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DE-FG07-03ID14497

AWARDEE NAME:
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PROJECT TITLE:
A New Method for Early Anomaly Detection of BWR Instabilities

Best Regards

Kostadin Ivanov

Principal Investigator

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A NEW METHODOLOGY FOR EARLY ANOMALY DETECTION OF BWR INSTABILITIES

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Contents

1	Project Abstract	3
2	Contact and Biographical Information.....	4
3	Description of Performed Work	6
3.1	Objectives.....	6
3.2	Development of Anomaly Detection Methodology.....	7
3.2.1	Symbolic Dynamics and Encoding	9
3.2.2	The Suboptimal <i>D</i> -Markov Machine	12
3.2.3	Anomaly Measure and Detection	15
3.2.4	Application to BWR Instabilities.....	16
3.5	Development and Qualification of the Reference BWR Model	19
3.6	Selection of Appropriate Input Stimuli.....	29
3.7	Identification of Appropriate Perturbed Parameters	32
3.8	Genration of Time-Series Data	35
3.9	Results of Application of Early Anomaly Detecion Methdology	40
3.10	Demonstartion of Capability to Detect BWR Instabilities	52
4	Project Schedule and Management.....	56
5	Bibliography	57

1 Project Abstract

Project Title: A New Methodology for Early Anomaly Detection of BWR Instabilities

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The objective of the performed research is to develop an early anomaly detection methodology so as to enhance safety, availability, and operational flexibility of Boiling Water Reactor (BWR) nuclear power plants. The technical approach relies on suppression of potential power oscillations in BWRs by detecting small anomalies at an early stage and taking appropriate prognostic actions based on an anticipated operation schedule.

The research utilizes a model of coupled (two-phase) thermal-hydraulic and neutron flux dynamics, which is used as a generator of time series data for anomaly detection at an early stage. The model captures critical nonlinear features of coupled thermal-hydraulic and nuclear reactor dynamics and (slow time-scale) evolution of the anomalies as non-stationary parameters. The time series data derived from this nonlinear non-stationary model serves as the source of information for generating the symbolic dynamics for characterization of model parameter changes that quantitatively represent small anomalies. The major focus of the presented research activity was on developing and qualifying algorithms of pattern recognition for power instability based on anomaly detection from time series data, which later can be used to formulate real-time decision and control algorithms for suppression of power oscillations for a variety of anticipated operating conditions.

The research being performed in the framework of this project is essential to make significant improvement in the capability of thermal instability analyses for enhancing safety, availability, and operational flexibility of currently operating and next generation BWRs.

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TEACHING

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PRINCIPAL PUBLICATIONS

1. J. Solis, M. Avramova, and K. Ivanov, "Temporal Adaptive Algorithm for TRAC-BF1/NEM/COBRA-TF Coupled Calculations in BWR Safety Analysis", Annals of Nuclear Energy, 29 (2002) 2127-2141.
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3 DESCRIPTION OF PERFORMED WORK

3.1 Objectives

The objective of this research, which has been supported by the US Department of Energy under the NEER program, is to develop an early anomaly detection methodology in order to enhance safety, availability, and operational flexibility of Boiling Water Reactor (BWR) nuclear power plants. The technical approach relies on suppression of potential power oscillations in BWRs by detecting small anomalies at an early stage and taking appropriate prognostic actions based on an anticipated operation schedule.

Gradually evolving changes in the parameters of a nuclear system over its service life may generate uncertainties in both stationary and dynamic behaviour. This problem is often addressed by overly conservative estimates of the critical design parameters due to lack of available information. Consequently, the engineering design of nuclear systems suffers from enforcement of large safety factors and results in reduced efficiency and unnecessarily expensive maintenance. Condition-based monitoring of plant health and performance is addressed in this research in regard to potential power oscillations in a BWR.

Sole reliance on model-based analysis for health monitoring is infeasible because of the difficulty in achieving requisite accuracy in modelling of gradually evolving parametric and non-parametric changes that lead to health and performance degradation of nuclear systems. For example, no existing model can capture the thermal-hydraulic-induced fatigue damage in critical structures (e.g., reactor pressure vessel and primary coolant pipelines) at the grain level based on the basic fundamentals of molecular physics. In general, small deviations in the initial conditions and critical parameters may produce large bifurcations in the expected dynamical behaviour, leading to chaos and strange attractors. Consequently, the analysis of time series data from the available sensors mounted at critical locations is essential for tracking the behavioral trajectory of the evolving health degradation.

Various signal processing applications deal with the analysis of time series data and attempts have been made to extract maximum useful information inherently present in the sensor data. Anomaly detection using symbolic time series analysis (STSA) is a pattern recognition method that has been recently developed based upon a fixed-structure, fixed-order Markov chain, called the *D-Markov machine*.

The model of coupled (two-phase) thermal-hydraulic and neutron flux dynamics, based on the US NRC coupled code TRACE/PARCS^{1,2}, is being used as a generator of time series data for anomaly detection at an early stage. The model captures critical nonlinear features of coupled thermal-hydraulic and nuclear reactor dynamics and (slow time-scale) evolution of the anomalies as non-stationary parameters. The time series data derived from this nonlinear non-stationary model serves as the source of information for generating the symbolic dynamics for characterization of model parameter changes that quantitatively represent small anomalies. This information is then used to develop algorithms of pattern recognition for power instability based on anomaly detection from time series data and to formulate real-time decision and control algorithms for suppression of power oscillations for a variety of anticipated operating conditions.

3.2 Development of Anomaly Detection Methodology

Behaviour identification in nuclear systems can be formulated as a two-time-scale problem if the underlying physical process is assumed to have stationary dynamics on the *fast* time scale and any observable non-stationary behaviour is associated with changes occurring on the *slow* time scale. In other words, the variations in the internal dynamics of the system are assumed to be negligible on the fast time scale, while pattern changes may become significant on the slow time scale. In general, a long time span in the fast time scale is a tiny (i.e., several order of magnitude smaller) interval in the slow time scale, over which the system dynamics are assumed to have stationary behaviour. For example, in the context of early detection of fatigue damage in structural materials, small load fluctuations in temperature and flow dynamics may take place on the fast time scale but the resulting damage evolution and anomaly growth (causing a detectable change in structural damage) occurs on the slow time scale; the fatigue damage behaviour is practically invariant on the fast time scale. Nevertheless, the notion of fast and slow time scales is dependent on the specific application and operating environment.

From the above perspectives, we utilized Symbolic Time Series Analysis (STSA) of calculated data to solve the problem of anomaly detection that is categorized as: (i) Forward Problem and (ii) Inverse Problem.

Forward Problem

The primary objective of the forward (or analysis) problem is to characterize the patterns followed by the process dynamics as its behavior changes on the slow time scale. The forward problem is executed off-line with an ensemble of collected data and its solution requires the following steps.

- Collection of sensor time series data to construct a pattern set spanning the system behavior under different operational conditions;
- Generation of symbolic sequences (on the fast time scale) from observed time series data at different epochs of the slow time scale;
- D-Markov machine} construction from the generated seworkymbol sequences and computation of the respective state probability vectors;
- Detection of behaviour changes by observing the deviations of the state probability vectors at various slow-time epochs from the one at the nominal condition.

Inverse Problem

The inverse (or synthesis) problem concentrates on inferring the anomalies based on the observed time series data and system response for the purpose of triggering control actions for behaviour control. This problem may not always be well-posed, i.e., there might be no unique solution. Therefore, analysis of time series data sets under various excitations might be necessary for solving the inverse problem.

The performed work in the framework of the project, focused on the construction and demonstration of the proposed early anomaly detection methodology³. The concept is based on the fact that nonlinear systems show bifurcation, which is a change in the qualitative behavior as the system parameters vary. Some of these parameters may change on their own accord and account for the anomaly, while certain parameters can be altered in a controlled fashion.

The non-linear, non-autonomous BWR system model considered in this research exhibits phenomena at two time scales. Anomalies occur at the slow time scale while the observation of the dynamical behavior, based on which inferences are made, takes place at the fast time scale. It is assumed that: (i) the

system behavior is stationary at the fast time scale; and (ii) any observable non-stationary behavior is associated with parametric changes evolving at the slow time scale. The goal is to make inferences about evolving anomalies based on the asymptotic behavior derived from the computer simulation. However, only sufficient changes in the slowly varying parameter may lead to detectable difference in the asymptotic behavior. The need to detect such small changes in parameters and hence early detection of an anomaly motivates the utilized stimulus-response approach. In this approach, the model of a BWR system is perturbed with an appropriate known input excitation to observe the asymptotic behavior at the fast time scale. A set of suitable input excitation parameters or stimuli are employed and the separate response of the BWR system to each of these stimuli is determined. As a result of the combination of the input stimulus and perturbed parameter(s), it is possible to observe a detectable change in the nature of asymptotic behavior that would otherwise remain unperceivable over a long period of time.

The developed early anomaly detection methodology is built upon the concepts of *Symbolic Dynamics*, *Finite State Automata*, and *Pattern Recognition* to qualitatively describe the dynamical behavior in terms of symbol sequences at the *fast-time* scale⁴. Appropriate phase space partitioning of the dynamical system yields an alphabet to obtain symbol sequences from time series data. To identify statistical patterns in these symbolic sequences, the tools of Computational Mechanics are used through construction of a (probabilistic) finite-state machine from each symbol sequence. Transition probability matrices of the finite state machines, obtained from the symbol sequences, capture the pattern of the system behavior by information compression. A detectable change in the pattern represents a deviation of the nominal behavior from an anomalous one and suffices for anomaly detection. The state probability vectors derived from the respective connection (state transition) matrices under the nominal and an anomalous condition, yield a vector measure of the anomaly. This vector measure provides more information than a scalar measure such as the complexity measure.

In contrast to the ϵ -machine that has an *a priori* unknown structure and yields optimal pattern discovery in the sense of mutual information, the state machine adopted here has an *a priori* known structure that can be freely chosen. Although this approach is suboptimal, it provides a common state machine structure where physical significance of each state is invariant under changes in the statistical patterns of symbol sequences. This feature allows unambiguous detection of possible anomalies from symbol sequences at different (slow-time) epochs. This fixed structure fixed-order Markov chain called the *D*-Markov machine is apparently computationally faster than the ϵ -machine because of significantly fewer number of floating point arithmetic operations. These are the motivating factors for introducing the *D*-Markov machine. The machines described above recognize patterns in the behavior of a dynamical system that undergoes anomalous behavior. In order to quantify changes in the patterns that are representations of evolving anomalies, we induce an *anomaly measure* on these machines denoted by *M*.

The early anomaly detection methodology is separated into two parts:

- i) Forward problem;
- ii) Inverse problem.

The major activity in the framework of this project was concentrated on the forward problem to build a firm foundation for further development of the methodology. The objective in the forward problem is to learn how the grammar underlying the system dynamics changes as the system parameters change. In other words, the forward problem is that of learning where the value of a parameter is associated with an anomaly measure. The following steps are identified to solve the forward problem:

1. Selection of appropriate Input Stimuli.
2. Signal-noise separation, time interval selection, and phase-space construction.

3. Choice of a phase space partitioning to generate Symbolic Dynamics.
4. State Machine construction using generated symbol sequence(s) and determining the connection matrix.
5. Selection of an appropriate metric for the anomaly measure M .
6. Formulation and calibration of a (possibly non-parametric) relation between the computed anomaly measure and known physical anomaly under which the time series data were collected at different (slow-time) epochs.

3.2.1 Symbolic Dynamics and Encoding

This section introduces the concept of *Symbolic Dynamics* and its usage for encoding nonlinear system dynamics from observed time series data. Let a continuously varying physical process be modeled as a finite-dimensional system in the setting of an initial value problem as:

$$\frac{dx(t)}{dt} = f(x(t), \theta); \quad x(0) = x_0 \quad (3.1)$$

where $t \in [0, \infty)$ is the time; $x \in \mathbb{R}^n$ is the state vector in the *phase space*; and $\theta \in \mathbb{R}^m$ is the (possibly slowly) varying parameter vector. The sole usage of the model in the Equation 3.1 may not always be feasible due to unknown parametric and non-parametric uncertainties and noise. A convenient way of learning the dynamical behavior is to rely on the additional information provided by (sensor-based) time series data. (Note: In this project the time-series data was produced by computer simulation).

A tool for behavior description of nonlinear dynamical systems is based on the concept of Formal Languages for transitions from smooth dynamics to a discrete symbolic description. The phase space of the dynamical system in the above equation is partitioned into a finite number of cells, so as to obtain a coordinate grid of the space. For simplicity, a compact (i.e., closed and bounded) region $\Omega \subseteq \mathbb{R}^n$ within which the motion is circumscribed is identified with the phase space itself. The encoding of Ω is accomplished by introducing a $\mathcal{B} \equiv \{B_0, \dots, B_{n_b-1}\}$ consisting of n_b mutually exclusive (i.e., $B_j \cap B_k = \emptyset, \forall j \neq k$) and exhaustive (i.e., $\bigcup_{j=0}^{n_b-1} B_j = \Omega$) cells. The dynamical system describes an orbit $O \equiv \{x_0, x_1, \dots, x_n, \dots\}$ which passes through or touches the cells of the partition $\mathcal{B}$. Let us denote the index of domain visited at the time instant i as the symbol $s_i \in \mathcal{A}$, where the set $\mathcal{A}$ of n_b distinct symbols that labels the partition elements is called the *symbol alphabet*. (Note: A symbol alphabet $\mathcal{A}$ is called a generating partition of the phase space Ω if a legal, i.e., physically admissible, symbol sequence uniquely determines a specific initial condition x_0 , implying that the mapping from the phase space to the symbol space is bijective) Each initial state x_0 in Ω generates a sequence of symbols defined by a mapping from the phase space to the symbol space as:

$$x_0 \mapsto s_i s_j \dots s_n \dots \quad (3.2)$$

The mapping in the Equation (3.2) is called Symbolic Dynamics as it attributes a legal symbol sequence to the system dynamics starting from an initial state. Although the theory of symbolic dynamics is well developed for one-dimensional mappings, very few results are known for two and higher dimensional systems. Recently, a technique for obtaining generating partition directly from the time series has been proposed by Kennel and Buhl. Figure 3.1 elucidates partitioning of a finite region of a phase space and a mapping from the partitioned space into the symbol alphabet, which becomes a representation of the system dynamics defined by the trajectories. It also shows the conversion of the symbol sequence into a finite state machine as explained in the later sections.

A data sequence (e.g., time series data) is converted to a symbol sequence by partitioning a compact region Ω (over which the data evolves) of the phase space into finitely many discrete blocks as shown in Figure 3.1. Let $\Psi \equiv \{\Phi_1, \Phi_2, \dots, \Phi_n\}$ be a partitioning of the phase space Ω , where Ψ is an exhaustive and mutually exclusive set of blocks. Each block $\Phi_j \in \Psi$ is labeled as the symbol $\sigma_j \in \Sigma$, where the symbol set Σ is called the *alphabet* consisting of m different symbols. As the system evolves in time, it travels through various blocks in its phase space and the corresponding symbol is assigned to it to convert a time series data sequence to a symbol sequence. $\dots \sigma_{i_1} \sigma_{i_2} \dots \sigma_{i_\ell} \dots$ as seen in Figure 3.1 that exemplifies partitioning of the phase space. Each block in Figure 3.1 is assigned to a particular symbol such that a symbol sequence is generated from the partitioned phase space at a given slow time epoch. Once the symbol sequence is obtained, the next step is the construction of the finite state machine. These steps are explained in details in the following subsections.

Figure 3.1 Phase Space Partitioning

A crucial step in symbolic time series analysis is partitioning of the phase space for symbol sequence generation. Several partitioning techniques have been reported in literature for symbol generation, primarily based on symbolic false neighbors. These techniques rely on partitioning the phase space and may become cumbersome and extremely computation-intensive if the dimension of the phase space is large. Moreover, if the time series data is noise-corrupted, then the symbolic false neighbors would rapidly grow in number and require a large symbol alphabet to capture the pertinent information on the system dynamics. Therefore, symbolic sequences as representations of the system dynamics should be generated by alternative methods because phase-space partitioning might prove to be a difficult task in case of high dimensions and in the presence of noise.

Finding a partitioning is a difficult task especially if the time series data is noise-contaminated. Several methods of phase-space partitioning have been suggested in literature. Apparently, there exist no well-established procedure for phase-space partitioning and this is a subject of active research.

We have used two approaches to find the partitioning needed to construct the symbol sequence. The first approach is the symbolic false nearest neighbors (SFNN) approach by Kennel and Buhl. The objective of this approach is to find a "generating" partition, where symbolic orbits uniquely identify one continuous space orbit, and thus the symbolic dynamics is fully equivalent to the continuous space dynamics. The method optimizes an essential property of a generating partition: avoiding topological degeneracies. The criterion is that short sequences of consecutive symbols ought to localize the corresponding state space point as well as possible. The central idea is to form a particular geometrical embedding of the symbolic sequence under the candidate partition and evaluate, and minimize, a statistics, which quantifies the apparent errors in localizing state space points. In a good partition, nearby points in the embedding remain close when mapped back into the state space. By contrast bad partitions induce topological degeneracies where symbolic words map back to globally distinct regions of state space. The *nearest neighbor*, in Euclidean distance, to each point in the embedding is found. Knowing symbolic neighbors, we find distances of those same points back in state space. Better partitions give a smaller proportion of *symbolic false nearest neighbors*. For concrete numerical calculations, the partitions are parameterized with a relatively small number of free parameters by defining the partitions with respect to a set of radial-basis "influence" functions. The statistics for symbolic false nearest neighbors is minimized over the free parameters using "differential evolution", a genetic algorithm suitable for continuous parameter spaces.

The second approach used, we will hereby call the wavelet space (WS) method is a new approach that we have introduced and that uses wavelet transform to convert the time series data to time-frequency data for generating the symbol sequence. The graphs of wavelet coefficients versus scale at selected time shifts are stacked starting with the smallest value of scale and ending with its largest value and then back from the largest value to the smallest value of the scale at the next instant of time shift. The resulting *scale series* data in the wavelet space is analogous to the time series data in the phase space. Then, the wavelet space is partitioned into segments of coefficients on the ordinate separated by horizontal lines. The number of segments in a partition is equal to the size of the alphabet and each partition is associated with a symbol in the alphabet.

The wavelet transform largely alleviates these shortcomings and is particularly effective with noisy data from high-dimensional dynamical systems. In this method, called *wavelet space partitioning*, the time series data are first converted by wavelet transform, where wavelet coefficients are generated at different scales and time shifts. The graphs of wavelet coefficients versus scale, at selected time shifts, are stacked starting with the smallest value of scale and ending with its largest value and then back from the largest value to the smallest value of the scale at the next instant of time shift. The arrangement of the resulting *scale series* data in the wavelet space is similar to that of the time series data in the phase space. The wavelet space is partitioned with alphabet size into segments of coefficients on the ordinate separated by horizontal lines such that the regions with more information are partitioned finer and those with sparse information are partitioned coarser. In this approach, the maximum entropy is achieved by the partition that induces uniform probability distribution of the symbols in the symbol alphabet. Shannon

entropy that is defined as $S \equiv - \sum_{i=1}^{|S|} p_i \log(p_i)$, where p_i is the probability of the i^{th} state and summation is taken over all possible states. Uniform probability distribution of states is a consequence of maximum entropy partitioning that might make the partition coarser in regions of low density of data points and finer in regions of high density of data points. For example, Figure 3.2 shows an example of the

maximum entropy partitioning in the wavelet space for alphabet size $|\Sigma|=6$, where the partitioned regions are marked by symbols ranging from 0 to 5.

Figure 3.2 Maximum entropy partitioning in the wavelet space

Having defined a partition, the time series or scale series data is converted to a symbol sequence that, in turn, is used for construction of a finite state machine using the tools of Computational Mechanics. Two alternative techniques of finite-state machine construction are: (i) the ϵ -machine construction; and (ii) a new technique based on D^{th} order Markov chains, called the D -Markov machine, for identifying patterns based on time series analysis of the observed data. Both techniques rely on information-theoretic principles and are based on Computational Mechanics. The anomaly detection methodology implemented in this research utilizes the D -Markov machine for finite-state machine construction.

3.2.2 The Suboptimal D -Markov Machine

This section describes the implemented technique for representing the pattern in a symbolic process, which is motivated from the perspective of anomaly detection. The core assumption here is that the symbolic process can be represented to a desired level of accuracy as a D^{th} order Markov chain, by appropriately choosing $D \in \mathcal{N}$. A stochastic symbolic stationary process $\mathbf{S} \equiv \dots, s_{-2}s_{-1}s_0s_1s_2\dots$, is called D^{th} order Markov Process if the probability of the next symbol depends only on the previous D symbols, i.e. the following condition holds:

$$P(s_i | s_{i-1}s_{i-2}\dots) = P(s_i | s_{i-1}\dots s_{i-D}) \quad (3.3)$$

For a given $D \in \mathcal{N}$ and neglecting the transient states, we define the following *effective* states of the symbolic process:

$$\mathcal{Q} = \{s^D : s^D \in A^D\} \quad (3.4)$$

The random vector for the above set of states is denoted by $\mathcal{Q}$ and the i th state as q_i . Given an initial state and the next symbol from the original process, only certain successor states are possible. This is represented as the allowed transitions between the states and the probabilities of these transitions as:

$$T_{ij}^{(s)} = P(\vec{S} = s, Q' = q_j | Q = q_i) \quad (3.5)$$

for all $q_i, q_j \in Q$. Note that $T_{ij}^{(s)} = 0$ for $q_i = s_1 s_2 \dots s_D$ and $q_j = s'_1 s'_2 \dots s'_D$ such that $s_2 s_3 \dots s_D \neq s'_1 \dots s'_D$. Thus, the stochastic matrix T is a branded matrix with at most $|A|^{D+1}$ nonzero entries.

The construction of a D -Markov machine is fairly straightforward. On a given symbol sequence, a window of length $D+1$ is slid by keeping a count of the frequency of occurrence of sequences $s_1 \dots s_D s_{D+1}$ and $s_1 \dots s_D$ which are respectively denoted by $N(s_1 \dots s_D s_{D+1})$ and $N(s_1 \dots s_D)$. Note that if $N(s_1 \dots s_D) = 0$ then the state $q = s_1 \dots s_D \in Q$ does not exist. The transitions probabilities are then obtained by these frequency counts as follows, (for $N(s_1 \dots s_D) \neq 0$):

$$T_{ij}^{(s)} = \frac{P(s_1 \dots s_D s)}{P(s_1 \dots s_D)} = \frac{N(s_1 \dots s_D s)}{N(s_1 \dots s_D)} \quad (3.6)$$

where, $q_i = s_1 \dots s_D$ and $q_j = s_2 \dots s_D s$.

Figure 3.3 State Machine with $D=2$, and $|A|=2$

As an example, Figure 3.3 shows construction of the finite state machine and the associated state transition matrix for a D -Markov process, where the alphabet size $|A| = 2$ and the states are chosen as words of length $D=2$ from the symbol sequence. Therefore, the total number of states is $|A|^D = 4$, which is the number of permutations of the alphabet symbols within a word of length D . The states are joined by edges labeled by a symbol in the alphabet. The state machine moves from one state to another upon occurrence of an event as a new symbol in the symbol sequence is received. The machine language is complete in the sense that there are different outgoing edges marked by different symbols; however, it is possible that the some of these arcs may have zero probability.

In general, the effects of an anomaly are reflected in the respective state transition matrices. Thus, the structure of the finite state machine is fixed for a given alphabet size and window length D . Furthermore,

the number of edges is also finite because of the finite alphabet size. The elements of the state transition matrix (that is a stochastic matrix) are identified from the symbol sequence.

The partitioning as described in the previous section is performed at time epoch t_0 of the nominal condition that is chosen to be a healthy condition having zero anomaly measure. A finite state machine is then constructed, where the states of the machine are defined corresponding to a given alphabet Σ and window length D . The alphabet size $|\Sigma|$ is the total number of partitions while the window length D is the length of consecutive symbol words forming the states of the Machine. The states of the machine are chosen as all possible words of length D from the symbol sequence, thereby making the number of states to be equal to the total permutations of the alphabet symbols within word of length D . The choice of $|\Sigma|$ and D depends on specific experiments, noise level and also the available computation power. A large alphabet may be noise-sensitive while a small alphabet could miss the details of signal dynamics. Similarly, a high value of D is extremely sensitive to small signal distortions but would lead to larger number of states requiring more computation power. Using the symbol sequence generated from the time series data, the state machine is constructed on the principle of sliding block codes.

The time series data under the nominal condition t_0 (set as a benchmark) generates the state transition matrix Π_0 that, in turn, is used to obtain the state probability vector p_0 whose elements are the stationary probabilities of the state vector, where p_0 is the left eigenvector of Π_0 corresponding to the (unique) unit eigenvalue. Subsequently, state probability vectors, $p_1, p_2, \dots, p_k$, are obtained at slow-time epochs $t_1, t_2, \dots, t_k$ based on the respective time series data. Machine structure and partitioning should be the same at all slow-time epochs. The *Anomaly Measure* at slow-time epochs t_k is obtained as an appropriately chosen distance function $d(p_0, p_k)$ such as the angle between the two vectors p_0 and p_k .

The following steps summarize the procedure of anomaly detection using Symbolic Time Series Analysis (STSA).

- Collection of time series data from appropriate sensor(s) at time epoch t_0 of the nominal condition, where the system is assumed to be in the healthy state (i.e., zero anomaly measure)
- Stacking of the wavelet transform coefficients (obtained with an appropriate choice of mother wavelet and range of scales) that are generated from the time series data at time epoch t_0 to generate the scale series data
- Partitioning of the scale series data into $|\Sigma|$ regions using maximum Entropy partitioning to obtain the symbol sequence \item Construction of the D -Markov machine states from the chosen alphabet size $|\Sigma|$ and the window length D and generation of the state probability vector p_0 at time epoch t_0 of the nominal condition
- Generation of time series data sequences at subsequent slow time epochs, $t_1, t_2, \dots, t_k$, and their conversion to the scale series data in the wavelet domain to generate respective symbolic sequences using the partitioning at time epoch t_0 of the nominal condition
- Generation of the state probability vectors $p_1, p_2, \dots, p_k$ at slow time epochs from the respective symbolic sequences $t_1, t_2, \dots, t_k$ using the finite state machine at time epoch t_0 of the nominal condition
- Computation of the *Anomaly Measures* at time epochs, $t_1, t_2, \dots, t_k$ relative to the probability vector p_0 at time epoch t_0 of the nominal condition

The two-tier architecture in Figure 3.4 presents a concept of decision and control for detection, prediction and mitigation of faults and disruptions in nuclear systems. The goal is to sustain order and normalcy in operation and control of the nuclear system infrastructures under various faults, disruptions, and threats. Nuclear systems are governed by both natural physical laws and human-engineered protocols. Therefore, their dynamics are hybrid in the sense that the continuously-varying processes (e.g., fluid flow and nuclear reactions) and occurrences of discrete events (e.g., faults, environmental disruptions, and human actions) dynamically interact with each other.

Figure 3.4 Hybrid decision and control architecture

3.2.3 Anomaly Measure and Detection

The machines described above recognize patterns in the behavior of a dynamical system that undergoes anomalous behavior. In order to quantify changes in the patterns that are representations of evolving anomalies, we induce an *anomaly measure* on these machines denoted by M . The anomaly measure M can be constructed based on the following information-theoretic quantities: entropy rate, excess entropy, and complexity measure of a symbol string S .

- The entropy rate $h_\mu(S)$ quantifies the intrinsic randomness in the observed dynamical process.
- The excess entropy $E(S)$ quantifies the memory in the observed process.
- The statistical complexity $C_\mu(S)$ of the state machine captures the average memory requirements for modeling the complex behavior of a process.

Given two symbol strings S and S_0 it is possible to obtain a measure of anomaly by adopting any one of the following three alternatives:

$$M(S, S_0) = \begin{cases} |h_\mu(S) - h_\mu(S_0)|, \text{ or} \\ |E(S) - E(S_0)|, \text{ or} \\ |C_\mu(S) - C_\mu(S_0)| \end{cases} \quad (3.7)$$

Note that each of the anomaly measures, defined above, is a *pseudo metric*. For example, let us consider two periodic processes with unequal periods, represented by $\mathcal{S}$ and $\mathcal{S}_0$. For both processes $h_\mu = 0$, so that $M(\mathcal{S}, \mathcal{S}_0) = 0$ for the first of the above three options, even if $\mathcal{S} \neq \mathcal{S}_0$.

The above measures are obtained through scalar-valued functions defined on a state machine and do not exploit the rich algebraic structure represented in the state machine. For example, the connection matrix T associated with the ε -machine can be treated as a vector representation of any possible anomalies in the dynamical system. The induced 2-norm of the difference between the T -matrices for the two state machines can be used as a measure of anomaly, i.e. $M(\mathcal{S}, \mathcal{S}_0) = \|T - T_0\|_2$. Such a measure was found to be effective. However, there is some subtlety in using this measure on ε -machines, because ε -machines do not guarantee that the machines formulated from the symbol sequences $\mathcal{S}$ and $\mathcal{S}_0$ have the same number of states; and these states do not necessarily have similar physical significance. In general, T and T_0 may have different dimensions and different physical significance. However, by encoding the causal states, T could be embedded in a larger matrix, and an induced norm of the difference between T matrices for these two machines can be defined. Alternatively, a (vector) measure of anomaly can be derived directly from the stochastic matrix T as the left eigenvector $\mathbf{p}$ corresponding to the unit eigenvalue of T , which is the state probability vector under a stationary condition.

In the case of D -Markov machines, which have a fixed state structure, the state probability vector $\mathbf{p}$ associated with the state machine have been used for a vector representation of anomalies, leading to the anomaly measure $M(\mathcal{S}, \mathcal{S}_0)$ as a distance function between the respective probability vectors $\mathbf{p}$ and $\mathbf{p}_0$ (that are of identical dimensions), or any other appropriate functional.

3.2.4 Application to BWR Instabilities

To develop a consistent and robust application of the Early Anomaly Detection of Instabilities (EADI) methodology, as outlined above, the following steps were followed:

- 1) Development and qualification of a reference BWR coupled three-dimensional (3-D) neutron kinetics/thermal-hydraulics code model including the power modal decomposition algorithm
- 2) Developing the methodology for the forward problem.
- 3) Developing the methodology for the inverse problem

The concept of the BWR EADI methodology is schematically outlined in Figure 3.5. Starting point is the generation of time series data using the coupled thermal-hydraulics/neutronics code TRACE/PARCS. The model of the BWR system is perturbed with an appropriate excitation stimulus to observe the asymptotic behavior at the fast time scale, making it possible to detect parametric or non-parametric changes in the BWR's dynamical behavior that may otherwise remain unperceivable over a long period of time. The approach followed in this research is shown in more details in Figure 3.6. Three major parts can be identified in this flow chart starting with the qualification of the coupled thermal-hydraulics/neutronics (TH/NK) code and Nuclear Power Plant (NPP) coupled code models and nodalization schemes. The TRACE/PACRS coupled time-domain code was qualified for stability analysis of BWRs using the data provided by the OECD Ringhals 1 Benchmark⁵. Methodologies and software tools developed in conjunction with the application of TRACE/PARCS for BWR instabilities simulations, which formed have formed a stability analysis "toolbox".⁶

Figure 3.5 Forward Problem Methodology

Figure 3.6 Flow Chart of EADI Methodology for BWR Applications

3.3 Development and Qualification of BWR Reference Model

The US NRC coupled code TRACE/PARCS is used to generate the time series data. The reference BWR model for this study is based on the Peach Bottom 2 (PB2) NPP, for which the TRACE/PARCS models have been validated using the OECD/NRC BWR TT Benchmark data⁷. The plant nodalisation scheme, which served to develop the system input deck of TRACE, is given in Figure 3.7.

TRACE Thermal-Hydraulic Model

TRACE PB2 model was developed in TRACE format, which consists of 67 components (see Figure 3.7). The reactor is modeled using the vessel component with 4 radial rings and 14 axial levels. The vessel model also uses 3 SEPD components utilizing the mechanistic separator option. The steam line is modeled using 2 TEE components and 3 VALVE components.

Figure 3.7 TRACE Thermal Hydraulics Model for PB2 TT2

Calculations to justify geometrical data and other parameters set forth in the input deck were performed. The Peach Bottom TRACE input model mainly consists of 67 components with

110 junctions. Thermal-hydraulic nodalization of the input model is illustrated in the Figure 3.7. The list of the components is:

- 1-33 core channels
- 50 Main feed water fill component
- 52 Main steamline tee component
- 53 Main steamline isolation valve
- 54 Main steamline tee component.
- 55 Turbine stop valve
- 57 Fill for guide tubes
- 58 Fill for guide tubes
- 59 Safety and relief valve
- 60 Pipe component
- 61 Recirculation pump
- 62 Tee component for recirculation loop
- 63 Jetpump
- 64 Pipe component which connects RPV and recirculation pump (Pump 65)
- 65 Recirculation pump
- 66 Tee component for recirculation loop.
- 67 Pipe component which connects jetpump 63 and recirculation loop
- 68 Jetpump
- 69 Manifold isolation valve which separates/connects two recirculation loops
- 70 Pipe component which connects jetpump 68 and recirculation loop
- 71 Steam separator and dryer component
- 72 Steam separator and dryer component
- 73 Steam separator and dryer component
- 76 Fill for guide tubes
- 80 Pipe component for guide tubes
- 81 Pipe component for guide tubes
- 82 Pipe component for guide tubes
- 83 Secondary fill for feedwater line
- 88 Tee component
- 90 Break for turbine stop valve
- 91 Break for safety and relief valve
- 93 Break for bypass valve
- 94 Pipe component which connects bypass valve (Valve 96) to Break 93
- 95 3-D Vessel Reactor Pressure Vessel (RPV)
- 96 Main steam bypass valve

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	
1										0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2								0	0	0	18	17	17	17	17	17	17	17	17	17	17	17	17	18	0	0	0	0	0	0	0	0	0	0
3							0	0	0	33	14	15	14	15	14	15	15	15	15	14	15	14	15	14	33	0	0	0	0	0	0	0	0	0
4					0	0	33	18	16	15	14	15	14	15	14	14	14	14	15	14	15	14	15	16	18	33	0	0	0	0	0	0	0	0
5				0	0	0	33	14	15	13	13	13	13	13	13	11	13	13	11	13	13	13	13	13	15	14	33	0	0	0	0	0	0	0
6			0	0	0	18	14	15	13	12	13	12	11	12	11	10	10	11	12	11	12	13	12	13	15	14	18	0	0	0	0	0	0	0
7		0	0	33	33	29	26	11	13	11	13	11	13	13	11	11	11	11	13	13	11	13	11	13	11	26	29	33	33	0	0	0	0	0
8	0	0	0	18	29	30	27	26	11	12	11	12	7	6	7	8	8	7	6	7	12	11	12	11	26	27	30	29	18	0	0	0	0	
9	0	0	33	29	30	13	13	27	25	7	7	7	7	7	8	8	8	8	7	7	7	7	7	25	27	13	13	30	29	33	0	0	0	
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25	0	0	0	18	29	30	27	26	11	12	11	12	7	6	7	8	8	7	6	7	12	11	12	11	26	27	30	29	18	0	0	0	0	
26		0	0	33	33	29	26	11	13	11	13	11	13	13	11	11	11	11	13	13	11	13	11	13	11	26	29	33	33	0	0	0	0	
27		0	0	0	18	14	15	13	12	13	12	11	12	11	11	10	10	11	12	11	12	13	12	13	15	14	18	0	0	0	0	0	0	
28			0	0	0	33	14	15	13	13	13	13	13	13	11	13	13	11	13	13	13	13	13	13	15	14	33	0	0	0	0	0	0	
29			0	0	33	18	16	15	14	15	14	15	14	14	14	14	14	14	15	14	15	14	15	16	18	33	0	0	0	0	0	0	0	
30				0	0	0	33	14	15	14	15	14	15	15	15	15	15	15	14	15	14	15	14	33	0	0	0	0	0	0	0	0	0	0
31					0	0	0	18	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	18	0	0	0	0	0	0	0	0	0	0
32						0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 3.8 Thermal Hydraulic Channel Mapping for PB2 TT2

PARCS Neutronics Model

The neutronics core model used in this study is based on the Peach Bottom Unit 2 core. This is a BWR/4 consisting of 764 fuel assemblies and 185 control rods. At the time of the TT2 test, there were 576 7x7 and 188 8x8 fuel assembly types. All fuel assemblies have Gadolinium as a burnable poison. The PARCS model represents each of the 764 fuel assemblies as a single neutronics node. The active core height is 365.76 cm, which is modeled in PARCS with 24 axial layers. The thickness of the axial layers is 15.24 cm. At the top and bottom of the active core, there are 15.24 cm-thick axial reflector regions. Full core geometry is modeled for the benchmark because the core is not symmetric because of the radial burnup distribution asymmetry.

The benchmark specifications provide a cross-section library with 432 sets of cross sections in the fuel region and 3 sets for reflector region (bottom, top, and radial reflector). The group constants for each set consist of two types of macroscopic cross section data, one for rodged and one for unrodged fuel assemblies. Peach Bottom Unit 2 is equipped with local power range monitors (LPRM). Forty-three detector strings are provided for the in-core instrumentation with each string containing four LPRM located at four axial elevations in the core. In the cross section library, the microscopic fission cross sections are provided for the fissile material of the fission chambers, as well as the assembly detector factors, which are the ratio between the flux in the detector location and the average flux of the neutronic cell. An LPRM model was developed and implemented in PARCS in order to compare the calculations with the measured in-core detector signals.

Coupled TRACE/PARCS Model

The TRACE/PARCS coupling is performed using a General Interface (GI), which was implemented using Parallel Virtual Machine. Overall controls of the coupled transient such as convergence checks and trip initiation are handled by TRACE. For fast steady state initialization, a neutronic calculation skipping strategy is used, i.e., PARCS calculation was done only once per every 20 time advances in TRACE. Fuel assemblies are mapped into 33 thermal-hydraulic channels as shown in Figure 3.8. The numbers indicate the channel assignments of the fuel assemblies and '0' corresponds to the reflector region. A thermal-hydraulic channel was not assigned to the reflector so that fixed reflector properties were used as provided in the final specifications. Minor modifications were made to the GI module in order to treat the fixed reflector nodes, as well as to handle the method specified for treating the moderator bypass density correction.

Steady State Initialization and Validation

Standalone Thermal-hydraulic Results

The developed TRACE input deck includes a by-pass model, and 33 core channels are modeled. Core inlet enthalpy, core average pressure drop and core averaged axial void fraction distribution are the selected parameters for steady-state comparisons for validation purposes. For these parameters, Table 3.1 compares TRACE predictions with reference values while Figure 3.9 illustrate the agreement of the TRACE result for core average axial void distribution as compared to the RETRAN prediction.

The correct modeling of initial steady state is important. TRACE results have shown excellent agreement for the steady state parameters. The maximum deviation for the core inlet enthalpy is less than 0.7%, and for the core pressure drop is less than 23%. The inlet enthalpy usually depends on the amount of steam carry-under from the separators. The transient response of the system is very sensitive to the separator modeling because this affects the initial location of the bulk boiling in the core channels. The accuracy of the core pressure drop calculations is affected by the predictions of the inlet enthalpy, which is related to the modeling of steam separators-dryers, and loss coefficients in the vessel and channels. The most challenging part of the steady state analysis is the prediction of the void fraction distribution. This prediction depends on the modeling of the core channels, vessel levels, steam dryers-separators, jet-pumps and recirculation loops, and also depends on the features of the system code. With all those challenges in mind one can consider that the core average axial void fraction distribution results have very good agreement. The results have shown slight differences at the axially lower (bottom) part of the core.

In summary, it is obvious that steady state simulation of this kind of large systems is very difficult and it needs an extensive work on the each component's model, as well as the correct simulation of the control phenomenon in the input models, such as controlling the water level, recirculation pump speed, jet-pump flows, feed water flow and steam line pressure.

For core inlet enthalpy:

Measured Value = 1209.06 kJ/kg

Calculated Value (TRACE) = 1210.36 kJ/kg

For core pressure drop (between upper plenum to lower plenum):

Measured Value = 250 kPa.

Calculated Value (TRACE) = 285 kPa

Table 3.1 Comparison of Steady-State Results with Measured Plant Data

Parameter	Measurement	TRACE
Core Thermal Power (MWt)	2028	2028
Core Flow (kg/s)	10445	10420
Core Bypass Flow (kg/s)	841.68	1100
Feedwater Flow (kg/s)	-980.26	991
Feedwater Temperature (K)	442.3	442.3
Core Inlet Enthalpy (kJ/kg)	1209.06	1210.36
Recirculation Flow (kg/s)	2871.24	2785
Steam Flow (kg/s)	-	991
Core Inlet Pressure (MPa)	-	7.275
Core Outlet Pressure (MPa)	-	6.990
Core Pressure Drop (MPa)	-	0.285
Steam Dome Pressure (MPa)	6.80	6.80
Average Core Exit Void Fraction	-	65.7
Core Average Void Fraction	-	33.4
Subcooling (K)	9.86	13.35

Figure 3.9 Core Average Void Fraction Distribution

Coupled Code Results

A comparison of the steady-state results predicted by TRACE/PARCS with measured plant data is shown in Table 3.2 and Figure 3.10. As indicated, the predicted and measured results are generally in good agreement.