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CHAOTIC BEHAVIOR CONTROL IN FLUIDIZED BED SYSTEMS USING ARTIFICIAL NEURAL NETWORK

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WALLACE ROAD, BUILDING 921
P.O. BOX 10940, MS 921-118
PITTSBURGH, PA 15236-0940

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BY

MOHAMMAD BODRUZZAMAN, Ph.D.
PRINCIPAL INVESTIGATOR

MAGDI A. ESSAWY, Ph.D.
RESEARCH ASSOCIATE

SCHOOL OF ENGINEERING AND TECHNOLOGY
TENNESSEE STATE UNIVERSITY
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DISCLAIMER

ABSTRACT

Coal-fired power plants are very important source for electric power generation in the United States and worldwide. This is because Coal is abundant and inexpensive compared to oil and gas. However, greater use of coal is constrained by the difficulties of solid fuel use and of cleanup of combustion products containing ash and gaseous pollutants. Results of innovative research can expand coal utilization by making it more convenient to handle and by increasing its reliability to that of liquid and gaseous fuels. Direct utilization of coal fluidized combustion is of interest because of potential cost savings and improved environmental performance. Thus, pressurized fluidized-bed combustors (FBC) are becoming very popular, efficient, and environmentally acceptable replica for conventional boilers in Coal-fired and chemical plants. In this paper, we present neural network-based methods for chaotic behavior monitoring and control in FBC systems, in addition to chaos analysis of FBC data, in order to localize chaotic modes in them. Both of the normal and abnormal mixing processes in FBC systems are known to undergo chaotic behavior. Even though, this type of behavior is not always undesirable, it is a challenge to most types of conventional control methods, due to its unpredictable nature. The performance, reliability, availability and operating cost of an FBC system will be significantly improved, if an appropriate control method is available to control its abnormal operation and switch it to normal when exists. Since this abnormal operation develops only at certain times due to a sequence of transient behavior, then an appropriate abnormal behavior monitoring method is also necessary. Those methods has to be fast enough for on-line operation, such that the control methods would be applied before the system reaches a non-return point in its transients. It was found that both normal and abnormal behavior of FBC systems are chaotic. However, the abnormal behavior has a higher order chaos. Hence, the appropriate control system should be capable of switching the system behavior from its high order chaos condition to low order chaos. It is to mention that most conventional chaos control methods are designed to switch a chaotic behavior to a periodic orbit. Since this is not the goal for the FBC case, further developments are needed. We propose neural network-based control methods which are known for their flexibility and capability to control both non-linear and chaotic systems. A special type of recurrent neural network, known as Dynamic System Imitator (DSI), will be used for the monitoring and control purposes.

INTRODUCTION

Coal fired power plants are important source of electric power in the united states and all around the globe. Due to the large amounts of coal reserve around the world, it is expected that coal will stay as one of the main sources of power for many decades to come. Improving the efficiency, performance, and safety of such power plants, and minimizing toxic pollutants coming from their stacks, will make them more economically and environmentally acceptable options.

In the recent years, attention was given to a new type of energy conversion device, a critical component of any coal fired plant. This new type of energy conversion system is known as a Fluidized Bed Combustor (FBC). In such a system, the direct utilization of the coal fuel enhances the energy conversion process and reduces the energy losses as compared to conventional energy conversion systems. Considerable efforts are being made to further improve the design and performance of FBC systems.

In this paper, we introduce a neural network-based system to monitor and control an undesirable abnormal behavior observed in FBC systems. In addition, to chaos analysis to both of the normal and abnormal behaviors. Such abnormal behavior may lead to inefficient performance, interrupted operation, or poor fuel utilization in an FBC system. Previous research show that both of the normal and abnormal behavior in FBC systems are chaotic.[1-4] A type of behavior known of its unpredictability, which makes it a challenge to any conventional monitoring or control method. This makes artificial intelligence methods a potential option due to their known abilities to deal with non-linearity, multidimensionality, and noise. Furthermore, the learning ability of neural systems will simplify the design process and will lead to more general and adaptive solutions.

Scientists in many fields often encounter systems that exhibit chaotic time evolution.[5] Chaos is abundant both in nature and man-made devices, to an extent that many scientists believe that it is the rule rather than the exception.[6] The chaotic behavior is known to be unpredictable, which may be unsafe to the operation of many devices, and make it unwelcome in many situations. 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. However, in many other situations, chaos is undesirable phenomena which may lead to vibrations, irregular operation, fatigue failure in mechanical systems, temperature oscillations which may exceed safe operational conditions in thermal systems, and increasing drag in flow systems.[6]

Chaotic motion has been regarded for many years as a troublesome property that is neither predictable nor controllable. Recently researchers have realized that chaos can actually be advantageous in many situations, and when it is unavoidably present, it can often be controlled to obtain desired results.[5,7] In 1990, Ott, Grebogi, and Yorke (OGY) demonstrated that one can convert the motion of a chaotic dynamical system to periodic motion by controlling one of the system's many unstable periodic orbits embedded in the chaotic attractor, through only small time-dependent perturbations in an accessible system parameter.[8-14] Ott and Spano [5], stated that if chaos control is practical in a system, then the presence of chaos can be an advantage. Any one of a number of different unstable orbits, in a chaotic system, can be stabilized, and one can select the orbit that gives the best system performance. Thus we have the flexibility of actually switching the system behavior by stabilizing another periodic orbit. On the other hand, if the system is actually stable and periodic, we can use control to only slightly change its performance, and we do not have similar flexibility to what is available in a chaotic system. Hence, we may even sometimes wish to build chaos into a system where it is naturally absent.

In this paper, we present a method where a recurrent type of neural network can be used to control the chaotic behavior in a chaotic system. We suggest to use this method to switch the abnormal chaotic behavior in an FBC system to its chaotic normal state. This control system should be accompanied with an on-line monitoring system that initiates the control actions once the abnormal behavior is monitored. We present a neural network-based strategy to identify the different chaotic behavior modes encountered in an FBC system. [15] This identification process can be achieved by comparing the actual measurement from the chaotic system with the time series predicted by neural network-based iterative predictor model, starting from a short time history of the actual data. A dynamic type of neural network will be used for both monitoring and control tasks. Dynamic neural networks are considered due to their time behavior and their ability to deal with transient conditions. A special type of recurrent neural network called the Dynamic System Imitator (DSI) will be used.

LOCALIZATION OF THE CHAOTIC BEHAVIOR IN THE FBC DATA AVAILABLE

Morgantown Energy Technology Center has built and operated a cold flow model to emulate fluid dynamics in an FBC system. As illustrated in Figure 1, the cold flow verification test facility consists of a ten foot high jetting fluidized bed made of clear acrylic and configured as a half cylinder vessel to facilitate jet observation. A central nozzle, made up of concentric pipes, continuously fed solids at 0 to 8 psig pressures. Separate flow loops controlled the conveyance of solids (inner pipe), the make-up air flow (middle pipe), sparger flow (outer pipe), and six air jets on the sloping conical grid. The half round fluid bed model provided useful information to study fluidization and design issues including jet penetration, chaotic pressure fluctuations, and mass flow rates of particles in various regions of the jetting fluid bed. The fluid bed tests were conducted using cork particles to simulate the relative density of gases to scale for a high pressure coal conversion reactor. As expected, the test generated chaotic pressure fluctuations. The differential pressures were measured at two location with each location consisting of two pressure taps spaced four inches apart. The lower pair of pressure taps were placed at a height just above the nozzle and the upper pair of pressure taps were placed at a height where the jet becomes evenly distributed across the diameter of the reactor. Differential pressure data collected at the higher sensor served as the primary data for the investigation of chaos. It clearly indicated the fluidization regime of the bed supported by visual observations. Data were collected on a data acquisition card at a rate of 50 Hz.

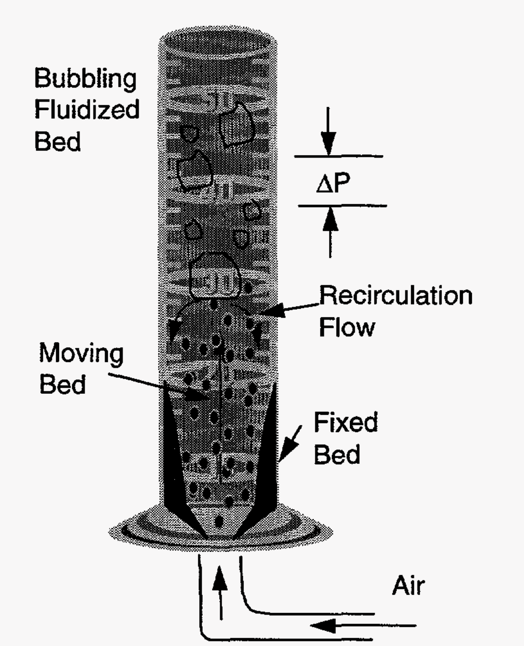

Figure.1 The general setup of the existing cold FBC experiment at METC.

Through our 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.[16] A two dimensional projection of attractors from a normal and abnormal FBC time series are shown in Figures 2 and 3, respectively. 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:[17]

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

where $\theta(x)=1$ for $x>0$ and $\theta(x)=0$ for $x<0$. The Kolmogorov entropy was computed according to the relationship:[18]

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

And the Lyapunov exponents were computed according to the Sano-Swada technique to compute the Lyapunov spectrum from a chaotic time series.[19]

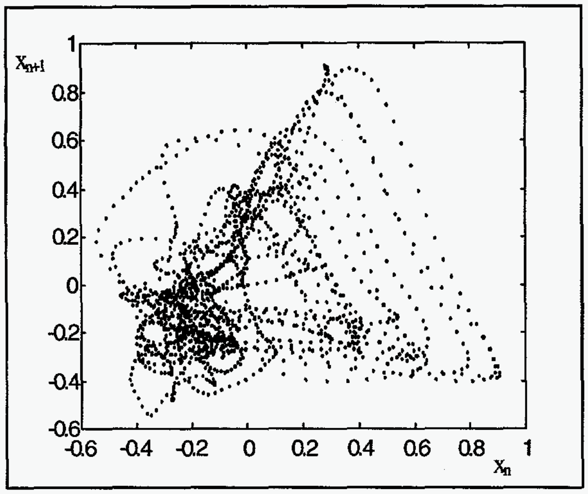

Figure 2 A plot of the FBC normal attractor projected onto two dimensional map.

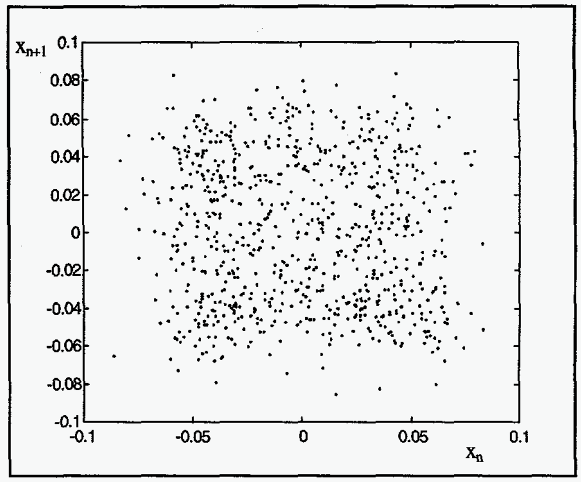

Figure 3 A plot of the FBC abnormal attractor projected onto two dimensional map.

The correlation integral graphs for the normal and abnormal attractors in a range of embedding dimensions are shown in Figures 4 and 5, 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	8	100

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.

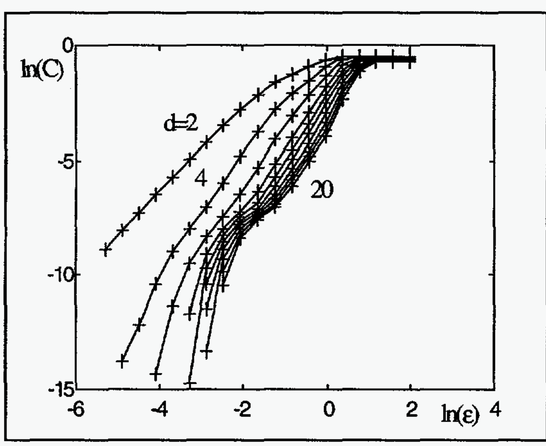

Figure 4 A plot for the correlation integral of the FBC normal attractor, for embedding dimensions 2-20.

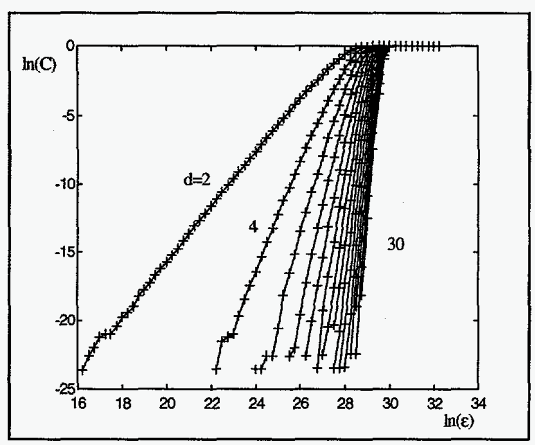

Figure 5 A plot for the correlation integral of the FBC normal attractor, for embedding dimensions 2.30

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 hours on digital computers. Instead, a chaotic time series predictor technique will be used.

METHODOLOGY

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 behavior using the difference of time history between the predicted chaotic time series predictor that we developed using the DSI neural network, and the actual time series collected using pressure sensors mounted on the FBC. Testing this chaotic time series predictor, we found that it 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 parameters 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 6. The only obstacle before executing and testing this control 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 neural 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.

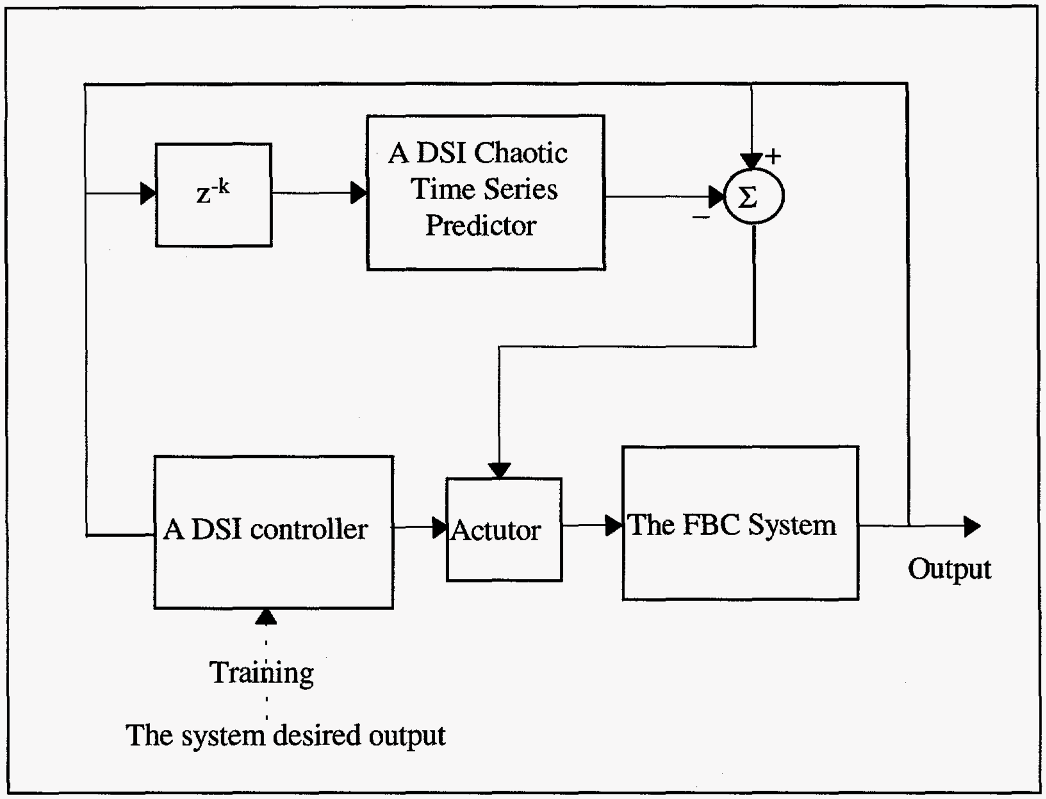

Figure 6 An illustration of a hybrid neural network-based monitoring and control method for the FBC abnormal behavior.

USING THE DSI NEURAL NETWORK FOR CHAOTIC BEHAVIOR CONTROL

In this section we will demonstrate how a special type of a neural network, the Dynamic System Imitator (DSI), can be used for chaotic behavior control. The DSI neural network is specially designed to model a wide variety of dynamic systems.[20] It is a multi-layer recurrent neural network supplied with integrators and extensive feedback connections to model the asynchrony and time lags in a real systems. The DSI neural network was used before for modeling complex dynamic behaviors through very simple configurations due to its temporal and spatial representations. The DSI controller described above was applied to control the chaotic behavior of the Lorenz system to a stable fixed point or a stable periodic orbit. Both system state point control and system parameter perturbation control strategies were implemented.

In this section, we will demonstrate how the DSI can be used to control the chaotic behavior in the Lorenz system, which is a typical chaotic system. The DSI neural network used, has one node in the input layer, three nodes in the hidden layer and one node in the output layer. The general training strategy for the DSI controller is shown in Figure 7. The DSI is trained to generate the necessary control signal to achieve certain system performance. One or more reference values in addition to feedback from the controlled system are used as inputs to the DSI. A pre-specified output behavior of the system is also supplied to the network as a target for the training. During training this pre-specified behavior is continuously compared with the actual behavior of the system to adjust the DSI parameters. Figures 8 and 9 show how the DSI neuro-controller was used to control the chaotic behavior in the Lorenz system, a typical chaotic system.

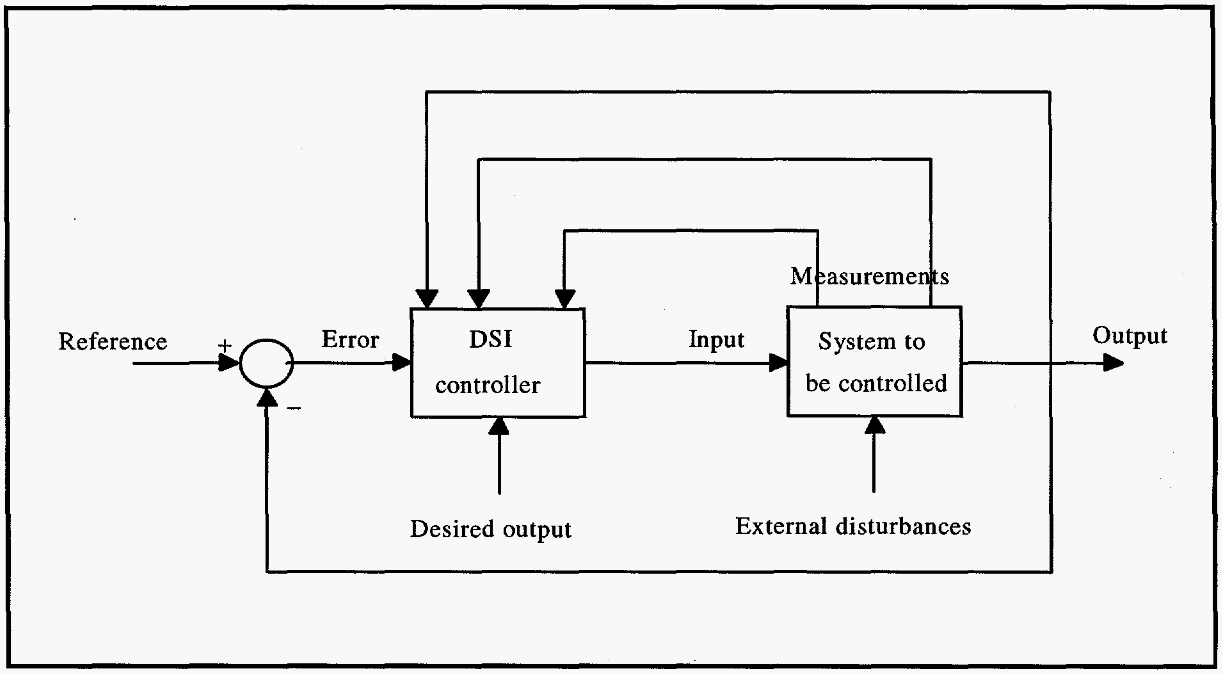

Figure 7 The general training strategy for the DSI controller.

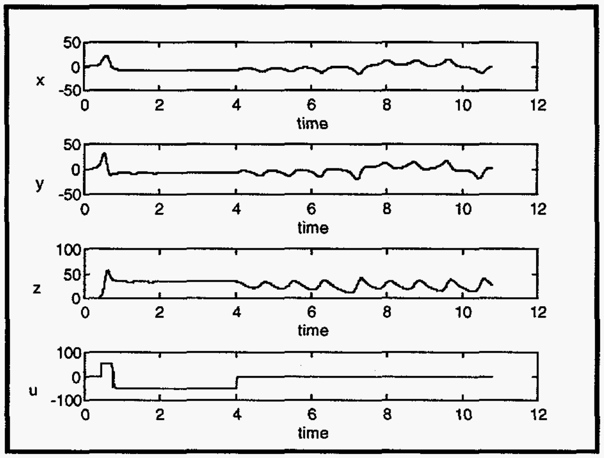

Figure 8 The DSI control signal (u(t)), and the time behavior of the Lorenz system after applying and then removing the control at the stabilized point.

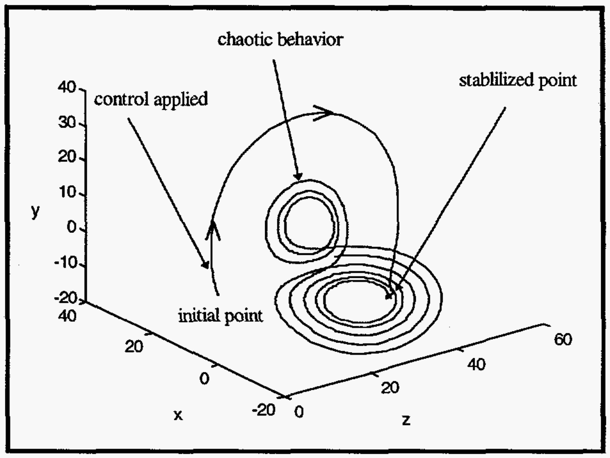

Figure 9 The trajectory of the Lorenz system, after applying and then removing the control action at the stabilized point.

ITERATIVE PREDICTION OF CHAOTIC TIME SERIES USING THE DSI NEURAL NETWORK

Chaotic systems are known for their unpredictability due to their sensitive dependence on initial conditions. When only time series measurements from such systems are available, neural network based models are preferred due to their simplicity, availability, and robustness. However, the type of neural network used should be capable of modeling the highly non-linear behavior and the multi-attractor nature of such systems. The prediction method presented in this paper is based upon predicting one step ahead in the time series, and using that predicted value to iteratively predict the following steps. This method was applied to chaotic time series generated from the logistic, Henon, and the cubic equations, in addition to experimental pressure drop time series measured from an FBC system, which is known to exhibit chaotic behavior.[1-4] The time behavior and state space attractor of the actual and network synthetic chaotic time series were analyzed and compared. The correlation dimension and the Kolmogorov entropy for both the original and network synthetic data were computed. They were found to resemble each other, confirming the success of the DSI based chaotic system modeling.

A simple configuration of the DSI neural network was used for the iterative prediction of a chaotic time series. This configuration has one node in the input layer, three nodes in the hidden layer, and one node in the output layer. The network was trained to predict one point ahead of the time series, using a set of previous values. These values are not explicitly used for prediction, but are implicitly used by adjusting the state of the network from which the prediction is performed. The prediction method is based upon the idea that once the network is trained to predict one point ahead with good accuracy, this same point can be used as an input to the network to predict the next point. This process can be repeated iteratively to predict many points in the time series. Naturally, the accuracy of prediction will deteriorate over time. During training, a time window of 200 points was used to cascade the time series to the network. The algorithm was applied to three types of simulated chaotic time series generated from the logistic, Henon, and cubic equations, in addition to one experimental time series taken from an FBC pressure measurement. The network was able to learn simple one step prediction in a reasonable number of training iterations. After training, the output of the DSI was used iteratively to generate the time series. However, the training initial conditions together with the first actual 25 points of the training time series should be used to start the DSI, in case the time behavior of the training time series must be generated. If not, any network initial conditions and any starting points can be used to generate the state space behavior of the system to which the training time series belongs.

Comparing the predicted time series to the actual time series, we found that the DSI was able to track the training time series time behavior for a short period of time (around 30 points), when started from the training initial conditions , and activated by the first 25 points of the training time series. However, it was able to track the state space attractor to which the training time series belongs, starting from any initial conditions, activated by any arbitrary set of starting points. The only case that fails is zero initial conditions together with zero starting points, which leads to zero solution. To quantitatively compare the results, the correlation dimension and Kolmogorov entropy for the actual and predicted attractors were computed. The results of the correlation dimension and Kolmogorov entropy of the different cases are summarized in Table.2. The correlation dimension is computed, according to the box-counting method, from the slope of the lines representing the correlation integral versus ε (the size of a computing box) on log-log curves for different embedding dimensions.

TABLE 2: COMPARISON OF THE ACTUAL AND DSI SYNTHETIC ATTRACTORS PARAMETERS

Time Series	Correlation Dimension	Kolmogorov Entropy
Logistic Map (actual)	1.0457±0.0057	0.6872±0.0198
Logistic map (synthetic)	1.2316±0.0374	0.6013±0.0435
Henon Map (actual)	1.2607±0.0331	0.3267±0.0135
Henon map (synthetic)	1.3171±0.0725	0.2962±0.0239
Cubic Map (actual)	1.2248±0.0090	0.4245±0.0183
Cubic Map (synthetic)	1.8171±0.01365	0.5340±0.0134
FBC normal (actual)	2.934±.065	5.034±.095
FBC normal (synthetic)	2.12±.07	6.3764±1.26

SUMMARY

Based on the results of FBC data analysis described above, we have developed some chaotic system control techniques and applied them to some typical chaotic systems. However, we were not able to test those techniques on an FBC system, because there is no suitable model available. In the same time it was not possible to build such a model from the available data, because they are all one dimensional single variable measurements which is not enough to model the input output relationships required to test our control techniques. However, we were able to find a prediction model for those pressure measurement time series that can be used for on line monitoring of the process. Two main types of chaotic system controllers were developed. The first is based on a special type of a recurrent neural network developed, known as the Dynamic System Imitator (DSI), which is specially designed to model a wide variety of dynamic systems. The second technique is based on the chaotic system control method known as the OGY, developed by Edward Ott, Yorke and Grebogi in 1990. We have developed an autoregressive algorithm to estimate a system map matrix necessary for the OGY method. The OGY control parameters can be estimated from one dimensional measurements from the system to be controlled. However, also the sensitivity of the control parameters with respect to the control variables in a form of derivatives has to be accurately measured. The OGY technique is designed such that to control a chaotic system in the vicinity of a periodic orbit or a fixed point and force it to stabilize to that periodic orbit or fixed point.

THE NECESSITY FOR MORE MEASUREMENTS

Other types of measurements are certainly necessary to build a simple model that well describes the chaotic behavior of the FBC system at both normal and abnormal operation. On the other hand this model has to describe the input output relationships between the control variables and the other variables and parameters in the system. In addition this model has to describe the system behavior under both transient and steady state conditions, and the system transients from normal to abnormal and visa versa. This type of model is necessary to train and test the neuro-controller and to test the OGY controller. Other specialized measurements are necessary to compute the derivative of a control parameter with respect to a control input around the periodic orbit or the fixed point to be controlled using the OGY technique.

THE PROPOSED EXPERIMENTAL SETUP

Taking all previous considerations and the existing setup of the cold FBC experiment shown in Figure 1 into account, we propose a setup that will enable the test procedure under the following conditions:

1. System pressure at different levels, the operating pressure, the air flow rate, and the cork flow rate, in addition to any other contributing inputs, parameters or conditions, such as humidity or temperature, have to be measured simultaneously and recorded carefully at all times in all tests. This is to simplify the utilization of such data and parameters in the following analysis, modeling and parameter estimation procedure.
2. Input/output tests will be performed by doing the measurements during input disturbances following some standard behaviors such as ramp, step, impulse, square, sinusoidal, triangular, or random. The only known effective input to the system at the time being is the air flow. However, other inputs might be considered, such as the cork feed rate and the working pressure. The system outputs in the case are the differential pressures at different levels.
3. Steady state tests will be performed for enough periods of times for both normal and abnormal conditions. More specifically, the system inputs will be adjusted to allow certain system condition either normal or abnormal, then they will be held constant at that level for certain time during which the system variables will be recorded.
4. Transients from normal to abnormal situations and the opposite will be created and monitored through measurements. First, certain condition will be created (normal or abnormal), then the disturbance necessary to kick the system to the opposite condition (abnormal or normal) will be applied. The system variables and parameters will be recorded during this process.
5. Steady state measurements will be performed at different values of operating parameters, such as the working pressure. Steady state recording will be performed at some value for that parameter, and then the measurement will be repeated with that parameter incremented up and down around its original value.

GOALS AND OBJECTIVES OD THE NEXT PHASE OF THE PROJECT

We summarize the goals and objectives of the next phase of the fluidized be experiment in the following points:

1. Develop and execute an experimental set up that will enable collecting the data necessary to develop a simple non-linear model for the FBC system, and further develop the chaotic system control techniques developed in the first phase of the experiment, including neural network control, and the conventional OGY method.
2. Build a simple and sufficiently fast computer model for the FBC system that can be used to train the neural controller and test its performance. This model will be also used to test the performance of the OGY controller.
3. Train and test the neural network based control techniques for the purpose of chaotic system control in general and FBC system control in particular.
4. Design and test a methodology to control an FBC system based on the OGY technique, and another methodology based on a combination of both neural and OGY controllers.

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