Deep Learning and Acoustic Signal-based Pool Boiling Monitoring System

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1. Introduction

In a nuclear power plant, an effective heat removal technology and internal safety monitoring are important to maintain the stability of the system in operation and accident situations. As an example, in the case of a sudden increase in reactor power due to careless withdrawal of the control rod from Hanbit Unit 1 in 2019, the possibility of the nuclear reactor abnormality was determined only by calculating the thermal output, but the actual physical phenomenon occurred inside the reactor could not be identified [1]. This was due to the lack of internal status monitoring technology in the reactor and the operator's calculation error on the internal condition, which led to the need for the development of human error reduction technology and internal monitoring technology of the reactor to prevent a recurrence. Besides, figuring out the flow and boiling phenomena inside the reactor was a major concern because the nucleate boiling phenomenon has accelerated CRUD (an acronym for chalk river unidentified deposits) deposition, leading to reduction of reactor safety margin and the occurrence of axial offset anomaly, which has drawn more attention to boiling phenomena [2].

The 4th industrial revolution and digital twin, which are recently emerging in the industry field, are expected to innovate maintenance, safety, and efficiency with the concept of digitalizing everything in the system and analyzing measured big data signals with artificial intelligence to provide users with real-time status and insights of the system [3]. This concept is expected to be sufficiently applied to the reactor condition monitoring system to produce data on the state of the system using various measurement sensors and to investigate the internal state of the system through it.

One of the non-destructive measurement technologies, acoustic signal technology, is a promising method for measuring the condition of inaccessible systems. Acoustics detects elastic signals emitted by irreversible elastic changes in the system, such as crack formation [4]. Several studies revealed that through acoustic signal instrumentation the internal phenomena were identified according to the flow of the system and behavior of nucleate boiling bubbles [5,6]. Besides, by applying deep learning technology the correlation between signal data and physical phenomena was effectively derived [7,8].

For the advanced reactor condition monitoring system, the acoustic measurement and deep learning-based analysis of the pool boiling system was conducted as a fundamental level. In addition, this study aims to figure out the feasibility and applicability of acoustic sensors on reactor condition monitoring system. We figured out the relationship between the pool boiling heat transfer phenomena and acoustic signals. Finally, a deep learning model that can identify the pool boiling heat transfer regimes was developed.

2. Methods

2.1 Pool Boiling Experiment

The acoustic signal according to the boiling phenomenon was measured while performing the pool boiling experiment. As shown in Fig. 1, the experimental apparatus consists of a data acquisition system, power supply, pool boiling chamber, cartridge heater, condenser, power supply, and resistance standard. All phenomena were captured by high-speed video (HSV) and the heater temperature was measured by Infrared (IR) camera. The experiment was conducted using two different heaters, one was the bare SiO_2/ITO heater and the other was the hydrophobic coating heater. The purpose of the hydrophobic coating heater was for observing the film boiling phenomena since the hydrophobic surface has very low critical heat flux and it could provide all the boiling regime phenomena.

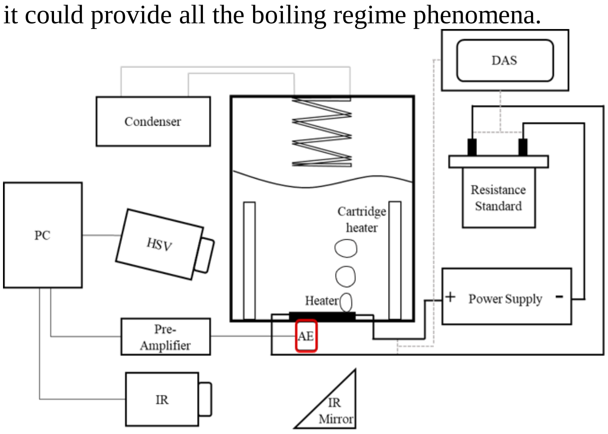

Fig. 1. Schematic diagram of pool boiling experimental apparatus for measuring the boiling acoustic emission signal

The acoustic signal of the boiling phenomenon was measured by attaching a broadband frequency contact AE sensor (*R15a, Physical Acoustics*) to the underside of the heater, and after measuring the background noise, the threshold amplitude was set and the acoustic signal measurement experiment was performed. The deionized water was used as a working fluid and all experiment was conducted under saturation condition at the atmospheric pressure.

2.2 Deep Learning Modeling

The heat transfer phenomena that can appear in the pool boiling experiment are natural convection, nucleate boiling, critical heat flux, and film boiling. To monitor the phenomenon in the pool boiling system, it is necessary to identify the phenomenon through acoustic signal data when four heat transfer phenomena appear. For this purpose, a deep neural network (DNN) was developed as shown in Fig. 2. The DNN model was composed of one input layer, 2~3 hidden layers, one output layer with 100~1000 neurons in one layer.

The acoustic signal measured in the experiment was transformed into power spectral density (PSD) using the Fast Fourie Transform (FFT) method to analyze the amplitude-frequency characteristics of the acoustic signal. This data was used as input data of the DNN model and four boiling heat transfer regimes were used as output data, and the performance of the model was identified by comparing the prediction result of the model with the experimental result.

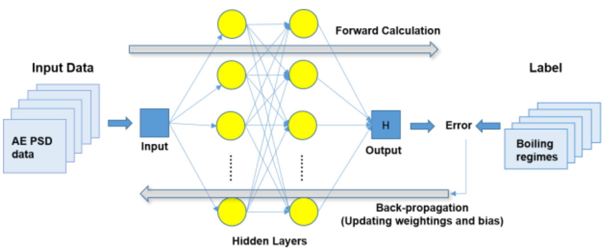

Fig. 2. Deep learning architecture for classifying the boiling regimes using acoustic signals power spectral density as an input data

3. Results and Discussion

3.1 Acoustic Analysis of Pool Boiling

The pool boiling experiment using two different heaters, which one was bare SiO_2/ITO heater and other was hydrophobic coating heater, was conducted for measuring the acoustic signals according to the four different boiling heat transfer regimes. As shown in Fig. 3, the natural convection, nucleate boiling, CHF, film boiling phenomena were captured by HSV and acoustic sensors, and this data was used to analyze and identify the acoustic characteristics for application to the deep learning-based monitoring system.

Each boiling regime was classified based on HSV images, and the graph on the right of Fig. 3 is the original acoustic signals measured at each boiling regime. In the natural convection regime, the signal according to the fluid transport due to the density difference was measured, and in the nucleate boiling regime, the signal due to the generation, growth, and release of the nucleate boiling bubble was measured. In CHF, intensive voltage signal was measured due to the collapse of the vapor, whereas in the film boiling regime, a very low voltage signal was measured due to the bubble departure above the vapor film.

The original acoustic signal can compare the amplitude of the voltage with measured signals over time duration 10ms, but it was difficult to derive features that can represent each boiling regime. Thus, the most widely used FFT method in the signal analysis method was applied to each signal for characterization, and the PSD frequency-amplitude results were obtained as shown in Fig. 4.

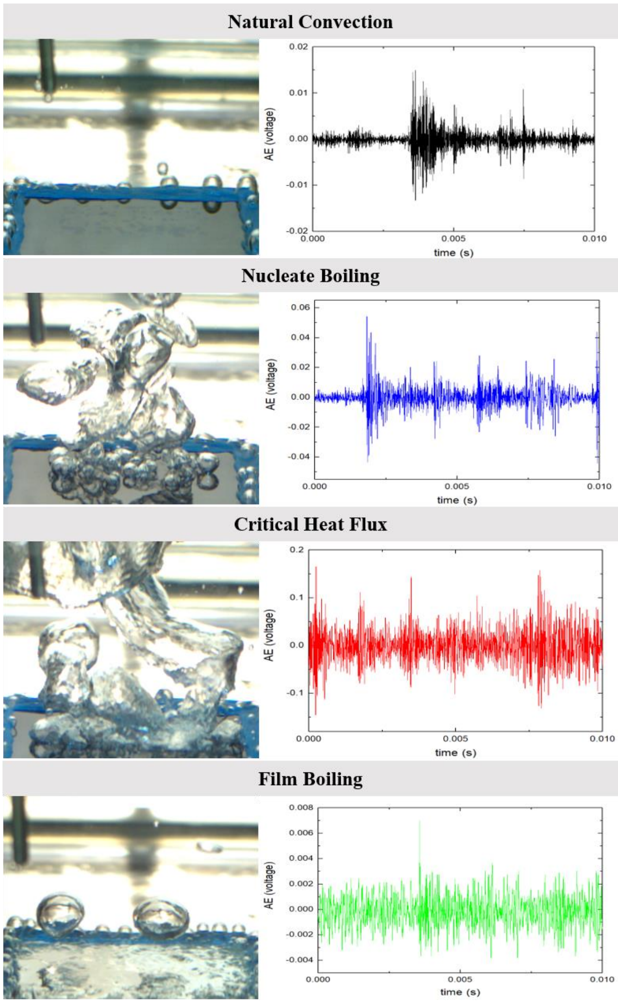

Fig. 3. High-speed images and AE signals of pool boiling phenomena according to boiling regimes

In Fig. 4, frequency characteristics were identified for each regime. When comparing the graphs of natural convection and nucleate boiling regime, it was found that amplitude peaks occurred in the range of 10 to 30 kHz and 40 to 50 kHz due to nucleate boiling. The two ranges of signals were very largely amplified in CHF, and very small signals were measured in the 10~30kHz range in the film boiling regime.

Table I. DNN model case study for identifying the optimum model

Case	Model	Hidden layers and neurons	Input data	Training Accuracy (%)	Test Accuracy (%)
1	DNN	(1000,1000)	Original acoustic signal	23.2	22.9
2	DNN	(1000,1000)	PSD data	71.1	70.9
3	DNN	(300,300,300,300)	Original acoustic signal	24.5	23.8
4	DNN	(300,300,300,300)	PSD data	73.6	74.0
5	**DNN**	**(500,500,500,500)**	**PSD data**	**99.9**	**96.4**
6	CNN+DNN	(1000,1000)	Original acoustic signal	20.3	27.1
7	CNN+DNN	(1000,1000)	PSD data	44.8	43.6

These features can be used as a criterion for roughly classifying boiling heat transfer phenomena, and each phenomenon can be more clearly distinguished through the developed DNN model.

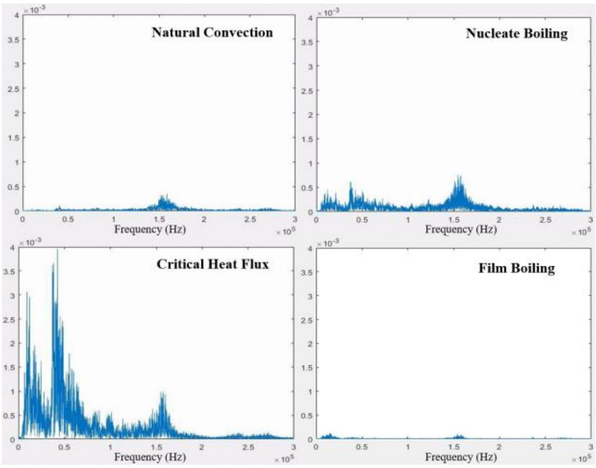

Fig. 4. Power spectral density of boiling AE signals according to the boiling regimes

3.2 Deep Learning and AE-based Monitoring System

To develop a system that can figure out the boiling heat transfer regime in the pool boiling system by using the DNN model and acoustic signal data, the optimization of the deep learning model was first performed. The total number of acoustic signal data and PSD data was 10,707, of which 9,634 data was used for deep learning training and 1,073 data was used for testing. As shown in Table I, seven case models were developed using the model configuration (DNN or with a convolutional neural network, CNN), the number of hidden layers, the number of neurons, and the input data type (original acoustic signal or PSD data). The optimal DNN model was found by comparing the prediction accuracy of each model. The case 5 model, a DNN model with 4 hidden layers and 500 neurons, showed the best prediction accuracy of 96.4%, and this model was selected as the optimal model.

The total prediction accuracy of the Case 5 model was 96.4%, but to understand the prediction performance of the model in more detail, the accuracy of each boiling heat transfer regime was compared and shown in Table II. In the case of natural convection and film boiling regime, the accuracy was 99.1% and 100%, respectively, showing nearly perfect predictions, and 95.9% slightly lower than the total accuracy of the nucleate boiling regime. On the other hand, CHF showed a prediction accuracy of 0%, which is due to the very limited learning (only 12 training CHF data and 3 test CHF data). The reason for the small number of CHF data was that if the CHF was reached during the experiment, the heater temperature rose rapidly, and the heater was destroyed. To prevent this, the experiment is stopped immediately after reaching the CHF.

Table II. The prediction accuracy of deep learning model for the pool boiling regime classification

	Natural Conv.	Nucleate Boiling	CHF	Film Boiling	Total
Test	217	819	3	34	1,073
Pass	215	785	0	34	1,034
Fail	2	34	3	0	39
Acc.	99.1%	95.9%	0 %	100%	96.4%

4. Conclusions

In this study, to develop a technology that monitors the internal heat transfer phenomenon of the pool boiling system with external measurement and deep learning technology, first, the acoustic signal was measured in the pool boiling experiment and the boiling heat transfer regime was classified from the HSV image. Through the PSD result of the acoustic signal, the frequency characteristics appearing in each regime were different, and frequencies in the range of 10 to 30 kHz and 40 to 50 kHz indicated the nucleate boiling. PSD data was used as the training input data of the DNN model, and the heat transfer regime prediction accuracy of 96% was achieved through the optimization process. Through this, we proposed a technique that can figure out the heat transfer phenomenon inside the pool boiling system without additional observation such as HSV by using acoustic signal measurement and deep learning.

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