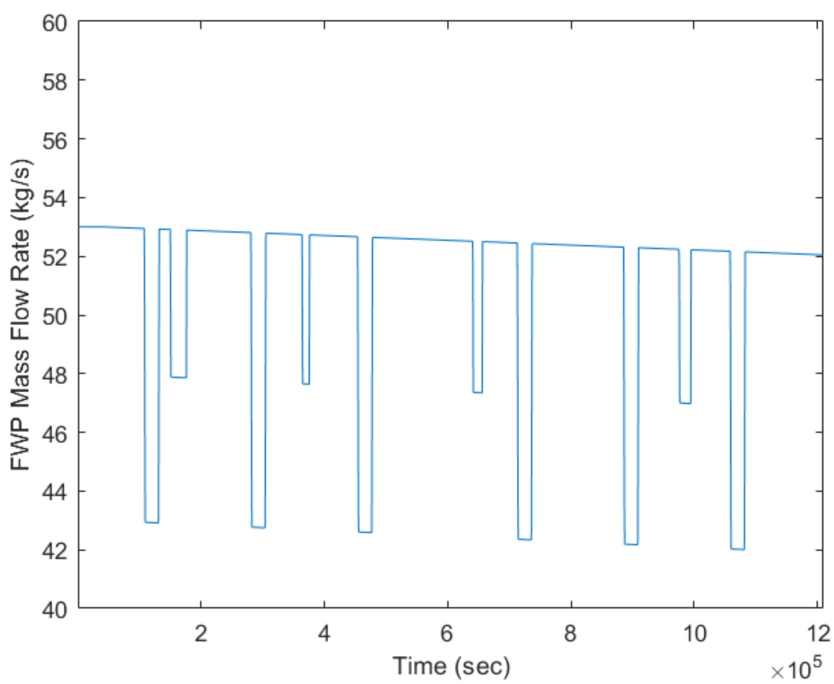

Figure 3.2: FWP Degradation in Load-Following Conditions

3.2 Anomaly Detection Methods

In order to determine if the data generated in the Dymola model is suitable for further system health analysis, anomaly detection methods are utilized to determine if the simulated fault can be detected using the data generated. The FWP degradation is the primary focus for the anomaly detection descibed in this section. The methods utilized include regression algorithms such as Principle Component Analysis (PCA), Auto-Associative Kernel Regression (AAKR), and a neural network auto encoder. By training these models with the healthy data, statistical methods can be applied to assess the unhealthy data to determine the state of the system. These methods are applied to both the steady state and load following conditions. The following sections give a detailed description of the data used and of each anomaly detection method utilized.

3.2.1 Data Selection

The output of the Dymola simulation consists of hundreds of variables across every component in the model so selecting the appropriate data for this analysis can be a challenge. Since the focus is on the FWP degradation, variables in the BOP model were selected moving forward. They were selected based on their correlations with one another which can be seen in figure 3.3. The following variable were selected:

- Steam Generator Temperature (K)
- Steam Mass Flowrate (kg/s)
- Low Pressure Turbine Output (Watts)
- High Pressure Turbine Output (Watts)
- Feedwater Pump Mass Flowrate (kg/s)
- Condenser Inventory (kg)

- Turbine Control Valve Controller Response
- Total Electrical Output (Watts)

3.2.2 Principal Component Analysis

Modeling using PCA reduces the dimensionality of the data by transforming the data into the PC variable space. The data is divided up into individual PCs in which each contain a specified amount of information. PCs can be compared by analyzing the relationship between the PC scores and loadings where scores show the relationship between observations and loadings show the relationship between variables. This is helpful in determining which PCs are valuable to keep in the analysis and which ones are not likely to contribute much at all.

$$T^2 = t_i \lambda^{-1} t_i^T = x_i P \lambda^{-1} P^T x_i^T \tag{3.1}$$

The way fault detection is performed using PCA is through two statistical methods, the Hotelling's T2 statistic and the Q statistic. The primary purpose of the Hotelling's T2 statistic is that it measures the variance within the model whereas the Q statistic measures the variance outside the model. The Hotelling's T2 statistic measures how far an observation is from the center of the PC model using the normalized sum of the squared scores. Equation 3.1 demonstrates how T2 statistic utilizes the t score vector and eigen values matrices.

The Q statistic evaluates the model by measuring the distance a point falls from the PC model. This method shows how well the predicted observation is explained by the model. Equation 3.2 represents the quantitative form of the Q statistic which is the sum of squares of each row of the error matrix

$$Q_i = \epsilon_i \epsilon_i^T = x_i (I - P_k P_k^T) x_i^T \tag{3.2}$$

Utilizing both of these statistical methods, thresholds can be set for both methods to determine if there is a fault present in the data. This is dependent upon the number of PCs used and the confidence interval established in which for this analysis was set to 95%.

3.2.3 Auto-Associative Kernel Regression

This next method of fault detection utilizes an Auto Associative Kernel Regression model (AAKR) which is a method of error correction used for process monitoring. The model is initially trained with the healthy data in order to predict what the measurements should result in. These predictions can then be used to compare the non-healthy data to determine is there is anomalous behavior. Kernel Regression is one type of Auto Associative algorithm used for developing the model, where equation 3.3 represents the quantitative form of the AAKR.

$$\hat{x}_q = \frac{\Sigma x_m K(x_m, x_q)}{\Sigma K(x_m, x_q)} \tag{3.3}$$

The AAKR method requires establishing a bandwidth for the algorithm to efficiently predict the outputs in which for this analysis a bandwidth of 0.10 is used. Performing the fault detection using this method is based on monitoring the system residuals. This is done via two different methods: Simple Signal Thresholding (SST) and Sequential Probability Ratio Test (SPRT). The threshold for each of these tests is 3% of the mean of the training data which should help to differentiate the inherent signal noise with the fault. Simple Signal Thresholding (SST) is a straightforward test which simply applies the threshold to the non-healthy data's residuals. The Sequential Probability Ratio Test (SPRT) is a hypothesis test that determines if a series of values is more likely from a normal or faulted distribution.

3.2.4 Neural Network

This final anomaly detection method involves utilizing a neural network for training the model and using the same statistical tests as the AAKR to identify the unhealthy data. An autoencoder built into the MATLAB environment which maps the input data to a hidden representation via an encoder and a decoder tries to map the representation to the original data, more information on the autoencoder can be found in reference. The use of the neural network is only applied to the load following scenario to determine if it is a suitable anomaly detection method for load following data. An example of this method can be found in the work by Pathirage et al. (2018) where an autoencoder is utilized for structural damage identification.

3.3 Anomaly Detection Summary

Anomaly detection methods can help to verify that the data generated in the Dymola environment is suitable for further system health analysis for the NPM. This analysis also helps to determine which anomaly detection routines would be suited for SMR based power plants with load maneuvering capabilities. By simulating a fault in the FWP, the data collected from the model can then be tested with anomaly detection routines which utilize PCA, AAKR, and Neural Network models for both steady-state and load following conditions.

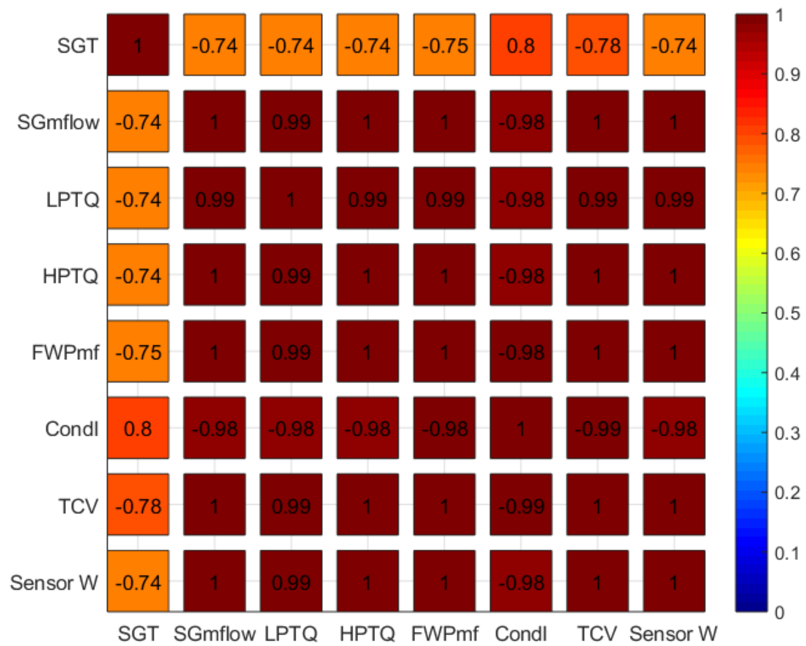

Figure 3.3: Data Correlation

Chapter 4

Anomaly Detection Results

The results presented in this section demonstrate each methods capability to detect the fault occurring for both the steady state and load following conditions. Each of the fault detection methods present different degrees of success in correctly identifying the fault occurring in the FWP except for the PCA method with did not work well with the load following data. The following sections describes the results of the PCA, AAKR, and neural network anomaly detection. These results provide insight into which anomaly detection methods are best suited for load following conditions.

4.1 Modeling Monitor Performance on Healthy Data

Before testing each of the detection methods with the faulted data, each method was first tested with healthy data to validate that they are suited for both steady-state and load following conditions. This primarily helps to determine which methods are suitable for the load following data where the models should recognize new healthy load following data as fault free. This is demonstrated in figures 4.1 and 4.2 for the AAKR SST test in both the steady-state and load following cases.

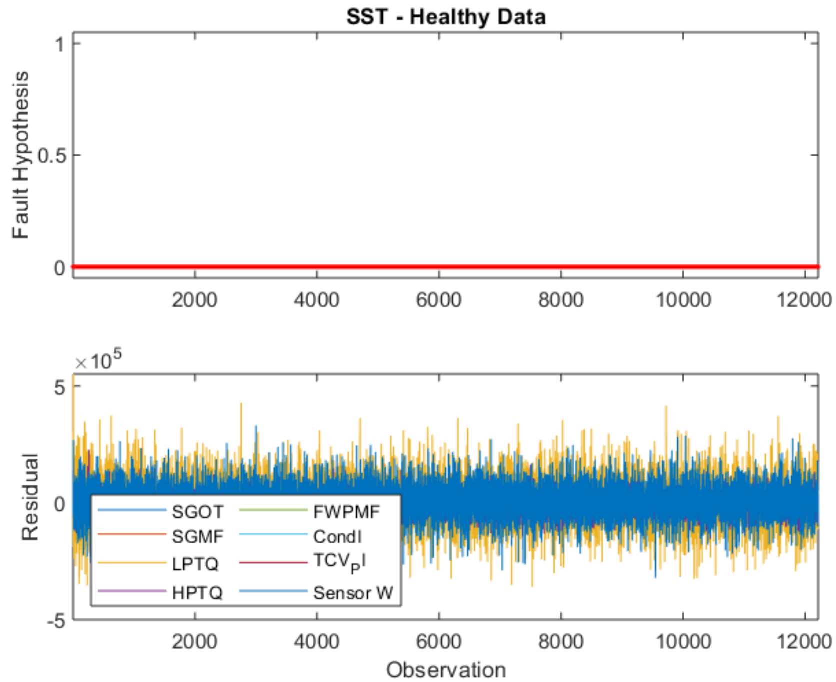

Figure 4.1: Steady-State Model Validation - AAKR

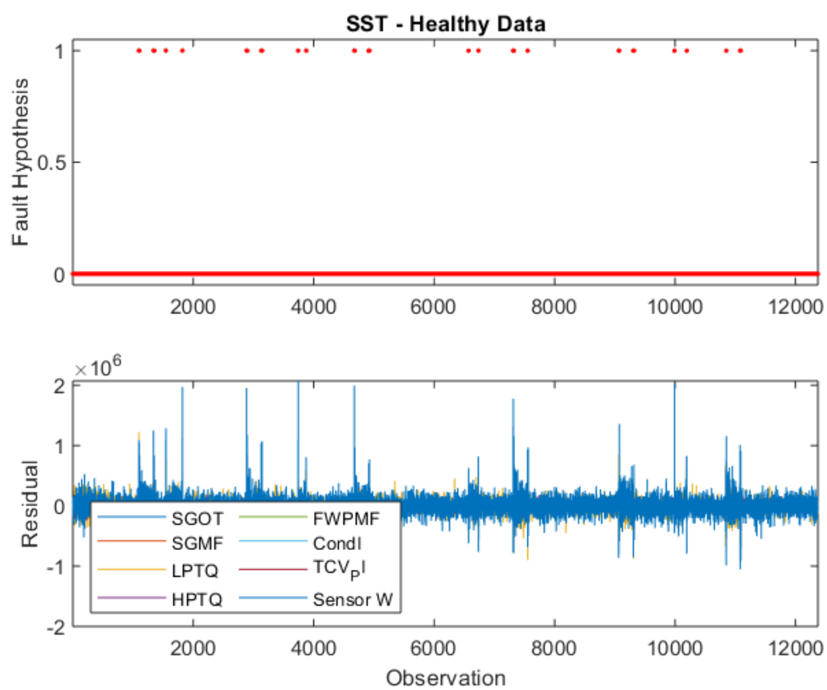

Figure 4.2: Load Following Model Validation - AAKR

Similar results were obtained for the Neural Network method as well so these two methods were selected moving forward. The PCA results were inconclusive when tested with the load following data which is likely due to the changing correlations in the data at each of the various power levels. PCA is just not able to effectively capture the nonlinearities in the load following data and distinguish between healthy and unhealthy data. This can be seen in figures 4.3 and 4.4 which compare the results for the Q statistical test for both the healthy and unhealthy data.

The T2 test presented similar inconclusive results as the Q statistical test when tested with the healthy and unhealthy data for the load following case. PCA still works well with the steady-state data but it is not a suitable method to utilize moving forward since the focus of this work is on operational transients.

4.2 PCA Results

As mentioned previously, PCA is not suited for load following data but it is able to handle steady-state conditions. For the steady-state case, a total of 8 PCs were created but in order to reduce the dimensionality of the data, only the PCs containing at least 90% of the information are kept in which for this case it was the first seven PCs. With the selected PCs, the model was trained and then utilized to detect the fault in the non-healthy data. Both the Hotelling's T2 statistic and the Q statistic test detect the fault based on the null hypothesis criteria. Figure 4.5 shows the results of the T2-test when analyzing the non-healthy simulation data. The T2-test demonstrates a clear distinction between the normal and degraded data in this case.

Similarly, the Q test is able to identify the fault precisely when it occurs at the 12 hours mark as seen in figure 4.6. This verifies that this method would be suitable for an iPWR system in steady-state conditions.

Figure 4.3: Load Following Healthy Data - PCA

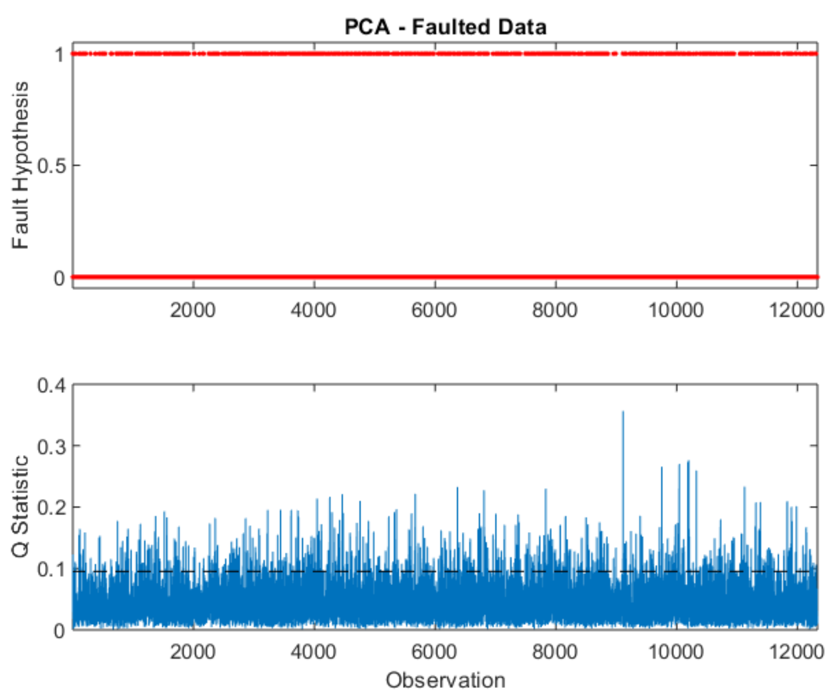

Figure 4.4: Load Following Faulted Data - PCA

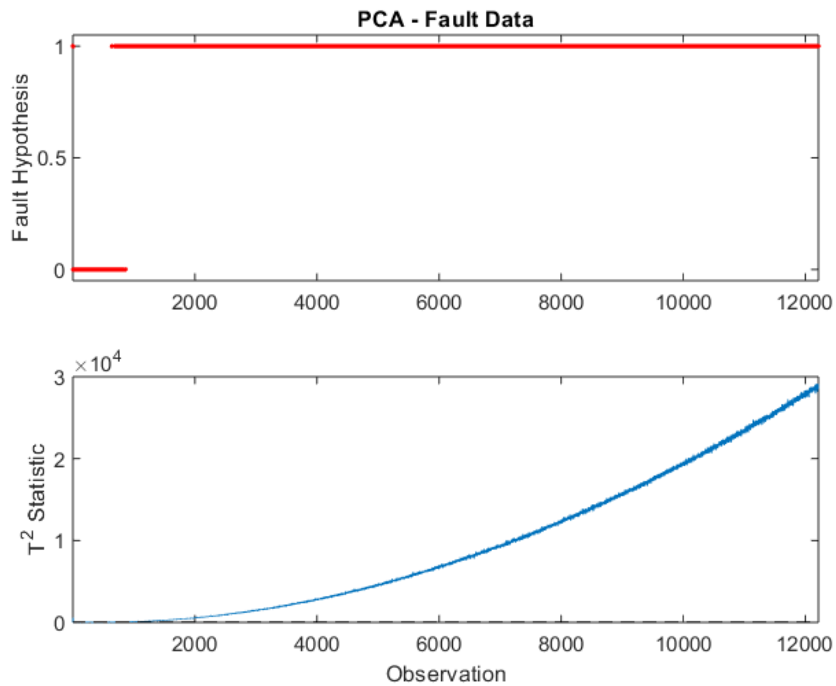

Figure 4.5: Steady-State T2 Test Results - PCA

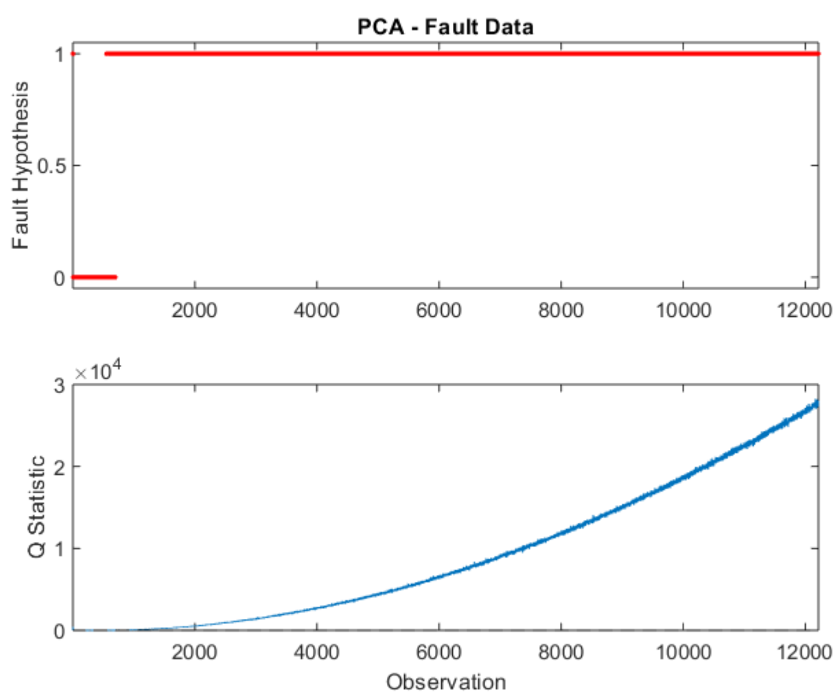

Figure 4.6: Steady-State Q Test Results - PCA

4.3 AAKR Results

The AAKR model coupled with an anomaly detection routine (SST or SPRT) performed an anomaly detection analysis with the same data used in the PCA and produced similar results for the steady-state case. As can be seen in figure 4.7, the SST fault detection test detects the fault, although there is a considerable delay compared to the PCA detection results. The SPRT method however is more definitive in its classification of the faulty data as shown in figure 4.8. The SPRT method is able to identify the fault as it happens but there are a significant amount false alarms in the section of the data where it should classify as healthy.

These anomaly detection methods demonstrate that they are suitable for steady-state conditions however the focus of this work is on load following operation. Using the same methods utilized for the steady-state case, the results for both the SST and SPRT demonstrate the anomaly detection methods ability to capture the nonlinearities in the data. As seen in figure 4.9, the SST detects the continuous fault occurring in the data. There are continuous false negatives that persist which can be resolved by optimizing the model.

Similarly, the SPRT test demonstrated this method's ability to clearly identify the fault precisely when it occurs which can be observed in figure 4.10. The SPRT method demonstrates an improvement over the SST method with the reduced amount of false negatives however there is still the issues of the false positives that occur at the start. This is likely due to the sensitive nature of the SPRT test which can be improved either through further optimization of the model or implementing a type of confusion matrix to reduce the misclassifications.

4.4 Neural Network Results

The Neural Network method utilizes the same anomaly detection routines (SST and SPRT) as the the AAKR method mentioned previously. Same as the previous

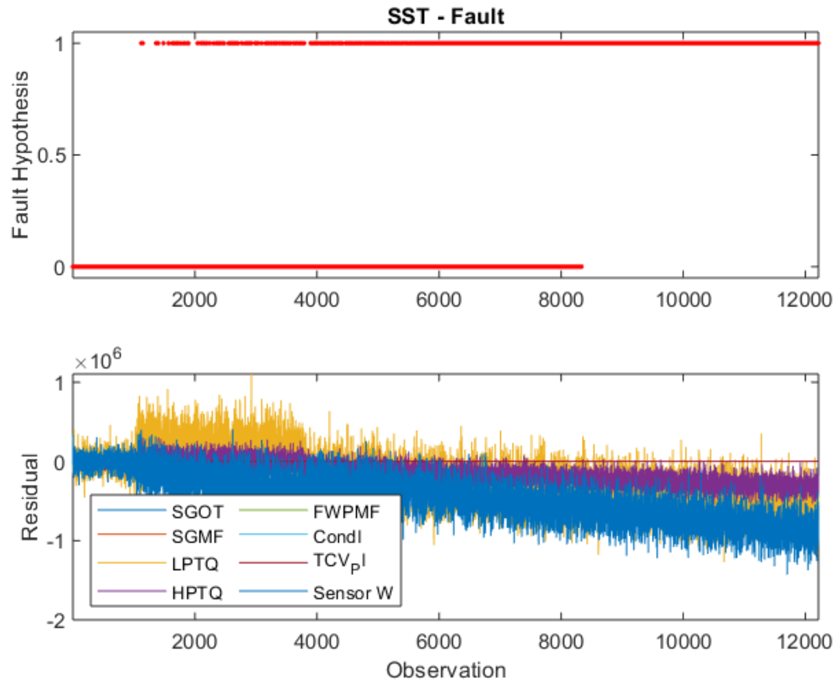

Figure 4.7: Steady-State SST Test Results - AAKR

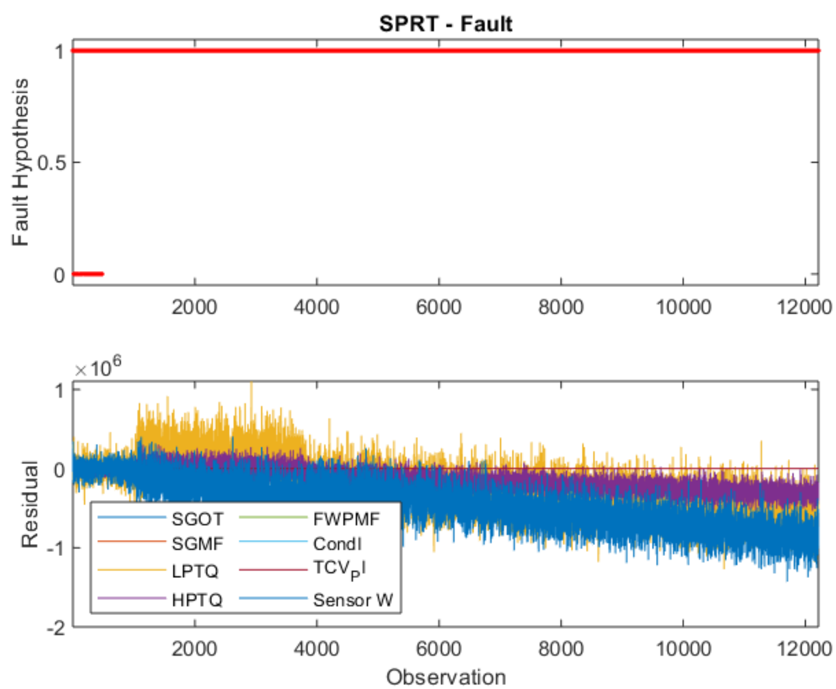

Figure 4.8: Steady-State SPRT Test Results - AAKR

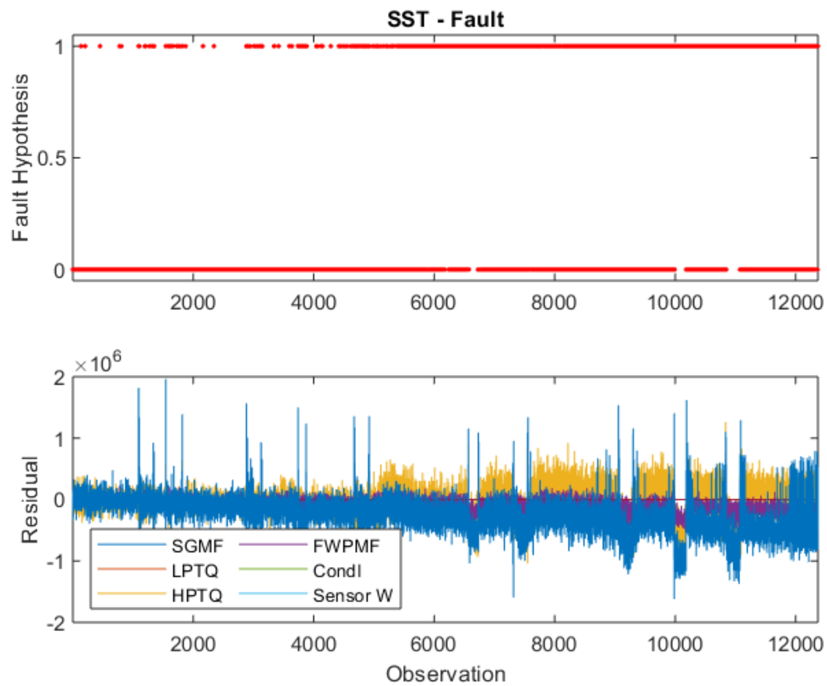

Figure 4.9: Load Follow SST Test Results - AAKR

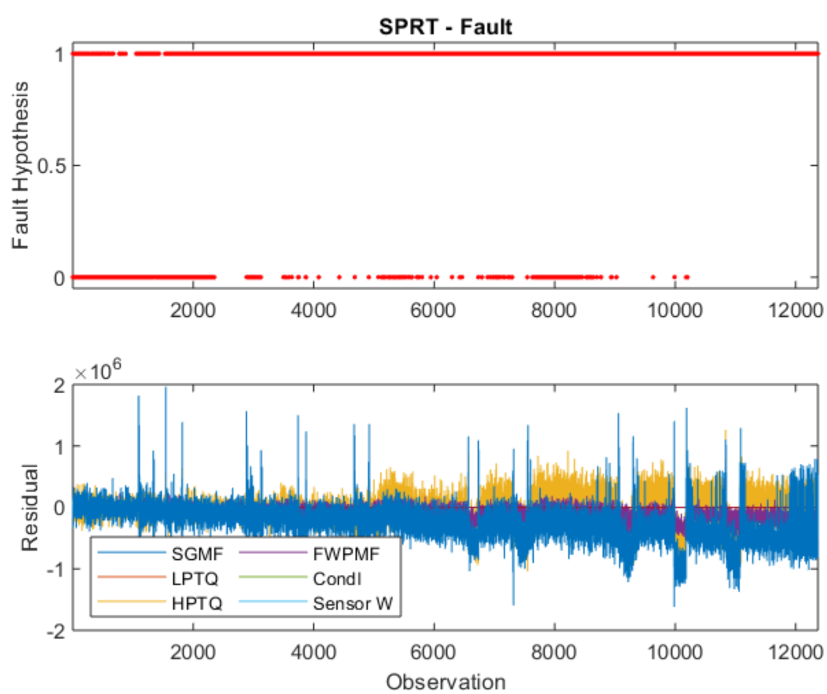

Figure 4.10: Load Follow SPRT Test Results - AAKR

methods, the neural network is tested with both the steady-state and load following conditions. A threshold of 3.5% of the mean of the training data is established as the optimal threshold for this data set. Figure 4.11 and 4.12 demonstrate this methods ability to clearly identify the fault in steady-state conditions. From an observation of the results, it can be seen that there is a delay in the detection of the fault with the SST method whereas the SPRT is able to clearly identify the fault far earlier.

In terms of the load following data, both the anomaly detection routines demonstrate the ability to identify the fault to a certain degree. The results can be observed in figure 4.13 and 4.14 which show that a continuous fault is occurring in the given data. A threshold of 3.5% is utilized in the SST method whereas a threshold of 7% is utilized in the SPRT method to account for the sensitivity of test. This method of course can be improved through the optimization of the neural network and perhaps further evaluation of the data to determine which features would be best suited for this method could also help to increase the detection accuracy.

4.5 Anomaly Detection Method Comparison

Each of the anomaly detection methods tested demonstrate various strengths and weaknesses. The PCA method displays a rapid response in detecting the fault the steady-state case which demonstrates how the PCA method works well with linear data. However, this presents as a weakness when load following data is introduced to the PCA method due to the nonlinearities in the system resulting from the changing conditions in the BOP. As for the AAKR method, it demonstrates its ability to capture both the linear and nonlinear features in the data however its response time to detecting the fault is somewhat delayed. In terms of the neural network, the autoencoder is not constrained by any linearities or nonlinearities in the data, however the response time to detect the fault is slightly more delayed when compared to the AAKR method.

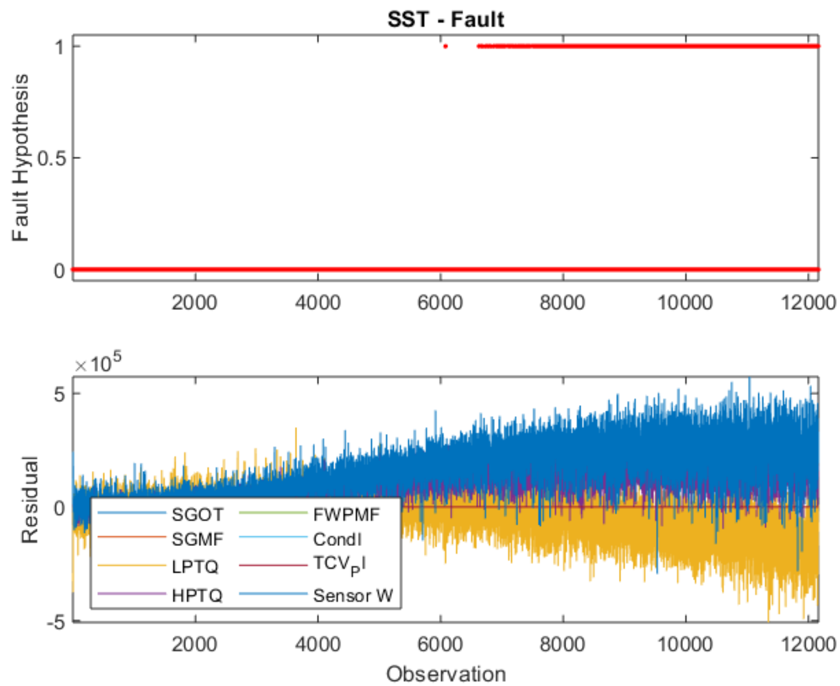

Figure 4.11: Steady-State SST Test Results - NN

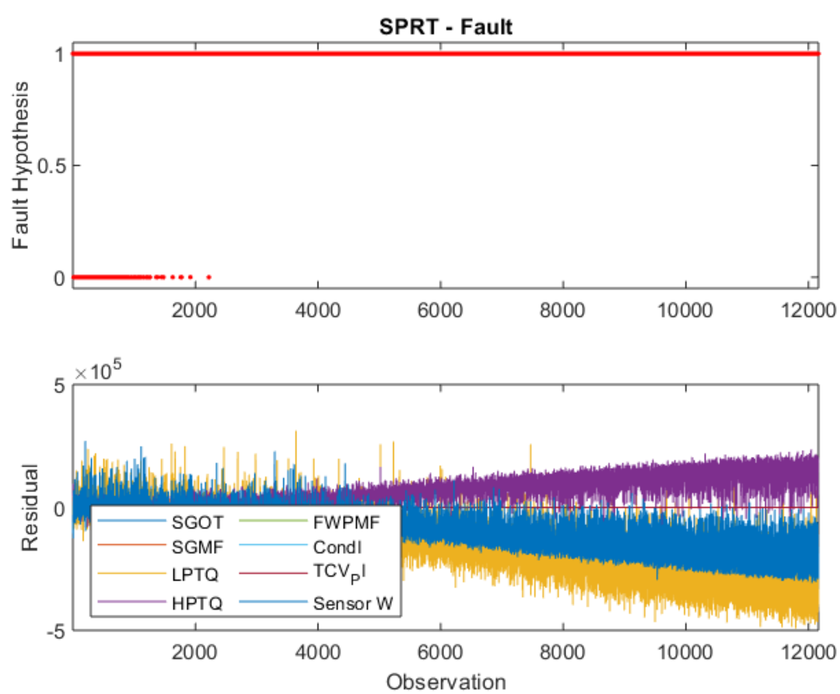

Figure 4.12: Steady-State SPRT Test Results - NN

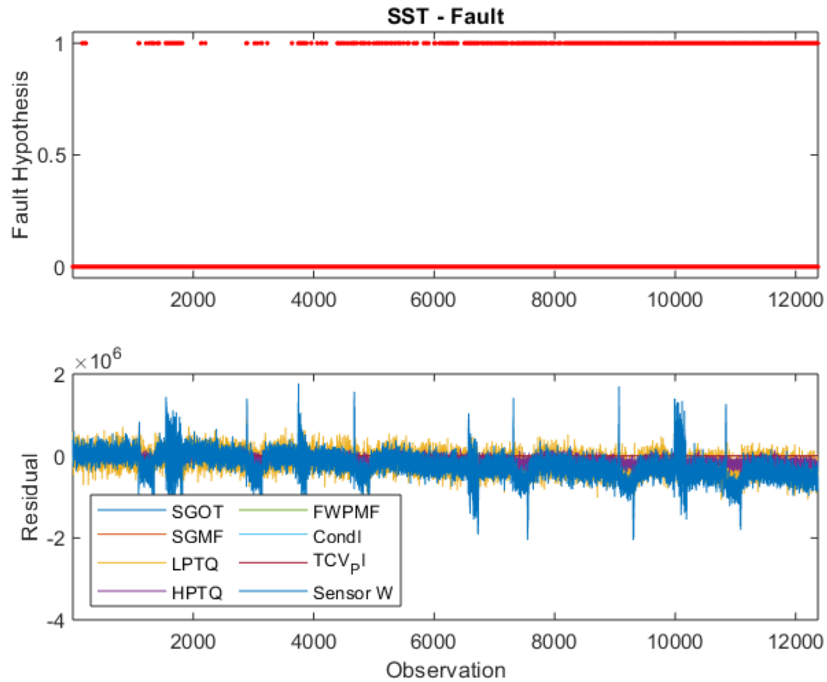

Figure 4.13: Load Follow SST Test Results - NN

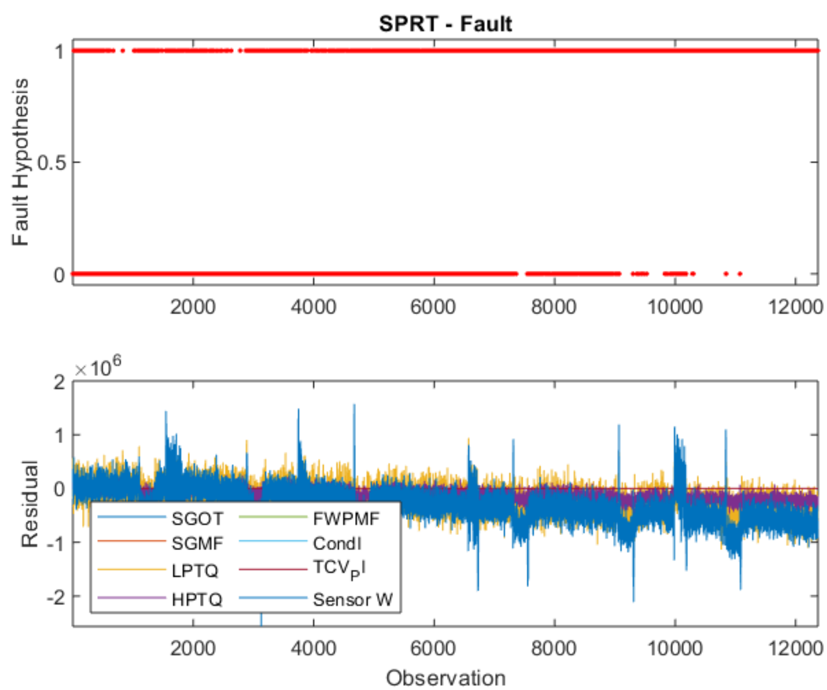

Figure 4.14: Load Follow SPRT Test Results - NN

4.6 Anomaly Detection Summary

PCA, AAKR, and a Neural Network are all used to determine if the data generated in the Dymola model is suited for further system health analysis. A fault is simulated in the feedwater pump over the course of 2 weeks of operation. Data is collected consisting of features originating in the BOP and utilized in each of the anomaly detection methods. Each method is first tested with healthy data in both operational cases to validate the models before evaluating the faulted data. This resulted in the AAKR and Neural Network being selected for further analysis involving the load following data. The PCA method however could not capture the nonlinearities in the data resulting in inconclusive results when the healthy data was introduced.

When assessing the faulted data, both the the AAKR and Neural Network were able to detect the fault in the data through anomaly detection routines (SST and SPRT) for both the steady-state and load following cases. However, there is still a need further optimization of these methods in order to achieve greater detection accuracy. Overall, this anomaly detection analysis validates that the data collected from the Dymola model is suitable for further system health analysis.

Chapter 5

Conclusions and Future Work

Small modular reactors will face many challenges before the first SMR based power plant will brought online. This is especially true in the area of prognostics and health management. One contributing factor is that there is no historical operational data for a SMR type plant currently available. The purpose of this work is to demonstrate that simulation data a of a SMR type plant can be utilized to perform system health analysis specifically during operational transients (e.g. load following).

The operational flexibility of SMRs provide greater incentive for the implementation of this reactor technology in the energy markets. However, this mode of operation introduces new challenges in ensuring system reliability. By maneuvering the entire system through various power levels, there is a risk of increased degradation developing in various assets throughout the system. To address these challenges, a model of an iPWR plant system based on the NuScale designe was developed with load following capabilities in this work. Then to validate that the model is suitable for system health analyses, a fault is simulated in the FWP where the model data can then be tested using anomaly detection routines. The following sections detail the primary achievements of this work.

5.1 Model Development Achievements

Since the focus of this work has been for load following operation of a SMR type plant, the first challenge was developing a full plant model with load following capabilities in the Dymola modeling environment. The reactor module was adapted from the INL SMR model library developed in the Dymola environment which also is based on the NuScale design. A simple regenerative reheat Rankine cycle BOP was also developed to simulate the steam and power conversion system paired with the reactor module. With control strategies developed to maintain reactivity, the feedwater pump mass flow rate, and the steam generator pressure, the model successfully simulates load following scenarios while maintaining system parameters at the various power levels consistent with the NuScale DCA NuScale LLC (2020).

5.2 Anomaly Detection Achievements

With the fully capable SMR plant model developed, the data generated in the model is tested to determine if the model is suitable for further system health analyses. A fault is introduced in the model to simulate a degrading feedwater pump. Methods such as PCA, AAKR, and Neural Networks are all utilized to detect the fault for both steady-state and load following conditions. This analysis also demonstrates which anomaly detection methods are best suited for load following data.

Each of the methods were successful in identifying the fault for the steady-state case however only the AAKR and Neural Network were successful in identifying the fault in the load following data. The PCA model failed to capture the nonlinearities in the data resulting in inconclusive results when the faulted data was introduced. Through this analysis, the data generated in model is validated for use in further system health analyses and both AAKR and Neural Network anomaly detection routines prove to be potential candidates for condition monitoring for SMR type power plants that plan on performing load following operations.

5.3 Future Work

In terms of future work, there are multiple pathways for this work to continue on. Currently, different fault modes, such as turbine control valve degradation, are in the process of being integrated into the Dymola model. Other components of interest include the control rod drive mechanism and components in the the condenser system. With these multiple fault modes integrated into the model, prognostics methods can then be developed to provide remaining useful life estimates for multiple fault modes integrated into the system.

This analysis could then lead to a method for determining the overall system remaining useful life based on the health status of individual system components. Another area requires further development is the optimization of the AAKR and the Neural Network anomaly detection methods in order to increase detection accuracy. Along with the optimization of the current methods in place, investigations can be made to find other anomaly detection methods suitable for the load following data.

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Vita

Matthew Scott is a native of Knoxville, TN which led him to first attend Pellissippi State Community College to later transfer to the University of Tennessee to complete his Bachelor's of Science in Nuclear Engineering. During his undergraduate studies, he worked as an undergraduate research assistant in the fuel development laboratory under Dr. Caen Ang. After graduating, he decided to continue his education at the University of Tennessee for a Master of Science in Nuclear Engineering under the advisement of Dr. Jamie Coble. He enjoys his work in system health analysis for iPWR systems where he was able to utilize skills in system modeling and machine learning to perform his research. He hopes to be able to continue in this type of work in his career moving forward.