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

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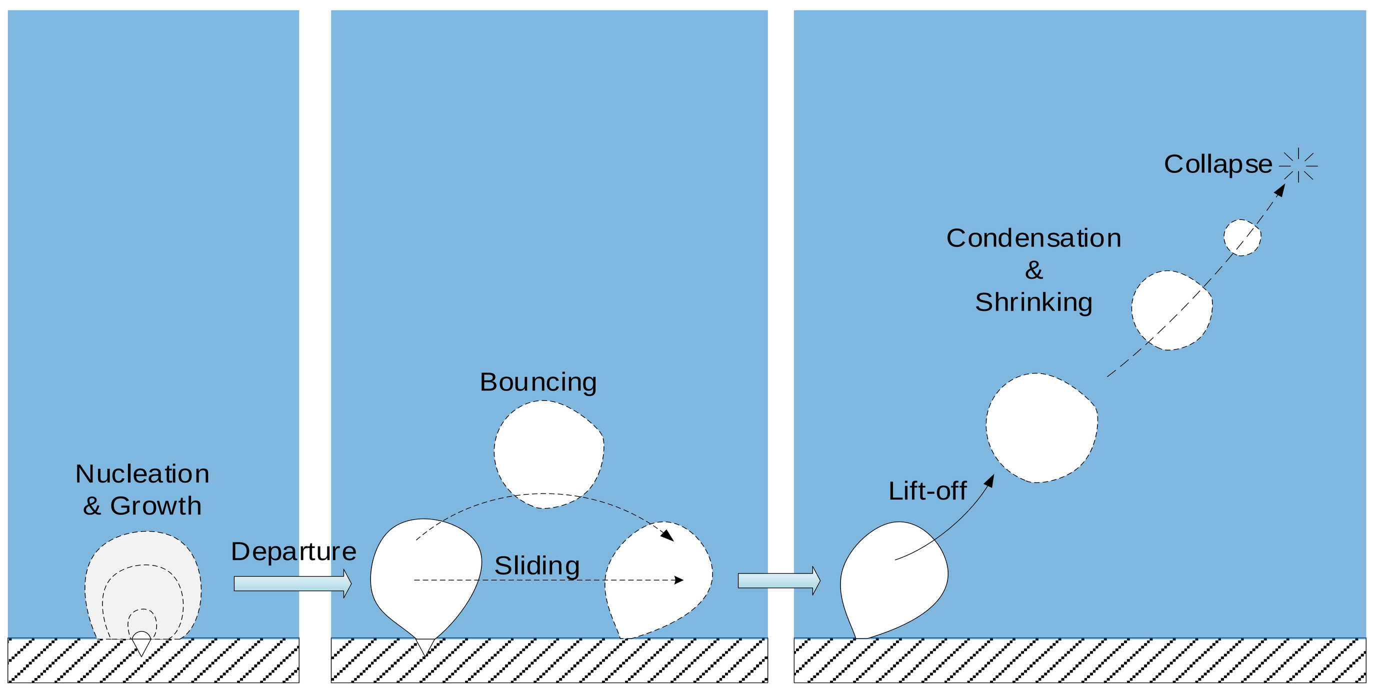
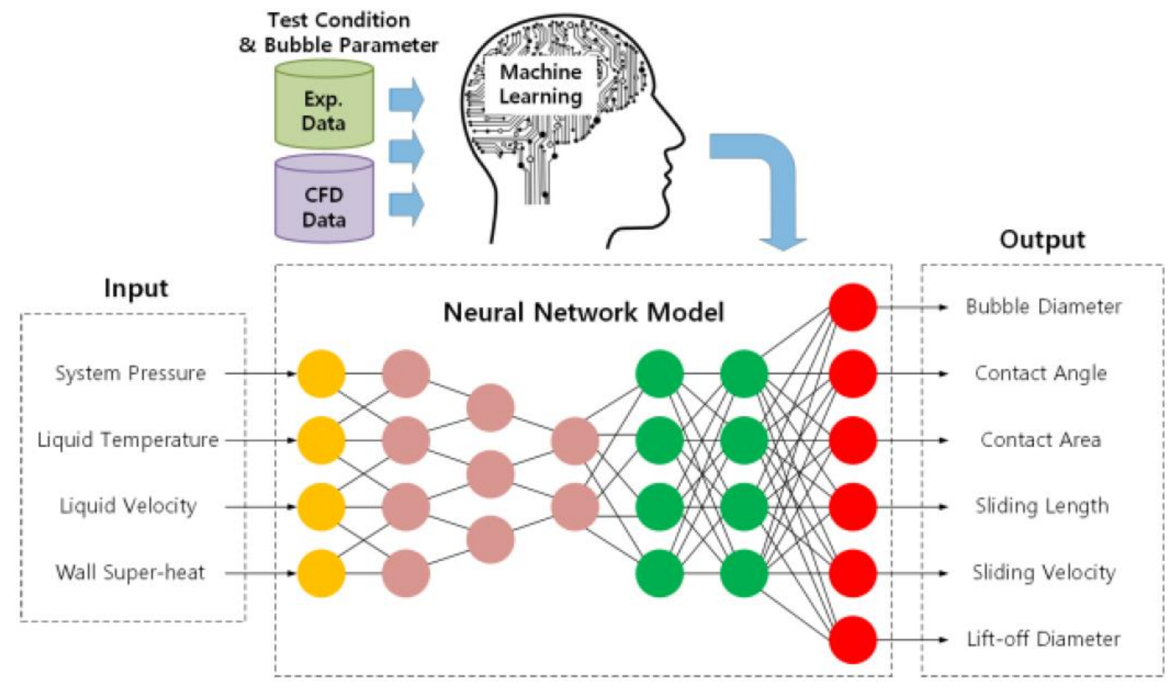
Introduction

- Many experimental analyses on bubble behavior have been conducted in various conditions, but it has been impossible to obtain complete information due to very complexity and difficulty to measure.
- So as a complement to experiments, there have been many CFD analysis, but it takes a lot of time.
- As a solution to this, this study seeks to introduce a neural network model, which is part of AI (Artificial Intelligence) technology, that has recently been utilized in variety of fields, to predict bubble parameters.
- In this work, we intend to develop an Artificial Neural Network (ANN) model using the Convolutional Neural Network (CNN) method widely used in deep learning.
- The ANN model to predict the bubble parameter is under development, and this presentation describes the main results of the study so far.



▪ Bubble behavior in sub-cooled boiling flow



▪ ANN model for predicting bubble parameter

Neural Network Model

- CNN is wall known for its efficiency in image processing of photographic data, and has the following differences compared to the exiting neural network.
  - ✓ 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.
- ✓ However, in this study, ANN model was applied like a fully connected layer, because the size of input data was too small to use CNN method.
- ✓ The input (pressure, sub-cooling, liquid velocity and wall heat flux) was used to get the bubble parameter in sub-cooled boiling flow.
- ✓ To obtain the output (maximum diameter, departure diameter, lift-off diameter, sliding length and sliding velocity), neural network model was designed.
- ✓ 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.

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	-

▪ Example data of parameter of single bubble experiment

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)

▪ ANN model for bubble parameter analysis

Analysis Results

- The data from literature survey 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 out values.
- First, in the ANN, it was confirmed how accurately each output values was studied as an input values through loss and average error.
- The validity of the ANN was insufficient for the maximum diameter and sliding length, so it is judged that additional input related to the output is required to obtain sufficient validity.
- On the other side, the results of the departure diameter showed some validity with four inputs.
- Therefore, additional tests were performed with untrained data.
- For untrained data, there was still a high error for the maximum error.
- To reduce this error, additional data are needed and sensitivity calculation for model optimization should be considered.

	Maximum Diameter	Departure Diameter	Sliding Length
Loss	0.112	0.049	0.346
Average Error	13.26%	5.78%	46.23%

▪ Loss and average error for each output values

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

▪ Relative error of departure diameter for untrained data

Conclusion and Future Work

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