Transactions of the Korean Nuclear Society Virtual Autumn Meeting
October 21-22, 2021

Preliminary Prediction of Bubble Parameter by Applying Artificial Neural Network (ANN)

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1. Introduction

Boiling heat transfer is a powerful heat transfer mode used in many industrial applications and is governed by bubble behavior. To develop the prediction models for boiling heat transfer, it is required to complete understanding of bubble parameters such as bubble shape, contact angle against wall, departure diameter, lift-off diameter, bubble velocity, moving trajectory and etc. (see Fig. 1) and obtain a lot of bubble data.

There have been many experimental analyses on bubble behavior. In these experimental studies, bubble parameters were investigated in various conditions. However, it has been impossible to obtain complete information about the bubble behavior. The shape and the area of the varying interface are very complex and thus difficult to measure. So as a complement to experiments, there have been many CFD analysis researches to simulate the bubble behavior directly [1]. However, CFD simulation takes a lot of time (~ many days) to calculate 1 Case, so there is a realistic constraint on generating large numbers of bubble data.

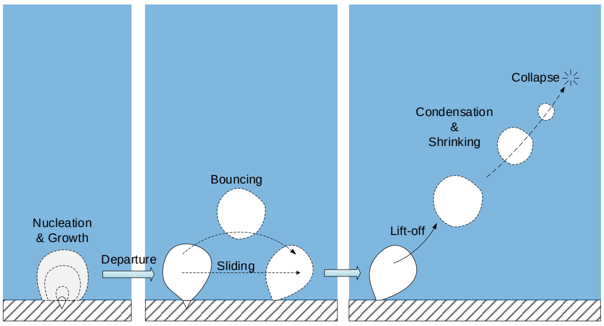

Fig. 1. Bubble behavior in subcooled boiling flow [2]

As a solution to this, this study seeks to introduce a neural network model, which is part of AI (artificial intelligence) technology, to predict bubble parameters. Artificial neural networks are algorithms created by mimicking the process of data-processing in the human brain, which have the advantage of predicting target values under arbitrary conditions at low time/cost based on machine learning.

Artificial neural network technology has recently been utilized in a variety of fields, and especially in the nuclear thermal-hydraulic field, it has been applied to predicting wall temperatures under CHF (critical heat flux) conditions, providing satisfactory results. In this work, we intend to develop an artificial neural network model using the convolutional neural network (CNN) method (see Fig. 2). The CNN model is an artificial neural network algorithm widely used in deep-learning, which can be learned efficiently with relatively little and simple data, and has the advantage of being able to learn with new data in existing models. Therefore, for the generation of bubble parameters under various conditions, it is necessary to develop a CNN-based artificial neural network model suitable for bubble parameter training and analysis.

In this study, the ANN model to predict the bubble parameter is under development. This paper describes the main results of the study so far.

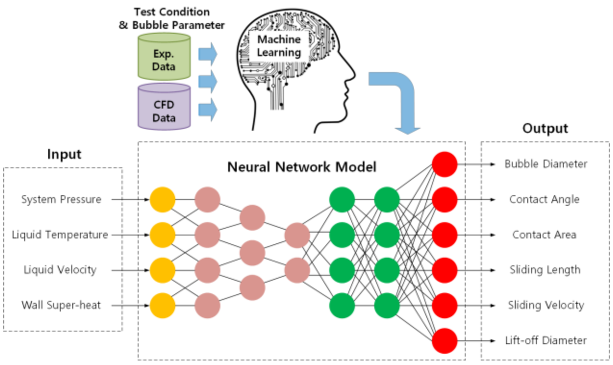

Fig. 2. ANN model for predicting bubble parameter

2. Neural Network Model

CNN is well known for its efficiency in image processing of photographic data. Specifically, CNN has the following differences compared to the existing neural networks.

- Maintain the shape of input/output data of each layer
- Effective recognition of features of adjacent images while maintaining spatial information of images
- Extracting and learning features of images with multiple filters
- Pooling layer that collects and enhances the features of the extracted image

Therefore the CNN model was applied first for the analysis of bubble parameter. And the basic ANN was also considered to analyze the bubble parameter. The input data was single dimension. The pressure, sub-cooling, liquid velocity and heat flux was used to get the bubble parameter in subcooled boiling flow.

2.1. Neural Network Model

To obtain the bubble parameters which were maximum diameter, departure diameter, liftoff diameter, sliding length and sliding velocity, a neural network model was designed. Firstly CNN was applied. However, the size of input data was too small to use a convolutional model. Therefore an ANN model was applied like a fully connected layer. Table I showed a single bubble parameter experiment data. There were 4 kinds of input and 5 kinds of output.

Table I: Single bubble parameter experiment data

Prodanovic et. al., 2002 | Orientation : Vertical									
Data Point Number	Pressure [bar]	Subcooling [K]	Liquid Velocity [m/s]	Heat Flux [MW/m^2]	Maximum Diameter [m]	Departure Diameter [m]	Liftoff Diameter [m]	Sliding Length [m]	Sliding Velocity [m/s]
1	1.05	30.0	0.42	0.300	1.5200E-3	1.3300E-3	-	1.3400000E-3	-
2	1.05	30.0	0.83	0.500	1.2600E-3	1.0800E-3	-	1.6300000E-3	-
3	1.05	30.0	0.83	0.600	1.5800E-3	1.1800E-3	-	3.4900000E-3	-
4	1.05	30.0	0.83	0.800	1.1400E-3	0.9400E-3	-	1.2900000E-3	-
5	1.05	30.0	0.83	0.900	0.8900E-3	0.8100E-3	-	1.4000000E-3	-
6	1.05	30.0	0.42	0.600	1.2800E-3	0.9300E-3	-	1.0800000E-3	-
7	1.05	30.0	0.42	0.800	0.9900E-3	0.8000E-3	-	1.0000000E-3	-
8	1.05	30.0	0.42	0.900	0.8700E-3	0.8000E-3	-	0.4800000E-3	-
9	1.05	20.0	0.84	0.600	1.4500E-3	1.2400E-3	-	2.2500000E-3	-
10	1.05	20.0	0.84	0.700	1.2400E-3	1.0600E-3	-	2.1100000E-3	-
11	1.05	20.0	0.42	0.300	2.6700E-3	2.1900E-3	-	2.6200000E-3	-
12	1.05	20.0	0.42	0.600	1.6400E-3	1.5300E-3	-	1.9400000E-3	-
13	1.05	20.0	0.42	0.700	1.3100E-3	1.2500E-3	-	1.7800000E-3	-
14	1.05	20.0	0.08	0.200	2.8600E-3	2.1800E-3	-	2.1300000E-3	-
15	1.05	20.0	0.08	0.300	3.2400E-3	2.6800E-3	-	-0.6300000E-3	-
16	1.05	10.0	0.42	0.300	2.1800E-3	1.9800E-3	-	2.4800000E-3	-
17	1.05	10.0	0.08	0.100	1.9300E-3	1.8500E-3	-	0.9800000E-3	-
18	1.05	10.0	0.08	0.200	2.5700E-3	2.4800E-3	-	2.0500000E-3	-
19	1.05	10.0	0.08	0.300	2.0900E-3	1.8200E-3	-	0.2300000E-3	-
20	1.05	30.0	0.08	0.200	1.5700E-3	1.1400E-3	-	0.2200000E-3	-
21	1.05	40.0	0.83	0.600	1.2300E-3	0.7700E-3	-	1.2100000E-3	-
22	1.05	40.0	0.83	0.900	1.2100E-3	0.5900E-3	-	1.2300000E-3	-
23	1.05	40.0	0.83	1.200	0.9200E-3	0.7500E-3	-	1.0500000E-3	-
24	1.05	60.0	0.82	0.600	0.9400E-3	0.6600E-3	-	0.8000000E-3	-
25	1.05	60.0	0.82	1.200	0.9000E-3	0.6800E-3	-	0.5600000E-3	-
26	2.00	20.0	0.41	0.400	0.5645E-3	0.5361E-3	-	0.2258000E-3	-
27	2.00	30.0	0.41	1.000	0.8429E-3	0.6769E-3	-	0.3203020E-3	-
28	2.00	30.0	0.41	0.800	0.8565E-3	0.6741E-3	-	0.3254700E-3	-
29	2.00	30.0	0.41	0.600	0.7498E-3	0.7193E-3	-	0.2699280E-3	-
30	2.00	30.0	0.41	0.400	0.9891E-3	0.9234E-3	-	0.4055310E-3	-
31	2.00	20.0	0.08	0.400	0.8274E-3	0.7569E-3	-	0.0992880E-3	-
32	2.00	20.0	0.82	0.400	0.7139E-3	0.6517E-3	-	0.6567880E-3	-
33	2.00	20.0	0.41	0.600	0.7848E-3	0.7121E-3	-	0.2982240E-3	-
34	2.00	20.0	0.82	0.600	0.7122E-3	0.6306E-3	-	0.3347340E-3	-
35	2.00	10.0	0.41	0.320	0.7343E-3	0.7343E-3	-	0.0440580E-3	-
36	2.00	10.0	0.82	0.360	0.7921E-3	0.7791E-3	-	0.5703120E-3	-
37	2.00	30.0	0.82	0.600	0.6822E-3	0.6821E-3	-	0.5866920E-3	-
38	2.00	30.0	0.82	0.800	0.5968E-3	0.5784E-3	-	0.3640480E-3	-
39	2.00	30.0	0.08	0.200	0.7907E-3	0.7907E-3	-	0.1027910E-3	-
40	3.00	29.9	0.82	0.600	0.4708E-3	0.4315E-3	-	0.7249990E-3	-
41	3.00	29.6	0.82	0.800	0.4231E-3	0.4033E-3	-	0.3150000E-3	-
42	3.00	29.5	0.82	1.000	0.4693E-3	0.4512E-3	-	0.7060000E-3	-
43	3.00	29.4	0.41	0.600	0.4860E-3	0.4700E-3	-	0.0980019E-3	-
44	3.00	30.4	0.41	0.800	0.3722E-3	0.3662E-3	-	0.1680111E-3	-
45	3.00	31.7	0.41	1.000	0.3779E-3	0.3077E-3	-	0.1519914E-3	-
46	3.00	28.7	0.08	0.200	0.5280E-3	0.5280E-3	-	0.2139614E-3	-
47	3.00	31.0	0.08	0.300	0.6043E-3	0.6043E-3	-	0.0030215E-3	-
48	3.00	20.2	0.82	0.600	0.5160E-3	0.4109E-3	-	1.0204055E-3	-
49	3.00	19.1	0.82	0.800	0.5119E-3	0.5119E-3	-	0.6963017E-3	-
50	3.00	18.9	0.41	0.400	0.4390E-3	0.4390E-3	-	-0.0700640E-3	-
51	3.00	22.5	0.41	0.600	0.3880E-3	0.3630E-3	-	0.0529581E-3	-
52	3.00	19.8	0.08	0.200	0.5790E-3	0.5500E-3	-	0.2521719E-3	-
53	3.00	20.8	0.08	0.300	0.5508E-3	0.5064E-3	-	0.2095243E-3	-
54	3.00	13.5	0.41	0.300	0.5330E-3	0.5330E-3	-	0.4106019E-3	-

The 4 kinds of input parameter were used for the input layer of neural network and each one of 5 kinds of output was used for the output layer of neural network. The Table II showed a simple neural network model for the analysis of bubble parameter.

Table II. ANN model for bubble parameter analysis

Layer	Output Shape
Input Layer	(1,4)
Hidden Layer (Fully Connected)	(1,168)
Hidden Layer (Fully Connected)	(1,84)
Hidden Layer (Fully Connected)	(1,84)
Hidden Layer (Fully Connected)	(1,42)
Hidden Layer (Fully Connected)	(1,21)
Output Layer	(1,1)

3. Analysis Results

The data from Table I were used for neural network model training. Using a total of 54 experimental data, the maximum diameter, departure diameter and sliding length were trained for each output values.

Firstly, how accurately each output value was studied on the ANN with input values. Table III showed the loss value and average error for each output values. For the maximum diameter and sliding length, the validity of ANN was not enough. It was assumed that additional input related to the output values was required to obtain sufficient validity. But the result of departure diameter showed some validity with 4 kinds of input. Therefore an additional test was done with untrained data. The result was shown in Table IV.

Table III: Loss and average error for each output values

	Maximum Diameter	Departure Diameter	Sliding Length
Loss	0.1122	0.0489	0.3475
Average Error	13.26%	5.78%	46.23%

Table IV: Relative error of departure diameter for untrained data

Average Error	Maximum Error	5% Excess Error
8.78%	21.34%	11.23%

For the untrained data, there was still high error for the maximum error. To reduce these kinds of error, additional experiment data or simulation data were needed and model optimization also need to be considered.

4. Conclusions

Artificial neural network (ANN) was applied in the prediction of bubble parameter in subcooled boiling flow. The results showed that departure diameter can be predicted with pressure, sub-cooling, liquid velocity and heat flux. To predict the maximum diameter, sliding length or other values, the additional data or optimized network models were needed.

Acknowledgments

This work was supported by the Korea Industrial Technology Association (KOITA) grant funded by the Korea government, MSIT (Ministry of Science and ICT). (No. KOITA-GO-2021-72)

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