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# Application of Artificial Neural Network for Prediction of Local Void Fraction in Vertical Subcooled Boiling Flow

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**Abstract:** This paper presents the feasibility study of potential application of multi-layer feed-forward Artificial Neural Networks (ANN) to predict local void fraction of subcooled boiling flows in vertical upward annular channel. A total of 638 experimental data points performed at KAERI and reported in literature was selected for training and testing ANN model. The seven basic parameters are chosen to be input variables and then the optimal structure of ANN which consist of two hidden layers with 131 neurons was determined based on traditional Trial-and-Error method after balancing the trade-off between the performance and training time. Results showed that the ANN model is capable to accurately predict the local void fraction with $R^2$ value of 0.99931 for training data, $R^2$ value of 0.99483 for testing data and $R^2$ value of 0.99828 for all data. Also, it proved that the ANN training will be more effective with an extensive experimental database.

**Keywords:** *Artificial Neural Network, Subcooled Boiling, Void fraction.*

## I. INTRODUCTION

Subcooled boiling flow at low pressure condition have become challenging issues in safety analysis of water-cooled nuclear power reactors since the physical mechanisms of void growth and related thermal-hydraulic behaviors of system are still not fully understood. The two-fluid model currently implemented in system codes and multiphase computational fluid dynamics (MCFD) solvers has been widely recognized as a promising tool for dealing with the boiling scenario and simulating transients and accidents in nuclear power plant. However, a lot of constitutive models and correlations are required to make the conservation equations solvable. The process of sequential calibration and validation to obtain model parameters and coefficients of correlation is prone to generating conflicting parameters tuned on different datasets from Separate-Effect and Integral-Effect Tests [1]. This classical approach could lead to unsatisfactory prediction for all quantities of interests over a variety of input conditions due to the uncertainties of model parameters and model forms [2].

The artificial neural network (ANN) is a powerful machine learning tool for modeling and solving some complicated physical problems that cannot be described with simple mathematical models, and thus can be able to cope with the uncertainty issues. Many investigators proposed ANN methods to predict the void fraction, flow pattern, pressure drop and heat transfer coefficient, demonstrating the predictive capability of the model [3-9]. It is worth to noting that there is no study on using ANN model to predict the local parameters of subcooled boiling flow in vertical channel. Therefore, the ability of ANN model for local void fraction prediction is investigated in this study.

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## II. METHODS

### 1. Data and Input Parameters Selection

Due to the complexity of the phenomena, the experimental study has been the main research approach to develop empirical correlations and models which provide the engineers and designers suitable choices in engineering practice [4]. With ANN approach, experimental databases are used in the training process in which the network and weights are modified to attain better approximation of the desired output. The subcooled boiling flow phenomena are primarily governed by the flow boundary conditions as well as the geometry of the flow domain, therefore these key parameters must be selected as inputs for ANN structure design and optimization. In this work, databases performed at KAERI [10-11] in the vertical annulus channel (radius of $r_{out}$) with an indirect heater rod (radius of $r_{in}$) at a channel center was selected for designing and training the ANN network. Five key parameters of flow boundary conditions including mass flux ($G$), heat flux ($q''$), inlet subcooling ($\Delta T_{sub}$), inlet and outlet pressures ($P_{in}$, $P_{out}$) are chosen as input variables of ANN structure. Additionally, two more variables indicating the location of measured and predicted points are the axial length ( $L/d_H$: the ratio between the flow length from the inlet of heated section $L$ and the hydraulic diameter $d_H$) and the radial length $r^*$ which is defined as:

$$r^* = (r - r_{in})/(r_{out} - r_{in}) \quad (1)$$

Table I presented 12 cases of SUBO experiments including total 638 data points used in this study.

**Table I.** Database of SUBO experiments used in this study

| Case | Heat flux | Mass flux | Inlet subcooling | Inlet pressure | Outlet pressure | Heating length | Hydraulic diameter |
|---|---|---|---|---|---|---|---|
| | (kW/m$^2$) | (kg/m$^2$s) | (K) | (kPa) | (kPa) | (m) | (mm) |
| C1 | 470.6 | 1132.6 | 19.1 | 192.9 | 157.3 | 3.087 | 25.52 |
| C2 | 363.7 | 1119.6 | 19.0 | 192.7 | 156.7 | 3.087 | 25.52 |
| C3 | 563.0 | 1126.9 | 18.3 | 188.9 | 155.7 | 3.087 | 25.52 |
| C4 | 465.7 | 2126.5 | 19.6 | 196.9 | 156.9 | 3.087 | 25.52 |
| C5 | 567.9 | 2128.8 | 19.5 | 197.6 | 158.0 | 3.087 | 25.52 |
| C6 | 465.5 | 1103.9 | 29.6 | 190.7 | 155.0 | 3.087 | 25.52 |
| C7 | 473.7 | 1124.7 | 17.7 | 193.9 | 161.6 | 3.087 | 25.52 |
| C8 | 373.6 | 1122.9 | 17.2 | 188.3 | 155.1 | 3.087 | 25.52 |
| C9 | 565.7 | 1115.3 | 17.5 | 192.8 | 161.5 | 3.087 | 25.52 |
| C10 | 471.4 | 2093.2 | 17.6 | 192.2 | 158.5 | 3.087 | 25.52 |
| C11 | 563.7 | 2086.6 | 18.1 | 195.7 | 162.1 | 3.087 | 25.52 |
| C12 | 470.8 | 1113.8 | 29.6 | 191.8 | 158.1 | 3.087 | 25.52 |
| Overall | 363.7-567.9 | 1103.9-2128.8 | 17.2-29.6 | 188.3-197.6 | 155.0-162.1 | 3.087 | 25.52 |

### 2. Structure of Neural Network

The type of ANN used in this work is the *multilayer feedforward net*. Most commonly used transfer function in input and output layer is linear transfer function (*purelin*), while the functions of hyperbolic tangent sigmoid (*tansig*) is commonly employed transfer functions in the hidden layer. It is worth noting that a three-layer network (two hidden layers) can approximate any non-linear function [12]. To determine the number of neurons in each hidden layer, a traditional Trial-and-Error method was utilized by changing the number of neurons in the hidden layer and checking the values of the mean square error (MSE) and the coefficient of determination $R^2$ as defined below:

$$MSE = \frac{\sum_{k=1}^{n}\left(y_{target} - y_{pred}\right)^2}{n} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n}\left(y_{target} - y_{pred}\right)^2}{\sum_{k=1}^{n}\left(y_{target} - y_{mean}\right)^2} \in [0,1] \quad (3)$$

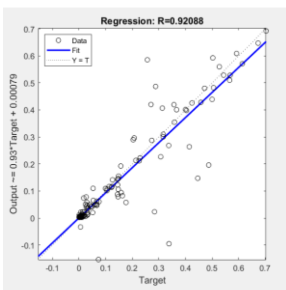
### *3. ANN Training and Testing*

The SUBO data is collected and randomly divided into two parts based on practical experience: 75% is used for training and 25% is used for testing. Each of these models has its weights and biases initialized using Nguyen-Widrow method and its subsequently trained with the Levenberg-Marquardt algorithm. The test data is considered to have the same role as the validation data. The error of the test data is continuously monitored during the training process. After a certain number of iterations (or epochs), if the test error keeps increasing, the training process is stopped. This method is called "early stopping" criterion applied to avoid overfitting, which occurs when the model produces high accurate results on the training set but does not work well on the testing set; in other words, the model is not generalizable.

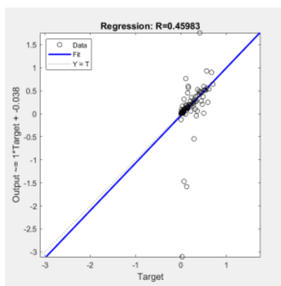
## III. RESULTS AND DISCUSSION

After testing different configurations of two hidden layers, some findings are listed as bellows:

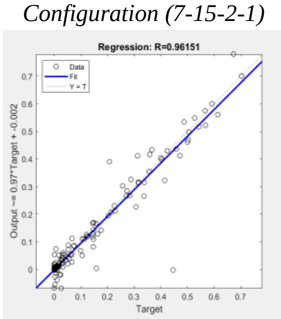
- Training performance will be better as the number of neurons in the hidden layer increases; however, training time will also increase. There is a need to balance performance and time accordingly.
- If the number of neurons in the last hidden layer is greater than 1 (2, 4, 9 and 16), the predicted values are negative as shown in Figure 1. Consequently, the number of neurons in the second hidden layer is set to 1.



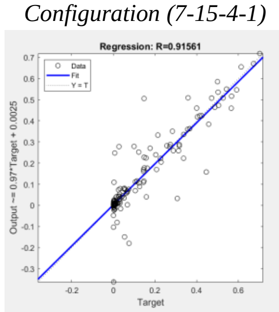

*Configuration (7-15-2-1)*



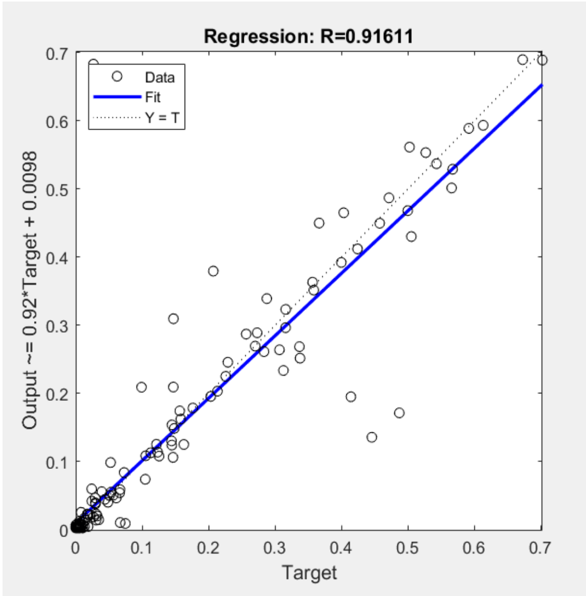

*Configuration (7-15-4-1)*




*Configuration (7-15-9-1)*




*Configuration (7-15-16-1)*




*Configuration (7-15-1-1)*

**Fig. 1.** Compare the prediction results with the Testing Data of some network configurations.

Therefore, the ANN configuration used in this study have a general structure as **[7 - (hidden layers) - 1 – 1.** The next step is to find the optimal number of neurons in the hidden layers. Each ANN configuration is trained **15** times with random initiated weights and biaes, and then the averaged values of training performance (or training accuracy) and coefficient of determination in test data were obtained.

Table II shown the gradual improvement of the performance (MSE) and the $R^2$ coefficient for testing data as the number of neurons in the hidden layer increase. However, the corresponding training time also increases, requiring a balance between training accuracy and time. After testing with many different configurations, it is possible to get notes and recommendations in choosing an appropriate ANN based on the values of MSE and $R^2$. It can be seen that the most suitable of ANN configuration is (**7-80-50-1-1**).

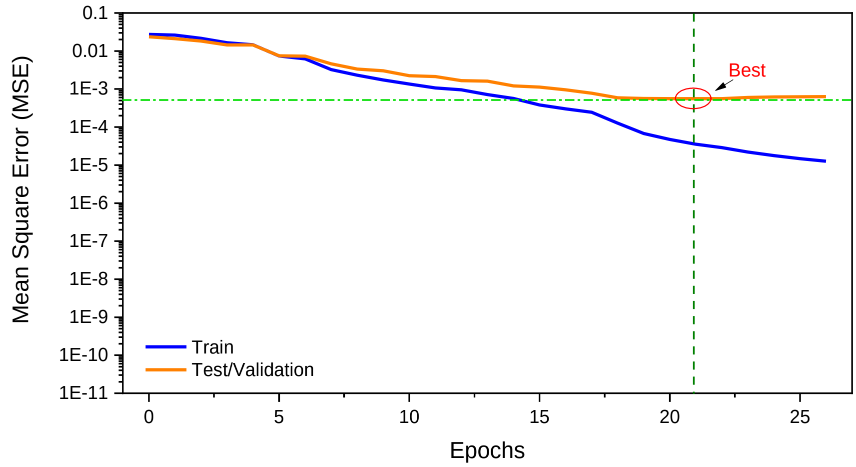
**Table II.** Comparison of different configurations

| No. of neurons | Configuration | Criteria | | |
|---|---|---|---|---|
| | | Training accuracy (MSE) | Testing accuracy ($R^2$) | Time (s) |
| 31 | 7 – 30 – 1 – 1 | 2.06E-05 | 0.75409 | 18 |
| | 7 – 15 – 15 – 1 – 1 | 3.99E-07 | 0.82398 | 31 |
| 61 | 7 – 30 – 30 – 1 – 1 | 3.91E-09 | 0.87638 | 242 |
| 81 | 7 – 50 – 30 – 1 – 1 | 1.38E-09 | 0.94452 | 268 |
| | 7 – 30 – 50 – 1 – 1 | 1.17E-09 | 0.92271 | 300 |

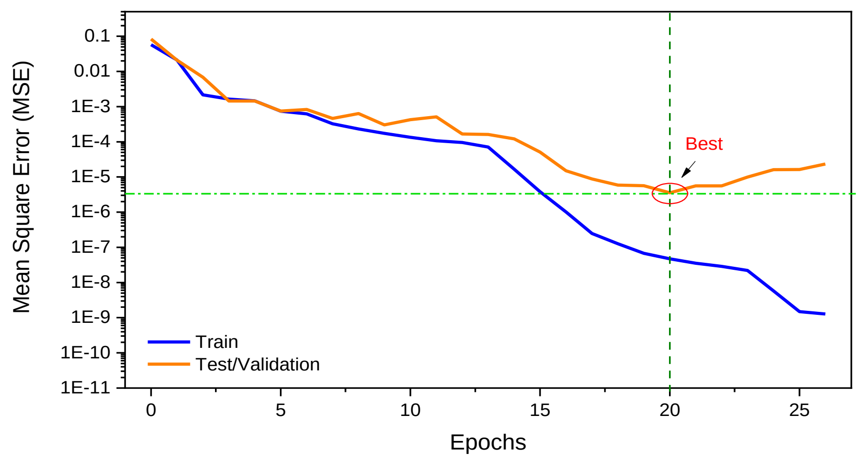
| | | | | |
|---|---|---|---|---|
| | 7 – 40 – 40 – 1 – 1 | 8.94E-10 | 0.93125 | 249 |
| 101 | 7 – 50 – 50 – 1 – 1 | 9.41E-10 | 0.94893 | 588 |
| 111 | 7 – 60 – 50 – 1 – 1 | 7.16E-10 | 0.95949 | 739 |
| 121 | 7 – 70 – 50 – 1 – 1 | 6.06E-10 | 0.95660 | 770 |
| | 7 – 60 – 60 – 1 – 1 | 6.21E-10 | 0.95459 | 748 |
| 131 | 7 – 70 – 60 – 1 – 1 | 5.72E-10 | 0.96277 | 1237 |
| | **7 – 80 – 50 – 1 – 1** | **5.30E-10** | **0.96622** | **1389** |
| 141 | 7 – 80 – 60 – 1 – 1 | 4.73E-10 | 0.96590 | 1422 |
| | 7 – 70 – 70 – 1 – 1 | 4.90E-10 | 0.96071 | 1410 |
| 151 | 7 – 80 – 70 – 1 – 1 | 4.30E-10 | 0.96041 | 1664 |
| 161 | 7 – 80 – 80 – 1 – 1 | 3.41E-10 | 0.96574 | 2440 |

Figure 2 show the comparison results between the training and the test errors (MSE values) during the training process of some ANN configurations which reflect the quality of the training model. The test error and the training error are similar and tend to decrease in the few starting epochs. However, after the "Best" point corresponding to the epoch where the test error reaches its minimum value, the value of the test error increases while the value of the training error decreases. This proves that overfitting occurs at the epochs behind the “Best” position. Therefore, the ANN model at the “Best” position is saved as the best model in the corresponding training session. From this point of view, overfitting can be avoided by using the early stopping method.

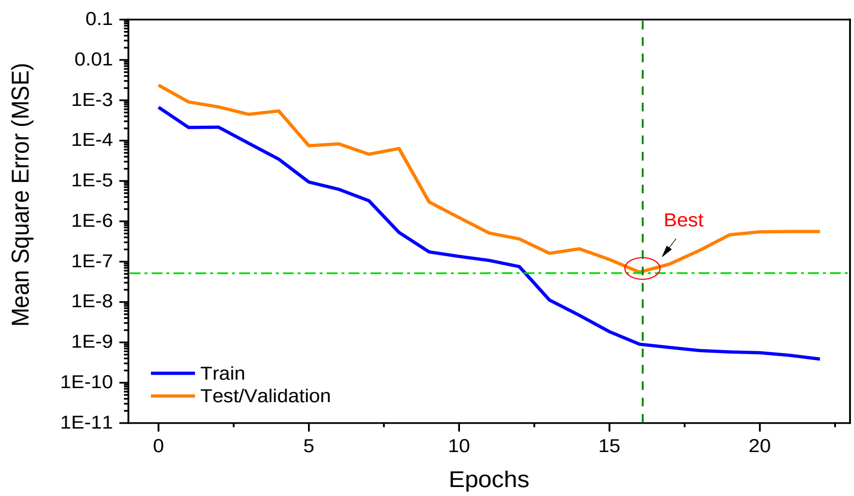
Figure 3 shown a comparison of the predicted results with experimental results using 75% data for training, with the coefficients $\mathbf{R_{Test}}$ = **0.99483** and $\mathbf{R_{All}}$ = **0.99828**. Most of the data points are located near the 1:1 linear regression line and within 15% error, showing good capability to accurately predict the local void fraction. The results predicted by the ANN model are also presented in Figure 4 in terms of the radial distribution of the Local Void Fraction for some cases at different heights $L/d_H$. It can be seen that the predictive power of the ANN is relatively consistent with the experimental data in which the ANN has been trained. There are some predicted results with high deviation because they are not in the training data (Figure 4a, 4f). Figure 5 shows a comparison results of local void fraction distribution at height $L/d_H$ = 18.4 of case C9 when training data has no information of experimental data points in this case (Figure 5a) and when the training data with information points in experimental data (Figure 5b). This is an example that shows the ability of ANN model to predict and interpolate in a data range.




*(a) Configuration (7-30-1-1)*

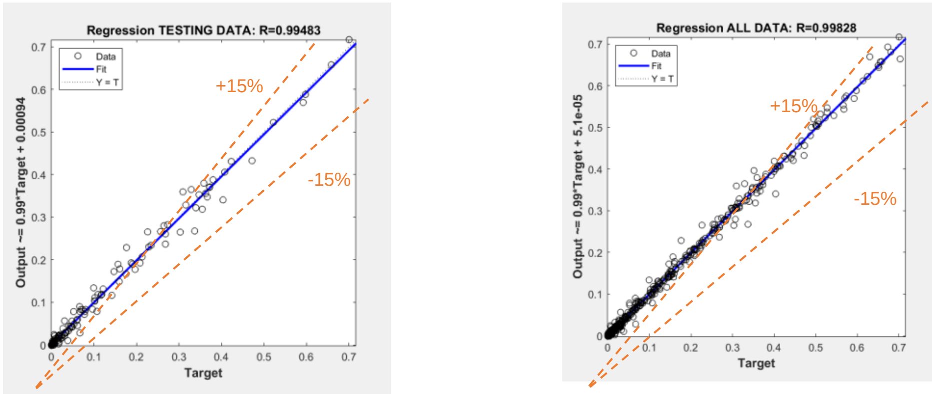



*(b) Configuration (7-50-50-1-1)*



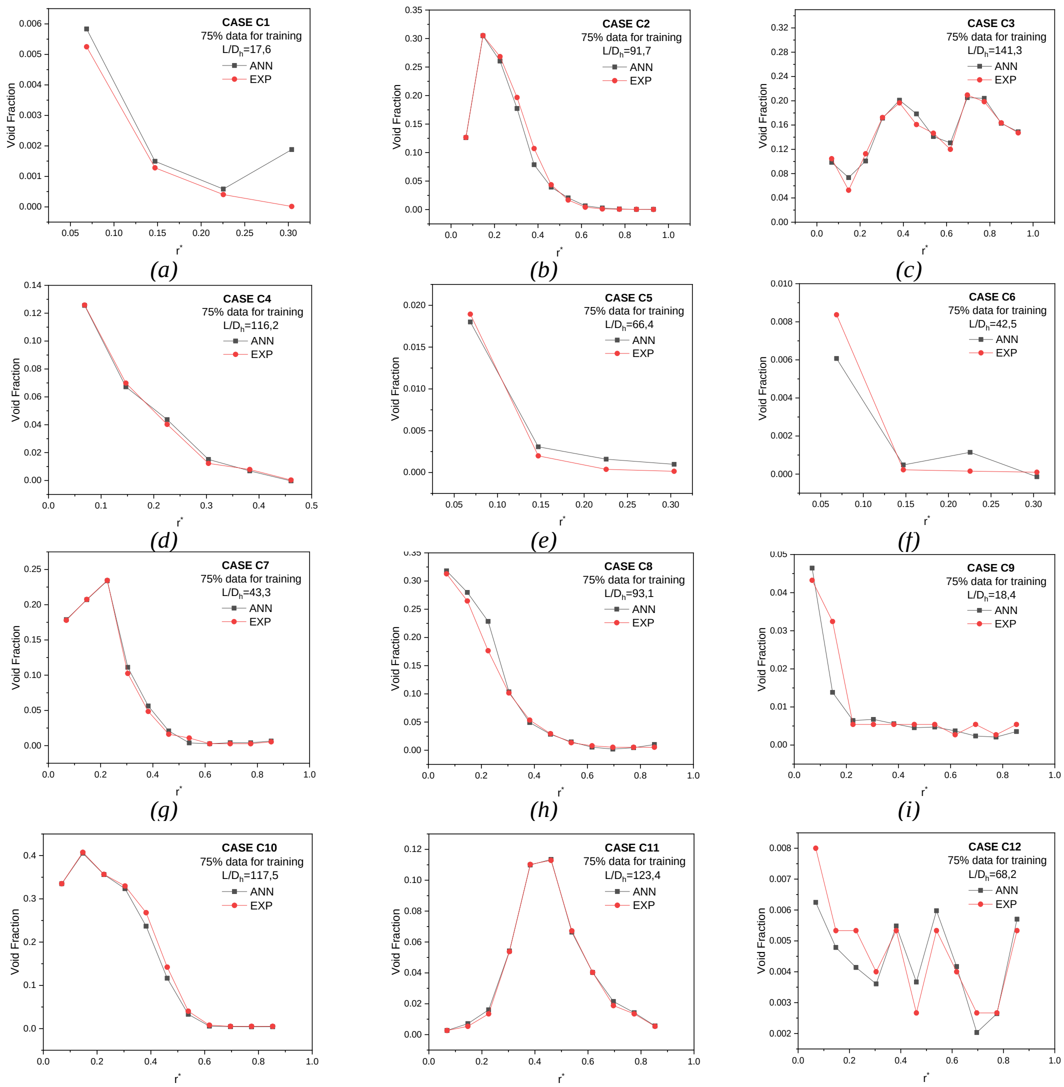

*(c) Configuration (7-80-50-1-1)*

**Fig. 2.** Comparison results between the training and test errors during the training process



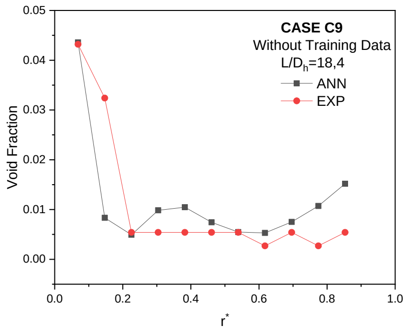

*(a)* *(b)*

**Fig. 3.** Compare predictive and experimental results for testing data (a) and all-data (b) uses 75% of the data for training

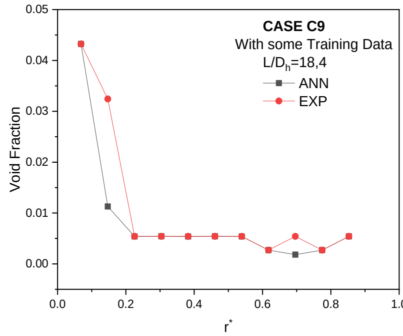



*(j)* *(k)* *(l)*

**Fig. 4.** Comparisons of radial distribution between the predicted results and experimental results




*(a)*




*(b)*

**Fig. 5.** Comparisons of the predictability of the neural network when there is no training data available (a) and when training data is available (b)

## IV. CONCLUSIONS

In this study, 638 experimental data points of SUBO test facility were used to train and test a 5-layers feedforward neural network with 7 input parameters and total **131** neurons for prediction of local void fraction in vertical annular subcooled boiling channel. The results clearly showed the possibility that the ANN could be used in predicting local parameters of two-phase flow. Due to the limitation in the training data, the ANN-based model in this study is recommended to be limited to the data region of the SUBO data. In order to improve the accuracy and extend the predictability of the model, it is necessary to add more databases. Besides, the next important research is to develop the method of optimization of ANN structural. This study is the first step to build the ANN model to replace mathematical models implemented in CFD code.

## ACKNOWLEDGEMENT

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