Modeling the Nonlinear Dynamics of Circulating Fluidized Beds Using Neural Networks

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1. Introduction

The performance of gas-solid fluidized beds is heavily depended on the local flow structure and dynamic contacting pattern between phases. In recent years, much attention has been given to the transient aspects and spatial inhomogeneities of two-phase flow in fluidized beds. The dynamic behavior of circulating fluidized beds (CFBs) is reported to be chaotic, and can be characterized by fractal dimensions and positive values of Lyapunov exponents or Kolmogorov entropy (Daw et al., 1990; Marzocchella et al., 1997; Ohara et al., 1999; Ji et al., 2000; Kikuchi et al., 2001). Because of the chaotic nature, it seems difficult to establish mathematical models which can completely describe the nonlinearity of the hydrodynamics in CFBs. However, in order to control and predict the behaviors of CFB reactors more accurate and more reliable, it is highly desirable to model the nonlinear dynamics in CFBs.

As an effective tool to perform nonlinear input-output mapping, artificial neural networks (ANNs) have been proven to be capable of solving a number of complex problems in diverse areas such as pattern recognition, computer vision, robotics, control, medical diagnosis, etc (Baughman and Liu, 1995). In recent years, ANNs have been successfully employed for prediction of time series in various fields (Wan, 1993; Al-Saba and El-Amin, 1999; Lisi and Schiavo, 1999; Coulibaly et al., 2000). Because ANNs are nonlinear computing tools, they can easily be applied to nonlinear processing problems. Moreover, compared to the empirical curve-fitted models, ANNs are relatively less sensitive to noise and incomplete information. Therefore, ANNs can deal with problems with uncertainty.

In the last few years, several articles have been devoted to applying ANNs for modeling and control of multi-phase reactors. Nakajima et al. (2001) examined the ability of the neural network model to approximate the dynamic behavior of pressure fluctuation in a circulating fluidized bed by comparing time-averaged characteristics, power spectra, and chaotic features of time series measured and generated by the ANN. They reported that dynamic behavior of the original time series is captured well by the ANN, and the ability of the ANN for generation improves with the number of iterations. Recently, Otawara et al. (2002) proposed a neural network model for non-linear behaviors of bubble motion in a three-phase fluidized bed. The trained ANN has successfully generated time-series data comprising temporal intervals, each of which is the period between two sequential signals of bubble or particle passages in the three-phase fluidized bed. The bifurcation diagrams of model-generated data demonstrate that the ANN is capable of predicting and modeling chaotic dynamics of three-phase fluidized beds. However, their model by using ANNs only can make a good short-term prediction but failed in the long-term prediction. The ANN

model was designed to predict the succeeding data point of time series from the present and preceding data points. At next step, the input of the neural network was updated with new data from the measured time series. This approach is usually referred to as the short-term (or single-step) prediction, in which the trained ANN can predict only single future data point based on measured time series.

In general, a long-term prediction is different from a short-term prediction in input data set and the number of prediction steps. By continuously adopting output data points as latest input data components, the ANN model can make the long-term prediction of the system. It is by now well known that the long-term value prediction of chaotic behavior is simply not possible due to the exponential divergence of trajectories observed in chaotic systems. However, it is quite possible to make a long-term structure prediction instead of making an accurate value prediction. This is because the chaotic trajectories from two near initial points may form the same chaotic attractor, although there is sensitive dependence on initial conditions. If we can obtain a predictive model which is an approximation to the true dynamical system, the attractor generated by iterating the model can be expected to be almost identical to the actual attractor (Cao et al., 1995). Bakker et al. (1997) tried to develop a neural network-based model for the long-term prediction of the chaotic hydrodynamics in a gas-solid fluidized bed. Although the ANN model can capture some important characteristics of the real system, the mean squared error in the long-term prediction by the trained ANN increases significantly with the prediction time. In our recent work (Lin et al., 2003), we have succeeded in the long-term prediction of the bubble interval series in bubble columns by using artificial neural networks. The time series generated by the ANN model with the random data as well as experimental data as the initial input show the similar statistic and chaotic characteristics with the time series measured.

In the present paper, modeling nonlinear hydrodynamics of a circulating fluidized bed (CFB) is conducted by using ANNs trained with the time series data measured. The effects of the number of iterations and nodes in input and hidden layers on the training behavior of ANNs were examined. An early stop approach was proposed to improve the long-term prediction. The prediction capability of the ANNs was evaluated in terms of time-averaged characteristics, power spectra and short-term predictability analysis.

2. Experimental

The schematic diagram of the experimental apparatus em shown is Fig. for measurement of the static pressure distribution in the riser. As a moving-bed downcomer a 0.20 m i.d. tube was used. The downcomer bottom was simply connected with the riser bottom by a screw feeder. The feeder controls solids circulating mass flux by adjusting rotation speed of the screw. The variation in the solid feed rate per rotation was less than 1% of the average rates. All experiments were carried out at ambient conditions using air as a fluidizing fluid. The solid particles used in this study were FCC catalyst (diameter 40-150 μ m, average 66 μ m, apparent density 890 kg/m^3). Superficial gas velocity U_0 and circulating solid mass flux G_s

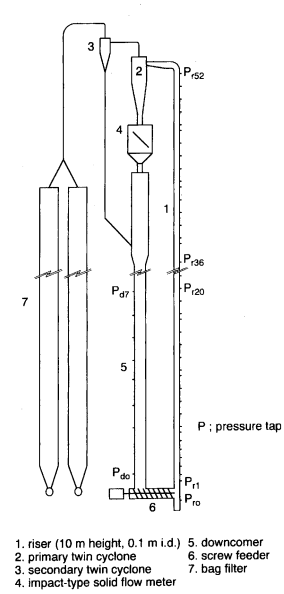

Fig. 1. Schematic diagram of the circulating fluidized bed

ranged from 1.2 to 2.35 m/s and 8 to 20 kg/m^{2}s, respectively.

Pressure, local voidage and local heat transfer fluctuations were measured simultaneously by using pressure transducers, optical transmittance probes and heat transfer probes, separately. The details of the probes were described in our previous paper (Ji et al., 2000). The voltage signals of pressure, voidage and heat transfer fluctuations were recorded with a data recorder and digitized with an A/D converter at a sampling frequency of 1000 Hz. A typical measured time series consisted of 32768 points and was used directly as a time series for the chaotic analysis.

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3. Artificial Neural Network Model

The subject of ANNs is well covered in literature and will not be reviewed here. Generally, the architecture of multi-layer ANNs can have many layers where a layer represents a set of parallel processing nodes. Theoretical works have shown that a single hidden layer is sufficient for ANNs to approximate any complex nonlinear function. Many experimental results also confirm that one hidden layer may be enough for most prediction problems. Thus, a feed-forward ANN with one hidden layer was employed in this study, as depicted in Fig.2. The ANN was designed to predict the succeeding data point, X_{n+1} of the time series of the local voidage measured in the CFB, from the present data point, X_n, and previous data points, $X_{n-k},\ldots X_{n-1}$. By successively adopting its own output to input layer, this ANN model can be used for the long-term prediction of local voidage fluctuations.

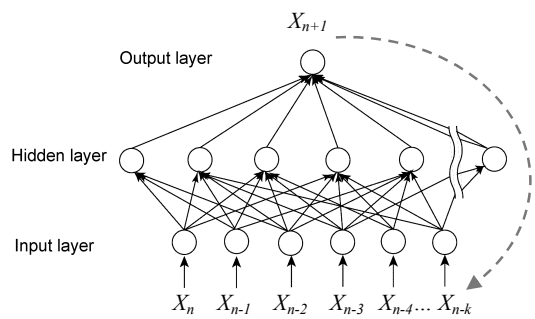

Fig.2. The ANN architecture

In this ANN model, the linear nodes in the input and out layers and sigmoid nodes in the hidden layer were considered. The training process of the ANN was carried out by using the error back-propagation algorithm to minimize the mean squared error (MSE) between the output and the target values.

The main issue in training an ANN model is the prediction performance. ANN models, like other nonlinear estimation methods, can suffer from either underfitting or overfitting. A complex ANN with too many hidden nodes may likely fit the noise leading to overfitting, while a simple network with insufficient hidden nodes can fail to detect the regularities in the data series, leading to underfitting. In order to avoid underfitting and overfitting, an early stop approach was employed in this work. The early stop approach allows the use of complex network without overfitting since we do not require the training process to converge; rather, the training process is used to perform a direct search of a model with better prediction performance. For this approach, the available data are split into three subsets. The first subset is the training set which is used to determine the weights and biases of the ANN. The second subset is the validation set. The validation set is for estimating the ANN performance and decide when we stop training. The effectiveness of the stopping criterion and the prediction ability of the ANN are further verified by the test

data set. In this work, the MSE and cycle number on the validation set were monitored during the training process. When the validation error and the deviation of cycle number increase for a specified number of epochs, the training is stopped.

Finding the suitable architecture of ANNs is particularly critical. Since currently there is no theoretical method for determining the appropriate number of each layer prior to training. Thus, we resort to the trial-and-error method commonly used for ANNs design.

4. Data Analysis

To evaluate the performance of the ANN model, the properties of measured and predicted time series were firstly characterized by statistical analysis in the time domain and spectral analysis in frequency domain. With respect to the chaotic feature, the short-term predictability analysis was applied to quantify the time-dependent behavior of a time series in the phase space.

Schouten et al. (1998) proposed an analysis method that uses the short-term predictability of time series of local pressure fluctuations in the fluidized bed to detect a possible change early in the hydrodynamic state of the bed. The short-term predictability is evaluated based on the growth rate of the distance between two points that are initially very close to each other in phase space. The prediction errors are computed for the experimental and predicted data sets using embedding theorem, and the growth of the distance between two points for a short period of time is measured by the so-called supremum norm. In order to examine if the experimental and predicted time series are from same underlying nonlinear dynamics, the Mann-Whitney statistic Z is calculated. Denote the prediction error set for the experimental and predicted time series as A and B, respectively, the Mann-Whitney rank-sum statistic is formed as:

$$U = \sum_{i=1}^{N_A} \sum_{j=1}^{N_b} \Theta(A_i - B_j) \tag{1}$$

where N_A and N_B represent the number of distances in the error sets A, B, respectively and Θ is the Heaviside step function. For N_A and N_B, which in practically means a few tens, the quantity:

$$Z = \frac{U - N_A N_B / 2}{\sqrt{N_A N_B (N_A + N_B + 1)/12}} \tag{2}$$

is normally distributed with zero mean and unit variance, under the null hypothesis that the two series A and B come from the same distribution.

In this work, a delay vector was formed using time delay of unity and embedding dimension of the order of 30 to reconstruct a phase space from experimental and predicted time series. The divergence of points, which were initially closer than the average absolute distribution of the time series analyzed, was measured within the period of 20% of the average cycle time. The average cycle time is defined as the average time that is needed to complete a full cycle after the first passage through the average of the time series signal.

Prediction error sets of 100 distances were computed for Mann-Whitney statistic calculation and Z-value was estimated with 10 repetitions according to Eq. (2) and then averaged. If the |Z|-value is larger than 3, it can be stated with more than 99% confidence that the experimental series and predicted series do not from the same underlying mechanism.

5. Results and Discussion

Figure 3 shows representative time series of instantaneous pressure, local voidage and local heat transfer rates. It can be seen from the figure that the pressure exhibits a low frequency fluctuation, while the local voidage exhibits a high-frequency fluctuation with sharp spikes. In our previous work (Ji et al., 2000), we found that fluctuations in pressure, local heat transfer and voidage represent the spatio-temporal patterns at the scale of the

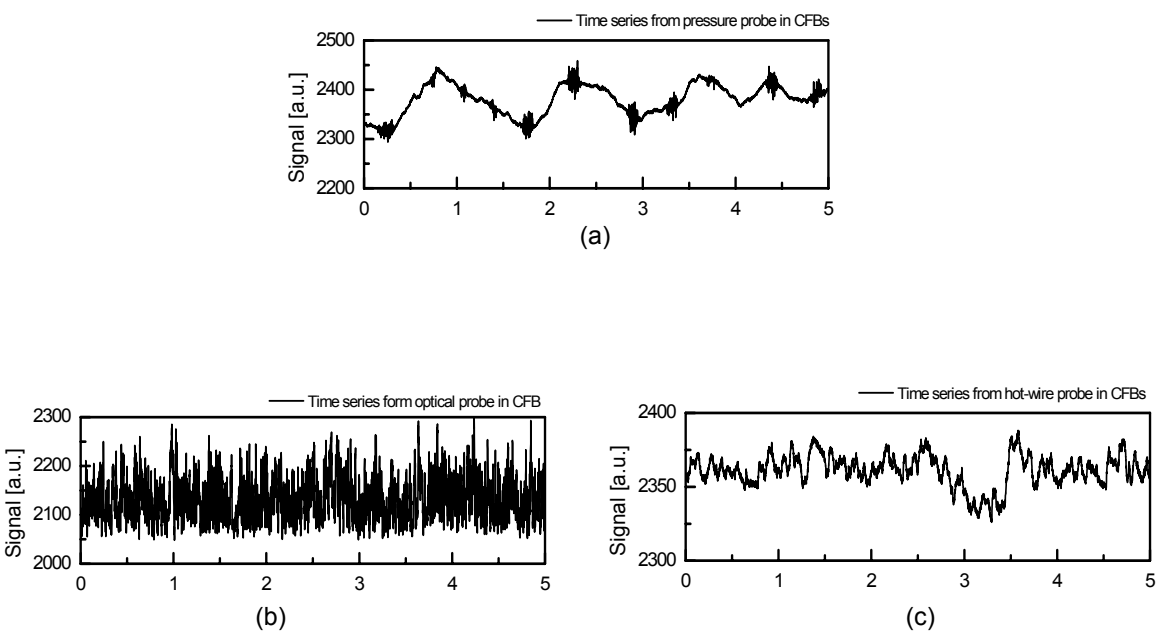

Fig. 3. Time series data measured in the CFB by: (a) the pressure probe; (b) the optical probe; (c) the hot-wire probe; U_g=2.3 m/s, G_s=20 kg/m^{2}s

column size, the cluster size and the particle size, separately.

In the following section, the time series of the local voidage was used as the characteristic variable to demonstrate the capability of the ANN model. As mentioned above, the data available were split into three parts. Under each measurement condition, the first 3000 points (i.e. 3s) of the measured time series, which corresponds to approximately 200 to 300 cycles of the fluctuating voidage and seems to be a minimum to identify the local dynamics in a CFB, was select to construct the training data set. The following data with the same period of time was used as the validation data set. All the remaining data were used for test the performance of the ANN model.

To determine an appropriate ANN model, the number of nodes in the input layer

varied from 5 to 55 and in the hidden layer from 10 to 70. Figure 4 shows the effect of input nodes on the training behavior of the ANN model. It can be seen that the increase in input nodes reduces the iteration steps (here refer to as epochs). While with the input nodes greater than 25, no significant change in epochs was observed. The learning rates for different hidden nodes are shown in Fig. 5. It is clear that in the training process the increase of the hidden nodes up to 50 can effectively reduce the epochs of training. Further increase of the hidden nodes does not affect the training behaviors considerably. Thus, in this study the numbers of input and hidden nodes are chosen to be 25 and 50, respectively.

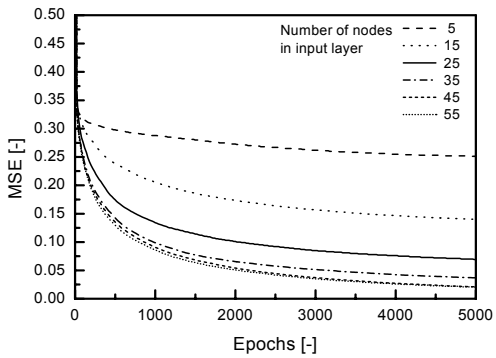

Fig. 4. Effect of number of input nodes on the training behavior of ANN, hidden nodes=50

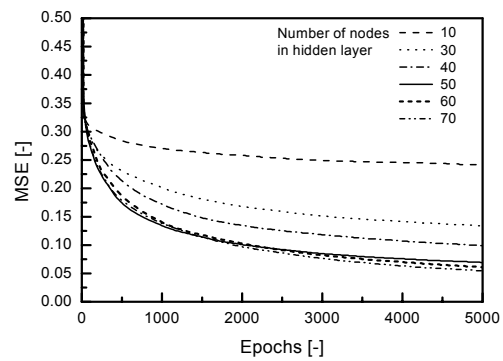

Fig. 5. Effect of number of hidden nodes on the training behavior of ANN, input nodes=25

The prediction ability of the trained ANN was first tested in making short-term (one-step) prediction. The data points generated by the ANN are compared with those in the test data set, as shown in Fig. 6, where only 300 points are plotted for a clear comparison. Obviously, the trained ANN provides very accurate single-step prediction. This indicates that the ANN is capable of capturing the underlying dynamics of the local voidage fluctuation based on the small training data set.

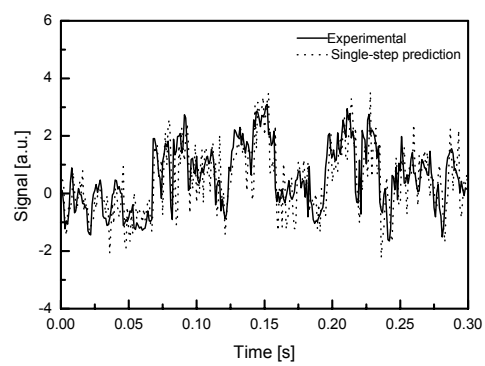

Fig. 6. Time series data generated by short-term prediction of the trained ANN model

The performance of long-term predictions of the ANN model is of particular interest for practical applications. Here the predicted time series with a length of 15000 data points is generated by the ANN using only 25 data points for the measure time series as the initial input. Figure 7 shows such time series predicted by ANNs trained with different epochs. For comparison, the corresponding data in the test data set are also given in Fig. 7 (a). From this figure, the advantage of the ANN trained using the early stop approach can be seen clearly. The ANN with insufficient training failed to detect the complex fluctuation pattern in the measured time series. As shown in Fig. 7(c), the long-term prediction by such a model appears obvious bias to the measured data. On the contrary, if the ANN is trained with excessive training epochs, the problem of overfitting may occur. The error on the training set is driven to a very small value after training, but when new data is presented to the network the prediction error is large (see Fig. 7(d)). In this case, the network has memorized the training examples including noise in the training set, but it has not learned to make a prediction to new situations. With the help of the early stop approach, the well-

trained ANN gives very similar fluctuation pattern with that of the measured data, as shown in Fig. 7(a) and (b).

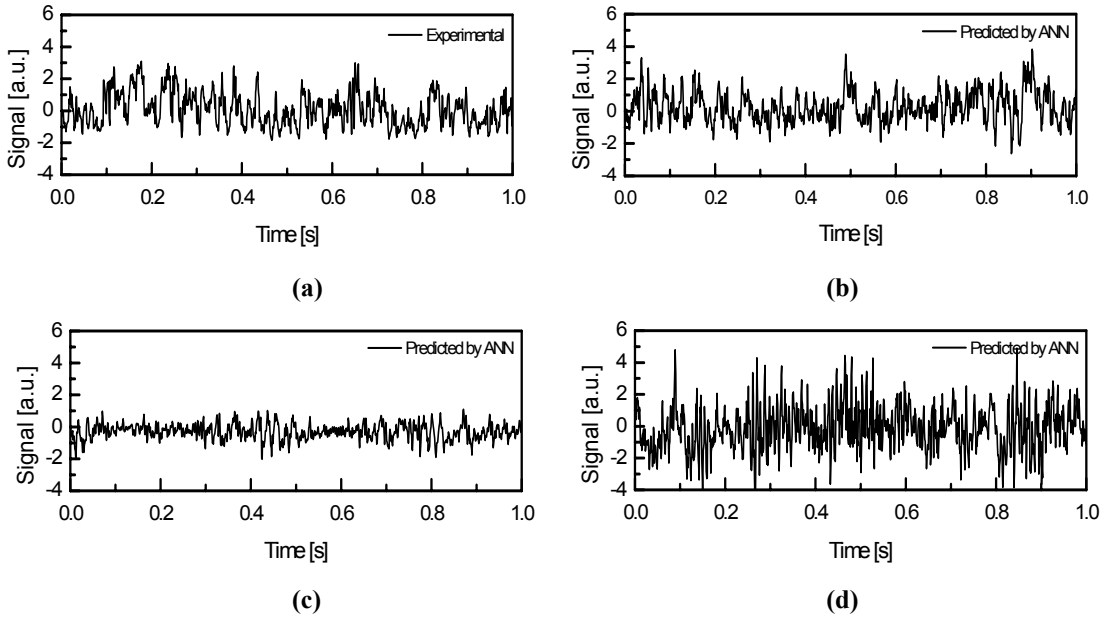

Fig. 7. Time series data: (a) measured by the optical probe in the CFB; (b) predicted by the ANN trained with the early stop approach, training epochs about 5000; (c) predicted by the ANN trained with training epochs of 1000, (d) predicted by the ANN model with training epochs of 9000

Figure 8 shows the power spectra of time series of local voidage fluctuations measured and predicted by the ANN. The power spectral density functions for both measured and predicted time series are observed to exhibit a continuous power spectrum with many spikes at high frequencies, which is the typical characteristic of chaotic system. It can be seen that over the whole frequency range the power spectral density of the predicted series overlaps that of the measured series. This suggests that the two time series hold similar characteristic time scales or frequency.

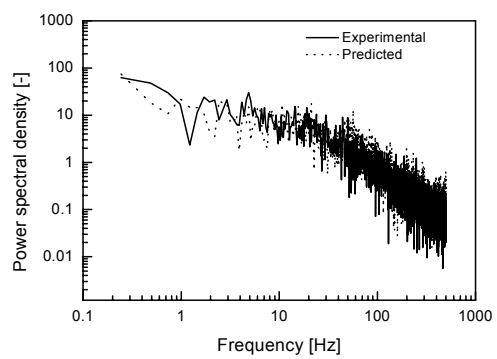

Fig.8. Power spectral density of time series data measured and predicted by ANN model

Table 1 summarizes the comparison of statistic and dynamic characteristic parameters of the measured and predicted time series, including absolute average deviation (AAD), minimum and maximum values, cycle time and |Z|-value. The comparison shows that the statistic parameters of the time series from short-term and long-term predictions of the well-trained ANN approximate closely to the values of the experimental time series. The short-term predictability analysis is an analysis method based on the characteristic feature of chaotic systems (i.e. the short-term predictability). As pointed out by Schouten et al. (1998), this method actually combines and integrates statistical, spectral and chaos analysis. Examination of |Z|-values shows that the |Z|-values calculated for the time series from both short-term and long-term predictions by the well-trained ANN are well below 3. This indicates that the predicted time series are chaotic and are most likely from the same deterministic chaotic mechanism as the measured time series.

Table 1. Comparison of statistic and dynamic characteristics of the measured and predicted time series

Training epochs	AAD	Minimum	Maximum	Cycle number, (1/1000 s)	|Z|-value
(measured)	0.81	-1.88	4.90	11.3	-
(short-term)	0.79	-3.23	4.53	9.93	1.57
1000	0.33	-2.07	2.15	7.62	5.26
5000	0.83	-3.61	4.29	9.45	2.78
9000	1.21	-1.61	5.83	7.40	7.49

6. Conclusions

An artificial neural network model was developed to model the nonlinear dynamics underlying in the time series data measured in a circulating fluidized bed. The experiments were performed in a circulating fluidized bed with a riser of 0.10m in inner diameter and 10m in height. The solid particles used in this study were FCC particles. The solid mass flux ranged from 8 to 20 kg/m^{2}s and the superficial gas velocity from 1.2 to 2.35 m/s. For the training of ANNs, the error back-propagation algorithm was used with the early stop training approach. The effects of the number of iterations and nodes in input and hidden layers on the training behavior of ANNs have been investigated. The trained ANN provides accurate value predictions of local voidage fluctuations. The effectiveness of the early stop training approach has been confirmed in the long-term prediction. Statistic, spectral and short-predictability analysis give the consistent results, and suggest that the well-trained ANN constitutes a virtual dynamical system in the long-term prediction which captured the certain nonlinear dynamic properties of the real system.

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