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Prediction of the Dynamics of a Fluidized Bed Reactor using Artificial Neural Networks

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PREDICTION OF THE DYNAMICS OF A FLUIDIZED BED REACTOR USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The dynamic behavior of fluidized bed has been studied based on the chaos theory. The experiments were done in a fluidized bed of 0.15 m diameter using an optical fiber probe. The interval between successive clusters in the fluidized bed were calculated from the time series signals and proved to be chaotic by calculating the correlation dimension. An artificial neural network (ANN) was adapted and trained to predict the generated time series. The ANN results were compared with the predictions of the *k*-Nearest Neighbor (kNN) method to show the superiority of ANN in chaotic time series prediction.

INTRODUCTION

Chaos dynamics represent numerous advantages over non-chaotic dynamics, since the chaotic systems are often considerably easier to control than other linear or non-linear systems, requiring only small, appropriately timed perturbations restricted inside specific unstable periodic orbits. Due to the chaotic nature, it is difficult to establish models based on the first principles to quantitatively predict the system behaviors of multi-phase reactors in real time. However, controlling of different parameters in industrial scale could be done by a hybrid control system comprising a time series forecasting model, for characterizing the nonlinear nature of chaotic time series data, and an expert system.

In the last decade, many attempts have been made to demonstrate the dynamics of the multi phase flows with the aim of chaos theory. Hay et al. (1) calculated the correlation dimension and Lyapunov exponents of a time series of pressure fluctuations and proved that these parameters remain constant over a range of operating conditions and could be used to recognize the regime transition in fluidized beds. Kikuchi et al. (2) used the signal of an optical transmitter probe and reconstructed the attractor from the bubble and particle frequencies in a gas-liquid-solid three phase system. Kwon et al. (3) determined the Hurst exponent for a time series of pressure fluctuations in a three phase fluidized bed.

Time series forecasting, or time series prediction, takes an existing series of data $x_{t-n}, \ldots, x_{t-2}, x_{t-1}, x_t$ and predict the x_{t+1}, x_{t+2} data values. The goal is to observe or model the existing data series to enable the future unknown data values to be forecasted accurately. Examples of data series include financial data series (stocks, indices, rates, etc.), physically observed data series (sunspots, weather, etc.) and mathematical data series (Fibonacci sequence, integrals of differential equations, etc.). There are several time series prediction techniques such as Auto-Regressive (AR), Moving Average (MA), Auto-Regressive-Moving Average (ARMA), *k*-Nearest Neighbor (kNN) and, recently, ANN. The ANN is one of the promising methods for the researchers (4-6) due to its prominent capabilities in capturing the overall static and dynamic model and predicting the long term behavior of the system. kNN is another nonlinear forecasting method used by researchers (7). However, is simpler than ANN because there is no model to train on the data series. Instead, the data series are searched for situations similar to the current one each time a forecast needs to be made.

In this study, first a new time series is created from the signal of an optical fiber probe by detecting the interval between the successive clusters and the correlation dimension as a chaos identification method is used to determine the chaotic nature of this time series. kNN and feed-forward ANN with introducing the output to input is then used to model the performance of fluidized bed reactors and predict the selected time-series signal. The results were used to determine the advantages and disadvantages of ANN and kNN methods in chaotic time-series predictions.

EXPERIMENTAL

A plexiglas fluidized bed of 0.15 m internal diameter and 2 m height was used in the experiments in which sand particles with average diameter of 250 μm were employed. The experiments were conducted at superficial gas velocities of 0.5, 0.7, 1 m/s, both in bubbling and turbulent regimes of fluidization. A light back scattering optical fiber probe was used to capture the dynamics of the fluidized bed unit. The probe and the experimental set-up employed in this study are illustrated in Fig. 1. The tip of the probe consisted of seven optical fibers. Three of the fibers were connected to the light detectors, each surrounded by two fibers connected to the light source which produce a uniform illumination area in front of the tip. Existence of three light gathering fibers made it possible to measure two values for either particle velocity or concentration and enhances the measuring precision, regardless of the method of calculating these parameters from the probe signal. The intensity of the light collected form the column was converted to the voltage through an ADVANTECH A/D converter at a sampling rate of 60 kHz. A typical data set comprised of 600,000 points.

RESULTS AND DISCUSSION

1. DETECTING CHAOS

It has been shown that the fluidized beds have chaotic behavior in terms of different parameters such as pressure fluctuations, voidage and heat transfer (8, 9). Although the original signal of the probe is a measure of the dynamics of the system, considerable amount of noise is also included in these time series data. This large number of noise could produce a lot of uncertainty in detecting the chaos and especially in the efficiency of time series prediction methods. Therefore, a detecting criterion should be applied on the original time series data first, in order to distinguish the clusters from the single particles and bubbles. It has been recommended that when the signal intensity of the optical fiber probe exceeds three times the standard deviation of the signal, it could be considered that a cluster has passed the probe (10). After detecting the clusters, a new time series was obtained by calculating the interval between successive clusters. This new time series is shown in Fig. 2.

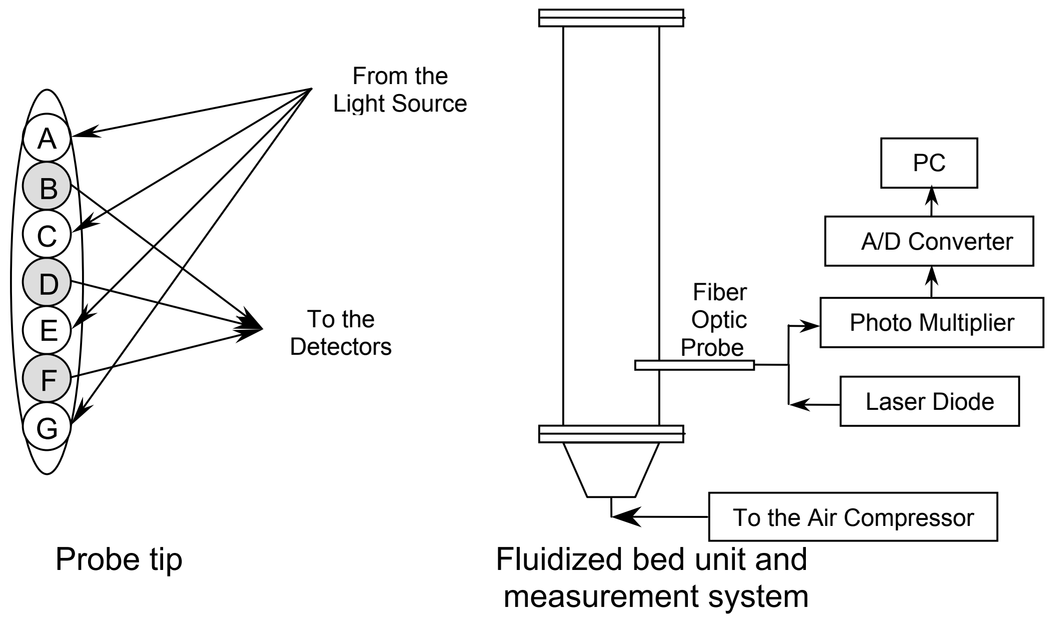

Figure 1. Schematic diagram of the experimental set-up and measurement system

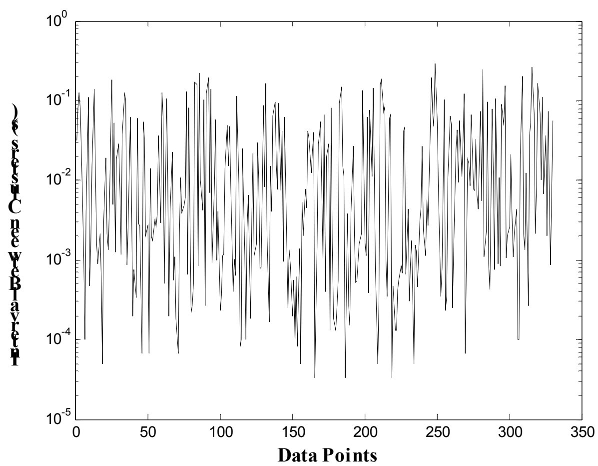

Figure 2. The data set obtained from the intervals between the successive clusters.

Various methods, such as correlation dimension, pointwise and average pointwise dimension and Lyapunov exponents, have been used in the literature for discriminating the chaotic nature of a time series (11). In the present study, the correlation dimension was used for this purpose. The correlation dimension could be calculated from the correlation integral defined as follows (11):

$$C(r) = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1; j \neq i}^{N} \theta\left(r - \left|X_i - X_j\right|\right) \tag{1}$$

The correlation dimension, D_C, could be obtained from the slop of the log(r)-log($C(r)$) plot at different values of r. Fig. 3 shows a sample of such a plot at different values of the embedding dimension, m. This figure illustrates that log(C_r) increases linearly with increasing log(r) from the slope of which D_c could be evaluated.

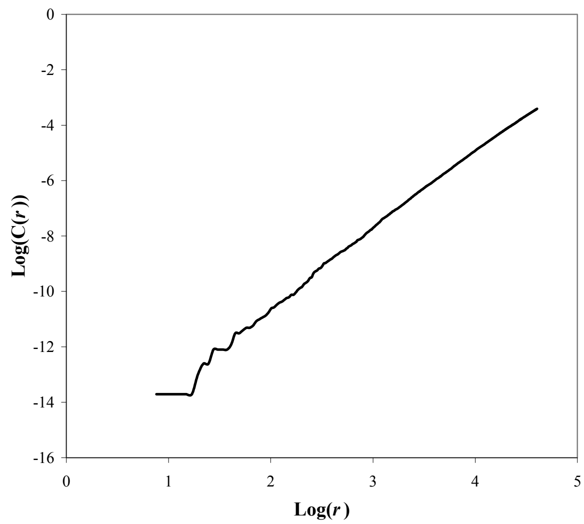

Figure 3. Calculation of correlation diameter from the correlation integral plot

2. PREDICTIG THE TIME SERIES DATA

The new data series was partitioned into two sets. One part was used for both training the network in ANN and finding the nearest neighbor in the kNN and the rest of data are used for validating of the predictions of these methods. Nearly 60 percent of the data was used for the network training.

K-NEAREST NEIGHBOR

Fig. 4 shows the kNN algorithm applied in this work. The last data points in the data series are the reference points. The length of the reference set is called the window size. The data series without the last data point is called the shortened data series. In order to forecast the next data point of the data series, the reference was compared with the first group of data points in the shortened data series, called a candidate, and an error was calculated. Then, the reference was moved one data point forward to the next candidate and another error was calculated, and so on. The smallest errors correspond to the k candidate that closest match the reference. Finally, the forecast would be the average of the k data points that follows these candidates. In order to forecast the next point, this process was repeated with the previously forecasted point appended to the end of the data series. This procedure could be iteratively repeated to forecast the desired number of data points. Values for the number of k matches and window size depend on the data series to be forecasted (7).

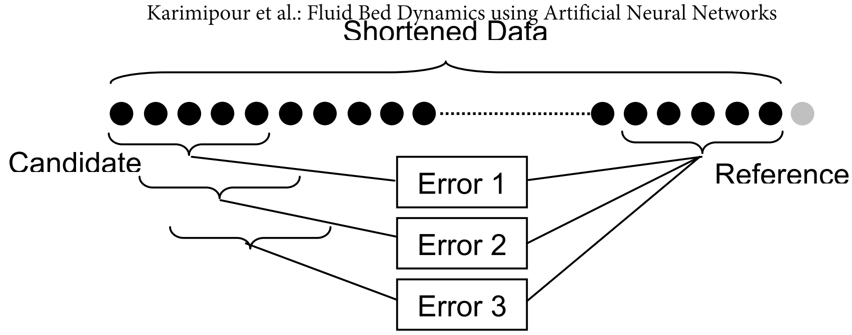

Figure 4. kNN algorithm with the window size of 5

This procedure was implemented to find the nearest neighbors and then to predict every data of the validation data set. Various values were tested for *k* and the optimum value was found to be 5. The window size was found to have no significant effect on the kNN predictions. Therefore, the window size was set to 10 points in the present work. Fig. 5 shows the prediction of kNN in terms of validation data set. As could be seen in this figure, this method could only predict the average and is not able to pursue the fluctuations.

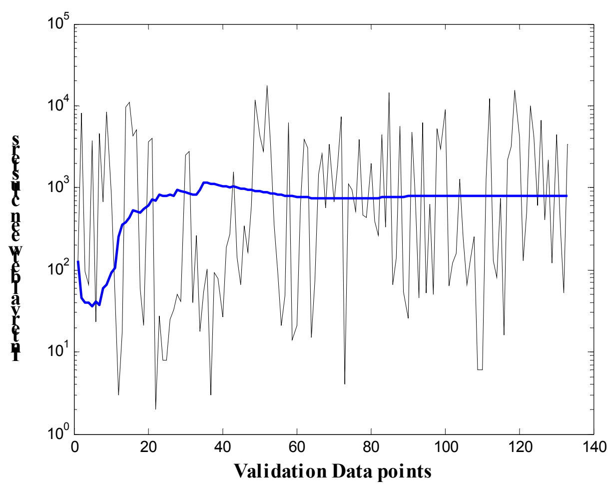

Figure 5. Original and *k*-Nearest Neighbor predictions of validation data set

ARTIFICIAL NEURAL NETWORK

According to the works of different researchers, a feed-forward network with one hidden layer has the ability to perform any mapping to an arbitrary degree of precision, provided that the hidden layer contains sufficient number of nodes (4, 5). Therefore, the same neural network with one hidden layer was used in this work. In order to create the examples in the form of input-output pairs, the time series data were first put into a one dimensional array. Then, as shown in Fig. 6, a moving window was used to create the examples. The window size was selected to be 10, the same size as the window in kNN, i.e., every input vector to the ANN contains 10 data points. The network was trained to predict one step ahead with a step-ahead size of one. In order for this network to be dependent to the operating conditions, the superficial gas velocity, *Ug*, was also included in the input vector as its first

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coordinate. As shown in Fig. 6, the next input vector to the ANN was built with 9 data from the previous example and the single ANN forecasted data in the prior step. When a forecast was made, it was used to forecast another step ahead, and so on. In this process, every forecast was made from the present and previous points in the time series and could be continued indefinitely.

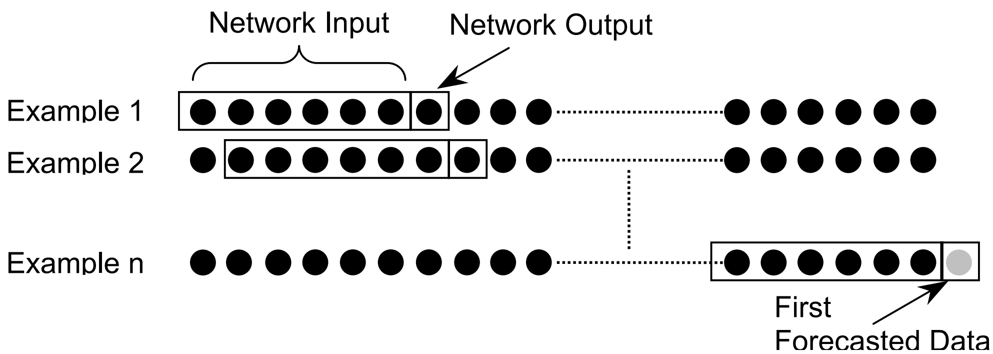

Figure 6. Creating examples with a moving window for a network with four inputs and one output

Predictions of ANN were compared with the original data of validation data set in Fig. 7. This figure shows that the ANN is capable of pursuing the perturbations in the time series. Number of neurons in the input, hidden and output layers was set to 25, 30 and 1, respectively. Variation of the correlation dimension with the superficial gas velocity is represented in the Fig. 8. As shown in this figure, the correlation dimension is dependent to the superficial gas velocity and could be used as a measure of changing the chaotic behavior of the fluidized bed.

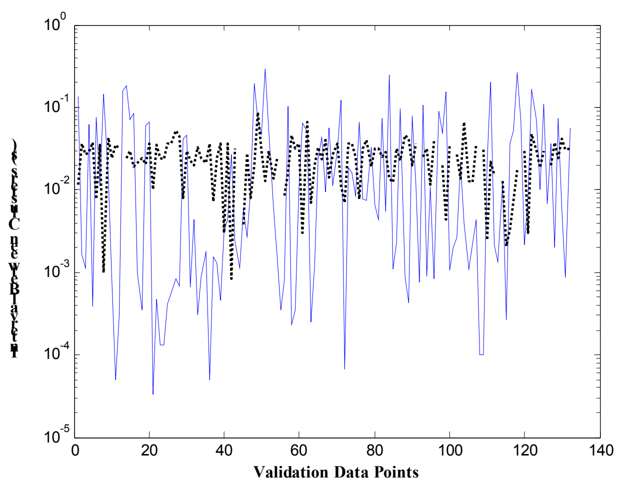

Figure 7. Original and ANN predictions of validation data set

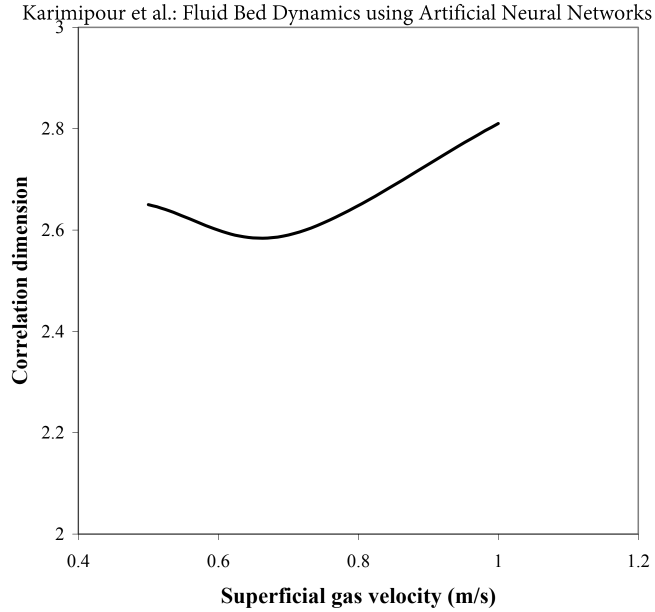

Figure 8. Variation of the correlation dimension with superficial gas velocity

CONCLUSIONS

Dynamic behavior of fluidized bed has been studied based on the chaos theory. The intervals between successive clusters in the fluidized bed were detected from the time series signals obtained by an optical fiber probe and a new noise free time series was produced. The chaotic nature of this time series was determined by computing the correlation dimension of the reconstructed data of the signal. The time series is then divided to two parts for training and validation and an ANN was adapted and trained to predict the generated time series. The kNN method is also used for predicting the validation data. The results showed that the kNN method is just able to produce a very rough estimate of the time series. In comparison the ANN is capable to pursue the fluctuations of the time series and capture the dynamics of the system and could be considered as a promising tool in chaotic time series studies of multi phase flows.

NOTATION

$C(r)$	correlation integral
D_C	correlation dimension
k	parameter in *k*-Nearest Neighbor method
N	number of data points in the time series
r	radius of the *n*-dimensional hypersphere centered on each sampled point on the reconstructed data
x_i	time series data
x_j	time series data
X_i	multi-dimensional vector that is the *i*th phase space co-ordinate of the reconstructed data

X_j multi-dimensional vector that is the jth phase space co-ordinate of the reconstructed data

Greek Letter

θ heavyset function

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