NEURAL NETWORK MODELING AND CONTROL OF COLD FLOW CIRCULATING FLUIDIZED BED

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ABSTRACT

Circulating Fluidized beds (CFB) are a relatively new method of forcing chemical reactions to occur in chemical and petroleum industries. Compared with conventional fluidized beds, CFB have many advantages including better interfacial contacting and reduced back mixing. The recycle nature of CFB allows for a better process, but also makes modeling and understanding it many more times difficult. The plant under consideration is a cold-flow circulating fluidized bed (CF-CFB), meaning there is no combustion component in it. In the absence of conventional means to derive a reliable model, we have devised a model of the CFB using Neural Networks (NN), which have the ability to characterize such complex systems. This stems from their ability to approximate arbitrary nonlinear mappings. The main objective is to train a NN model and controller to simulate and control the CFB operation. It has been shown that a NN can be used effectively for the identification and control of nonlinear dynamical processes. Results are presented.

KEYWORDS

Circulating Fluidized Bed, Neural Networks, Nonlinear, Backpropagation, Levenberg-Marquardt Algorithm, Modeling and Control.

1. INTRODUCTION

Fluidized bed technology brings solid particles into contact with gas phase in very controlled conditions. CFB is a relatively new method of forcing chemical reactions to occur in the chemical and petroleum industries. It has also gained acceptance in a wide variety of fields including catalytic cracking, power generation, mineral processing and many other processes. This is because fluidized bed offers many advantages over conventional reactors and unit processes. Compared to conventional fluidized beds, CFB have many advantages including better interfacial contacting and reduced back mixing. Understanding the fluidized bed technology is not a quick process. The recycle nature of CFB allows for a better process, but also making the tasks of modeling and controller design many time more difficult. The CFB under investigation is a Cold-flow circulating fluidized bed (CF-CFB), meaning there is no combustion component in the process. A schematic of the CF-CFB is shown in Fig. 1. The reason for eliminating the combustion from this unit is to isolate and study the effects of the internal pressure of system, independent of temperature effects. The CFB can be considered as a nonlinear closed loop system having two major components: Standpipe and Riser, as shown in Fig. 1. The standpipe is a 50-ft vertical pipe where the solid is initially loaded and

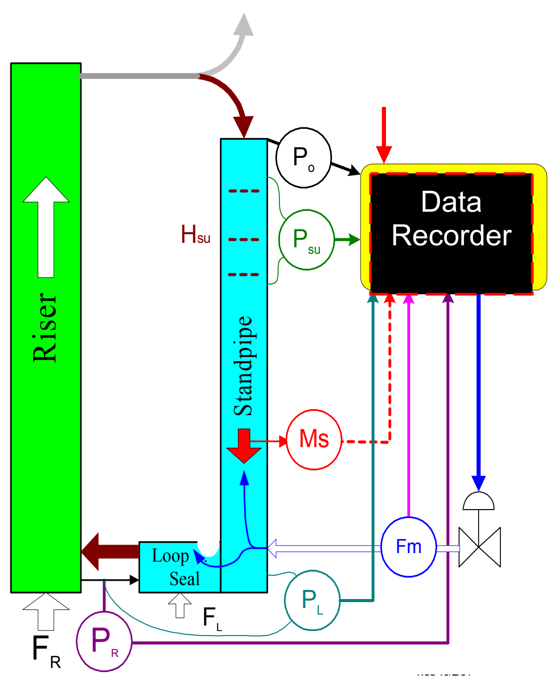

Fig 1. Schematic Diagram of CF-CFB

stored. Once the CFB begins operating, gas pressures forces the solids into the riser, which is also a 50-ft vertical pipe where the solids mix with the gas. Gas pressures then forces the mixture back into the standpipe. One of the major problems in the study and design of controller of this large, complex system is the prediction of its characteristic behavior. Sharp flow angles and inconsistent pressures make the system too complex to easily predict and characterize. Currently, there is no way to construct a reliable model and controller of a system this complex using traditional methods. NN provide a way to construct both of these tools, which stems from their ability to approximate arbitrary nonlinear mappings [5, 6]. Since their rebirth in 1980's, NN applications to various problems have been ever increasing. The effectiveness of NN is due to its learning ability and versatile mapping capabilities from input to output. Control of nonlinear systems is a major application area for NN. Some interesting progress has been made in this field using NN. It has been shown that a NN can be effectively for the identification and control of nonlinear dynamical processes. The versatile mapping capability provides a means of modeling and controlling nonlinear plants which may not be possible by conventional methods. And the learning ability reduces the human effort in designing controllers and also suggests a potential for discovering better control schemes than presently known.

2. CFB DYNAMIC ANALYSIS

The CF-CFB consists of two primary parts with numerous secondary parts. The riser and standpipe have the primary functions in the unit. Solids entering the bottom of the riser are carried to the top of the riser by high velocity air. The riser section of the unit is a 50-feet tall, 1-foot diameter pipe with two inlets near the bottom and one outlet near the top which goes to primary and secondary cyclones for particle separation. Pressure drop in the riser is assumed to be proportional to the mass of the solids in the riser. Solids separated in the primary cyclone fall into the standpipe. The standpipe has two distinct regions of solid flow: the freeboard and the moving packed bed region. The region in standpipe where the particles fall freely is called the freeboard. The loop seal is used to regulate solids flux out of the standpipe. The exit of the loop seal is connected to the bottom of the riser. The standpipe is a reservoir for solids waiting to pass back into the riser. The bulk air-flow through the standpipe is understood to be a function of the pressure gradient and the void fraction of the bed. Since measuring the pressure drop is an important factor, the standpipe was divided into sections with pressure transducers at each of these sections. The ports at the lowest two heights are the most significant and are referred to as the Base aeration and Move aeration, respectively. The air injected into the process at these points is most commonly used to adjust the rate that the solids circulate. The facility at NETL, Morgantown, WV has a supply of 250,000-scfh air with the ability to obtain superficial velocities of 10 to 30 ft/sec in the riser, 0.02 to 0.07 ft/sec in the CFB. The operating pressures range from 0 to 15 psig at the riser outlet and up to 30 psig in the CFB.

The mechanisms of CFB provide the advantage of exposing solids and fluids in close contact during transport. Recirculation of solids provides repeated exposure to fluid reactants. Recirculation also assures that thermal and reactant mass of solids is retained in close and controlled contact with the reaction zone. A standpipe leg of a CFB can provide an effective means of reintroducing solids inventory to the reaction zone. A pressure balance dominated operation of the standpipe provides a means of recovery of a portion of solid transport energy. Tightly coupled interactions between components of CFB make it difficult in modeling and controller design. Predictive analysis of prospective designs requires knowledge that models are representative of dynamic mechanisms that may be exhibited by an operational process. The three major obstacles in characterizing such large and complex systems are:

1. Chaotic nature of system,
2. Non-linearity of the system, and
3. Number of immeasurable unknowns internal to the system and their interdependence.

Even in such situations, NN have been able to provide a suitable solution for modeling and control problems.

3. NEURAL NETWORKS

NN generally consist of a number of interconnected processing elements or neurons. How the inter-neuron connections are arranged and the nature of the connections determines the structure of a network. Its learning algorithm governs how the strengths of the connections are adjusted or trained to achieve a desired overall behavior of the network. In feed forward NN, the neurons are generally grouped in to layers. NN are inherently nonlinear and multivariable and are suitable for use in conventional modeling and control structures. A learning process driven by minimization of the mean square error between required and actual outputs achieves the nonlinear modeling. Thus, the NN is capable of learning input-output maps from the system being studied through the adaptations of the connection weights between neurons, using specific training algorithms.

Prior to learning a NN can be considered as an empty (of knowledge) black box. After training the network becomes a full black box. The problem thought remains is that it is still seen as a black box that for some unknown reasons classifies or predicts correctly given an input pattern. The knowledge of a NN is stored in the weights of the connection but because of their numerical nature it is difficult to interpret them. The typical procedure of application of NN to the problem would consist of first analyzing the problem and collection of all available data, and to choose a NN type which is most suitable to the problem. We select the most important features of the data available and select an appropriate NN topology, number of neurons, etc by trial and error. With data divided into two sets, a training and test set, the trained NN is tested for performance on test data set, and is compared with different trained NN's and the best results accepted. More detailed analysis has been outlined in [3].

4. MODELING AND CONTROL USING NEURAL NETWORKS

Modeling and Control of nonlinear systems is a major application area for NN. Some interesting progress has been made in this field using NN. It has been shown that a NN can be effectively for the identification and control of nonlinear dynamical processes [5]. The versatile mapping capability provides a means of modeling and controlling nonlinear plants which may not be possible by conventional methods. The trained network often produces surprising results and generalizations in applications where explicit derivations of mappings and discovery of relationships is almost impossible. But there is one major flaw that has to be considered in these mappings. Sufficient information is to be provided in the training data so that the NN can converge and find the exact relationship. There are no preset rules in this regard to attain the target, but the generalized procedures provide a probable solution. In recent years a number of reports have been published which using mathematical theorems establish that a two or three layer multi-layer perceptron with sigmoid units can approximate any given real-valued, continuous multivariate function to a desired degree of accuracy, if a sufficiently large number of nodes are used in the hidden layer [6].

Although backpropagation has become popular on grounds of simplicity and capability to learn sequentially from training instances, we have used one of its variants, Levenberg-Marquardt algorithm (LM) [7, 8] for training the NN by minimizing the sum of square errors. LM algorithm is a second order optimization method. Most algorithms for least-square optimization use either steepest descent or Taylor series models. The LM algorithm uses an interpolation between the approaches based on the maximum neighborhood in which the truncated Taylor series gives an adequate representation of the nonlinear model. The method has been found advantageous compared to other methods that use only one of the two approaches. The method has been found advantageous compared to other methods that use only one of the two approaches. This method is a nice compromise between the speed of Newton's method and the guaranteed convergence of steepest descent.

In first stage of modeling, experiments or test runs are done on the plant. The purpose of this stage is to collect a set of data points that describe how the system behaves over its complete range of operation. The idea is to vary the input(s) and observe the response of the output(s). As the CFB we are considering is an unstable system by itself, we conducted the experiment in a closed loop, using a stabilizing feedback controller and/or human operator for controlling the system. The plant was subjected to a sinusoidal change in its aeration rate, and during the whole operation, the plant was subjected to different conditions of operation by manipulating other variables. For NN used for modeling the input is a moving window of time series of data. The next time step value for the system is predicted. After the NN was trained, the performance was evaluated by using unseen test data set by NN. In real process, the input/output signals include noise and disturbance. This may impose unknown parameters such as time constants, delay times and so on. In addition, the sampling rate and time may be less than ideal. In such situations, when a NN is used for modeling, that input layer needs a large number of input nodes to enable it to gain sufficient information about the target plant. With more number of input nodes the training time increases but not necessarily its prediction capability. Therefore, the number of delayed inputs that should be given to the NN was selected appropriately, as outlined in [3]. Initial attempts of modeling [1, 2, and 3], were using a MISO approach, and there were different models for predicting pressure differentials, aeration rate and mass circulating rate, but in [4] it has been clearly shown that a single MIMO NN can successfully model all the pressure differentials and the mass circulation rate simultaneously. Fig 2 shows a prediction sample window of MIMO model predicting the Mass circulating rate. The data range from 0-1800 sec was given for the training of the NN, and after that the NN predicts without any additional training. It can be clearly noted that the NN model has been not only effective in predicting in the training set but also extrapolates effectively into unseen future. It should be however noted that even though the circulation rate in the plot seems to be sinusoidal, various other parameters in the CFB have been constantly been changed and hence the plant state is not the same all time.

NN control designs are divided into two main categories: the Direct Design where the controller is a NN and the Indirect Design where the controller is not itself a NN, but uses NN in its design and adaptation [9]. Many learning algorithms have been proposed for NN. However, there is one main obstacle in the way to adapt NN controller. Backpropagation cannot be applied directly to NN controller training. The basic objective of a controller is to provide the appropriate input parameters to plant to obtain the desired output. In our case by varying the move aeration we control the mass circulation rate. The NN uses the difference between the actual outputs of the plant Y_α and the desired output Yd_α to change the weight of connections. Specialized learning avoids several drawbacks of general training: there is no longer a specific training stage, and the network learns directly on the domain of relevant Y_α. Moreover, the network learns continually and is therefore *adaptive*. Yet, the evaluation of the error from the output requires prior knowledge of the plant. They propose to consider that plant can be thought of as an additional, though unmodifiable, layer of the neural controller. The weights of the connections leading to this layer are fixed to the values $\partial Y_\alpha / \partial U_\beta$. A modification of the back-propagation algorithm is done to take this layer into account and compute the errors δ_α at the output layer as:

$$\delta_\alpha = f^{'}(net_\alpha)\sum_\beta \frac{\partial Y_\beta}{\partial U_\alpha}(Y_\beta - YD_\beta) \qquad (1)$$

this is similar to what we use in general back-propagation. However, the Jacobian of the plant $\partial Y_\alpha / \partial U_\beta$ can be unknown and difficult to determine. There are different methods which differ in the method how the Jacobian of the plant $\partial Y_\alpha(k+1) / \partial U_\gamma(k)$ is calculated or estimated which is unknown. A simple way to do this is to approximate the partial derivative by their sign, which can be known a priori when we have some information about the orientation in which the control parameters influence the outputs of the plant:

$$\frac{\partial E_S}{\partial U_\gamma(k)} = \sum_\alpha Y_\alpha(k+1) - Yd_\alpha(k+1) sign\left(\frac{\partial Y_\alpha(k+1)}{\partial U_\gamma(k)}\right) \qquad (2)$$

where $\partial E_S / \partial U_\gamma(k)$ is the gradient approximation by sign. If the network converges, it will drive the error to zero, providing the plant to follow a reference signal. Finally the weights $w_{\alpha\beta}(n)$ of the connection between unit $U_\alpha(n)$ at layer *n* and unit $U_\beta(n-1)$ at layer *(n-1)* is modified by:

$$\Delta w_{\alpha\beta}(n) = -\eta \frac{\partial E_S}{\partial w_{\alpha\beta}(n)} \qquad (3)$$

where η is the learning rate. This error can then be back propagated to the hidden layers using the general rules of backpropagation. The signs are chosen on the basis of prior qualitative knowledge of the plant: they represent the direction in which the control parameters $U_\alpha(k)$ must be modified to produce an increase of the outputs $Y_\beta(k+1)$ of the plant. In contrast to the indirect adaptive control, there are direct adaptive controller techniques that are quite easier to train and implement. The direct training method used here is trained by using the systems output errors directly with little a priori knowledge of the controlled plant. This direct method of training the NN controller has been outlined in [10]. If the system is positive-responded (or negative-responded), then the system direction is written as D(G)=1 (or D(G)= -1). Now this replaces $sign\left(\frac{\partial Y_\alpha(k+1)}{\partial U_\gamma(k)}\right)$ in (2) and the weights are updated via backpropagation. In the case of CFB, the aeration rate is always aiding the increased mass circulation rate, hence we use D(G)=1 for the training. The NN controller is trained and is used to provide control action to make the mass flow rate follow a randomly given reference input signal, as shown in Fig 3. It is clearly observed that the direct adaptive NN controller has been able to achieve the set points. The controller is calculating the control action every instant, and is updating itself with respect to response from the plant. The controller was perturbed by varying the other variables to check the stability of the controller and the results were satisfactory.

5. CONCLUSIONS

The main objective of this work has been to provide a NN model capable of approximating with sufficient accuracy the highly nonlinear process of the CFB that can be later used to device a control strategy. Fig 2 shows that the trained NN model was able to predict not only on the training data set but also was able to extrapolate the results into unseen data set. This model can be used to understand the behavior of the CFB off-line and do certain analysis which may not be possible on the real plant. A suitable controller was designed which was stable and providing good tracking control as shown in Fig 3. Future work is directed in trying to improve the efficiency of the model and controller and also compare the performance with different methods.

6. ACKNOWLEDGMENT

This work is supported by DOE/NETL under grant No. DE-PC26-98FT40143

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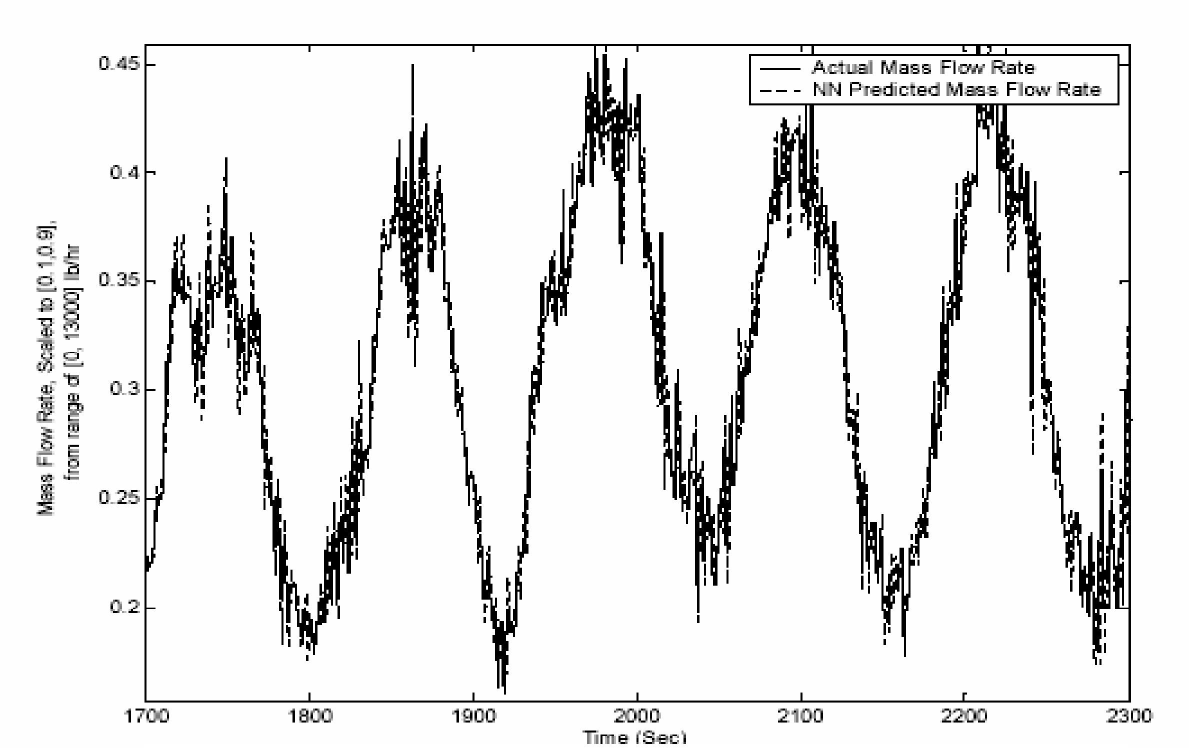

Fig 2. Prediction of Mass Flow Rate over the range of 1700-2300 Sec, NN was trained on 0-1800 Sec data set

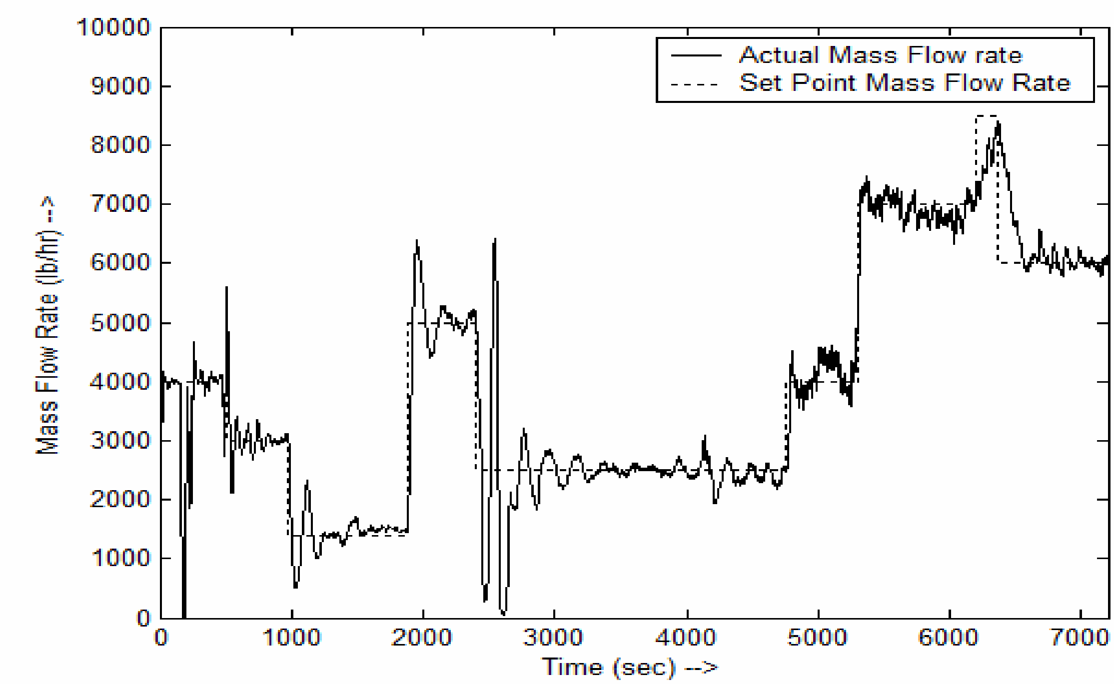

Fig 3. Response of NN Controlled CFB