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Development of Methodology for Early Detection of BWR Instabilities

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INTRODUCTION

The objective of the presented in this paper research, which is 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.

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 utilized 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 reaction 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.

DESCRIPTION OF THE ACTUAL WORK

The performed work during the first year of the project, which is described in this paper, focused on the construction of proposed anomaly detection methodology[3]. 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 motivate 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 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* scale. 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 anomaly detection methodology is separated into two parts: (i) Forward problem; and (ii) Inverse problem. The described here first year activity has been 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 othe words the forward problem is that of learning where the value of a parameter is associated with an anomaly measure.

RESULTS AND DISCUSSION

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), for which the TRACE/PARCS models have been validated in the framework of the OECD/NRC BWR TT Benchmark[4]. The selection of the set of stimuli to be applied to the system is a critical step for the proposed methodology. The selected perturbation must not interfere with the normal operation of the plant (or, in this case, with the numerical simulation of the plant). In particular, unstable or excessive oscillations must not occur as a consequence of the input perturbations and the plant must return to the original state after the perturbation is terminated. On the other hand, the stimulus imposed to the system has to be ample enough in order for the analyst to infer the stability characteristic of the plant. These observations are especially true for externally applied small perturbations. Different types of perturbation have been identified and subsequently applied to PB2. Among them the system pressure perturbation is selected to be presented in this paper. Utilizing the control block capability of TRACE for each of the selected input stimuli, the following three perturbations shapes have been simulated: 1) continuous sinusoidal shape, 2) fragmented sinusoidal shape and 3) square shape. The pressure perturbation by acting on the turbine control valve beginning at a time of 2000 seconds is shown in Figure 1.

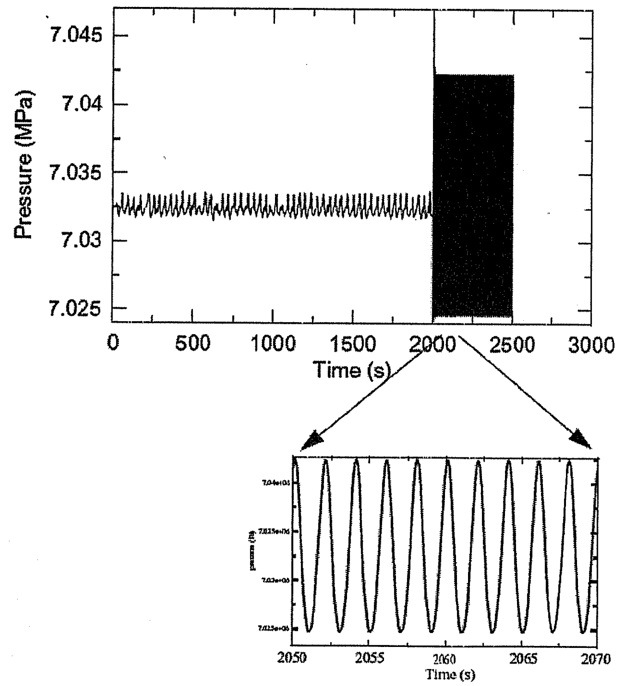

Figure 1. System pressure perturbation

Another critical step of the methodology is the selection of suitable perturbed (possibly slowly) parameters. The followed approach consists in taking into account a combination of the most sensitive stability variables. Based on the investigated parameters and on their relevance on BWR stability, nine no-dimensional groups of parameters have been identified and used in the anomaly detection methodology. In particular four of them are resulted the more viable to detect difference in the asymptotic behavior by slow and small changes in their values. Among them β_3, which represents the importance of the feedback reactivity effects, is selected to be presented here. Extensive code simulations have been performed for different core conditions such as beginning of life (cycle) BOL and end of cycle (EOC). For each simulation after 2000 seconds of 'null' transient, the pressure perturbations described above are applied for 500 seconds. The identification of small changes in the behavior of nonlinear dynamics systems requires the selection of appropriate time series data. The following ones have been taken into considerations: core mass flow in, core mass flow out; reactor power; feed water flow rate, steam line flow rate; steam dome pressure and etc. Figures 2 shows the results obtained by the application of the early anomaly detection of BWR instabilities respectively for BOL. In this case the time series data for mass flow out and β_3 have been considered.

Three different regions can be identified in Figure 2: 1) a first zone where the anomaly curve increases quite rapidly outlining the features of early anomaly methodology; 2) a plateau region that corresponds to the 'critical' combination of parameters; 3) a third zone where the anomaly curve restarts to increases, identifying the possible incoming BWR instabilities. As β_3 increases, one can see a rapid rise in anomaly measure. This indicates that the methodology is successful in detecting early growth in anomaly. In addition the anomaly curve is bounded with uncertainty bands with a confidence level of 98%.

CONCLUSIONS

In this research, a new methodology for early detection of BWR instabilities has been developed and an initial demonstration of the capability of the methodology to predict the BWR instabilities has been demonstrated. A more sophisticated qualification process for the proposed methodology is under way and it will constitute one of the main goals to be achieved during the second year of the NEER project.

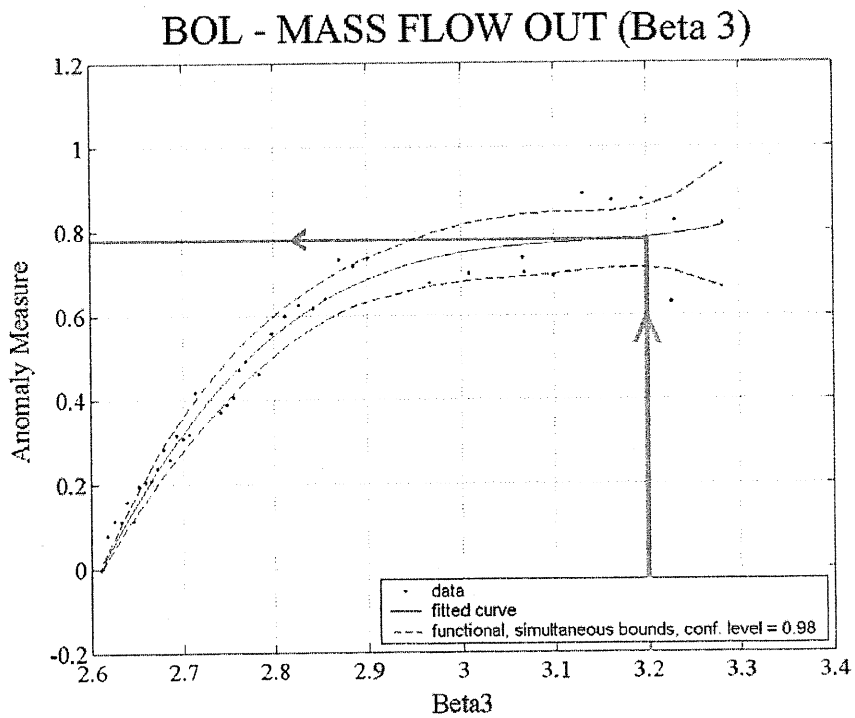

Figure 2. Demonstration of the capability to detect BWR instabilities

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