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**NEURAL NETWORK-BASED MONITORING AND CONTROL OF
FLUIDIZED BED**

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Abstract

In this report, a summary on the work done on the chaotic behavior control in FBC systems project will be given. And an update to the chaos control method we design to control the chaotic behavior in an FBC system will be discussed. This method includes a fully recurrent neural network called the Dynamic System Imitator (DSI). The DSI was specially designed to mimic the behavior of a wide variety of dynamic systems in the real world. It is found to be capable of learning both the transient and steady state behavior of a dynamic system. The DSI was applied for modeling of linear, non-linear and chaotic systems. It is also successfully used for iterative prediction of chaotic system behavior. A general methodology for using the DSI to control a non-linear system is studied. This methodology is applied to control the chaotic behavior of the Lorenz System as a typical chaotic system. A plan is also outlined for this method to be applied to the Fluidized Bed Combustion (FBC) system for the prediction and control of its chaotic behavior. The chaotic pressure data, from an experimental fluidized bed combustion system, was obtained from the Morgan town Energy Technology Center (METC). These data represent some normal and abnormal mixing process in an FBC system. The results of chaos analysis, applied to these data, will be presented. These techniques are used to identify the system behavior at different conditions, to estimate the system order, to construct the system attractor, and to locate the chaotic behavior in the pressure-drop time series data. Preliminary analysis show that both the normal and abnormal conditions of the FBC have chaotic characteristics. The overall objective is to know more about the characteristics of the time series at different conditions, to find an appropriate model for the system, and to apply a neuro-chaos controller to preserve the normal operational performance of the system.

Introduction

In the recent years lots of attention has been given to study systems that exhibit a type of behavior known as chaotic. Those systems were confused in the past with stochastic systems. Recently, it has been found that chaotic behavior can be driven by low order deterministic phenomena.^[1] Simple models for those phenomena are achievable. However, general solution to those systems can not be found, and any long term prediction can not be realized. The reason is the sensitive dependence of such systems on initial conditions. One example is the n-body system problem for which no general solution was found, and also known for its sensitive dependence on initial conditions. Chaos has been sought for many years as undesirable phenomena. It was found though that this is not always the case. On occasion, chaos is a beneficial feature as it enhances mixing and chemical reactions and provides a vigorous mechanism for transporting heat and/or mass.^[2] It is also the secret behind the survival of biological systems under extremely different conditions, due to their multiple attractor structure, which enables those systems to easily switch their parameters to adapt to new environment and maximize their performance. In the past few years several methods have been developed to control the chaotic behavior of chaotic systems.^[1-6] These methods were applied to both theoretical models and actual chaotic systems in many fields. They were applied to control chemical reactions,^[7] communication,^[8] nonlinear oscillators, lasers,^[9] diodes,^[6] heat convection,^[2] mechanical vibrations, myocardial tissue (biological systems),^[10] magnetoelastic systems,^[1,3] and several other applications. Chaotic systems' behavior control, in case it is achievable, gives them an advantage over non-chaotic systems, due to the ability to switch the chaotic systems' performance between several different modes.^[1,4] For that same reason we might sometimes wish to build chaos into a system where it is naturally absent. In this paper we will present a method to monitor and control the chaotic behavior in a Fluidized Bed Combustion (FBC) system. This method is based on analysis we performed on data obtained from an experimental fluidized bed combustion system at the Morgan-town Energy Technology Center (METC). These data represent some normal and abnormal operating conditions of that FBC system. Previous work in this area can be reviewed in references 11-13. A special type of a recurrent neural network, called the Dynamic System Imitator (DSI),^[14] will be adopted as a neuro-controller and a short term chaotic time series predictor in the proposed method. The DSI network was used to control the chaotic behavior in the Lorenz system. Sample results from the analysis performed on the FBC data will be presented, and an outline of the proposed method will be introduced.

The Chaotic Behavior in FBC Systems

Through the analysis of both the normal and abnormal FBC pressure data, it is evident that they have strange attractors, and both belong to a chaotic system. This means that the prospective control method needs to switch the system from one chaotic state to another chaotic state, which has been achieved before in simple chaotic systems such as the logistic map.^[15] A two dimensional projection of the reconstructed attractor from a normal and abnormal cases are shown in Figures 1 and 2, respectively.

Figure 1 A plot of the FBC normal attractor projected onto two dimensional map.

Figure 2 A plot of the FBC abnormal attractor projected onto two dimensional map.

As it appears in the two figures the normal data attractor looks much more well behaved than the abnormal data. We performed several methods to compute the parameters of both attractors. We computed the correlation dimension, the Kolmogorov entropy, and the Lyapunov exponents of the normal and abnormal attractors. The correlation integral was computed according to the following equation:^[16]

$$C(N, \varepsilon) = \frac{2}{N(N-1)} \sum_{j=1}^N \sum_{i=j+1}^N \theta(\varepsilon - |x_i - x_j|), \quad (1)$$

where $\theta(x)=1$ for $x>0$ and $\theta(x)=0$ for $x<0$. The Kolmogorov entropy was computed according to the relationship:^[17]

$$K_{m,d} = \frac{1}{m} \ln \frac{C_d(\varepsilon)}{C_{d+m}(\varepsilon)} \quad (2)$$

And the Lyapunov exponents were computed according to the Sano-Swada technique to compute the Lyapunov spectrum from a chaotic time series.^[18] The correlation integral graphs for the normal and abnormal attractors in a range of embedding dimensions are shown in Figures 3 and 4, respectively. The results of the chaos analysis of the FBC data are summarized in Table 1. These analysis show that both the normal and abnormal modes of the system live on a chaotic attractor, because both have fractal dimensions, positive Kolmogorov entropy, and positive Lyapunov exponents.

	Normal Data	Abnormal data
Correlation Dimension	3.07	17.35
Kolmogorov Entropy	0.008	0.1

Table 1 Results of chaos analysis of the FBC data.

However, the correlation dimension for the abnormal attractor is much higher than the normal one, which is an indication that when the system changes from its normal to its abnormal behavior,

it goes from low order to high order chaos. This situation is a big challenge to any traditional control method. However, we believe that the system parameters can be adjusted through chaos control method to move the system from its high order chaotic behavior to the normal low order chaotic state. A proposed method for the FBC system monitoring and control is discussed below. Even though the chaos analysis methods described above are the best to define the condition of a chaotic system, they are not suitable for on-line monitoring because they need intensive calculations that might run several ours on digital computers. Instead, a chaotic time series predictor technique will be used.

Figure A plot for the correlation integral of the FBC normal attractor, for embedding dimensions 2-20.

Figure A plot for the correlation integral of the FBC normal attractor, for embedding dimensions 2-30.

The Proposed Monitoring and Control Method

For any control method to function properly with the prescribed system, there should be some monitoring device that will monitor the system state and switch the controller on, in case of detection of any abnormal behavior. We will monitor the system using a chaotic time series predictor that we developed using the DSI neural network. This chaotic time series predictor was able to predict the chaotic behavior of chaotic time series generated by several chaotic systems such as the logistic map, the Henon map, and the cubic map. In all cases the DSI predictor was able to predict the chaotic behavior of the time series for a short time starting from some time history of the signal. It was also able to predict the state space system attractor for the rest of the time. If we train the DSI predictor to predict the normal behavior of the system, starting from some initial measurements, then the average error between the actual and predicted time series over a certain period of time will give us an indication of how much drift did the system make from its normal condition. Once a certain threshold is violated we can switch the controller on. To be able to design a controller for such a system we need to study the effect of different system parameter on the behavior, and find which parameters are responsible for the system drift from normal. If any of these parameters would be accessible for control, we can implement a control method as illustrated in Figure 5. The only obstacle before executing and testing this method is to find an appropriate model that will describe the prescribed system behavior in all modes. This model will be used to study the effect of system parameters on the system behavior and to test the performance of the proposed control methodology. The reason we chose to use the DSI neural network in this situation is the known dynamic characteristics of such a network. The DSI is a fully recurrent neural network that was specially designed to model a wide variety of dynamic systems. It has feedback connections and integrators to form a compact representation of time lags and interactions in real systems. It is suitable for on-line applications due to its fast response and realistic interface with the outside world. It is also equipped with a multidimensional optimization technique and dynamic windowing which allows it learn system dynamics from long time series. The DSI network has been used before to control the chaotic behavior in the Lorenz system, and stabilize it into either a fixed point or a periodic orbit. In that application, one state variable was fed back as an input to the DSI, and the output of the DSI was used to control the system. The error between the actual output of the system and a target behavior was used to train the DSI network. State point perturbation control and parameter perturbation control methods have been demonstrated. We wish that a similar technique will work with the FBC system, even though we believe that the FBC system is a much more difficult problem, due to its complex behavior under both normal and abnormal conditions.

Conclusion and Future Work

In this paper, analysis to data measured from an FBC facility has been presented. The purpose of this analysis is to build basis for a neuro-controller design that can be used to control some undesirable abnormal behavior in FBC systems. This analysis shows that both the normal and abnormal behavior represented in the data available are chaotic. The system's normal and abnormal attractors have fractal dimensions, some positive Lyapunov exponents and positive Kolmogorov entropy.

Figure 5 An illustration of the proposed control method for the chaotic FBC system.

However, the correlation dimension of the abnormal case is much higher than the normal case. This indicates that when the system switches to its abnormal situation it suffers a very complex behavior, most likely belongs to a higher order chaos. An appropriate controller is desired to control the system abnormal chaotic behavior to its normal chaotic behavior. A general method to monitor and control the chaotic behavior in an FBC system has been outlined. A recurrent neural network called the Dynamic System Imitator (DSI) was adopted. The only missing chain to test the proposed method is an appropriate non-linear model that will describe the FBC in different modes. Finding this model, and testing the proposed monitoring and control method, will be our main focus of future work in this project.

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Post Doctoral Research Associate:

Magdi A. Essawy, was hired as a full time Postdoctoral Research Associate at the Department of Electrical and Computer Engineering, starting October 1995; Previously, a part time Postdoctoral Research Associate at the Department of Nuclear Engineering, University of Tennessee; Received his Ph.D. in Nuclear Engineering from the University of Tennessee, Knoxville, in August 1995; has an M.S. and B.S. in Electrical Engineering; and has experience and academic interest in the fields of: Applied Artificial Intelligence, Artificial Neural Networks, Non-linear System Dynamics, Chaotic System Analysis, Chaotic System Control, Wavelet Analysis, Gabor and Fourier Analysis, Signal Processing, Dynamic System Simulation and Control, System Monitoring, Check Valve Monitoring in Power Plants, Expert Systems, Fuzzy Logic, and Electric Power System Analysis.

Student Involvement:

Mr. James Osa, Graduate Student. He is working on his Master Thesis, and is supported by this grant. He is involved on doing some preliminary analysis on FBC data. He is also working on some neural network models for chaotic series, and neural network model for chaotic system controllers.

Mr. Deepak Arulraj, Graduate Student. He is working on his Master Thesis, and is supported by this grant. He is involved on doing some preliminary analysis on FBC data.

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