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Using Machine Learning to Estimate Bubble Size in Turbulent Bubbly Flows

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1. Introduction

The two-fluid model based on Eulerian-Eulerian approach has been widely used for simulating two-phase flows in many industrial applications [1]. However, the two-fluid approach needs accurate modeling for interfacial momentum exchange such as drag, shear-induced lift, and wall-induced lift. In particular, it is important to accurately model the interfacial area (or bubble size) in bubbly pipe flow. Hence, there have been many studies on modeling of bubble size so far. However, the bubble size has not been well estimated because it is closely associated with the complex turbulent flow. Recently, the methods of machine learning are proven to be extensively and successfully used in many areas [2,3], so they could provide us a useful tool in modelling the bubble size in turbulent bubbly flows. Therefore, we aim to investigate the applicability of machine learning for estimating the bubble size in turbulent bubbly flows and evaluate its accuracy.

2. Methods and Results

2.1 Machine learning and training

In the present study, the artificial neural network (ANN) is considered as the method of machine learning. Generally, the ANN is composed of two procedures called training and testing as shown in Fig. 1. In the training procedure, the ANN is trained and optimized by training data composed of input and target output. Then, in the testing procedure, with the ANN built in the training procedure, the fitted output value is determined corresponding to certain input data.

For the training, the target output and input variables should be chosen. In the present study, the Sauter mean diameter is output variable because it is typically used to estimate the bubble size in bubbly flows.

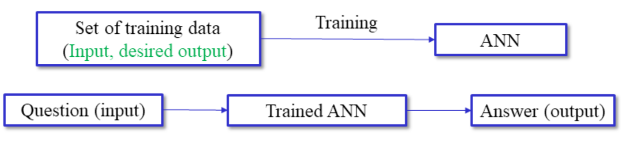

Fig. 1 Framework of artificial neural network (ANN) considered in the present study.

Also, as input variables, J_f and J_g are chosen as global parameters, and α_g, u_f, u_g, r are chosen as local ones. Subscripts f and g denote liquid and vapor phases, respectively. As a result, the following functional form of the Sauter mean diameter is considered:

$$D_{sm} = f(J_f, J_g; \alpha_g, u_f, u_g, r) \qquad (1)$$

Usually, there exist many developed libraries for the training of ANN. In the present study, Tensorflow is used as ANN library. The number of hidden layers is two, and the number of neurons in each layer is set to 12. As the activation function, Hyperboilc tangent function is considered because it is most widely used and known to predict nonlinear problems well. Also, it is used in optimization of connection strength Adam algorithm which is efficient in the cases with more than one hidden layer.

For the training, the data provided by Hibiki et al. (2001) were used. As the training data, the flow condition of J_f =0.986m/s is considered. Table 1 shows the results of sensitivity study on the number of neurons. In this study, the number of neurons in each hidden layer remains the same. With increasing the number of neurons up to 12, the relative maximum and mean errors decrease. However, with the further increase in the number of neurons, they increase a little. So based on this result, the number of neurons is selected to be 12.

Fig. 2 shows the overall training results for Hibiki et al. (2001)'s data. As shown in Fig. 2, the accuracy of the model built from the present ANN looks quite good.

2.2 Preliminary testing

In order to verify our model, we solve turbulent bubbly flow in a vertical pipe under the same condition of Hibiki et al. (2001). The size of the computational

Table 1. Results of sensitivity study on the number of neurons

Number of neuron	Relative max error (%)	Relative mean error (%)	Correlation coefficient
4	1.60	0.49	0.9998
8	0.0056	0.0017	1.0

10	0.0021	0.0087	1.0
12	0.0012	0.00033	1.0
15	0.0014	0.0053	1.0

Fig. 2 Training results for Hibiki et al. (2001)'s data.

domain is 2800mm(x)×25.4mm(r), and the number of grid points is 1400(x) ×80(r).

Under the assumption of 2D axisymmetric flow, developing flow is simulated. At inlet, the seventh power law (of single-phase turbulent pipe flow) is used for water and air velocity profiles, and the uniform void fraction is adopted. At the outlet, a pressure boundary condition is prescribed.

Fig. 3 shows the distribution of void fraction at a fully-developed location. The data of Hibiki et al. (2001) measured at x/D=53.5 and the RANS results with the correlation suggested by Hibiki & Ishii (2002) are included for comparison. For the testing data, the case of J_g =0.473 m/s was chosen among those of J_f =0.986m/s. As shown in Fig. 3, the results with the bubble size model based on the present ANN are in good agreement with the experiment of Hibiki et al. (2001), and show better performance than those with the correlation.

3. Conclusions

In this study, we investigated the artificial neural network (ANN) approach to estimate the bubble size in turbulent bubbly flows. For both the training and testing procedures, Hibiki et al. (2001)'s data were considered. Both the training and testing procedures showed that the present ANN model could estimate bubble size quite well in turbulent bubbly flows. In the future, we will consider further training and testing of ANN with more data available in the literature as well as from our own numerical and experimental studies.

ACKNOWLEDGEMENT

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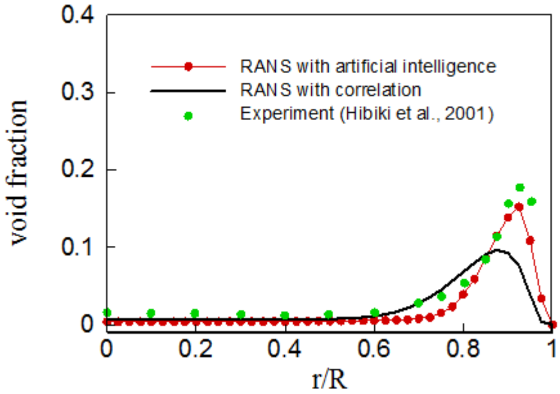

Fig. 3 Preliminary testing results for Hibiki et al. (2001)'s data.

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