DE/MT/94015--T2

NEURAL NETWORK-BASED MONITORING AND CONTROL OF
FLUIDIZED BED

QUARTERLY PROGRESS REPORT
(July, 1995 - September, 1995)

SUBMITTED TO

U.S. DEPARTMENT OF ENERGY
DOCUMENT CONTROL DIVISION, PITTSBURGH ENERGY TECHNOLOGY CENTER
(PETC)

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

GRANT NUMBER: DE-FG22-94MT94015

BY

MOHAMMAD BODRUZZAMAN, Ph.D.
PRINCIPAL INVESTIGATOR

MAGDI A. ESSAWY, Ph.D.
RESEARCH ASSOCIATE

SCHOOL OF ENGINEERING AND TECHNOLOGY
TENNESSEE STATE UNIVERSITY
SEPTEMBER 27, ~~1994~~ 1995

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1. Introduction

This report is to review the work done for the fluidized bed combustion (FBC) project in the past three months, and introduce a general research plan for the next six months. In the last two months, a literature review has been performed on most of the previous work done in the areas of chaotic system analysis,^{1,2} chaotic system identification,³⁻⁶ chaotic system control,⁷⁻²⁷ neural network models for non-linear and chaotic systems,²⁸⁻³² fluidized bed behavior analysis,³³⁻³⁵ and fluidized bed behavior modeling and control.^{36,37} A clear view has been developed on the status of the FBC technology and the main problems that need to be solved.

2. Characteristics of Pressure Drop Data

We received sample data from the FBC facility in Morgan town, West Virginia. Most of the data are for FBC working under normal conditions. We performed some Fourier analysis, statistical analysis, and phase plane analysis on the data. The embedding method was used to reconstruct the system attractor in several dimensions from the digitized data available. The reconstructed phase plane attractor for the data looks very complex. It seems that the system performance can not be identified just by looking to the shape of the attractor. Therefore, further computations need to be performed on the system attractor to extract some quantitative parameters that can be used for the purpose of system performance identification. Some of these parameters are the Lyapunov exponents, the Kolmogorov entropy, the Lyapunov number, and the embedding dimension

for the system attractor.^{38,39} However, the normal state data only will not be enough to develop a general state identifier process, and we are definitely in need for some data from several other abnormal cases.

This month, a Matlab algorithm has been developed to compute the Lyapunov exponents from experimental data file. This algorithm is being tested using some standard chaotic systems as the Lorenz system for which the Lyapunov exponents are already known. This is, to gain some confidence in the results of the algorithm developed. On the other hand, a recurrent neural network was trained to learn a system predictor model for the FBC data, which is a preliminary test for using this type of neural network for FBC state identification and prediction.

3. Plan for the Next Quarter

The plan for the next quarter is to complete the computer program library needed to compute the chaotic system attractor parameters. These parameters will be used to identify the system status through the system observer, which will be a necessary basis for the chaotic system control procedure. It is also needed to find a satisfactory simulation model and/or a neural network model for an FBC system, that is capable of modeling the system in both normal and abnormal situations. This model is necessary for the chaotic system controller design and testing.

4. Neural Network Based Chaos Control

A neural controller will be developed based on a recurrent neural network controller that was used before to control and stabilize the chaotic behavior of the Lorenz system.^[40] The recurrent neural network is called the Dynamic System Imitator (DSI), and it is capable of modeling a wide variety of dynamic and control systems. A block diagram representation of the chaotic system neural controller design process is shown in Figure 1. This diagram shows how to train a DSI network to generate the control action necessary to control a chaotic system, using one of the system's output signals as a feedback, and some reference values to switch between several control modes. During training, the actual output of the system is compared to a pre-specified system time behavior, and the error is used to adjust the network parameters, using a multi-dimensional optimization

Figure 1 A general organization of the DSI controller during training.

technique (the simplex method). This technique has been already applied to the Lorenz system, for which it has demonstrated very good control capabilities. Sample results will be shown below.

The Lorenz system is a three dimensional system of ordinary differential equations that was historically used by Lorenz to model the convection currents in the atmosphere, for the purpose of weather prediction. Lorenz has discovered a sensitive dependence of the system on initial conditions, while running the model on a primitive digital computer. Sensitive dependence on initial conditions is one of the basic attributes of chaotic systems. It was found later that the Lorenz attractor has a fractal dimension, which means that it is a strange attractor. It was also found that the Lorenz system has one negative, one zero, and one positive Lyapunov exponents.

The time behavior ($x(t)$, $y(t)$, and $z(t)$) and phase plane chaotic attractor of the Lorenz system are shown in Figure 2 and Figure 3, respectively. The controlled Lorenz system time behavior, the control action ($u(t)$) and three dimensional phase plane trajectory, using a DSI neural controller trained to stabilize the system to a fixed point, are shown in Figures 4 to 5. Also Figure 6 and Figure 7 show the time behavior, control action and phase space trajectory of the same system starting at a different set of initial conditions. The time behavior, the control action and phase plane trajectory of the Lorenz system after applying and then removing the DSI neural controller are shown in Figure 8 and Figure 9. The controlled Lorenz system time behavior, control action and phase plane trajectory, using a DSI neural controller trained to stabilize the system to a periodic orbit, are shown in Figures 10 and Figure 11.

The following is an estimated time table for the next quarter:

October, 95	Develop the programs necessary to compute the chaotic system attractor parameters.
November, 95	Apply those methods to the FBC data for both normal and abnormal cases, locate the range of parameters for those cases, and find the best set of parameters to be used for the reconstruction of the FBC attractor (as the time delay, and embedding dimension)
December, 95	Work on a simulation and/or a neural network model for an FBC system under both normal and abnormal conditions.

Figure 2 The chaotic time behavior of the Lorenz system starting at $(0.05, 0.05, 0.05)$ for $r = 28$.

Figure 3 The Lorenz system attractor for $r = 28$.

Figure 4 The time behavior for the Lorenz system, controlled by the DSI, starting at $(5,5,1)$, for $r = 28$.

Figure 5 The trajectory for the Lorenz system, controlled by the DSI, starting at $(5,5,1)$, for $r = 28$.

Figure 6 The time behavior of the Lorenz system, controlled by the DSI, starting at $(10,10,10)$, for $r = 28$.

Figure 7 The trajectory of the Lorenz system, controlled by the DSI, starting at $(10,10,10)$, for $r = 28$.

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 (time 4), for $r = 28$.

Figure 9 The trajectory of the Lorenz system, after applying and then removing the control action at the stabilized point, for $r = 28$.

Figure 10 The time behavior of the Lorenz system, controlled by the DSI to achieve a periodic orbit, starting at (1,5,10), for $r = 28$.

Figure 11 The trajectory for the Lorenz system, controlled by the DSI to achieve a periodic orbit, starting at (5,5,1), for $r = 28$.

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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, 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.