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Investigation of artificial neural network methodology for modeling of a liquid–solid circulating fluidized bed riser

Shaikh A. Razzak [a,*], Syed M. Rahman [b], Mohammad M. Hossain [a], Jesse Zhu [c]

[a] Department of Chemical Engineering, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
[b] Center for Environment and Water, RI, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
[c] Department of Chemical and Biochemical Engineering, the University of Western Ontario, London, Ontario, Canada N6G 5B8

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ABSTRACT

An artificial neural network (ANN) approach is investigated to model and study the phase holdup distributions of a liquid–solid circulating fluidized bed (LSCFB) system. The ANN model is developed based on different operating parameters of the LSCFB including primary and auxiliary liquid velocities, and superficial solids velocity. The competency of the model is examined by comparing the model predicted and the experimental phase holdup of the LSCFB riser reactor. It is also found that the ANN model successfully predicted the radial non-uniformity of phase holdup that is observed in the experimental runs of the riser. When compared, the model predicted output and trend of radial flow structure for solids holdup are in well agreement with the experiments. The mean absolute percentage error is around 6% and the correlation coefficient value of the predicted output and the experimental data is 0.992.

1. Introduction

Since its first inception for coal gasification in 1920 by Winkler, the fluidized bed systems have found wide range of applications in chemical, petrochemical and biochemical industries. Liquid–solid fluidization is defined as an operation in which a bed of solid particles is suspended in liquid media due to the net drag force of the liquid flowing opposite to the net gravitational force or buoyancy force on the particles. Such an operation generates considerable, intimate contact between the liquid phase and solid particles in these systems, and provides substantial advantages for applications in physical, chemical or biochemical processing involving gas, liquid and solid phases [1–6].

Recent studies suggest that the liquid–solid circulating fluidized bed (LSCFB) has many advantages in wastewater treatment, desulphurization of petroleum products and other environmental and chemical processes involving solids particles (i.e., carriers, sorbents, catalysts etc.). In LSCFB, solid particles are circulated between the riser and the downer at higher velocities compared to conventional fluidized beds, which allows a better solid–liquid contact efficiency resulting enhanced mass transfer between phases. The solid particles move upward with the influence of upward liquid flow in column (riser) then collected and separated at the top of the riser (separator) and finally recirculated through particle inventory of the downer column [5,7]. Generally, the solid catalyst particles are expensive and need to be continuously regenerated as most of the reactor systems prefer continuous mode of operation. In a typical LSCFB system, the principle reactions or adsorption processes are accomplished in the main reactor, usually in a riser. After reaction/adsorption, the deactivated catalyst/adsorbent is circulated to the regenerator (downer). The regeneration/desorption of absorbents is generally completed by a suitable physical or chemical technique. Finally, the reactivated catalyst/adsorbent from the regenerator is recycled back to the main reactor.

Analysis of the hydrodynamic characteristics of LSCFB plays an important role in explaining its behavior under wide range of operating spectrums. At low liquid velocity, the riser section operates like conventional fluidization regime where particles are homogeneously distributed in both radial and axial directions [8]. When the liquid velocity is further increased, the fluidization regime changes from the conventional fluidization regime to circulating fluidization regime. In such liquid velocity, the solid particle distributions in both radial and axial directions become non-uniform throughout the reactor bed [2,5,9]. In an idea to optimize the performance of LSCFBs, there is a need to carry out detailed study on the process parameters and their respective effects on the overall performance of the system. The correlations and models based on the experimental observations are often useful in describing a given process.

Recently, computational intelligence models such as artificial neural network (ANN) are explored in the hydrodynamic study. ANNs are biologically inspired systems consisting of massively connected processing elements, organized in layers and tied together with weighted

* Corresponding author. Tel.: +966 3 860 7460; fax: +966 3 860 4234.
E-mail address: srazzak@kfupm.edu.sa (S.A. Razzak).

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connections corresponding. Lahiri and Ghanta [10] developed an ANN model to predict holdup in slurry pipelines. They considered holdup as a function of solid concentration, particle diameter, slurry velocity, pressure drop and solid and liquid properties. The ANN model showed reasonable prediction of holdup and its trend over a wide range of operating conditions, physical properties and pipe diameters. ANN as a representative of non-linear modeling is also being considered to design and scale-up of fluidized beds rather than relying on the concept of uniform flow and one-dimensional steady-state modeling. Nakajima et al. [11] investigated the performance of ANN model to approximate the dynamic behavior of pressure fluctuation in a circulating fluidized bed. Otawara et al. [12] proposed an ANN approach to model the non-linear behaviors of bubble motion in a three-phase fluidized bed.

It is possibly relevant to mention here that all the after mentioned ANN modeling works have been concentrated mainly on the low velocity fluidized bed systems. In our knowledge, no such models are available in literature concerning the high velocity fluidized beds, in particular for the LSCFB systems. The present investigation is focused on developing an ANN model for a LSCFB system in order to examine the radial and axial distribution of solids holdup of a LSCFB for wide ranges of operating conditions. The detail of hydrodynamic behaviors in a wide operating parameters ranges and wide distribution of flow characteristics are carried out by modeling of phase holdup in LSCFB riser by using the ANN technique. The developed model is validated with a set of experimental data obtained in a pilot scale LSCFB riser. ANN model used to predict phase holdup with the change of operating parameters such as primary, secondary liquid flow rates, and superficial solids velocity of the riser of both reactors and the results are verified with the experimental data.

2. Experimental set-up

A pilot scale LSCFB system is considered for model development and evaluation. The pilot LSCFB system is available at Particle Technology Research Centre (PTRC), Department of Chemical and Biochemical Engineering at the University of Western Ontario, Canada. A schematic diagram of the LSCFB is shown in Fig. 1. The system consists of two main sections, the riser and the downer, both made of Plexiglas. The detail of the experimental set up can be found elsewhere [5]. The riser is 5.97 m tall with 0.0762 m in diameter while the downer is 5.05 m tall with 0.2 m in diameter. There are two liquid distributors at the bottom of the riser. The primary liquid distributor is made of seven stainless tubes occupying 19.5% of the total riser cross-section and extending 0.2 m into the riser. The auxiliary liquid distributor is a porous plate with 4.8% opening area at the base of the riser. The solid particles are fluidized and moving up inside the riser by the influence of liquid flow. These particles entrained in the solid–liquid separator at the top of the riser are returned to the downer by gravity.

The electrical resistance tomography (ERT), an imaging technique was employed for flow characterization by simultaneous measurements of phase holdup. The application of ERT in liquid–solid systems is limited to the measurement of conductive phase only, which was applicable to the LSCFB for complete phase holdup. The phase holdup measurement technique using ERT and other instruments like pressure transducers, optical fiber probe were reported by Razzak et al. [5,15]. The employed ERT system was manufactured by En' Urga Inc., USA. This system consists of a sensor and PC based data acquisition system. The inner diameter of the sensor is built in sixteen equally spaced electrodes. These electrodes simultaneously send current and receive voltage signals. The AC current was applied to the electrodes. The ERT measures the electrical potential distribution through the electrodes flush mounted on the wall for each driving current. During each operating frame, multiple driving currents are sequentially fed into a pair of neighboring electrodes. The voltages are measured on all other electrodes except the current injecting electrodes pair. The way in which the driving pair is switched and the voltage measurements are collected varies. With the applied current source, the electrical potential distributions are generated within the fluids and the wall. The electronic circuits capture voltages between the electrodes, and send them to a PC-based data acquisition system. The saved data are processed with an image reconstruction algorithm, which provides the phase distributions occurred in the experiments.

3. The ANN approach and model development

As mentioned in the introduction, ANNs are biologically inspired systems which consist of massively connected processing elements analogous to functionality of biological neurons that are organized in layers and tied together with weighted connections corresponding to brain synapses. These are typically designed by numerical-learning-based algorithms. In response to training signals, the learning tool provides a given network with the capacity of adjusting its parameters. By adjusting the weights of the network corresponding to a set of input and output exemplars, ANNs can be “trained” to approximate virtually any nonlinear function to a required degree of accuracy [13]. If sufficient numbers of hidden units (neurons) are available, then conventional ANN using a single hidden layer and arbitrary squashing functions can theoretically approximate any measurable function from a finite-dimensional space to another finite-dimensional space to any desired degree of accuracy [14]. Having this feature, the ANN is often considered as a class of universal approximators.

The topologies of ANNs refer to the ordering and organization of the nodes from the input layer to the output layer and the way the nodes and the interconnections are arranged within the layers of a given ANN determines its topology [14]. The selection of any topology depends on the type of concerned problems. Depending on the data processing nature, ANN topologies can be divided into feed forward and recurrent architecture. A network with feed forward architecture has its nodes hierarchically arranged in layers starting with the input layer and ending with the output layer, and in between, a number of

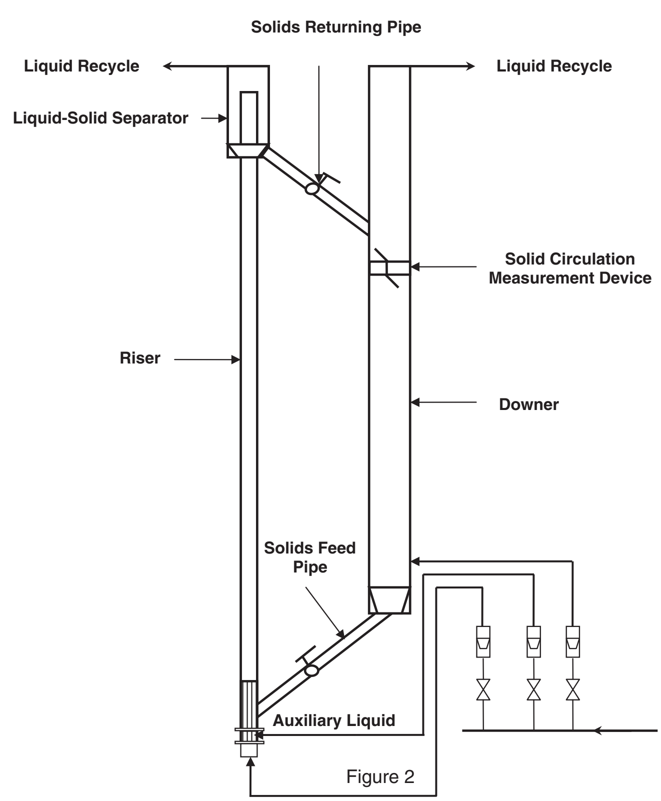

Fig. 1. Schematic diagram of the LSCFB system.