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ANN applicability in gas holdup prediction in tapered bubble columns using non-Newtonian pseudoplastic liquids

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Abstract : Applicability of Artificial Neural Network (ANN) for the prediction of gas holdup in tapered bubble columns using non-Newtonian pseudoplastic liquids have been reported. The experimental data used for this analysis are taken from our earlier publication (Jana S. K., A. B. Biswas and S. K. Das, Gas holdup in tapered bubble column using pseudoplastic non-Newtonian liquids, Korean J.. Chem. Engg., 31(4) (2014) 574-481). The ANN with multilayer perceptron (MPL) with one hidden layer and four different transfer functions with backpropagation algorithm were used to demonstrate the applicability of ANN in the prediction of gas holdup.

Keywords : Gas holdup; Tapered bubble column; Non-Newtonian liquid; Artificial neural network; Multilayer perceptron, Backpropagation.

INTRODUCTION

Bubble column is a device in which a gas-phase is bubbled through a column of liquid and it can promote a chemical or biochemical reaction in the presence or absence of a catalyst suspended in the liquid phase. Bubble column is very popular and widely used in industry as absorber, stripper, reactor and fermenter etc. It has simple construction and absence of any moving parts, good mixing, control of temperature, high heat and mass transfer rate, minimum maintenance and low capital cost involved. Bubble coalescence, high pressure drop, considerable back mixing in both phases, short residence time of gas and complex hydrodynamics flow patterns are the main disadvantages in bubble column. However, it is extensively used in biotechnology, food processing, pharmaceutical processes and waste water treatment processes. Jana et al. (2014) reviewed on the bubble columns and modified bubble columns in detail.

Straight cylindrical bubble column, slurry bubble column have been extensively used in the process industries. Taper bubble columns are also used in industrial practice in the field of biochemical reactions, biological wastewater treatment for more than few decades[21, 16, 18, 13]. Zhang et al. (2003) reported that the gas holdup in cylindrical bubble column does not change in the axial direction at low gas velocity but decreases slightly at high gas velocity from the bottom to top, whereas in tapered bubble column the axial gas holdup decreases from bottom to the top. So in the tapered bubble column flow is always developing nature, i.e., bubbles are rising from the bottom as a spherical shape and then coalesce to form bigger bubbles, structure of the big bubble changes continuously from circular to slightly flattened and rapture of the big bubbles to small bubbles. Jana et al. (2014) reported detail bubble characteristics and flow regime in taper bubble column. Literature review suggested that most researchers used Newtonian liquids in their study. The rheological behavior of non-Newtonian liquids is complex and hence the bubble flows in these liquids has different characteristics than that of Newtonian liquids[7, 8]. Only few literatures are available using non-Newtonian liquids in bubble column[9, 20, 10, 17, 15].

Artificial neural network has gain a widespread application in many engineering fields[12]. One of the advantage of ANN that it can learn from example, incorporate a large number of variables, provide quick response to the new information and predict most accurately[3]. Shaikh and Al-Dahhan (2003) concluded that the ANN correlation gives better prediction than the empirical correlation for the prediction of gas holdup in bubble column. Bar and Das (2011, 2012) showed that the MLP with backpropagation algorithm is useful for the prediction of hydrodynamic parameter in two-phase gas-non-Newtonian liquid flow through bends and horizontal pipeline. Bar et al. (2011) used MLP with backpropagation algorithm for the prediction of frictional pressure drop in two-phase gas-non-Newtonian liquid flow through helical coils in horizontal orientation. This research investigates the experimental determination of the gas holdup in taper bubble columns and the use of artificial neural network for the gas holdup prediction.

ANN methodology

In artificial neural network, ANN model of system, feed-forward architecture namely Multiple Layer Perception (MLP) is most commonly used. Figure 1 shows schematic diagram of it. It has three layers: an input layer, hidden layer(s) and an output layer. Each layer consists of a number of elementary processing units known as neurons. Each neuron in the input is connected to its hidden layer through weights. Also there is connection between hidden and output layers. When an input is introduced to the neural network, the synaptic weights between the neurons are simulated and these signals propagate through layers and the output result is formed. The main objective is to form output by the network should close to the expected output, the weights between the layers and the neurons are modified in such a way that next time the same input will provide an output that are closer to the expected output. Various algorithms are available for training of the neural networks. Backpropagation algorithm is the most versatile and robust technique, provides most efficient learning procedure for MLP networks. This

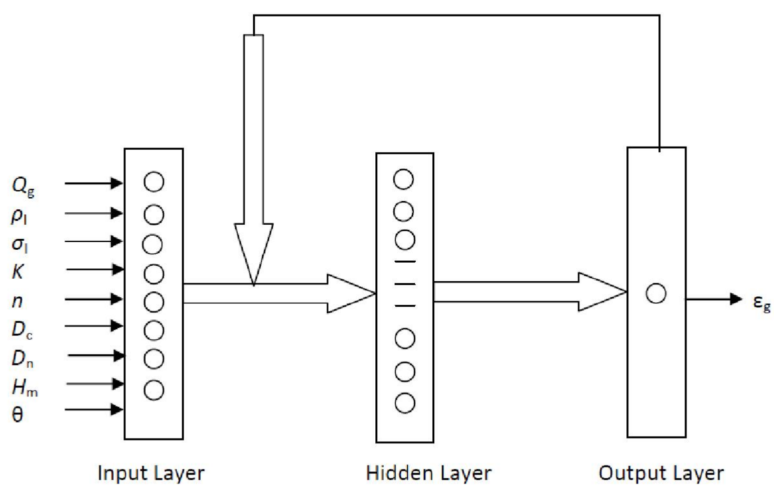

Figure 1 : Schematic diagram of neural network

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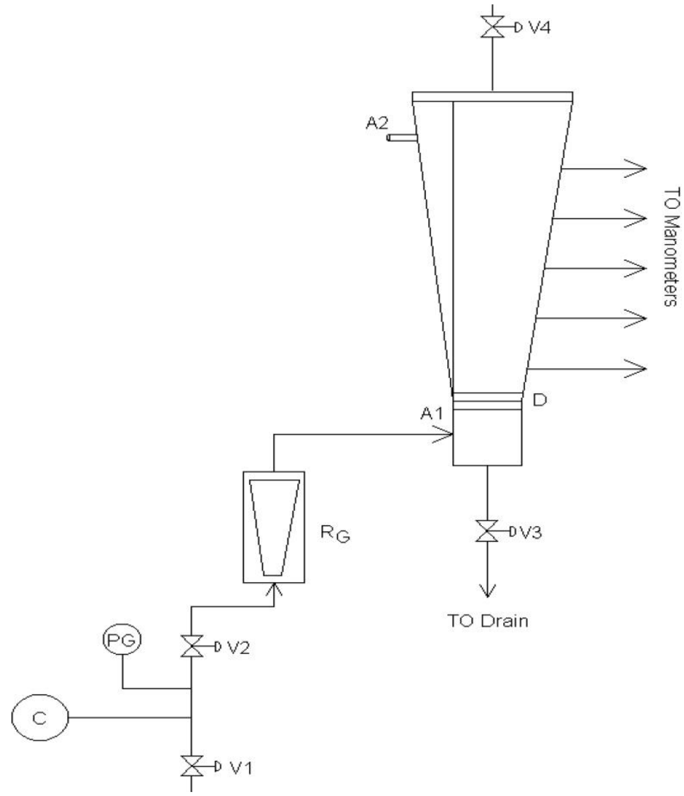

Figure 2 : Schematic diagram of experimental setup; A1: Air inlet; A2: Air outlet; Manometers; D: Distributor; C: Compressor; PG: pressure Gauge; RG: Rotameter for gas; V1-V4: Control valves

algorithm is especially capable of solving predictive problems[11, 1]. Literature survey suggested that a network with single hidden layer using different popular transfer functions like sigmoid, hyperbolic tangent etc. are extensively used for prediction and it performed successfully. Bansal et al. (1993) and Tamura and Tateishi (1997) observed that the single hidden layer can solve most of the problems for more input variables and outputs. Hence this study is based on MLP using a single hidden layer. The values of the learning rate and momentum constant of networks are 0.01 and 0.9 respectively. Four different transfer functions in a hidden layer are used in the network and are shown in TABLE 1. Transfer function 5 represents the output function. So the prediction of the gas holdup is carried out using multilayer perceptron (MPL) with one hidden layer and four different transfer functions and is trained with very popular backpropagation (BP) algorithm using MATLAB R2010b as a computational tool.

Experimental details[14]

A schematic diagram of the experimental setup has been shown in Figure 2. It consists of tapered bubble column, manometers for pressure measurement, distributor (D) to distribute the air, compressor (C), pressure gauge (PG), rotameter (R_G) for flow measures and other accessories. The tapered bubble columns were made of thick perspex and square shaped. A perforated plates made of Perspex of 50 holes of different diameters were used for air distribution and connected with the column by means of flanges. Air inlet would be provided in column by means of nozzles of 4mm diameter and then the air is distributed through the distributor plate and enters into the column. Two tapered bubble columns of different cross-section areas are used for the experiment. Detailed dimension of the columns are shown in TABLE 2. Columns were fitted to vertically by means of clamps to avoid any vibration.

The desired amount of Sodium salt of carboxymethyl celluse (SCMC) were dissolved in tap water, a few drop of formaldehyde was added to avoid biological degradation and kept around one night for aging. Four different SCMC concentrations, 0.2 - 0.8 kg/m^3 were used for the experiment. The dilute

TABLE 1 : Different transfer functions

Case	Name of activation function	Equation
Transfer function 1	Tan hyperbolic function (tansig)	$y = \tanh(net)$
Transfer function 2	Logsigmoid function (logsig)	$y = \frac{1}{(1+\exp(-net))}$
Transfer function 3	Radial basis function(radbas)	$y = \exp(-net^2)$
Transfer function 4	Triangular basis function(tribas)	$y = 1 - abs(net)$ if -1? (net)? 1 $y = 0$ otherwise
Transfer function 5 (Output function)	Linear function(purelin)	$y = (net)$

TABLE 2 : Dimension of bubble columns

Characteristic parameters	Smaller Tapered Bubble Column TB1	Larger Tapered Bubble Column TB2
Thickness of Perspex sheet, m	0.0127	0.0127
Height of column, m	1.83	1.83
Top area of the column m^2	0.0762×0.0762	0.1016×0.1016
Bottom area of the column, m^2	0.0508×0.0508	0.0508×0.0508
Equivalent diameter, i.e., log mean diameter based on bottom equivalent diameter and the equivalent diameter of the gas-liquid interface, m	0.0605? D_c? 0.0614	0.0692? D_c? 0.0710
Hole diameter of the air inlet and outlet, m	0.0127	0.0127
Taper angle(deg)	0.44	0.86
Hole diameter of different sieve plates used, m	0.00277,0.00357,0.00436	0.00277, 0.00357, 0.00436
Hole number of sieve plate	50	50

TABLE 3 : Physical properties of the SCMC solutions

Concentration Kg/m^3	Flow behavior Index (n)	Consistency index K (Ns^n/m^2)	Density P (Kg/m^3)	Surface tension σ (N/m)
0.2	0.9013	0.0138	10001.69	0.07834
0.4	0.7443	0.1149	1002.13	0.08003
0.6	0.6605	0.3454	1002.87	0.08142
0.8	0.6015	0.6486	1003.83	0.08321

solution of SCMC is a time independent pseudoplastic fluid and its rheology is described by Oswald de-Waele or Power law model,

$$\tau = K\left(-\frac{dV}{dr}\right)^n \quad \textbf{(1)}$$

where K and n are the constants for the particular liquid with n <1. The constant K is known as consistency index of the liquid and the higher the value of K the more viscous is the fluid. The rheological properties of the SCMC solutions were measured by means of pipeline viscometer. DuNouy tensiometer and specific gravity bottle measured surface tension and density respectively. The physical properties of the liquid are shown in TABLE 3.

The liquid height used for the experiments were 1.12m, 1.17m and 1.22m for both columns. The air at a pressure of $1 kg/cm^2$ gauge was introduced into the column, and under steady state condition, reading of manometers attached to the taping were noted and also the height of liquid in the column was also noted. Flow pattern was observed visually and it was bubble and plug according to the increasing air flow rate. The experiments were repeated a number of times to ensure the reproducibility of the data. The temperature was maintained at atmospheric temperature30±2^{0}C.

The gas holdup for particular gas flow rate is the fraction of the total gas-liquid volume that is occupied by the gas. This gas holdup is measured experimentally by subtracting the initial liquid volume from the volume of the gassed system and dividing this difference by the volume of the gassed system as expressed by the following expression,

$$\varepsilon_g = \frac{V - V_o}{V} \quad (2)$$

RESULTS AND DISCUSSION

Figures 3-5 show the effects of different parameters on gas holdup. The gas holdup increases with increasing gas flow rate. As bed height increases the gas holdup decreases compare to the smaller bed height and is due to bubbles coalescence to form bigger sized bubbles which are found to concentrate in the central core of the column and it rise quickly through the liquid. With increasing SCMC concentration the effective viscosity of the liquid increases, this decreases the gas holdup, and is due at higher concentration dense medium will tend to suppress and coalescence the bubbles to form bigger bubbles. With increasing the distributor hole diameter the gas holdup decreases due to bigger size bubble generation.

Performance of the ANN

Range of variables investigated is show in TABLE 4. Initially the total data of 646 was randomized. The 90% of the data are used for training and 10% for testing. The synapse that connects a hidden layer to the input layer adjusts the weights and learning rate. It is always desired that the number of processing elements in the hidden layer must be kept at a minimum to reduce the complexity of network. Hence one hidden layer is used. The numbers of nodes in the hidden layer were selected by varying the nodes from 5 to 25, each case the mean square error (MSE) was calculated and then by comparison of minimum MSE value the number of nodes are selected. Figure 6 shows the variation in MSE with the number of nodes. The optimum number of

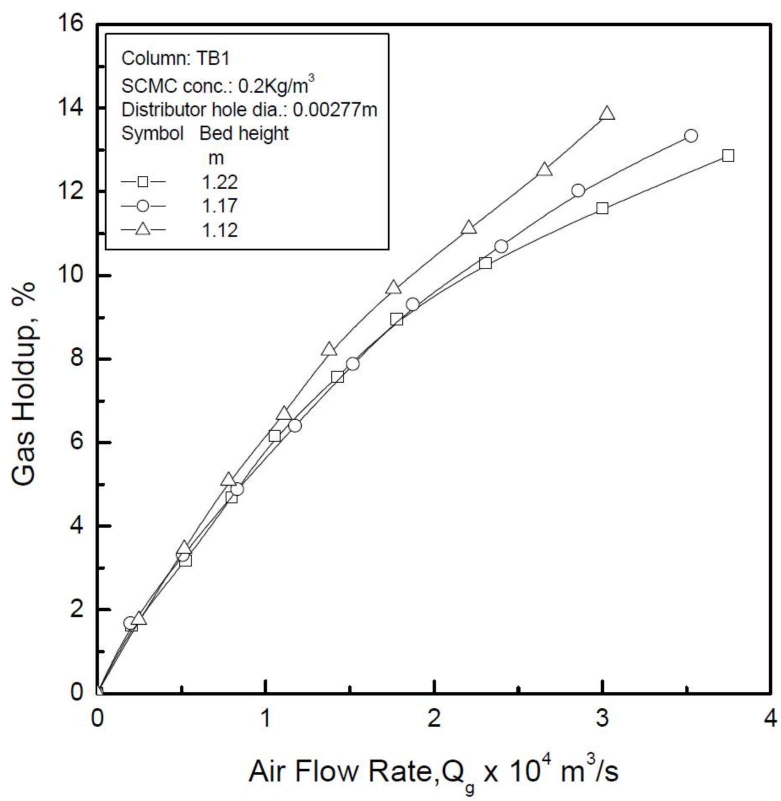

Figure 3 : Variation of gas holdup with the gas flow rate

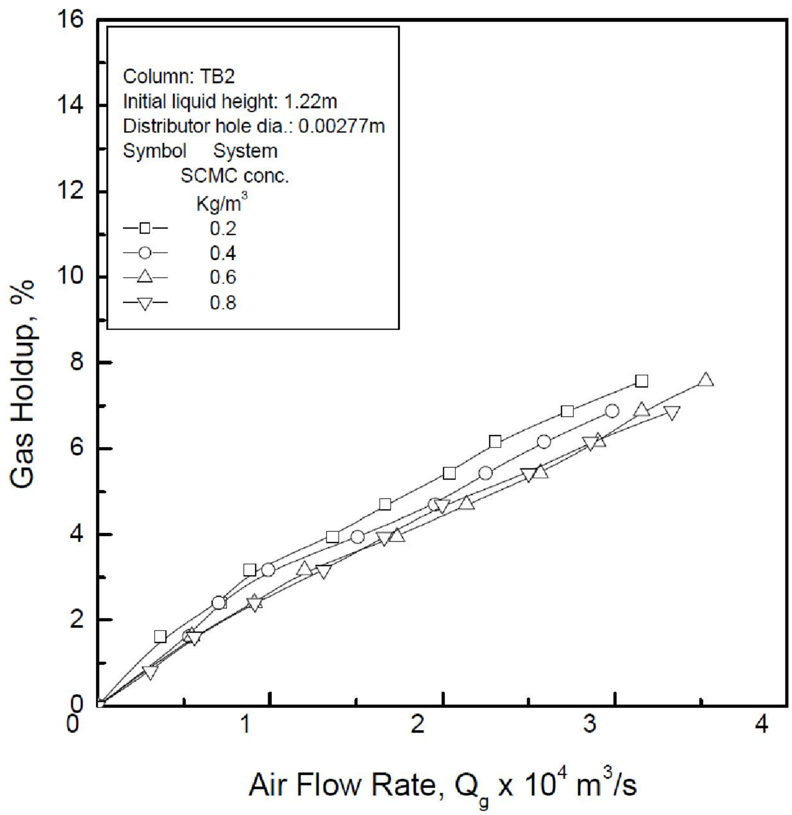

Figure 4 : Variation of gas holdup with the gas flow rate as the SCMC solution concentration as parameter

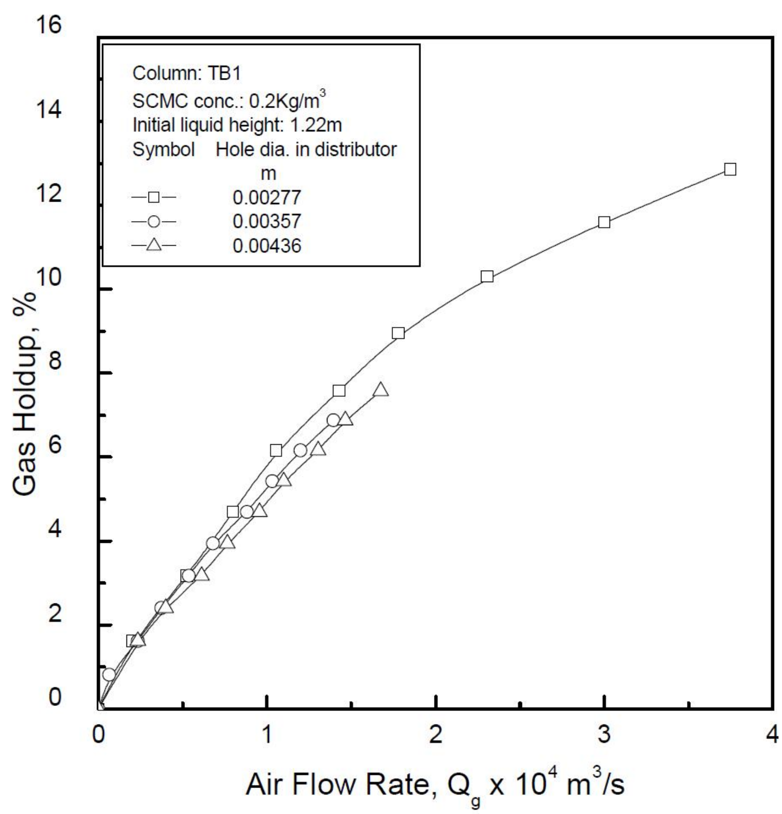

Figure 5 : Variation of gas holdup with the gas flow rate as the distributor hole diameter as parameter

nodes is that node where the MSE is minimum. These optimum numbers of node are used for the analysis.

TABLE 4 : Range of variables investigated

Measurement type	Range
Q_g, Gas flow rate, m^3/s	$0.0000058 \leq Q_g \leq 0.00046154$
ρ_l, Density of liquid, Kg/m^3	$1001.69 \leq \rho_l \leq 1003.83$
σ_l, Surface tension, N/m	$0.07834 \leq \sigma_l \leq 0.0832$
K'Consistency index, $Ns^{n'}/m^2$	$0.0138 \leq K' \leq 0.6486$
n, Flow behaviour index	$0.6015 \leq n' \leq 0.9013$
D_c, Diameter of column(log mean), m	$0.0605 \leq D_c \leq 0.0710$
D_n, Distributor hole diameter, m	$0.00277 \leq D_n \leq 0.00436$
H_0, Clear liquid height, m	$1.12 \leq H_0 \leq 1.22$
H_m, Gas–liquid mixture height in the column, m	$1.13 \leq H_m \leq 1.4$
θ, Taper angle(deg)	0.44 and 0.86
ε_g, Gas hold-up(dimensionless)	$0.00813 \leq \varepsilon_g \leq 0.138462$

The output is generated by using the transfer function 5 and compare with the desired output. The error passes to backpropagation for corrective adjustment of synaptic weight of network for training. The backpropagation process propagates the errors backward through the network and allows adaptation of hidden processing element and a closed-loop control system is thus established. The weights are automatically adjusted using a gradient-descent-based algorithm.

The performance of the network is checked by calculating mean square error (MSE), average absolute relative error (AARE), standard deviation (σ), cross-correlation coefficient (R) and Chi-square test (χ^2),

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - y_i\right)^2 \qquad (3)$$

$$AARE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{(y_i - x_i)}{x_i}\right| \qquad (4)$$

$$\sigma = \sqrt{\sum_{i=1}^{N}\frac{1}{N-1}\left[\left|\frac{(y_i - x_i)}{x_i}\right| - AARE\right]^2} \qquad (5)$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}} \qquad (6)$$

$$\chi^2 = \sum_{i=1}^{N}\frac{(x_i - y_i)^2}{y_i} \qquad (7)$$

The chi-square test was performed to find the best-fit network model when the values of cross-correlation coefficient are close to each other. The minimum value χ^2 give best model.

Input parameters are the physical and operating variables of the system

Gas holdup is expressed as a function of liquid and gas physical properties, geometric variables of the system and dynamic variables. The operating variables include the gas flow rate, Q_g, density of liquid, ρ_l, surface tension of the liquid, σ_l, consistency index, K, flow behavior index, n, log mean diameter of column, D_c, gas-liquid mixture height in the column, H_m, distributor hole diameter, D_n, the taper angle of the column, θ. Other parameters like, density of air, number of holes in the distributor plate and the acceleration due to gravity are not the input parameter in ANN as they are constant in all cases. The diameter of the column was calculated by first calculating the equivalent diameter of the base and at the gas-liquid interface, then calculates the log mean diameter, D_c, of the column. Hence, for each gas flow rate the diameter, D_c, varies according to the height of the gas-liquid interface. The range of variables investigated is shown in TABLE 4. For this system the optimum result was achieved using 2000 epochs for training. The gradual decrease of the value of average MSE as shown in Figure 6 in-

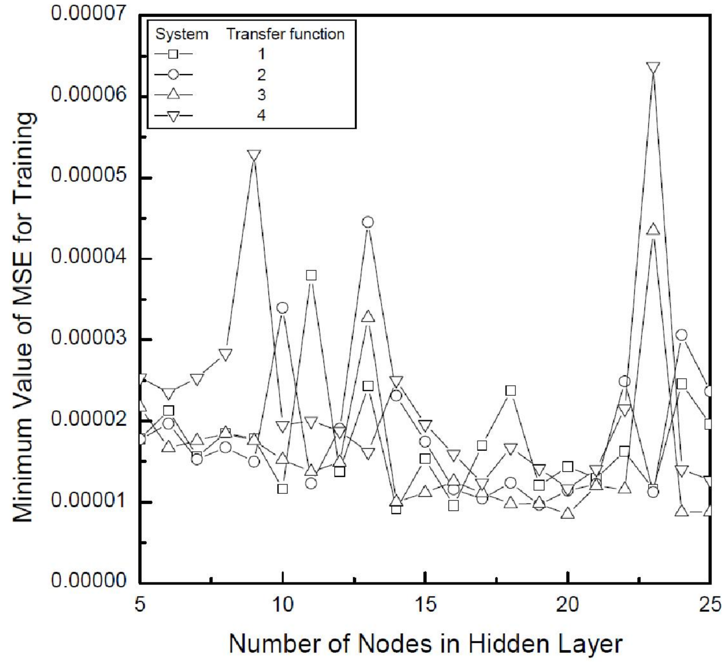

Figure 6 : Variation of MSE with the number of nodes in hidden layer

TABLE 5 : Performance of best neural network for testing in gas holdup

Measurement type	Transfer function 1	Transfer function 2	Transfer function 3	Transfer function 4
AARE	0.1001	0.095332	0.100901	0.120589
SD(σ)	0.11425	0.114004	0.10781	0.10925
MSE	0.0000288693	0.0000276932	0.0000440029	0.10925
CCC(R)	0.97284	0.9713	0.97441	0.95798
χ^2	0.035501	0.03953	0.035601	0.049578
Optimum no. of processing elements in hidden layer	14	19	20	20

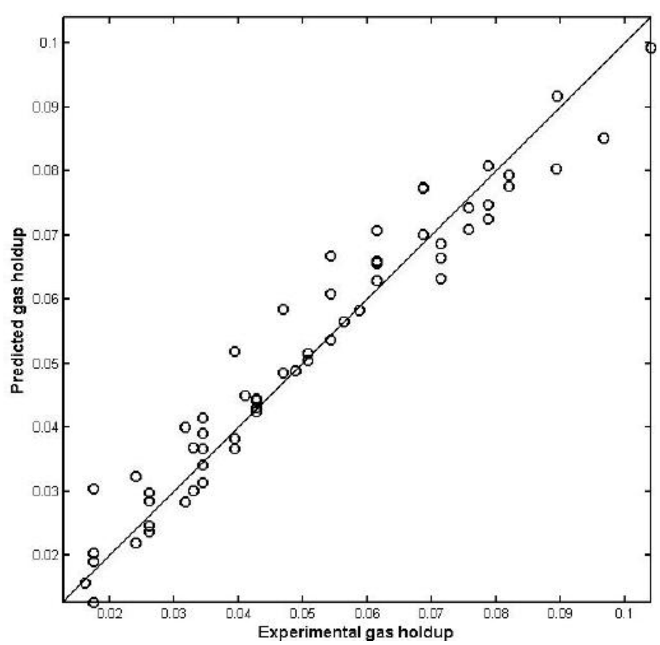

Figure 7 : Comparison of gas holdup for the prediction

dicates that the training procedure is accurate enough. The training is acceptable as the cross-correlation coefficient (R) obtained 0.9917.

TABLE 5 represents the performance of the artificial neural network for prediction of the gas holdup for different transfer functions used in a hidden layer after optimization. These comparisons prove the effectiveness of the artificial neural network analysis. For the holdup prediction the cross-correlation coefficient, R value is greater than 0.97 for all four different transfer functions used in the hidden layer. Hence, all the transfer functions used is acceptable for the prediction of the gas holdup. The chi-square test was performed to find the best transfer function to be used in future for the prediction of the gas holdup. The chi-square test results are shown in TABLE 5 and it confirms that the best network is the transfer function 1 with 14 processing elements in a hidden layer. Figure 7 shows the comparison between the experimental to the predicted output.

CONCLUSIONS

The gas holdup were measured in two different tapered bubble columns using non-Newtonian liquids. The effects of gas holdup on different operating parameters were investigated. An applicability of artificial neural network model using multilayer perceptron with backpropagation algorithm was used to predict the gas holdup. The ANN model accurately predicts the gas holdup. The chi-square test confirms that the transfer function 1 with 14 processing elements in a hidden layer gives better predictability.

Nomenclature

K consistency index, Ns^n/m^2
D_c log mean diameter of column, m
D_n hole diameter in the distributor, m
g acceleration due to gravity, m/s^2
H_m gas-liquid mixture height in column, m
N total number of data set
R cross-correlation coefficient (dimensionless)
x experimental value of gas holdup (dimensionless)
y predicted value of gas holdup (dimensionless)
n flow behaviour index(dimensionless)
Q_g gas flow rate, m^3/s

Greek letters

θ taper angle of the column
ε_g gas hold-up, dimensionless
ρ_l density of liquid, Kg/m^3
σ_l surface tension, N/m
σ standard deviation (dimensionless)

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