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# Prediction of Bubble Size in Bubble Columns using Artificial Neural Network

Ahmmed S. Ibrehem and Mohamed A. Hussain
Department of Chemical Engineering, University of Malaya 50603, Kuala Lumpur, Malaysia

**Abstract:** In the literature, several correlations have been proposed for bubble size pre-diction in bubble columns. However, these correlations fail to predict bubble di-ameter over a wide range of conditions. Based on a data bank of around 230 measurements collected from the open literature, a correlation for bubble sizes in the homogenous region in bubble columns was derived using Artificial Neural Network (ANN) modeling. The bubble diameter was found to be a function of six parameters: gas velocity, column diameter, diameter of orifice, liquid density, liquid viscosity and liquid surface tension. Statistical analysis showed that the proposed correlation has an Average Absolute Relative Error (AARE) of 7.3% and correlation coefficient of 92.2%. A comparison with selected correlations in the literature showed that the developed ANN correlation noticeably improved the prediction of bubble sizes. The developed correlation also shows better prediction over a wide range of operation parameters in bubble columns.

**Key words:** Bubble size, bubble columns, ANN

## INTRODUCTION

The design and scale-up of bubble columns have gained considerable attention in recent years due to complex hydrodynamics and its influence on transport characteristics. Although, the construction of these columns is simple, accurate and successful design and scale-up require an improved understanding of multiphase fluid dynamics and its influences. The design and scale-up of bubble column reactors generally depend on the quantification of three main phenomena; (1) heat and mass transfer characteristics, (2) mixing characteristics and (3) chemical kinetics of the reacting system. Thus the reported studies emphasize the requirement of the multiphase fluid dynamics and its influence on phase hold up, mixing and transport properties (Degaleesan *et al*., 2001). Scale-up problems basically stem from the scale dependency on the aforementioned phenomena. Scale -up methods used in biotechnology and chemical industry range from know-how based methods that are in turn based on empirical guidelines, scale-up rules and dimensional analysis to know why based approaches that begin with regime analysis. This analysis is then followed by setting-up appropriate models that may be simplified to deal with the complex hydrodynamics (Deckwer and Schumpe, 1993). More specifically, in order to design bubble column reactors the following hydrodynamic parameters are required: specific gas-liquid interfacial area, axial dispersion coefficients of the gas and liquid, sauter mean bubble diameter, heat and mass transfer coefficient, gas hold up, physicochemical properties of the liquid medium. In order to estimate these design parameters for the system, experimental studies benefit from specialized measuring devices and accessories. The fluid dynamic characterization of bubble column reactors has a significant effect on their operation and performance. Bubble populations, their hold up contributions and rise velocities have significant impact on altering the hydrodynamics, as well as heat and mass transfer coefficients. Many literature correlations are proposed to predict sizes of bubbles and most important ones are presented in Table 1. The average bubble size in a bubble column has been found to be affected by gas velocity, liquid properties, gas distribution, operating pressure and column diameter (Kantarci *et al*., 2005). Since, the early 80s, Artificial Neural Networks (ANNs) have been used extensively in chemical engineering for such various applications as adaptive control, model based control, process monitoring, fault detection, dynamic modeling and parameter (Bhat and McAvoy, 1990). The ANN

Table 1: Correlations for bubble size

| Researcher | Correlation |
|---|---|
| Moo-Young and Blanch | $d_b = \left[\frac{6\sigma\, d_o}{g(\rho L - \rho g)}\right]^{1/3}$ |
| Moo-Young and Blanch | $d_b = 0.19 d_o^{0.48}\, Re_o^{0.32}$ |
| Luibson *et al.* | $d_b = 0.18 d_o^{1/2}\, Re_o^{1/3}$ |
| Kumar and Kuloor | $V_b = \left[\frac{4\pi}{3}\right]^{1/3}\left[\frac{15\mu Q}{2\rho L g)}\right]^{3/4}$ |
| Bahavraju *et al.* (1978) | $\frac{d_b}{d_o} = 3.23\left[\frac{4\rho Q}{\pi\mu d_o}\right]^{-0.1}\left[\frac{Q^2}{d^2 g)}\right]^{0.21}$ |

Kantarci *et al.* (2005)

**Corresponding Author:** Ahmmed S. Ibrehem, Department of Chemical Engineering, University of Malaya 50603, Kuala Lumpur, Malaysia Tel: +60-1-49360913

provides a non-linear mapping between input and output variables and is also useful in providing cross-correlation among these variables. The mapping is performed by the use of processing elements and connection weights. The neural network is a useful tool in rapid predictions such as steady-state or transient process flow sheet.

## MATERIALS AND METHODS

ANNs are being applied to an increasing number of real-world problems of considerable complexity. It is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available. In this study, a multilayer neural network has been used, as it is effective in finding complex non- linear relationships. Training was accomplished using NeuroSolutions by Mathlab version 7.

The MLP (Multi-layer perceptron) is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. This type was used which is multilayered Feed Forward Network (MLFF), trained with static back propagation (Bp) of error using the generalized Delta rule. Bp was one of the first general techniques developed to train multi-layer networks, which does not have many of the inherent limitations of the earlier, single -layer neural nets. The Bp algorithm is an iterative gradient algorithm designed to minimize the mean-squared error between the desired output and the actual output for a particular input to the network (Lendaris, 2004). Basically, Bp learning consists of two passes through the different layers of the network: a forward pass and backward pass. During the forward pass the synaptic weights of the network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with an error-correction rule (Lippmann, 1987). This algorithm may be found elsewhere (Lendaris, 2004). Bp is easy to implement and has been shown to produce relatively good results in many applications. It is capable of approximating arbitrary non-linear mappings. The success of Bp methods very much depends on problem specific parameter settings and on the topology of the network (Leonard and Kramer, 1990).

Training a Back-Propagation Network The steps for back- propagation training can be shown as follows (Leonard and Kramer, 1990):

- Initialize the weights with small, random values
- Each input unit broadcasts its value to all of the hidden units
- Each hidden unit sums its input signals and applies its activation function to compute its output signal
- Each hidden unit sends its signal to the output units
- Each output unit sums its input signals and applies its activation function (hyperbolic tan in the present simulation)to compute its output signal
- Each-output unit updates its weights and bias

Therefore after careful training of the network, testing showed that ANN structure of Akhtar *et al.* (2007), Cai *et al.* (1994) and Lippman (1987) using the activation function of (tanh), momentum rate of 0.7 and after 5000 iterations, had correlated the bubble diameter in the homogenous region in bubble columns successfully. The result of prediction is plotted with experimental values as shown in Fig 1 and 2. Statistical analysis based on the test data is calculated to validate the accuracy of the output for pervious correlation model based on ANN. The

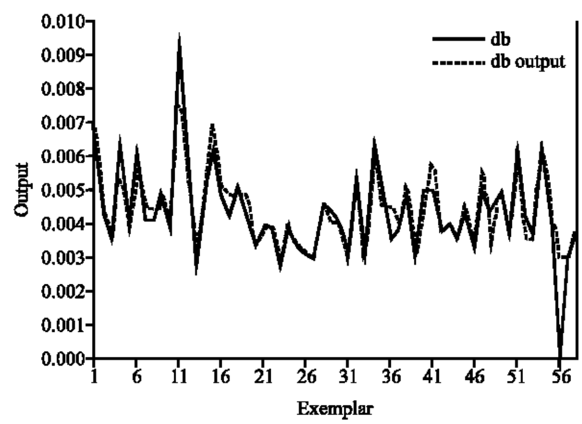


Fig. 1: Desired (measured) and the actual (predicted) values vs. testing exemplars

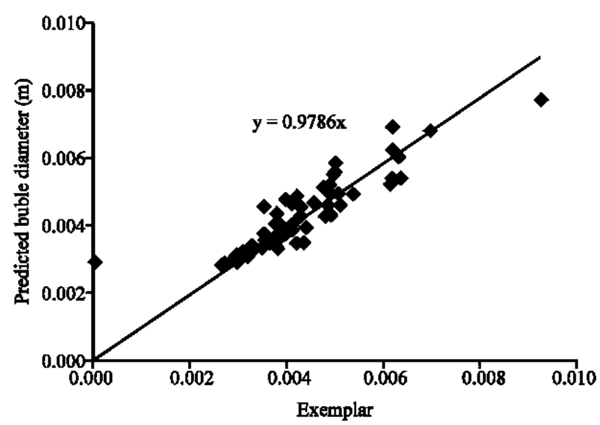


Fig. 2: Predicted bubble diameter versus desired values for ANN structure of Akhtar *et al.* (2007), Cai *et al.* (1994) and Lippman (1987)

Table 2: Statistical analysis for the proposed model

| Performance | Error |
|---|---|
| Min Abs Error | 9.19866E-06 |
| Max Abs Error | 0.001536108 |

structure for each model should give the best output prediction, which is checked by using statistical analysis. Results are given in Table 2.

## CONCLUSION

From the present study of using ANN in predicting the bubble size in the homogenous region in bubble columns. It is concluded that ANN structure of (Akhtar *et al*., 2007; Cai *et al*., 1994 and Lippman, 1987) was chosen as the best to implement the target of the present study. MLP architecture of six inputs in the first layer (gas velocity, column diameter, diameter of orifice, liquid density, liquid viscosity and liquid surface tension) with 12 PEs in the 1st hidden layer and 12 Pes in the 2nd hidden layer and one output in the third layer which is the desired output of bubble size. Momentum rule was 0.7, hyperbolic tan activation function and 5000 numbers of iterations were used. Artificial neural network predicted well the diameter of bubbles which is better than those, obtained for the selected literature correlations; it yielded a minimum AARE of 7.3% and a correlation coefficient

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