COMPUTATIONAL INTELLIGENCE IN NUCLEAR ENGINEERING

ROBERT E. UHRIG and J. WESLEY HINES
Department of Nuclear Engineering,
University of Tennessee, Knoxville, TN, USA
E-mail : ruhrig@utk.edu, jhines2@utk.edu

Received February 2, 2005

Approaches to several recent issues in the operation of nuclear power plants using computational intelligence are discussed. These issues include 1) noise analysis techniques, 2) on-line monitoring and sensor validation, 3) regularization of ill-posed surveillance and diagnostic measurements, 4) transient identification, 5) artificial intelligence-based core monitoring and diagnostic system, 6) continuous efficiency improvement of nuclear power plants, and 7) autonomous anticipatory control and intelligent-agents. Several changes to the focus of Computational Intelligence in Nuclear Engineering have occurred in the past few years. With earlier activities focusing on the development of condition monitoring and diagnostic techniques for current nuclear power plants, recent activities have focused on the implementation of those methods and the development of methods for next generation plants and space reactors. These advanced techniques are expected to become increasingly important as current generation nuclear power plants have their licenses extended to 60 years and next generation reactors are being designed to operate for extended fuel cycles (up to 25 years), with less operator oversight, and especially for nuclear plants operating in severe environments such as space or ice-bound locations.

KEYWORDS : condition monitoring, sensor validation, anticipatory control, intelligent agents, ill-posed problem, noise analysis, surveillance

1. INTRODUCTION

The overall performance of America's fleet of 103 nuclear power plants has improved dramatically in the past decade through the use of increased and more effective training and a significant increase in the use of on-line maintenance. As a result, the availability of plants is asymptotically approaching the theoretical maximum in which the refueling activities define the length of the outage. Yet, there are major issues that should be of concern to the nuclear industry and the Nuclear Regulatory Commission (NRC) that bear directly on the continued safe and efficient operation of these plants. Most of these concerns arise from a combination of "stresses" on the reactor core being introduced by three trends: 1) longer fuel cycles, 2) increases in thermal power, and 3) proposed increases in the maximum allowable burnup in the fuel. There are also concerns about unforeseen issues that may arise as plants continue to operate for up to 60 years. The first line of defense against such problems is continuous, on-line surveillance and, when possible, concurrent diagnosis of problems when they occur.

The role of Computational Intelligence (CI) in the nuclear power industry is in constant transition due to plant operating objectives, future needs, and regulatory requirements. For example, as plants move towards longer plant licenses, improved maintenance practices become vital. Past practices of corrective maintenance is not practical with one-day outages costing up to a million dollars. Current periodic or predictive maintenance practices may not be optimal when precursors to degradation or failure may be inferred. Many top performing plants are moving towards condition-based maintenance practices when technology permits. This allows a plant to optimize their maintenance by performing maintenance only when the condition requires it. These techniques require robust and reliable estimates of the plant condition, that in many cases requires the use of CI to process the plant data to infer condition.

Many of the techniques developed over the past thirty years such as reactor noise analysis are now reaching maturity and paying dividends. Other techniques, such as on-line sensor calibration monitoring, are nearing the maturity in their development; however, just beginning implementation. Still others, such as on-line efficiency optimization and on-line transient identification, still have not yet proven their worth. And lastly, several new techniques, such as autonomous control and multi-intelligent agents are still in their formative years.

2. APPLICATIONS OF REACTOR NOISE ANALYSIS

Applications of reactor noise analysis to determining the state of a system have been ongoing for the past forty years and are well documented. The first two conferences on nuclear reactor noise analysis with proceedings, organized by the University of Florida in 1963 and 1966 were international in scope [1, 2]. Two pioneering books of that era clearly established the practicality and usefulness of reactor noise technology [3, 4]. The first of eight SMORN (Specialist Meeting on Reactor Noise) Symposia, organized by OECD/NEA, occurred in 1974. Additionally 29 IMORN (Informal Meeting on Reactor Noise) meetings were hosted between 1969 and 2004.

The analysis of random signals has been used for vibration monitoring of key structural components, noise monitoring of process noise measurements, metal to metal impact and loose parts monitoring, acoustic leak monitoring, main reactor coolant pump shaft vibration monitoring, turbine condition monitoring, valve and pump condition monitoring, and even sensor and instrumentation degradation monitoring [5]. An example of a critical save involves the detection of an 80% through crack of a German PWR reactor coolant pump shaft using eddy current sensors. The 5 MW pump problem was detected before it became apparent by traditional means, and it was replaced before damage to the plant could occur [6].

Another application of reactor noise analysis has dealt with the monitoring of loose parts of internal components of the reactor primary system. These techniques, which were first investigated in the 1960's, have advanced significantly over the past decade. Currently, every German Nuclear Power Plant has a Loose Parts Monitoring System (LPMS) and almost every peak in the power spectral densities have been correlated with a specific component. Through the collection, storage, and trending of this data over many years, diagnosis of impact related abnormalities can be performed as never before. These advanced data collection and processing algorithms, combined with a comprehensive signature database that contains trend information from a multitude of German plants, can now identify the type, location, and cause of the abnormal patterns [7]. Both German and French nuclear power plants routinely transfer plant vibration data to a central laboratory where it is scanned, analyzed, and filed with notification to plant personnel if anomalies appear.

3. IMPLEMENTATION OF ON-LINE MONITORING AND SENSOR CALIBRATION VERIFICATION

On-Line Monitoring of Nuclear Power Plants has been an active area of research for the past twenty years. Monitoring activities from many research laboratories and universities have included core monitoring, transient identification, alarm management, general equipment monitoring, and on-line sensor calibration verification. Beginning in the late 1980s and continuing through the 1990's the Department of Energy initiated and coordinated original research in the area of sensor calibration monitoring. Argonne National Laboratory led the activities with the development of the System State Analyzer [8], which was the predecessor of the Multivariate State Estimation Technique (MSET) [9]. During the same era, the University of Tennessee developed an Autoassociative Neural Network (AANN) based technique [10, 11] and later improved the system [12]. In the 1990's several other modeling techniques were studied including Probabilistic Neural Networks and later Non-Linear Partial Least Squares (NLPLS) [13]. At about the same time, the Halden Research Project developed PEANO, which is a sensor monitoring product that combines locally trained AANNs and Fuzzy Logic [14].

The Electric Power Research Institute (EPRI) conducted and managed research in this area beginning in the 1990's, developed the *Instrument Calibration and Monitoring Program* (ICMP) for monitoring redundant sensors [15], and explored modeling techniques for non-redundant sensors. EPRI submitted Topical Report TR-104965, *On-Line Monitoring of Instrument Channel Performance*, to the NRC [16]. In 2000, the U.S. Office of Nuclear Reactor Regulation Application issued a safety evaluation (SE) [17], which accepted on-line monitoring for calibration extension if several requirements, i.e., quantitative evaluation of the errors involved, were met.

Research then shifted to making the techniques more accurate through the use of regularization techniques for MSET [18], and Neural Networks [19], and general modeling [20, 21]. In 2000, EPRI formed the Instrument Monitoring and Calibration (IMC) Users Group to demonstrate On-Line Monitoring (OLM) technology in operating nuclear power plants for a variety of systems and applications. Systems were pilot tested at several Nuclear Plants.

The most recent research is focused on preparing these techniques for NRC approval for monitoring safety critical instruments and thus reducing the manual calibration frequencies. The NRC SER listed 14 requirements including an Uncertainty Analysis of the predictions and V&V (verification and validation) of the system. The V&V was funded by the Department of Energy NEPO program and conducted by Argonne National Laboratory (ANL). The V&V results are described in Chapter 8 of EPRI's *Implementation of On-Line Monitoring for Technical Specification Instruments* [22].

3.1 Uncertainty Analysis

Both ANL and the University of Tennessee developed uncertainty analysis methods for the empirical models of interest. ANL focused their uncertainty analysis methods on Monte Carlo Techniques using Latin Hypercube Sampling and Wavelet denoising [23]. These techniques provide an uncertainty measure for a particular model that uses a specific training set. The technique is limited in that it provides a value for only a small operating region; however, the NRC SER allows for monitoring data at a single point and refers to this as single point monitoring. A statistical analysis was performed on drifting sensors quantifying the probability that a specific drift type could be detected at a single monitoring point. Performing single point monitoring, usually at the 100% power condition, is permissible if an additional uncertainty penalty is taken. If single point monitoring is implemented, then the Monte Carlo method is expected to give valid uncertainty estimates.

The Monte Carlo Technique has some assumptions that should be considered. The first of these is that a noise free estimate of each of the process signals can be determined. Sometimes this is referred to as the "True Signal." Two techniques have been developed to meet this need. The Reactor Parameter Signal Simulator (RPSS) was developed by ANL in the early 90's [24]. This technique uses Fourier Transformations and was originally developed to whiten data residuals that were evaluated by Sequential Probability Ratio Test (SPRT) based detection algorithms [25]. A wavelet-based denoising method, the Stochastic Parameter Simulation System (SPSS), was developed by Miron [26, 27] and is an integral tool for Argonne's current uncertainty analysis method. This method decomposes a process signal into its deterministic and stochastic components, and then reconstructs a new, simulated signal that possesses exactly the same statistical noise characteristics as the actual signal. This is necessary in the Monte Carlo analysis, which repeatedly constructs and tests models using process data with different noise instantiations to determine average uncertainty values. SPSS is also used as a filtering device. For filtering, it isolates the principal serially-correlated, deterministic components from the analyzed signal so that the remaining stochastic signal can be analyzed with signal validation tools.

The University of Tennessee took a more general approach in assessing the predictive uncertainty. These techniques provide a prediction interval for each prediction being made [28]. This technique is more general in that it dynamically estimates the predictive uncertainty at each operating point. Additionally, the use of Monte Carlo techniques have proven that the prediction intervals are accurate and depend on several items such as the noise in the predictor and response variables, the model complexity, and the training data coverage [29].

3.2 Equipment Monitoring

The most recent work in this area focuses on the application of sensor monitoring techniques for equipment condition monitoring (ECM) [30]. These MSET-based techniques have been applied to the Palo Verde Nuclear power plants by SmartSignal Inc. [31]. In an EPRI funded cost benefit analysis, it was shown that the use of the systems for ECM could accelerate the payback and should be an area of research focus and application [32].

One of the major roadblocks to the implementation of OLM techniques for ECM is that all possible faults cannot be simulated or even pre-enumerated. There are no available data to train models to recognize the sensor patterns for a wide range of failures. Two categories of solution implementations exist. In the first implementation, the OLM system would only be used to detect the failure with human experts performing the diagnostics. A second method builds a database of past failures. When a fault is detected and properly diagnosed, the fault signature is stored in a database along with the diagnosis. When a future fault occurs, it's signature is compared to those in the fault signature database and the operator will be informed of any prior faults that created a similar signature. Over time, the fault database will grow and recall a greater percentage of faults. Currently this technique is being implemented fleet-wide in fossil power plants, resulting in a faster growing fault signature database.

3.3 OLM Future

Although nuclear plants in the U.S. have not adopted OLM for calibration extension, AMS has applied the techniques to Sizewell B in Great Britain [33] and Electricity de France (EdF) also uses OLM techniques for calibration monitoring. At the time of this writing, one U.S. Nuclear Power Utility has made it known that they will submit a license amendment to the NRC early in 2005. This will be the first of its kind and may prompt others to follow suit.

4. REGULARIZATION OF ILL-POSED SURVEILLANCE AND DIAGNOSTIC MEASUREMENTS

Many predictive empirical modeling techniques have an inherent weakness in that they may give unstable or inconsistent results when the predictor data are highly correlated or the approach is under-constrained or "ill-posed." [21] This section presents an example ill-posed diagnostic problem and a regularization method used to obtain accurate and consistent prediction results. The example is the inferential sensing of feedwater flow in a nuclear power plant using a neural network model and ridge regression. Recently, the focus of the work on on-line surveillance systems has been on optimizing the predictive models to assure their accuracy and repeatability using several different regularization techniques [34, 21].

For decades mathematicians have known that many very important practical problems are underdetermined because the data does not provide enough information to determine a single unique solution [21]. Examples of underdetermined problems are spectrum analysis, image reconstruction, deconvolution, interpolation and extrapolation from numerical data, and neural network training-just to name a few. Such underdetermined problems have a special name: ill-posed problems or incorrectly posed problems in a sense that it is incorrect to ask a person to solve a problem that does not have a unique solution. An important sub-class of ill-posed problems is inverse problems that deal with the inversion of cause-effect relations. While inverse and ill-posed problems are not synonymous, most problems we deal with in surveillance and diagnostics are both inverse and ill-posed. In machine and plant diagnostics and surveillance, truly well-posed problems are practically unknown. In spite of this, the implications and significance of inverse and ill-posed problems are not fully understood or appreciated by the vast majority of technical personnel.

In many empirical surveillance and diagnostic problems, the relationships in historical plant data are modeled for use in present and future predictions. For example, the inferential measurement of feedwater flow is based on its correlation with other plant parameters. The problem with using highly correlated parameters as predictors is that they are not only highly correlated with feedwater flow, but they are also correlated with each other. If this degree of correlation is quite high, the data matrix becomes ill-conditioned and the problem of drift detection becomes ill-posed in the sense that the solution does not meet all of the following conditions: 1) the solution for the problem exists, 2) the solution is unique, and 3) the solution is stable under small perturbations [35]. If any of these conditions are not met, the problem is ill-posed and special procedures must be used to provide a solution, if one exists.

Inferential sensing is the prediction of a sensor value through the use of correlated plant variables. Most calibration monitoring systems produce an inferred value and compare it to the measured sensor value to determine the sensor status. There are a number of techniques that have been proposed for on-line inferential sensing during recent years. Most notable are AANN [20], MSET [18, 36], and NLPLS which inherently contains regularization [13]. All of these methods use related sensors as inputs to estimate models (sets of weights) that are subsequently used to infer the sensor's value based on the input values. Necessary features of all on-line sensor validation systems is that they accurately infer the sensor's value and should also be robust to moderate changes in input values such as those caused by noise.

We can illustrate the ill-posed nature of this problem with an inferential measurement of feedwater flow in a nuclear power plant under the condition of fouling of the venturi meter that is typically used as a standard flow measuring device. Venturi meters are susceptible to measurement drift due to corrosion products building up near the meter's throat orifice. This increases the measured pressure drop across the meters, which results in an over-estimation of the flow rate. Consequently, the reactors' thermal power is also overestimated. Since the thermal power is the limiting quantity in the license of a nuclear power in the United States, this fouling effectively derates the power plant. A well-posed or regularized evaluation inferred from a model based on correlated data will give a unique prediction of flow rate.

Regularization involves augmenting the data by some additional information and has been implemented by a number of methods and under different names to solve the problem of learning from data. Normally, regularization methods implement a prior belief that the relationships should be smooth, which results in lower variance results. Methods of stable numerical matrix inversion such as Tikhonov regularization [37], truncated singular value decomposition (SVD) [34], and ridge regression are applicable to most ill-posed engineering problems. One of these solutions to an ill-posed problem is "ridge regression" [34] where instead of minimization of a "self-evident" least squares functional in fitting data to a model, a "non-self-evident" cost function consisting of two terms: a least squares function and a norm or semi-norm of the vector of regression coefficients, is minimized.

Application of regularization as shown in Gribok [38] leads to stable and reasonable solutions. The unregularized and regularized solutions to the feedwater flow problem are shown in the figures 1 and 2 respectively. These plots show the PDF (probability density function) of "bootstrap" estimations of feedwater flow based on 100 individual calculations. Figure 1 presents the PDF of 100 estimates of true values of feedwater flow rate that are based on ordinary least-square solution. These estimates are extremely inconsistent with many peak values of low probability. Application of regularization dramatically reduce that variance as shown in Figure 2 which provides a single peak value with a high probability and is consistent and reasonable from an engineering view point. While the regularized value of flowrate indicated by Figure 2 is consistent, it may still be subject to a small bias with respect to the true value.

5. TRANSIENT IDENTIFICATION IN NUCLEAR POWER PLANTS

Nuclear power plants are highly complex systems that are operated and monitored by humans. When faced with an unplanned transient, such as an accident scenario, equipment failure or an external disturbance to the system, the operator has to carry out diagnostic and corrective actions. Anomalous operating conditions must be diagnosed and identified through the process' instrument readings. The sheer number of instruments can make the diagnosis process fairly difficult. Hence,

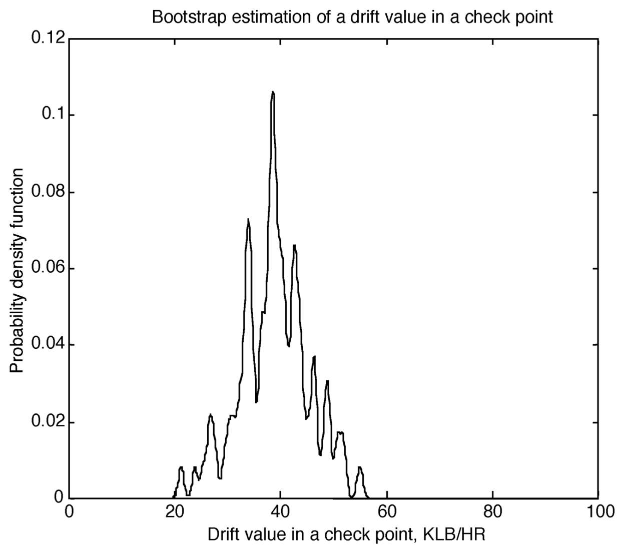

Fig. 1. Bootstrap Estimator without Regularization

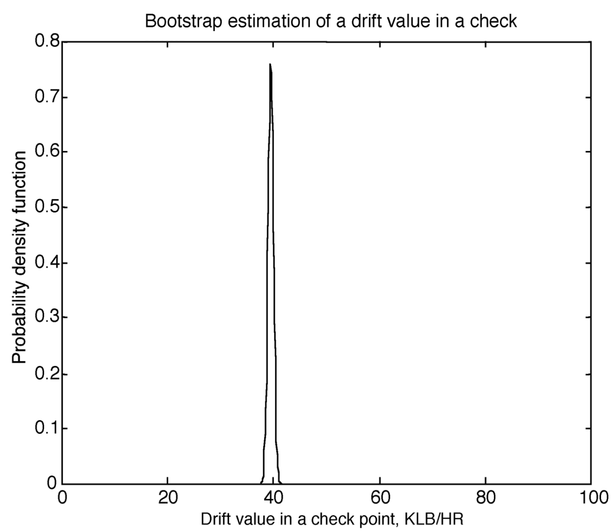

Fig. 2. Bootstrap Estimator with Regularization

depending on the severity of accident, instruments' readings might not give a clear indication of an anomaly at its incipient stage. The operator's response may be too late to mitigate or minimize the negative consequences of such anomalies. The objective of transient identification is to develop an instrumentation system that is based on artificial intelligence technologies to assist the operator in identifying transients at the earliest stages of their developments. Early detection may help in minimizing or even mitigating the negative consequences of such transients. It is equally important to identify the type of transient correctly. Misidentification of transients might result in incorrect action by the operator or an automated safety system.

When a nuclear power plant is operating normally, the readings of the instruments in a typical control room form a pattern (or unique set) of readings that represents a normal state of the plant or system. When a disturbance occurs, the instrument readings undergo a transition to a different pattern, representing a different state that may be normal or abnormal, depending upon the nature of the disturbance. The fact that the pattern of instrument readings undergoes a transition to a different state may be sufficient to provide a basis for identifying the transient or the change of state of the system. In implementing such a transient diagnosis system in a nuclear power plant, a set (perhaps 5 to 20) of output variables from the plant are sampled simultaneously, normalized to expected maximum values, preprocessed if appropriate, and transmitted to the input layer of a neural network. The unique relationship between these variables represents the condition of the plant at that particular instant as presented by the output of the neural network. When the system is operating at a steady state or changing slowly, the pattern of variables at each sampling instant remains the same or changes slightly, and the output of the neural network remains the same. However, at a time Δt after a transient begins, the sampled values form a different pattern (i.e., the relationship between the variables changes and continues to change as the transient progresses). When successive sets of sampled values are fed to a trained neural network, each set indicates that the same transient is underway if the pattern is adequately developed. Indeed, there is a whole group of patterns associated with each unique transient that must be calculated or obtained from a simulator so that they can be included in the training set of the neural network.

There are two different methods used to identify transients in nuclear power plants. The first involves recording and observing the overall behavior of a small number, perhaps 5 to 8, of variables over the lifetime of a transient. The transients used for training the neural network have to be generated in a simulator or calculated using conventional reactor physics software. In this method, no effort is made to identify the transient until it is virtually complete. Then all of the traces of these variables vs. time are sampled (perhaps a total of 20 to 50 simultaneously sampled sets per variable over the lifetime of the transient to give the overall shape of each variable), and all sampled values for all variables are inputs to the neural network. This is the method originally used at the University of Tennessee to identify transients in a steam generator [39]. The main disadvantage of this method is that the transient, and hence the fault, can be identified only after the transient is complete and the plant is probably shut down.

The other approach, also developed at the University of Tennessee, [40, 41] is to use a larger number of variables (typically 15 to 20) and instantaneously examine the relationship between these variables at a series of small time intervals. Each variable is sampled at discrete intervals (typically several sample sets per second), and each of these sets of simultaneously sampled values is entered sequentially into a trained neural network. The data from the nuclear power plant are being treated as if each set of input samples is independent, which represents at least a quasi-equilibrium condition. If the transient is too fast to be treated as being in quasi-equilibrium, then it will be necessary to use recurrent neural networks (which have feedback connections) or to simultaneously introduce several successive sets of samples as inputs to the neural network. This results in more complex, larger neural networks, which are harder to train. The advantage of this method is that identification of the transient takes place very early in the transient at a time when it may still be possible for an operator (or an automatic system) to take mitigating action (e.g., power reduction), if appropriate. Experience indicates that transient identification in nuclear power plants typically occurs within the first few sets of samples after the initiation of the transient. The main problem is identifying the beginning and the length of the transient. A summary of the early work on transient identification is given by Uhrig and Tsoukalas [42].

Transient detection can be considered to be a pattern recognition problem. When a transient occurs, starting from steady state operation, instrument readings develop a time dependent pattern. These patterns are unique with respect to the type of accident, severity of accident, and initial conditions. For example, the system's response to a main steam line break will differ from its response to a control rod ejection accident. Therefore, by properly selecting the variables used by the pattern recognition system, the relevant features will be extracted from the measurements. The choice of inputs for each transient is usually made from simulator studies. Signal responses to various transients on a simulator fall in three categories: none, minor, and significant. To robustly identify the transients, only input signals that produce significant responses during the transient to be monitored are selected as inputs to the neural network.

Nuclear Regulatory Commission (NRC) regulations list thirty-six different transient scenarios that licensed reactor operators are required to be able to identify. A pattern recognition system utilizing neural networks can be used for transient detection because plants' sensors develop unique dynamic patterns for each given transient. A set of simple neural networks, one for each transient being evaluated, can be used to identify individual transients almost instantly. The use of this approach is often chosen because it is possible to expand the number of transients identified without adversely affecting the existing system by adding an additional trained neural network for each new transient to be identified. Training the network to give a "1" for the specific transient and a "0" for all other transients works very well and all transients investigated can be rapidly identified. Additionally, a different neural network can be used to measure the magnitude of that transient using training data with several degrees of magnitude of the individual transients. For large transients, the results were quite satisfactory, but for small transients, the presence of feedback in the plant tended to degrade the results. When transients are of very minor severity, then the control systems and water make-up systems tend to minimize the evidence of such transients. Hence, it is difficult, if not impossible to detect minor transients.

Standard pattern recognition techniques will classify any pattern to fit the closest matching pattern. However, since the neural network cannot be trained on all possible transients, it is important that it does not classify transients on which it has not been trained. To overcome this problem, Bartal, Lin and Uhrig [43] used probabilistic neural networks. These networks have a parameter that will classify a pattern depending on its probability of matching a specific pattern. Hence, when a pattern has low probability of being any of the "learned" patterns, it will be classified as "Don't Know". To minimize the pitfall of false identification of transients on which the network has not been trained, a network is trained to identify each individual transient; each network has only one transient associated with it. Each network is not only trained to identify each transient, but it is also trained to reject the other transients as being that specific transient. In other words, the neural network that is trained to identify loss of coolant accidents can also be trained to classify the other transients as "No Transient" to minimize misidentification of transients.

Faults can be inserted in the simulator at any level of severity, from 0% to 100%. For some transients (e.g., control rod ejection accidents), there is no variation in the severity. The event either takes place or it does not. As for the other transients, the percentage represents the fraction of flow relative to a guillotine break that would have 100% severity. Since these events can take place at any severity level, the neural networks can be trained to detect these transients at a number of different severity levels. The objective is to make the detection networks insensitive to the severity level of the transient while retaining the ability to assess the severity with another neural network.

The data from the reactor may be noisy and even contaminated by spikes and false readings. Hence, the data has to be filtered and processed before being input to the network. Even after the signals are processed, some noise will still be present. To make the network robust to noise in the test data, the training data must also be contaminated by noise. Noise of the order of +/- 1% should be added to all training and testing data. The added noise proved to be essential for having a noise insensitive network. For example, when the network was trained on noise free data and then tested on noisy data, the results are very unstable. However, when the network was trained and tested on noisy data, the output is consistent and stable [44].

More recent work on transient identification at the OECD Halden Reactor Project by Roverso [45] utilized wavelets to examine signal fluctuations caused by transients. This approach overcomes two problems, namely the requirement for a trigger signal to indicate the beginning of a transient and the requirement for each transient to be of a fixed predefined length. These restrictions were due to the necessity of compressing the transients to make them treatable (i.e., so that the neural network would learn the transients). This approach involved the use of wavelet features extracted from a sliding window on the multivariate transient signals and utilized recurrent neural networks to deal with the transient aspects of the signals.

The choice of the window size can be used to strike a balance between a high level of transient compression (which greatly improves the performance of the recurrent neural network), and a resolution still sufficient to discriminate among the event classes. Successful tests of this system were obtained using data from one of Electricite de France's PWR 900 MW nuclear power plants. In these tests, it was possible to discriminate among seven different transient classes [45]. A series of controlled tests were conducted using an artificially generated multivariate time-series to demonstrate the ability of the system to base its classification decision on a range of discriminating features, from low frequency to high frequency features, and from early to late developing features.

All of the above work was performed using the Halden ALADDIN system, a multi-purpose data acquisition and information processing system using various artificial intelligence technologies (e.g., neural networks, fuzzy logic, wavelets, etc.) to perform alarm structuring/suppression in a nuclear power plant alarm system. Their most recent work combines recurrent neural networks ensembles, wavelet on-line preprocessing, and autonomous recursive task decomposition to improve the practical application and scalability of ALADDIN to real processes and machinery [46]. One method consists in basing the alarm structuring/suppression on a fast recognition of the event generating the alarms. This allows a subset of sufficient magnitude to effectively handle the current fault and notifying the operator, minimizing the operator's workload in a potentially stressful situation. The scope of application of a system like ALADDIN goes beyond alarm handling to include diagnostic tasks in general.

6. ARTIFICIAL INTELLIGENCE-BASED CORE MONITORING AND DIAGNOSTIC SYSTEM

Of special concern recently for the operators of nuclear power plants is the detection and identification in a timely manner of serious problems developing in the reactor core in fuel associated with a combination of long fuel cycles using fuel with high boron content, high burnup, and significant power upgrades. The average discharge burnup in PWRs has increased from 36,000 to almost 50,000 MWD/MTU (megawatt-days per metric ton uranium) since 1983 with many fuel assemblies having significantly higher discharge burnups. The current limit on burnup is 62,000 MWD/MTU with some utilities seeking a 75,000 MWD/MTU limit. Failure of control rods to insert completely are increasingly common as indicated by incidents at Wolf Creek, South Texas, TMI-1 and Crystal River-3 where control rods in fuel with an average burnup of 45,000 to 50,000 MWD/MTU) failed to insert completely upon shutdown due to deformed fuel and channels. Power uprates inevitably decrease safety margins and challenge the integrity of the fuel. When combined with changes in fuel design for long (24 month) fuel cycles that have been introduced, unexpected changes in the boron chemistry, and the continued pressure to increase fuel burnup limits, the state of nuclear fuel technology appears to be approaching unexplored areas where unforeseen events are increasingly common.

The combination of longer fuel cycles and high burnup can lead to unanticipated operational difficulties such as the "axial offset" anomaly at Callaway. Again, the first line of defense against such problems is an advanced surveillance and diagnostic system. Indeed, it was a core protection calculator (CPC) at Arkansas Nuclear One-2 that diagnosed a non-normal flux shape and initiated a shutdown. Unfortunately, only about half of the ABB/CE plants and none of other vendors' plants have CPCs. The CPC technology, which monitors DNBR and linear power per unit length of the fuel elements, is almost three decades old. Given recent advances in computers and the use of advanced artificial intelligence technologies, there are valid reasons to expect that a core monitoring system coupled with the advanced "smart" diagnostic systems being proposed here can automatically detect and characterize for the operator any unforeseen events arising out of the extended operation of today's and tomorrow's reactors.

The core monitoring and diagnostic module described here is only one example of a modern system. It uses flux measurements from the commercial in-core flux measuring instrumentation system installed permanently in the reactor core. For purposes of this discussion, the three-dimensional array of core detectors in the Crystal River-3 Nuclear Power Plant will be utilized as being the standard reference flux measuring system. It can also be used with Halden's SCORPIO system and others. The reference system has a horizontal array of 52 self-powered rhodium neutron flux detectors located at each of seven levels. This arrangement gives two-dimensional horizontal neutron flux maps of the core at seven levels. Readings from the Crystal River-3 detectors are averaged over six minutes, thereby setting the basic time interval at six (or some multiple of six) minutes. The system also has a background detector which provides the background to be subtracted from all readings. Depletion of the rhodium as a function of integrated neutron irradiation over time is taken into account.

The six core regions between the seven levels of detector can be modeled individually. The 52 signals from each pair of adjacent levels (or mathematical transforms of these signals) then become the input and desired output to the six neural network "modeling" modules. After each neural network is properly trained, the magnitude and location of differences between the actual flux measurements and the neural network predictions for flux values in the core region defined by the two adjacent detector arrays indicate whether a change in the neutron flux pattern has or has not taken place in that region. Once an anomaly has been detected, the flux changes over time in sub-regions of the six core regions can be monitored and compared by algorithms and three-dimensional visualization methods to diagnose anomalies.

The neural network model module could utilize the "multi detector" technique developed by UT under EPRI sponsorship for monitoring the operability of check valves [47]. This technique effectively crosscorrelates out the influence of global driving functions such as power level and fluctuations, boron concentration in PWRs, and others. It uses a neural network that has three layers with the same number of neurons in the input and output layers and a smaller number of neurons with non-linear activation functions in the middle layer. It is trained using the signals from a given level in the core as the input and the signals from the next higher level as the desired output. The output layer has linear activation functions that allow the use of regression and SVD to almost instantaneously recalibrate the network to compensate for system changes. After the neural network has been trained, it is connected in a monitoring mode where the actual flux measurements at the upper lever of the core region is compared with the flux values predicted by the neural network. The differences, if any, indicate that changes have taken place, and the magnitude and nature of these changes can be used to infer the existence and nature of the anomalies.

7. CONTINUOUS EFFICIENCY IMPROVEMENT OF NUCLEAR POWER PLANTS

There has been significant research in the area of thermodynamic optimization and efficiency improvement over several decades. Most of the commercial techniques have been based on first principal models and resulted in products such as PEPSE® (**P**erformance **E**valuation of **P**ower **S**ystem **E**fficiencies), which is the industry standard heat balance computer program. The objective of these programs is to monitor the thermodynamic performance of a plant, to help diagnose operating problems, and predict the effects of changes in equipment and operating parameters. PEPSE is not a performance optimization product, it is a performance monitoring product that can be used to identify deficiencies.

True performance optimization products have not been used in the Nuclear Power Industry even though they have shown promise in fossil power and chemical industries. Products from such vendors as Vali and SimSci Essor have had successful applications in reducing NO_x emissions from fossil power plants and optimizing petro-chemical processes; however, these products have not been used for thermodynamic efficiency improvement. The reason for that may be the limited number of controllable variables in the secondary side of a nuclear power plant and the expense in developing first principle models for an entire rankine cycle.

The University of Tennessee performed some of the seminal research in empirical performance modeling and optimization for nuclear power plants [48]. Initial work was performed for TVA in which Sequoyah Nuclear Power Plant (NPP) Unit #1 was modeled. Estimated heat rates were within 0.1% of the calculated values. When the trained model was used on Unit #2 (nominally, an identical unit), heat rates were within 0.5%. This validates that the NPP heat rate can be modeled from plant data. A sensitivity analysis was used to determine how to change the most important variables to improve plant performance but changes were not implemented on the plant because most involved changes in hardware.

More recent work [49] verified the ability of feed forward neural networks to model plant heat rates using hourly measurements, but the modeling of the sensitivity of heat rate with respect to input variables required very frequent inputs (i.e., time sample intervals of about one-tenth of the system time constant, typically one or two minute sample intervals) and feedback within the neural networks. Subsequent research gave UT researchers valuable experience in applying regularization techniques to get repeatable, robust, reliable results from empirical modeling techniques [21, 50]. With the application of these techniques, on-line empirical performance optimization will be possible.

Recently completed results show that online empirical modeling techniques may be used to monitor and optimize thermodynamic efficiency, which could save power plants hundreds of thousands, even millions, of dollars a year. As shown in Figure 3, the optimization method makes use of an empirical inferential MSET model that has training vectors covering the different operating conditions. The inferential model is used to predict the thermodynamic efficiency for different conditions. The non-linear optimization function is used to perform a

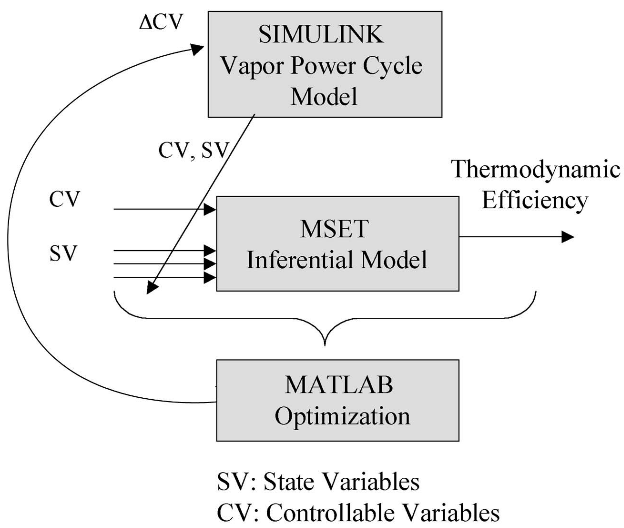

Fig. 3. Optimization Method

constrained optimization of the inferential model. The model has inputs of state variables (SV) and controllable variables (CV). Early experiments selected the controllable variables to be the bypass flow rate to the feedwater heater and the reheat flow. Eight state variables such as secondary side temperatures, flow rates, and pressures are chosen to represent the plant condition. The inferential model determines the optimal change in the controllable variables at the current state through the use of response surface optimization techniques [51]. These changes are then made to the plant and a new operating condition exists. The procedure is repeated periodically to assure that the efficiency remains near its maximum.

Early simulation results show that the method can find the optimal operating condition and can even search outside the trained space. Simulations show that simply optimizing the bypass flow rate for 15 degree F changes in cooling water temperature can save a plant $200,000 a year. The data-based method has several advantages over model based methods including correct adaptation to the actual system, reduced engineering development time and cost, and robust and reliable optimization techniques [52].

Researchers at the Halden Reactor Project have developed an on-line Thermal Performance Monitoring and Optimization (TEMPO) system. This system uses data reconciliation based on first principal models. Rather than only performing optimization, TEMPO also has the ability to monitor the plant and detect sensor and equipment degradation and faults [53, 54]. It is implemented as an object oriented process modeling tool. Data reconciliation techniques have also been investigated at utilities, such as Electricity de France, solely to detect sensor degradations [55].

8. AUTONOMOUS ANTICIPATORY CONTROL AND INTELLIGENT AGENTS

The Department of Energy has stimulated the development of several “Generation-IV” nuclear power reactor concepts (generally described as reactor concepts that will emerge twenty to thirty years in the future) that are rejuvenating the interest in advanced concepts in nuclear power plants. Generally, these plants have safety characteristics (e.g., core damage frequencies) that are one to two orders of magnitude smaller than the current Generation-II and -III nuclear power plants, and their construction and operating costs are projected to be significantly less than current plants. Many of these concepts (but not all) are modular plants with many prefabricated major components.

To achieve the expected lower operation costs, most of the Generation-IV concepts utilize semi-autonomous operation[1] in which a few (perhaps two to four) operators monitor and manage up to a dozen modular plants. Many such plants anticipate operation for periods of five to eight years without shutdown. While the robust design of these plants contributes to efficient operation and effective safety under normal conditions, they are not immune to normal wear and fatigue concerns due to operation as well as the occurrence of failure modes that were not anticipated during the design. This latter concern is particularly true of “first of a kind” plants like the Generation-IV plants. The normal “first line of defense” against normal and unexpected deterioration is continual surveillance and predictive diagnostics. Semi-autonomous operation imposes a higher level of safety assurance on the plant designers and operators. To assure that this challenge is met, special “multi-agents” may carry out safety and performance assurance activities in Generation-IV plants [56].

Such an approach exploits a simple but powerful idea: *In order to regulate themselves in a semi-autonomous manner and be protected from potential anomalies, Generation-IV plants should act proactively, that is, effect control in anticipation of (not just in response to) possible contingencies.* Preliminary work suggests that the proposed approach may

1. Address “wear and fatigue” problems emerging during long-term operation,
2. Effectively deal with unanticipated design basis events,
3. Monitor deterioration of plant and component performance,
4. Reduce maintenance costs (by reducing/eliminating excessive control actions), and
5. Determine when the plants need to shutdown for safety

[1] Semi-autonomous operation can be defined as autonomous operation in which operators can intervene under certain conditions and in which operator action may be required to proceed to a different state of operation.

and other reasons.

Conceptually, each Generation IV plant is surrounded by a set of controllers that can be considered the *normal monitoring and control blanket*. In addition, a multi-intelligent agent system envelops the plant with two additional *anticipatory control blankets*, one pertaining to problems emerging due to "wear and fatigue" phenomena and the other pertaining to unanticipated events [57].

An "agent" (sometimes called an "intelligent agent") is defined by the Object Management Group [58] as "a person, a machine, a piece of software, or a variety of other things, i.e., one who acts." While the application of individual agents is possible, their greatest potential is realized when multiple-agents work together to achieve a common goal. These collectives are known as multi-agent systems. A requirement that is essential for multi-agents to cooperate is that they share a common "view" of their world and be able to communicate in a common "language" or ontology. An agent is characterized by knowledge (i.e., beliefs, goals, plans, assumptions, etc.), and it interacts with other agents using an agent communication language. An agent can also possess additional characteristics, such as being autonomous, interactive, adaptive, proactive, cooperative, competitive, etc. For purposes of carrying out the safety and perfo-rmance assurance activities on Generation-IV nuclear power plants, available agents will be utilized and additional specialized agents that utilize legacy (existing) software to perform specific monitoring and safety assurance functions can be developed.

Long-term semi-autonomous operation imposes special requirements on the control of nuclear power plants; namely, the ability to respond to fluctuating loads and to adapt to a variety of operating conditions without any intervention by a human being for weeks, months and perhaps years. The management system of the plant must be able to anticipate the consequences of the various future states of operation (e.g., increasing and decreasing power, operational transients, design basis transients, etc.), and be prepared to respond to anticipated conditions while the characteristic parameters of the reactor vary over their entire range of operation. The ability to anticipate the consequences of the various operating conditions is not possible in current reactor design. Such a control technology offers unique advantages that support automated operation by anticipating events and trends and taking preventative action.

Nuclear power plants are by their design well suited for the application of multi-agents to carry out the safety assurance function as they are well instrumented for purpose of defining the plant's safety status. In modern nuclear power plants, information is collected and processed by a central plant computer. Each of the monitoring and control subsystems can be "agentized;" i.e., legacy (existing) code can be encapsulated in an agent "wrapper," enabling critical information to be autonomously distributed to any agent that needs it to perform its prescribed task.

While there is general agreement on the concepts expressed above, there is little agreement on how multi-intelligent agents should be implemented. One approach that seems attractive is to use existing intelligent controllers (IC) that contain both a perception module that performs sensor data fusion, fuzzy inferencing, information integration, and interpretation, and a response module that performs operational assessment, mission management and control, planning (and replanning), and plan execution [59]. Such systems are very robust with respect to unforeseen situations and recovering from failures under autonomous operation, yet they will accept human interaction and collaboration. They use low-bandwidth (simple, high level) communications and utilize self reorganization in reaction to recognized partial or complete failure of a component or in response to unforeseen environmental changes. They do not depend upon data-based models, so the issue of ill-posed problems does not arise. They can generate confidence factors on their conclusions that can be very helpful. An architecture for such a multi-IC system has been developed by the Applied Research Laboratory[59]. In summary, the IC would appear to be an ideal basic system around which to build an agent-based system to manage large complex systems such as a semi-autonomous nuclear power plant or a reactor in an orbiting space station.

9. CONCLUSION

The role of computational intelligence in nuclear engineering has been illustrated through the discussion of several current approaches to surveillance and diagnostics in nuclear power plants. However, this list of applications and researchers is a small fraction of the research currently underway throughout the world. The development and use of such techniques is critically important to the safe, efficient and reliable operation of future nuclear power plants, particularly those Generation IV plants that are expected to operate semi-autonomously for long periods of time.

REFERENCES

[1] Uhrig, R.E., Editor, "Proceedings of the Symposium on 'Noise Analysis in Nuclear Systems', U.S.A.E.C. Symposium Series, Number 4, TID-7679, 1964.

[2] Uhrig, R.E., Editor, "Proceedings of the Symposium on 'Neutron Noise, Waves, and Pulse Propagation,'" U. S. A. E. C. Symposium Series, Number 9, CONF 660206, 1967.

[3] Thie, J.S., "Reactor Noise" Rowman and Littlefield, New York., 1963.

[4] Uhrig, R.E., "Random Noise Techniques in Nuclear Reactor Systems, Ronald Press, New York, (Translated into Russian and published in 1974 by MOCKBA

ATOM ИЗДАТАТ), 1970.

[5] Wach, D., “Condition Monitoring for Improved Performance in German NPPs”, *4th International Topical Meeting on Nuclear Plant Instrumentation, Control and Human Machine Interface Technology (NPIC&HMIT ’04)*, Columbus Ohio, 2004.

[6] Sunder R., D. Wach, R. Heinbuch, J., Irlbeck, “Main Coolant Pump Shaft Crack Detection in the Isar-2 Nuclear Power Plant”, VGB-Kraftwerkstechnik, Vol. 4, 1989.

[7] Olma, B.J., “Experience and Standardization in Loose Parts Monitoring of German NPPs”, *4th International Topical Meeting on Nuclear Plant Instrumentation, Control and Human Machine Interface Technology* (NPIC&HMIT ’04), Columbus OH, 2004.

[8] Mott, J., S., Young, and R.W. King, “Pattern Recognition Software for Plant Surveillance”, US DOE Report, 1987.

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

[10] Upadhyaya, B.R., “Sensor Failure Detection and Estimation”, Nuclear Safety, 1985.

[11] Upadhyaya, B.R., and E. Eryurek, “Application of Neural Networks for Sensor Validation and Plant Monitoring,” Nuclear Technology, vol. 97, pp. 170-176, 1992.

[12] Hines, J. W. and Uhrig, R. E., “Use of Autoassociative Neural Networks for Signal Validation”, *Journal of Intelligent and Robotic Systems*, Kluwer Academic Press, 1997.

[13] Rasmussen, B., J.W., Hines, J.W., and R.E. Uhrig, “Novel Approach to Process Modeling for Instrument Surveillance and Calibration Verification”, *Third American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation and Control and Human-Machine Interface Technologies*, Washington DC, 2000.

[14] Fantoni, P., S. Figedy, A. Racz, “A Neuro-Fuzzy Model Applied to Full Range Signal Validation of PWR Nuclear Power Plant Data”, FLINS-98, Antwerpen, Belgium, 1998.

[15] Electric Power Research Institute EPRI, Instrument Calibration and Monitoring Program, Volume 1: Basis for the Method, EPRI, Palo Alto, CA: 103436-V1, 1993.

[16] Electric Power Research Institute EPRI, EPRI Topical Report (TR) 104965, “On-Line Monitoring of Instrument Channel Performance”, Final Report, 1998.

[17] NRC Memorandum to Stephen Dembek from Evangelos C. Marinos, Subject: The Staff Review of EPRI Topical Report (TR) 104965, “On-Line Monitoring of Instrument Channel Performance,” Final Report, November 1998, June 22, 2000.

[18] Zavaljevski, N., K.C. Gross, and S.W. Wegerich, Regularization Methods for the Multivariate State Estimation Technique (MSET), *Proc. of the Int. Conf. on Mathematics and Computations, Reactor Physics and Environmental Analysis in Nuclear Applications*, Madrid Spain, pp.720-729, 1999.

[19] Hines, J.W., Gribok, A.V., Attieh, I.,and Uhrig. R.E., “Neural Network Regularization Techniques for a Sensor Validation System”, Transactions of the American Nuclear Society Annual Meeting, San Diego, California, June 4-8, 2000.

[20] Hines, J. W., Gribok, A. V., Attieh, I., and Uhrig, R. E., “Regularization Methods for Inferential Sensing in Nuclear Power Plants”, *Fuzzy Systems and Soft Computing in Nuclear Engineering*, Ed. Da Ruan, Springer, 1999.

[21] Gribok, A.V.; Hines, J. W.; Urmanov, A. M.; and Uhrig, R. E., “Regularization of Ill-Posed Surveillance and Diagnostic Measurements,” Workshop on Power Plant Surveillance and Diagnostics, Halden, Norway, September 3-4, 2001. Chapter in Intelligent Systems for Process Monitoring and Diagnostics, *Physica-Verlag*, D. Ruan and P. F. Fontoni, Editors, 2002.

[22] Electric Power Research Institute EPRI, *Implementation of On-Line Monitoring for Technical Specification Instruments*, EPRI, Palo Alto, CA: 1006833, 2002.

[23] Zavaljevski, N., A. Miron, C. Yu, and E. Davis, “A Study Of On-Line Monitoring Uncertainty Based On Latin Hypercube Sampling And Wavelet De-Noising”, *4th Int. Topical Meeting on Nuclear Plant Instrumentation, Control and Human Machine Interface Technology (NPIC&HMIT ’04)*, Columbus Ohio, 2004.

[24] Gross, K.C., K.K. Hoyer, “Reactor Parameter Signal Simulator”, *Fourth International Conference on Simulation Methods in Nuclear Engineering*, Montreal Canada, June, 1993.

[25] Gross, K.C., K.K. Hoyer, “Spectrum Transformed Sequential Testing Method for Signal Validation Application”, *8th Power Plant Dynamics Control and Testing Symposium*, Knoxville, TN, 1992.

[26] Miron, A., Ph.D. Dissertation, “A Wavelet Approach for Development and Application of a Stochastic Parameter Simulation System,” University of Cincinnati, Cincinnati, Ohio, August 2001.

[27] Miron A. and J. Christenson, “The stochastic parameter simulation system: a wavelet-based methodology for perfect signal reconstruction,” *ANS Topical Meeting in Mathematics and Computations*, Gatlinburg, TN, 2003.

[28] Rasmussen, B., J.W. Hines, “Uncertainty Estimation for Empirical Signal Validation Modeling”, *4th International Topical Meeting on Nuclear Plant Instrumentation, Control and Human Machine Interface Technology (NPIC&HMIT ’04)*, Columbus Ohio, 2004.

[29] Rasmussen, B. and J.W. Hines, “Uncertainty Estimation Techniques for Empirical Model Based Condition Monitoring”, *6th International FLINS Conference on Applied Computational Intelligence*, Blankenberge, Belgium, 2004.

[30] Wegerich, S, R. Singer, J. Herzog, and A. Wilks, “Challenges Facing Equipment Condition Monitoring Systems”, *Proc. Maintenance and Reliability Conference*, Gatlinburg, TN, 2001.

[31] Coppock, S., and T. Holton, “Advanced Software Detects Temperature Indicator Failure”, *Transactions of the American Nuclear Society*, New Orleans, LA, 2003.

[32] EPRI, On-Line Monitoring Cost Benefit Guide, EPRI, Palo Alto, CA: 1006777, 2003.

[33] Hashemian, H.M., G.W. Morton, B.D. Shumaker, D. Lillis, S. Orme, Calibration Reduction System at the Sizewell B Nuclear Power Plant, *4th International Topical Meeting on Nuclear Plant Instrumentation, Control and Human Machine Interface Technology (NPIC&HMIT ’04)*, Columbus Ohio, 2004.

[34] Gribok, A. V., Attieh, I., Hines, J, W., and Uhrig, R. E., “Regularization of Feedwater Flow Rate Evaluation for Venturi Meter Fouling Problems in Nuclear Power Plants,” *Nuclear Technology*, vol. 134, pp.3-14, 2001.

[35] Hadamand, J., Lectures on "Cauchy's Problem in Linear Partial Differential Equations," Yale University Press, New Haven, CN, 1923.

[36] Gross, K. C., Singer, R. M., Wegerich, S. W., Herzog, J. P., Van Alstine, R., and Bockhorst, F. K., Application of a Model-based Fault Detection System to Nuclear Plant Signals, *Proc. of the International Conference. on Intelligent System Application to Power Systems*, Seoul, Korea. pp.60-65, 1997.

[37] Tikhonov, A.N., "Solution of Incorrectly Formulated Problems and the Regularization Method, Doklady Akad. Nauk., USSR 151, pp 501-504, 1963.

[38] Gribok, A. V., Attieh, I., Hines, J, W., and Uhrig, R. E., "Stochastic Regularization of Feedwater Flow Rate Evaluation for Venturi Meter Fouling Problems in Nuclear Power Plants," *Inverse Problems in Engineering*. Vol.0, pp.1-26, 2001.

[39] Uhrig, R. E. and Z. Guo, "Use of Neural Networks in Nuclear Power Plant Diagnostics," *Proceedings of the "International Conference on Availability Improvements in Nuclear Power Plants*," Madrid, Spain, April 10-14, 1989.

[40] Bartlett, E., and R. E. Uhrig, "Nuclear Power Plant Status Diagnostics Using an Artificial aNeural Network," *Nuclear Technology*, Vol. 97, pp 272-281, March 1992.

[41] Gou, Z., and R. E. Uhjrig, "Use of Artificial Neural Networks to Analyze Nuclear Power Plant Performance," *Nuclear Technology*, Vol. 99, pp 36-42, July 1992.

[42] Uhrig, R.E. and L.H. Tsoukalas, "Soft Computing Technologies in Nuclear Engineering Application," Invited State-of-the-Art Paper, *Advances in Nuclear Science and Technology*, Volume 34, pp 13-75, Plenum Press, 1998.

[43] Bartal, Y., J. Lin, and R. E. Uhrig, "Nuclear Power Plant Transient Diagnostics Using Artificial Neural Networks, that Allow "Don't Know'; Classifications," *Nuclear Technology*, Vol 110, No. 3, pp 436-449, June 1995.

[44] Attieh, I., J. W. Hines, and R. E. Uhrig, "Transient Detection in Nuclear Power Plants, *Proceedings of the Expanded Halden Programme Group Meeting on Instrumentation and control*, Lillihammer, Norway, March 28-31, 2001.

[45] Roverso, D., "Multivariate Temporal Classification by Windowed Wavelet Decomposition and Recurrent Neural Networks," *Proceedings of the 3rd ANS International Topical Meeting on Nuclear Plant Instrumentation, Control and Human-Machine Interface Technologies*, NPIC&HMIT 2000, Washington D.C.

[46] Roverso, D., "Plant Diagnostics by Transient Classification: the ALADDIN Approach," Special Issue on *Intelligent Systems for Plant Surveillance and Diagnostics*, International Journal of Intelligent Systems, Vol. 17, No. 8, pp. 767-790, Wiley Periodicals Inc., July 31, 2002.

[47] Uhrig, R.E.; Tsoukalas, L.H.; Ikonomopoulos, A., Essawy, M., Black, C.; and Yancey, S., "Using Neural Networks to Monitor the Operability of Check Valves," *Proceedings of the Conference on Expert System Applications for the Electric Power Industry*, Phoenix, AZ, Dec. 8-10, 1993.

[48] Guo, Z. and R.E. Uhrig, "Use of Artificial Neural Networks to Analyze Nuclear Power Plant Performance," *Nuclear Technology*, Vol. 99, pp 36-42., 1992.

[49] Irvine, C., "A Study of Nuclear Plant Heat Rate Optimization Using Nonlinear Artificial Intelligence and Linear Statistical Analysis Models", PhD Dissertation, The University of Tennessee, Nuclear Engineering Department, Knoxville, TN, 2000

[50] Hines, J.W, A. Gribok, A. Urmanov and R.E. Uhrig, "Heuristic, Systematic, and Informational Regularization for Process Monitoring", *International Journal of Intelligent Systems* on Intelligent Systems for Process Monitoring, Wiley Publishers, Vol. 17, No. 8, pp. 723-750, 2002.

[51] Box, G.E.P. and Draper, N.R., *Empirical Model-Building and Response Surfaces*, J.Wiley, New York, 1987.

[52] Hines, J.W and A. Usynin, "On-Line Thermodynamic Efficiency Monitoring and Optimization Using Empirical Modeling Techniques", 15th Annual Joint ISA POWID/ EPRI Controls and Instrumentation Conference 48th Annual ISA POWID Symposium, Nashville, TN, June 2005.

[53] Sunde, S., Berg, Ø., Jonson, A., Sonesson L.P., and Hafstad, S., Optimizing "Nuclear Steam-Turbine Cycles: Data Reconciliation and Real-Time Optimization", *Proceedings of the 3rd ANS International Topical Meeting on Nuclear Plant Instrumentation, Control and Human-Machine Interface Technologies, NPIC&HMIT 2000*, Washington DC. 2000.

[54] Sunde, S., Berg, Ø., "Data reconciliation and fault detection by means of plant-wide mass and energy balances", Progress in Nuclear Energy, Vol 43, no ¼, 2003.

[55] Favennec, J.M., A. Viette, S. Szaleniec, P. Ambos, and M. Kuntz, "*Improving power plant performance with process data reconciliation*", International Atomic Energy Agency Technical Meeting on "Increasing instrument calibration interval through on-line calibration technology", OECD Halden Reactor Project, Halden, Norway, September 2004.

[56] Uhrig, R.E., "Trends in Computational Intelligence in Nuclear Engineering", *5th International Conference on Fuzzy Logic and Intelligent Technologies in Nuclear Science (FLINS)*, Gent, Belgium, 2002.

[57] Uhrig, R.E., "Multi-Agent Based Anticipatory Control for Enhancing the Safety and Performance of Generation IV Nuclear Power Plants during Long-Term, Semi-Autonomous Operation," SMORN-8 (*Special Meeting on Reactor Noise*), Goteborg, Sweden, 2002.

[58] Agent Working Group, "Agent Technology Green Paper", OMG Document ec/2000-08-01, Version 1.0, Object Management Group, Needham, MA, 2000.

[59] Weiss, L. G. and Nicholas, N. C., "Intelligent Controller Architecture for Full Autonomy and HMI," *10th International Conference on Robotics and Remote Systems for Hazardous Environments*," Gainesville, FL, 2004.