

Adaptive Monitoring, Fault Detection and Diagnostics, and Prognostics System for the IRIS Nuclear Plant

Jamie Coble¹, Matt Humberstone¹, and J. Wes Hines¹

¹ *The University of Tennessee, Knoxville, TN, 37909, USA*
jcoble1@utk.edu
mhumbers@utk.edu
jhines2@utk.edu

ABSTRACT

Ideally, health monitoring of new, complex engineering systems should occur from initial operation to decommissioning. Health monitoring typically involves a suite of modules, including system monitoring, fault detection, fault diagnostics, and system prognostics. However, for systems which have not yet operated, this is challenging. Most available health monitoring modules are empirically based, meaning they are derived from available historic data. For new system designs, such data simply does not exist. This research proposes an adaptive modeling system which initially builds empirical models from high-fidelity simulated data. This data suffers from the common problems of data simulation caused by complicated physical models mechanisms and simplifying assumptions made in model development. As actual system data becomes available, the empirical models adapt in an automated and intelligent way to account for real-world, nominal data relationships.

A key challenge in automatically adaptive empirical models lies in differentiating between faulted operation and nominal operation which is not well-described by the physics-based data. Nominal operation may extend beyond the simulated data for many reasons: the system may be operating in unanticipated environments; the assumptions made in model development may cause inaccuracies in the data; or the relationships modeled may simply be incorrect. Traditional fault detection methods such as those using the sequential probability ratio test are not able to distinguish between unexpected nominal operation and truly faulted operation. However, the main benefit of using adaptive models lies in their ability to accurately learn

expanded nominal relationships while detecting and differentiating faulted conditions. For the purposes of accurately adapting a monitoring system, a principal component-based method is proposed to distinguish between these two cases.

As faults are detected, fault diagnostics and system prognostics are employed to provide a complete health monitoring system. The proposed adaptive monitoring system is applied to simulated data of the newly designed International Reactor Innovative and Secure (IRIS) nuclear plant.*

1. INTRODUCTION

Development of traditional health monitoring systems requires either large amounts of operational data spanning all expected operating conditions or high fidelity first principle models (FPMs) which capture the physics of failure relationships. However, in some cases neither of these is available. New designs of complex systems may be too complicated to adequately model using first principle approaches, but operational data is not available until the system has been in service for some time. Monitoring these systems can be challenging. An adaptive monitoring method is proposed which extends traditional auto-associative kernel regression (AAKR) models. A principal component analysis (PCA) model is used to differentiate between faulted operations and expanded nominal operations. If a fault is detected, traditional fault diagnostics and prognostics methods are applied to determine the fault type and RUL, respectively.

This research applies the proposed health monitoring system to the new Westinghouse designed International Reactor Innovative and Secure (IRIS)

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nuclear plant, shown in Figure 1. The IRIS design is a medium-sized Grid Appropriate Reactor (GAR) designed for implementation in developing electric grids. These reactors have additional monitoring concerns over nuclear plants built in developed nations; these needs include increased availability, longevity between refueling and maintenance cycles, and safety and proliferation resistance. Additionally, these reactors are designed to operate remotely in countries with limited infrastructure and skilled personnel.

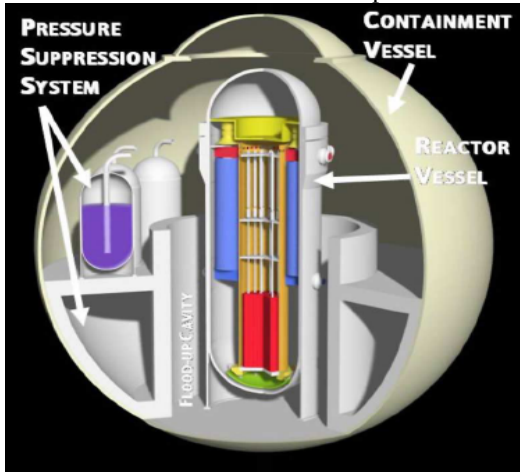


Figure 1: IRIS Reactor Design

The following section discusses the methodology used to build an adaptive health monitoring system. An application of the system to simulations of the IRIS reactor is given. Finally, conclusions and areas of ongoing work are outlined.

2. METHODOLOGY

A full health monitoring system consists of several modules, as shown in Figure 2 (Callan et al., 2006; Jardine et al., 2006; Kothamasu et al., 2006). Data collected from a system of interest is monitored for deviations from normal behavior. Monitoring can be accomplished through a variety of methods, including FPMs, empirical models, and statistical analysis (Hines et al., 2006). The monitoring module can be considered an error correction routine; the model gives its best estimate of the true value of the system variables. These estimates are compared to the data collected from the system to generate a time-series of residuals. Residuals characterize system deviations from normal behavior and can be used to determine if the system is operating in an abnormal state. A common test for anomalous behavior is the Sequential Probability Ratio Test (SPRT) (Wald, 1945). This statistical test considers a sequence of residuals and determines if they are more likely from the distribution that represents normal behavior or a faulted distribution, which may have a shifted mean value or

altered standard deviation from the nominal distribution. If a fault is detected, it is often important to identify the type of fault; systems will likely degrade in different ways depending on the type of fault, and different prognostic models will be needed. Fault diagnostic results are used to identify the appropriate prognostic model. Expert systems, such as fuzzy rule-based systems, are common fault diagnosers. Finally, a prognostic model is employed to estimate the Remaining Useful Life (RUL) of the system. This model may include information from the original data, the monitoring system residuals, and the results of the fault detection and isolation routines.

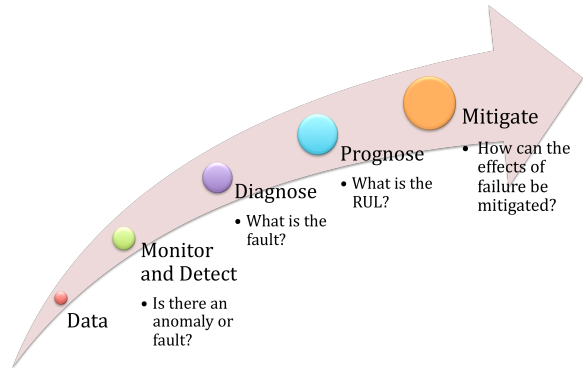


Figure 2: Full Health Monitoring System

For monitoring new equipment designs, the traditional monitoring models and fault detection routines are not sufficient. An adaptive AAKR model is proposed which is initially populated with data simulated from a high fidelity physics model and adapts to actual nominal operating data as it is collected while still correctly detecting faulted conditions (Humberstone et al., 2009a). The following sections describe the adaptive non-parametric model (ANPM), the expanded operating condition monitoring method, fault detection and diagnostics, and, finally, the prognostic method used.

2.1 Adaptive Monitoring Models

The ANPM is developed as an automated method for hybrid model adaptation; it acts as a bridge between data generated from FPMs and actual operational data. The proposed ANPM builds on the AAKR model (Hines et al., 2007a). This model is attractive for many reasons. AAKR is primarily an error-correction method; when presented with a new observation, it attempts to determine the “correct” sensor readings based on previous experience. Additionally, it is a non-parametric, memory-based model, which means that the model consists primarily of a matrix of exemplar memory vectors, X . The vectors contained in X can be chosen through a number of different algorithms: vector ordering, min-max selection, clustering methods,

etc (Garvey and Hines, 2006). The goal of any of these methods is to select a set of memory vectors which adequately covers the operating region, both in range and in intermediary relationships. When a new observation is presented to the model, its “correct” value is determined as a weighted sum of the most similar exemplar vectors. These weights are based on the Euclidean distance metric and the Gaussian kernel; the weight of the i^{th} exemplar vector is given by (1):

$$w_i = \exp\left(-\frac{d_i^2}{h^2}\right)$$

$$d_i = \sqrt{\sum (x_j - X_{i,j})^2} \quad (1)$$

where x_j is the j^{th} sensor value for the new observation, $X_{i,j}$ is the j^{th} sensor value for the i^{th} exemplar vector, and h is the kernel bandwidth. The prediction of the “correct” vector of sensor values is given by (2):

$$\hat{x} = \frac{\sum w_i X_i}{\sum w_i} \quad (2)$$

where X_i is the i^{th} exemplar vector. Because the model is based entirely on the memory matrix, new observations can be appended to it in order to be included in future calculations. This makes adaptation quick and straightforward.

A three-phase model development method is proposed for the ANPM (Figure 3). During the first phase, observed signal values are candidates for replacing the simulated FPM data. Because this adaptation is automatic, it is crucial to determine if observations that are not well described by the simulated data are due to faulted operation or expanded operating conditions. Expanded conditions may occur for many reasons: the system may be operating outside the expected region, the assumptions made in model development may be inaccurate, or the sensor noise may contaminate the nominal data to the point of appearing faulted. The proposed PCA method to differentiate between true faults and expanded conditions is discussed in the following section. After model adaptation is complete, the data vectors from FPM simulation should be completely replaced by the observed data, resulting in an AAKR model built entirely on nominal operation data. Then, a full fuel cycle (in the case of a nuclear power plant) is suggested for model validation. During this time, the performance of the model should be closely evaluated to determine if it has been adequately adapted from the first principle data to the actual operating data. If model performance is determined to be poor, the model should re-enter the adaptation phase to expand the memory matrix coverage of the operational region. Finally, the third phase covers the remaining reactor operation to the next maintenance activity. This process may be repeated after refueling or maintenance

activities to adapt the model to slight deviations in sensor relationships due to recalibration or maintenance.

During the first phase of model development, new observations of nominal operation are appended to the

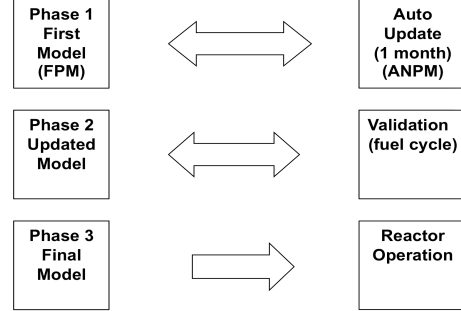


Figure 3: Model Adaptation

memory matrix as they are available. As new exemplar vectors are added, it becomes necessary to remove the simulated exemplars so that future predictions are based solely on the observed behaviors. This is accomplished by simply deleting the simulated exemplars which have been weighted most heavily in the past, indicating that they are most similar to the added observations. A new vector is used to track the sum of the weights for each of the simulated exemplars. At designated intervals, the simulated exemplar with the highest sum of weights is deleted; this interval is set such that all of the simulated exemplars are deleted by the end of the adaptation phase.

2.2 Fault Detection and Expanded Condition Monitoring

Fault detection within the adaptive framework is particularly challenging. The model must be elastic enough to allow for some deviation of nominal operating data from the simulated first-principle data; this is expected due to inaccuracies in the simulation. However, the model must also be able to determine which observations are the result of faulted operation to ensure these observations are not added to the memory matrix. The SPRT is statistically shown to be one of the fastest methods for identifying deviations in residuals. However, in an adaptive framework, the sequential nature of the SPRT is a hindrance. Because small faults may not be identified immediately, the SPRT would allow the ANPM to adapt to a growing fault without ever detecting it. This has long been one of the major drawbacks of automated adaptation. However, a principal component analysis (PCA) based method is proposed which can determine if a new observation vector is nominal, faulty, or the result of an expanded operating condition. A full discussion of the

PCA Expanded Condition Monitoring (ECM) system is available in (Humberstone et al., 2009b).

PCA transforms data into an orthogonal vector set which facilitates dimensionality reduction. By choosing the most useful Principal Components (PCs), generally considered those with the most variance, the data set can be reduced to a smaller number of inputs. When a new observation is gathered, it is transformed to the PC space to determine if it is consistent with the data seen in the past. Two metrics are used to determine how well a new observation fits in to the PC model: Hotelling's T^2 statistic and the Q-statistic. Figure 4 shows a two-dimensional PC model of three-dimensional data to illustrate the two statistics. Hotelling's T^2 statistic describes variation within the model, as shown in the figure on the left. Conversely, the Q-statistic measures the deviation of the new observation outside the model.

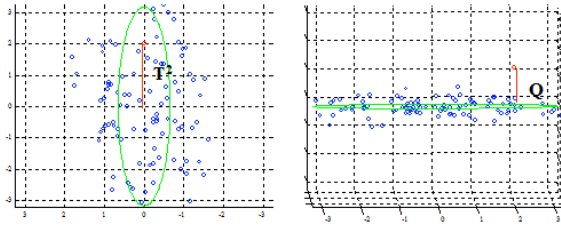


Figure 4: PCA Statistics

The T^2 - and Q-statistics can be used to determine if a new observation is in one of three classes: expected nominal operation, expanded nominal operation, or faulted operation. A PC model is developed using the simulated first-principle data, and limits on acceptable T^2 - and Q-statistic values are determined from this data. If both statistics for a new observation are within these limits, the observation is the result of expected nominal operation. If the T^2 -statistic is outside the expected limit, but the Q-statistic is within its limit, the new observation is due to expanded nominal operations. This large T^2 -statistic indicates that the new observation deviates from the center of the model more than what has been seen in the past, but the acceptable Q-statistic indicates that it is still described by the underlying relationships in the model. Finally, if the Q-statistic is outside of its designated limit, regardless of the value of the T^2 -statistic, the observation is considered faulted and is not included in the model adaptation. The large Q-statistic indicates that the new observation deviates significantly from the model relationships seen in the past. It is important to note that traditional PCA is a linear data analysis technique. The method described here is applicable to data which enjoys linear or nearly-linear relationships, at least within some region. The methodology may be extended to non-linear systems through Kernel PCA;

however, that is beyond the scope of the current work. The interested reader is referred to (Humberstone, 2010) for more information on the use of Kernel PCA for non-linear systems.

2.3 Fault Diagnostics

After a fault has been detected using the proposed PCA method, an expert system or classification algorithm may be used to determine the fault type. The diagnostic system utilized in this research uses monitoring system residuals to determine fault type. The faulted system residuals are compared to those contained in a database of historical residual signatures to determine under which fault the system is operating. Similar systems may be built using additional features, such as the results of the PCA fault detection routine, including PC values or T^2 - and Q-statistics. For the current application, this added complexity was unnecessary.

2.4 System Prognostics

The final step in the proposed health monitoring system is prognostics. The prognostic module contains a bank of models, one for each fault type. The results of the fault identification routine determine which prognostic model is used to make a RUL estimate for the system. These estimates are continuously updated as the system runs.

For nuclear power plants and other expensive, safety-critical systems, an individual-based, or Type III (Hines et al., 2007b), prognostic estimate is ideal. This research utilizes a bank of General Path Model (GPM) prognostic models. A full prognostic module would likely include many types of prognostic algorithms depending on the fault type and its progression to failure. Many prognostic algorithms have been proposed and studied (Kothamasu et al., 2006). The results presented here focus on the GPM methodology.

GPM was first proposed by Lu and Meeker (1993) to move traditional reliability analysis from failure-time analysis to failure-process analysis. The model was developed to capitalize on censored test units. It attempts to track degradation as a function of time or duty cycles and extrapolate that degradation path to some predefined critical failure threshold, giving an estimate of when the unit would have failed had testing continued. The GPM reliability methodology has a natural extension to estimation of RUL. If degradation of a system or component can be either directly measured or inferred, the degradation progression of a specific component can be used to estimate its RUL. This measure of degradation is termed a prognostic parameter. Methods for automatically identifying an optimal prognostic parameter from data have been

developed and were utilized here. The interested reader is referred to (Coble, 2010) for more information on prognostic parameter identification.

GPM analysis begins with some assumption of an underlying functional form of the degradation path for a specific fault mode. The degradation of the i^{th} unit at time t_j is given by (3):

$$y_{ij} = \eta(t_j, \phi, \theta_i) + \varepsilon_{ij} \quad (3)$$

where ϕ is a vector of fixed (population) effects, θ_i is a vector of random (individual) effects for the i^{th} component, and $\varepsilon_{ij} \sim N(0, \sigma^2_e)$ is the standard measurement error term. Application of the GPM methodology involves several assumptions. First, the degradation data must be describable by a function, η ; this function may be derived from physics-of-failure models or from past degradation data. In order to fit this model, historical degradation data from a population of identical components or systems must be available, or appropriate data may be simulated. This data should be collected under similar use (or accelerated test) conditions and should reasonably span the range of individual variations between components. Because GPM uses degradation measures instead of failure times, it is also not necessary that all historical units are run to failure; censored data contains information useful to GPM forecasting. The final assumption of the GPM model is that there exists some defined critical level of degradation, D , beyond which a component no longer meets its design specifications, i.e. the component has failed. Therefore, some components should be run to failure in order to quantify this degradation level. Alternatively, engineering judgment may be used if the nature of the degradation parameter is explicitly known.

As data is collected on a faulted unit, the GPM may be used to estimate the RUL, as shown in Figure 5. Here, the known parametric function is fit to the available degradation data to give a unit-specific prognostic model. The fitted parametric model is then extrapolated to the degradation threshold to give an estimated failure time and corresponding RUL. For systems with very little data or significant noise contamination, Bayesian methods may be used to include prior information in the model fit. Including this information helps “force” the fitted parametric

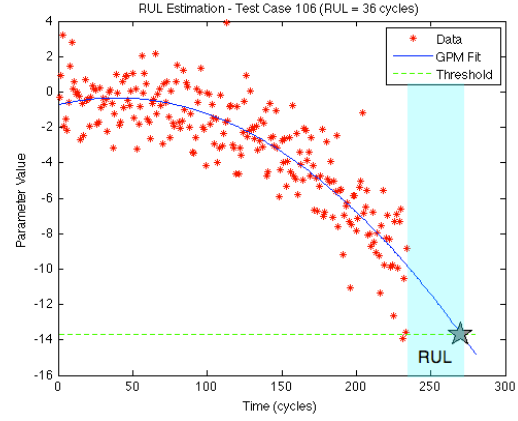


Figure 5: Parameter Trending and RUL Estimation

model to take the shape seen in previous cases. For a complete discussion of Bayesian updating methods in the GPM, the interested reader is referred to (Coble and Hines, 2009).

The following section presents the application of the adaptive health monitoring system to the IRIS plant design.

3. APPLICATION AND RESULTS

The proposed adaptive monitoring and health management architecture was applied to the IRIS nuclear plant design. The IRIS design is a Westinghouse generation IV small- to medium-size modular reactor design that has a proposed 335MW output. The IRIS reactor is an integral Pressurized Water Reactor with eight helical coil steam generators. There are a number of advantages that the IRIS reactor has over traditional pressurized water reactors; most of these are safety related benefits necessary for remote operation in developing nations. Because the IRIS reactor is still in the design stage, no actual operation data is available. However, two simulators have been developed. Data obtained from those simulations is used in this research. Because the two simulators do not track the same set of sensors, model development and evaluation was performed in two phases. First, the nominal condition adaptation of the ANPM was tested using a reduced number of sensors to utilize both simulators. Then, the PCA-based expanded operation monitoring system was tested using the full data set from the high-fidelity simulation. The two simulators and ANPM results are described next.

3.1 ANPM Results

The first simulator, considered to be a low-fidelity simulator, was built by researchers at the University of Tennessee using MATLAB Simulink® (Li et al., 2009). The Simulink model is a modular model which

includes the reactor core, the helical coil steam generators, and the balance of plant. In testing the adaptation phase of the ANPM model, the results of this simulator are considered the first-principle model results and are used to seed the original memory matrix.

The second simulator used was developed by Dr. Michael Doster at North Carolina State University (NCSU). NCSU has demonstrated experience in developing high fidelity, full plant simulators for predicting the dynamic response of pressurized water reactors during normal and off-normal operational conditions. An IRIS specific simulator has been developed which includes a model of the IRIS Pressurizer, a six delayed neutron group kinetics model, a decay heat model and a hot channel/Departure from Nucleate Boiling (DNB) model. In the IRIS design, the steam generators are helical coils, where the secondary fluid flows on the tube side of the heat exchanger. Detailed models have been developed to describe the dynamics of steam generators of this design. For testing model adaptation, the results of this simulator are used as the high fidelity, “operational” data.

The two simulators share five common sensor measurements: hot leg temperature, cold leg temperature, feed flow rate and steam flow rate per steam generator, and feedwater temperature. The adaptation phase of the ANPM utilized these five, highly correlated sensors to illustrate adaptation to nominal operating data. Both simulators generated data for a load-following power profile, which is more likely in a GAR than steady-state operation. The load profile used is shown in Figure 6. Figure 7 shows the Steam Flow Rate residuals for three models. The worst performer is the model based solely on first-principle generated data. The figure shows that this model was not able to predict the behavior during periods of lower power demand. The ANPM residual remains centered around zero, indicating that it was able to adapt from the low-fidelity first principle model to a more accurate model. Finally, the “final” model is the result of the adaptation phase, a model which has completely adapted to the collected data and contains no simulated exemplars. This final model has the lowest residuals, slightly better than the adapting ANPM model. The mean squared errors of the predictions for all models and each of the five sensors are shown in Table 1.

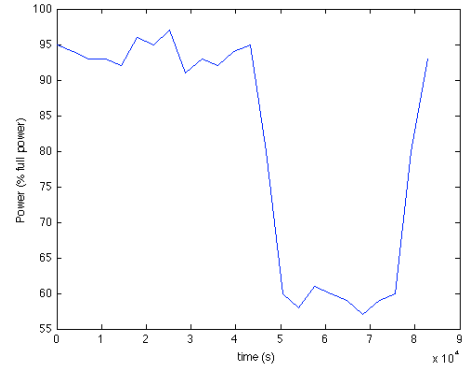


Figure 6: Load-Following Power Profile

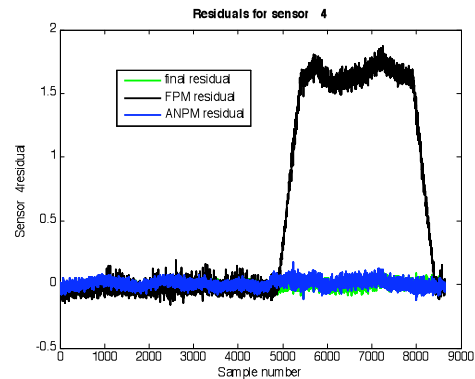


Figure 7: Model Residuals for Steam Flow Rate

Table 1: Mean Squared Error of Predictions

	Sensor Number				
	1	2	3	4	5
FPM	4.27	0.178	0.899	0.898	0.066
ANPM	0.0011	0.0011	0.001	0.001	0.0002
Final	0.00037	0.00027	0.00066	0.00069	0.00016

These results indicate that the ANPM adapts correctly from low-fidelity simulated data to high-fidelity operating condition data. However, the ANPM must be able to identify observations which result from faulted behavior in order to exclude these observations from the adapting memory matrix. To test this feature, a larger model was built using thirteen highly correlated sensors from the NCSU simulator. This model was used with the proposed PCA-based ECM methodology to identify known faulty data. The NCSU simulator was used to generate data with a heat exchanger fouling fault. The generated data includes one day per month of operation under the nominal load profile for twelve months with increasing fouling levels at each month, ranging from 1.4% fouling to 30% fouling. The results of the PCA-based ECM for the

first month are shown in Figure 8. This included only 1.4% heat exchanger fouling and was not detectable as a fault. However, the second month of this fault, which included 3.3% fouling, was identified as faulty (Figure 9). For each month following, the PCA-based ECM was able to correctly identify the faulted data.

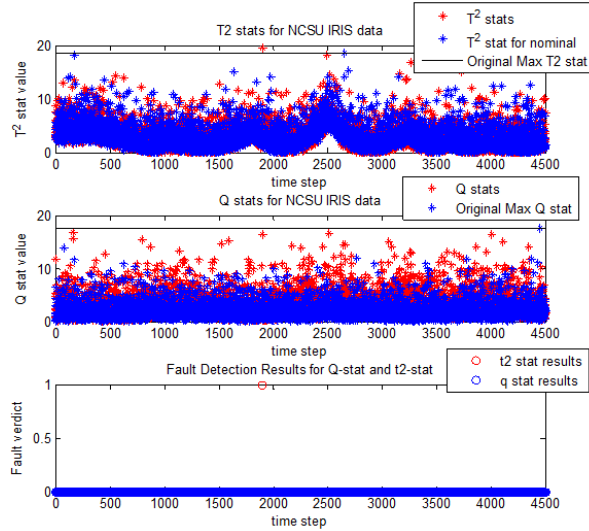


Figure 8: PCA-based ECM for Month 1

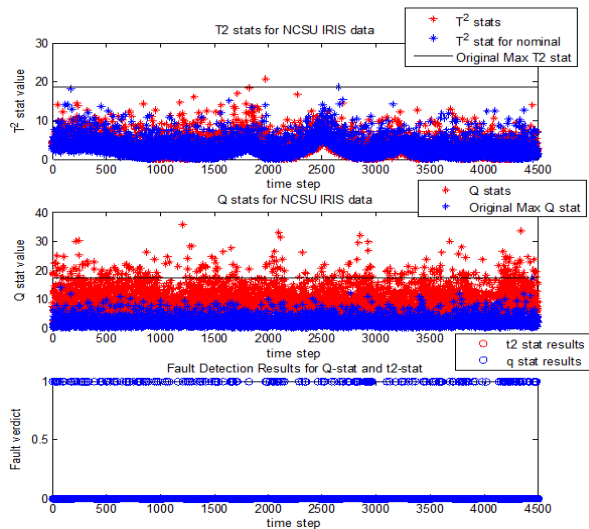


Figure 9: PCA-based ECM for Month 2

After determining through the proposed ECM method or traditional fault detection methods that a fault is present, the health monitoring system would normally turn to a fault diagnostic routine to identify the type of fault experienced. Due to time constraints and the run time of the NCSU simulator, only one fault type is currently available. Integration of a diagnostic routine is an area of ongoing work as additional data becomes available. The final step after detecting and diagnosing a fault is system prognostics. The results of

a prognostic model to track heat exchanger fouling are given next.

3.2 Prognostics

A GPM prognostic model was used to estimate RUL for heat exchanger fouling faults. This failure mode presents an interesting case. When the plant is operating in a lower power demand, the heat exchanger is not stressed as highly, and the effects of the fault are somewhat muted. However, when only the periods of high power operation and the resulting residuals are considered, the fault has a very noticeable trend in the Steam Generator Exit Temperature, as shown in Figure 10. Again, due to constraints of the simulator, only one example of heat exchanger degradation is available. However, this example was used to generate additional degradation paths to develop a GPM model.

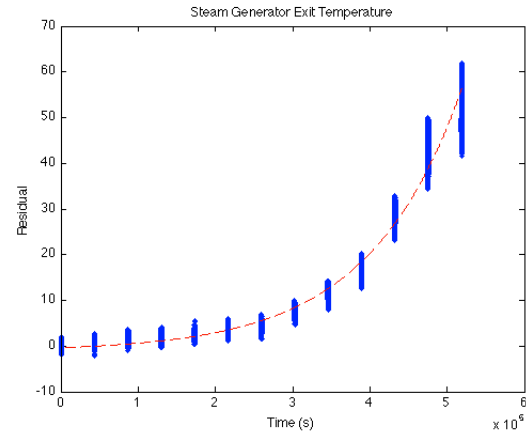


Figure 10: Steam Generator Exit Temperature High Power Residuals

One hundred generated degradation paths were used to develop a GPM model, which the simulated data shown above was applied to for testing. The RUL estimation results are shown in Figure 11. The blue line shows the actual system RUL over thirteen months of operation. It is traditional to consider the RUL at any time before failure to be simply the time between the current time and the failure time. Klinger (1992) shows that the assumption that failure time is inversely proportional to the degradation rate is valid for systems which are autonomous in the variable representing time. The inverse relationship should be accepted for systems running under an effectively constant load and environment, which is often seen in nuclear power plants. During the first month, operation is nominal and no prognostic estimate is made. As discussed previously, during the first month of faulted operation, the fault detection routine does not detect the small degradation of the heat exchanger; again, no prognostic model is activated. Finally, at the second month of

faulted operation, the fault is detected and the prognostic algorithm is activated to make RUL estimates. The prognostic model performs well, with RUL estimates within 5% of the actual RUL by the 7th month of faulted operation, five months before failure. As new faults are detected and identified, a bank of prognostic models can be developed to account for each of the expected faults. During actual operation of similar IRIS plants, if unforeseen faults occur, this information can also be incorporated into the fault diagnostic and prognostic modules. In this way, the health monitoring system will continue to adapt as operating data becomes available and the entire fleet of IRIS plants can leverage the experiences of each individual reactor. In an actual prognostic system, a Type I, or reliability-based, prognostic model can be used to estimate the system RUL before a fault has been detected and identified. This will facilitate full life cycle prognostics from beginning of operation, through fault detection and identification, to system failure.

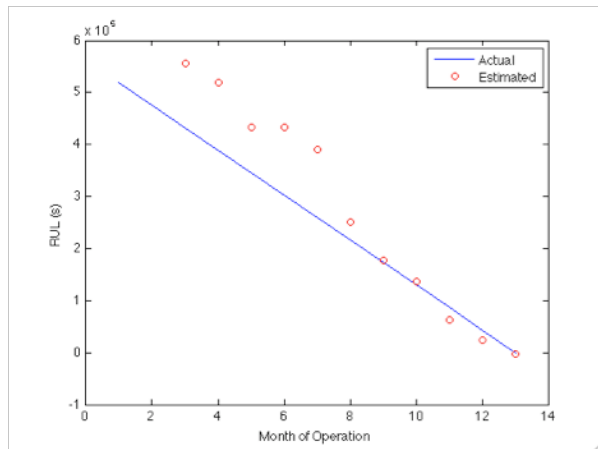


Figure 11: Heat Exchanger Fouling RUL Estimation

CONCLUSION

4.

Recent efforts have pushed health monitoring technologies for legacy nuclear power plants which capitalize on the significant amount of data available from their operation. However, as new plants come online which differ significantly from current designs, these monitoring systems will not be directly applicable. High-fidelity first-principle simulations are available for new plant designs, and the existing empirical modeling technology can leverage this data to provide system monitoring beginning with plant start-up. With the addition of an automated adaptation method, these models based on simulated first principle data will better learn the behaviors and operating regions of a specific plant as nominal operational data

becomes available. The proposed ECM method helps ensure that only nominal operations are learned and faults are identified. This adaptation technology is not only useful for new plant designs, but could also be applied to restarts after refueling outages when sensor relationships routinely change slightly due to recalibration and maintenance activities.

This research presented key components in a full health monitoring system. Beginning with an adaptive monitoring module, the ANPM, the ability to adapt to nominal operations and to detect faults using the proposed PCA-based ECM method was illustrated. After the detection of a fault, a GPM prognostic model was applied to estimate system RUL. This information could be used to determine if the plant can run to the next scheduled maintenance cycle or if additional maintenance must be planned.

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NOMENCLATURE

AAKR	Auto-Associative Kernel Regression
ANPM	Adaptive Non-Parametric Model
DNB	Departure from Nucleate Boiling
ECM	Expanded Condition Monitoring
FPM	First Principle Model
GAR	Grid Appropriate Reactor
GPM	General Path Model
IRIS	International Reactor Innovative and Secure
NCSU	North Carolina State University
PC	Principal Component
PCA	Principal Component Analysis
RUL	Remaining Useful Life
SPRT	Sequential Probability Ratio Test

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- Jamie B. Coble** received a B.S. in Nuclear Engineering and Mathematics from the University of Tennessee in May, 2005. She earned an M.S. in Nuclear Engineering in 2006 and an M.S. in Reliability and Maintenance Engineering in 2009. She completed her PhD in Nuclear Engineering in May, 2010 with a dissertation entitled, "Merging Data Sources to Predict Remaining Useful Life – An Automated Method to Identify Prognostic Parameters." She is currently completing research in health monitoring for the IRIS nuclear plant as a post-doctoral researcher at the University of Tennessee. Her research interests include empirical methods for monitoring complex engineering systems, fault detection and diagnostics, and system prognostics. She is a member of the American Nuclear Society, Women in Nuclear, the IEEE Reliability Society, and the IEEE Women in Engineering society.
- Matt Humberstone** was born in Albuquerque, NM in 1983. He attended New Mexico State University in Las Cruces, NM where he graduated with a Bachelor's of Science in Engineering Physics. He then attended the University of Tennessee in Knoxville, TN where he graduated with a Ph.D. in Nuclear Engineering and a Master of Science in Statistics in 2010, and Master of Science in Nuclear Engineering in 2007. His research interests which include Empirical Modeling, Monitoring, Detection, Prognostics, Reactor Analysis, along with other areas. He worked as an intern at Sandia National Laboratories in their Advanced Nuclear Concepts division and currently works for the Nuclear Regulatory Commission in their Advanced Reactor department. He is currently working with the Nuclear Regulatory Commission.
- J. Wesley Hines** is a Professor of Nuclear Engineering at the University of Tennessee and the director of the Reliability and Maintainability Engineering Education program. He received the BS degree in Electrical Engineering from Ohio University in 1985, and then was a nuclear qualified submarine officer in the Navy. He received both an MBA and an MS in Nuclear Engineering from The Ohio State University in 1992, and a Ph.D. in Nuclear Engineering from The Ohio

State University in 1994. He teaches and conducts research in artificial intelligence and advanced statistical techniques applied to process diagnostics, condition based maintenance, and prognostics. Much of his research program involves the development of algorithms and methods to monitor high value equipment, detect abnormalities, and predict time to failure. He has authored over 250 papers and has several patents in the area of advanced process monitoring and prognostics techniques. He is a director of the Prognostics and Health Management Society, and a member of the American Nuclear Society and the American Society of Engineering Education.