Feasibility Study of Deep Learning and Acoustic Vibration-based Two-phase Monitoring Technology on Nuclear Reactor

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1. Introduction

The use of instruments is limited in nuclear reactors due to its high temperature, high pressure, and high radiation environment. Although the reactor is designed so that boiling does not occur in the nuclear fuel of PWRs, partial subcooled flow boiling and consequent CRUD deposition and reactor power AOA (Axial offset anomaly) occur [1]. Subcooled flow boiling that occurs in nuclear reactor is difficult to diagnose with pressure, flow, and temperature measuring instruments because the boiling bubble immediately condenses.

To diagnose the occurrence of boiling inside the system, studies using vibration or acoustic signals have been conducted [2–4]. However, there are still doubts about the applicability of this technology to the nuclear reactor. If it is possible to diagnose boiling inside the reactor through vibration or acoustic signal measurement non-destructively, it will be possible to contribute to the prevention of CRUD deposition and the enhancement of the reactor protection system.

This study aims for feasibility examination on technology development for diagnosis of boiling or two-phase flow inside the nuclear power plant, which is difficult to capture directly internal phenomena. To this end, a convergence study was conducted between acoustic signal measurement technology, which is excellent for detecting minute changes, and deep learning technology, which has excellent predictive diagnostic performance.

Acoustic sensor converts high-frequency vibrations propagated along the surface into an electrical signal and measures that signal. Due to the high sensitivity of signal measurement, it is possible to detect minute changes such as boiling and two-phase flow. It is a technology widely used in real-time diagnostic technology because it enables continuous signal detection regardless of the fault direction or progress of the measuring system.

In addition, as the collaborative technology of acoustic, deep learning is a data-driven modeling method that uses a multi-layered neural network to achieve patterns, prediction, classification, and detection of data to reach human expert level or higher results. This methodology has applied to many environments that require quick and accurate judgment without human assistance.

Since the characteristics of the acoustic signal are different for each boiling regime[5], it is expected that the boiling and two-phase flow inside the nuclear power

plant could be observed using acoustics. In addition, since the nuclear power plant has various noise due to pump rotation, valve activation, or other machineries, deep learning technology was applied for diagnosing the two-phase or boiling phenomenon with the signal of the acoustic sensor that measures the surface wave. In this paper, we focused on figuring out whether it is possible to actually apply deep learning technology to nuclear power plants where complex and various noises exist through acoustic signal measurement. For this, single and two-phase signals were measured by attaching the acoustic sensor to the APR1400 1/8 scale thermal-hydraulic integral effect test facility, URI-LO (UNIST Reactor Innovation LOop). After that, through deep learning, study was conducted to develop the model that can diagnose two-phase signals even in a noise environment.

2. Experiment and Methods

2.1 Experimental facility and condition

As shown in Fig. 1, URI-LO is the thermal-hydraulic integral effect test facility that is reduced to 1/8 height and 1/144 area from APR1400 as a reference nuclear power plant [6]. All components were made of transparent acrylic material to enable visualization experiments. Because URI-LO was designed as a residual heat test, it can produce a maximum output power of 198 kW, which is 2% of the maximum heat output, and the working fluid was water, and the pressure was atmospheric pressure. URI-LO, which can be visualized, can easily determine whether two-phase flow has occurred inside the primary system.

For acoustic signal measurement, the total of 8 sensors were attached to the bottom of the reactor vessel, reactor vessel head, high-temperature tube, low-temperature tube, and reactor coolant pump as shown in Fig. 2. The attached position was the most advantageous position to measure the acoustic signal when two-phase flow occurs in the core. The signal measurement performance according to flow and heating experiments were performed according to the experimental conditions in Table I, and the purpose was to measure acoustic signals in single-phase natural convection, two-phase natural convection, single-phase forced convection, and two-phase flow conditions.



Fig. 1. Schematic design of URI-LO facility for two-phase test in reactor[6].



Fig. 2. Acoustic signal measurement of two-phase flow from URI-LO facility.

Table I: Experimental condition of URI-LO facil	ity.
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Case	Power [kW]	Flowrate [kg/s]	Initial temp. [°C]	Pressure [bar]
1	0	3.6, 4.8, 6.0		
2	5	0	40	1
3	198	0, 3.6, 4.8		

2.2 Deep learning monitoring system

In classifying two-phase flow signals containing various noises, the deep learning model built in the previous study [5] showed excellent performance in capturing fine features, so it will be possible to utilize it in this study. We were to determine whether the builtup deep learning model from previous study for boiling regime classification can diagnose single-phase flow and two-phase flow of URI-LO. To do so, convolutional neural network-based deep learning model, ResNet18, were trained with single and twophase flow acoustic experimental data. This model aims for diagnosing the two classes, single-phase and twophase flow, from acoustic inputs. We converted the acoustic signals to spectrogram image by Short Time Fast Fourier Transform (STFT) for feature extracting of acoustics.

Table II: Deep learning model for diagnosing two-phase
through acoustic signals.

Algorithm	Input data	Prediction class
Resnet18	Spectrogram image	1) Single-phase
(CNN)	of acoustic signal	2) Two-phase

3. Results and Discussion

3.1 Acoustic results of two-phase flow

In the visualization results of the internal flow phenomenon of each experiment in Fig. 3, the internal flow phenomenon shows single-phase flow due to forced circulation up to 3.6 and 4.8 kg/s when there is no output in Case 1 and only the flow rate is changed. On the other hand, at the flow rate of 6.0 kg/s, bubbles and two-phase flow occurred due to the air mixing effect according to the high flow rate.

The experiment with an output of 198 kW and the flow rate of 0 showed natural convection, and noncondensable air bubbles due to high-power heating occurred in the heater. The output of 198 kW, flow rate of 3.6 kg/s, and flow rate of 4.8 kg/s also generated the non-condensable bubble on heater due to high-power heating under forced convection conditions, resulting in two-phase flow.

In this URI-LO experiment, since CHF, transition boiling, and nucleate boiling could not be tested due to the experimental condition restriction, only two regimes, single-phase and two-phase flow, were identified. Through the visualization results, two cases of 3.6 kg/s and 4.8 kg/s in Case 1 were single-phase flows, and 6.0 kg/s in Case 1 and three cases in Case 3 showed twophase flow. It was investigated whether the occurrence of two-phase flow phenomenon could be diagnosed through acoustic emission signal analysis.



Fig. 3. Visualized images of single and two-phase flow of URI-LO reactor according to flowrate and power.

Fig. 4~6 shows the spectrogram image analysis result of the acoustic signal measured in the URI-LO experiment. First, Fig. 4 compares the case of a singlephase flow with the flow rate of 4.8 kg/s and two-phase flow with the flow rate of 6.0 kg/s when there is no applied power in Case 1. In the case of the single-phase flow with the flow rate of 4.8 kg/s, 7 of the 8 signals except for the RCP had almost no acoustic signal, and only the 0~80 kHz and 150 kHz signals according to the pump operation were generated in the RCP. On the other hand, when the two-phase flow occurred with a flow rate of 6.0 kg/s, the signal of 0-50 kHz was commonly generated in the lower part of the RPV and the hot-leg, and the signal of 0-50 kHz was also generated in the RCP. This comparison shows that the acoustic signal measured from the URI-LO can capture the characteristics of the two-phase flow well.

Fig. 5 shows the results of natural convection conditions with applied power of 198 kW and no flowrate. As shown in Fig. 5, 0~50 kHz frequency signals were commonly generated due to two-phase flow in the lower part of the RPV and the hot-leg. In addition, as shown in Fig. 6, even at applied power of 198 kW and flowrate of 4.8 kg/s or more, the 0-50 kHz frequency signal was generated according to the occurrence of two-phase flow in the lower part of the RPV and the hot-leg. Therefore, it was easy to measure the two-phase flow phenomenon in the lower part of the RPV and the hot-leg among the five measurement positions.



Fig. 4. Acoustic spectrogram images for single phase (upper) and two-phase (bottom) flow at 0W, flow rate of 4.8 kg/s and 6.0 kg/s condition.



Fig. 5. Acoustic spectrogram images for two-phase natural convection at 198W, flow rate of 0 kg/s condition.



Fig. 6. Acoustic spectrogram images for two-phase forced convection at 198W, flow rate of 4.8 kg/s condition.

3.2 Deep learning prediction of two-phase flow

In the spectrogram image result, the difference between the single-phase flow and the two-phase flow of URI-LO was clear and can be easily distinguished at a glance. However, it will be difficult to know what the signal will be like in an actual nuclear power plant as it contains various noises that cannot be applied to this experiment. In addition, the continuous monitoring system through the application of the deep learning model is required because human-level classification ability is required for real-time monitoring.

As a result of predicting single-phase and two-phase flow of URI-LO through the CNN-based model using acoustic spectrogram data built in Section 2.2, it showed 99% accuracy, which were 100% of singlephase and 98% of two-phase flow as shown in Table III. Through this, the possibility of using the acoustic signal system and deep learning model described in this study to diagnose internal phenomena of nuclear power plants was revealed through URI-LO experiment.

Table III: Regime	prediction	of deep	learning m	odel
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	Single-phase	Two-phase
Test data	101	107
Prediction	101	105
Accuracy	100%	99.0%

4. Conclusions

In this paper, with the aim of diagnosing boiling and two-phase flow in nuclear power plants, feasibility study was performed to classify the two-phase flow through acoustic signals and deep learning technology. Using URI-LO (APR1400 1/8 scale reduction thermalhydraulic integral effect test facility), the possibility of diagnosing the occurrence of two-phase flow phenomena in the primary system through the measurement and analysis of acoustic signals and the CNN model was investigated. Through this, it is expected that the results of this study will be utilized to confirm the safety of the two-phase heat transfer system and used as fundamental study results necessary for real-time diagnosis and prediction of safety margin.

Acknowledgement

This work was supported by the A.I. Incubation Project Fund (1.210075) of UNIST (Ulsan national Institute of Science & Technology) and by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No.2021M2D2A1A-03048950).

REFERENCES

[1] J. Deshon, D. Hussey, B. Kendrick, J. McGurk, J. Secker, M. Short, Pressurized water reactor fuel CRUD and corrosion modeling, The Journal of The Minerals, Metals & Materials Society, Vol. 63, p.64–72, 2011.

[2] M. Shibahara, K. Fukuda, Q.S. Liu, K. Hata, S. Masuzaki, Boiling incipience of subcooled water flowing in a narrow tube using wavelet analysis, Applied Thermal Engineering, Vol.132, p.595–604, 2018.

[3] K.N.R. Sinha, V. Kumar, N. Kumar, A. Thakur, R. Raj, Deep learning the sound of boiling for advance prediction of boiling crisis, Cell Reports Physics Science., Vol.2, 100382, 2021.

[4] S. Bin Seo, I.C. Bang, Acoustic analysis on the dynamic motion of vapor-liquid interface for the identification of boiling regime and critical heat flux, International Journal of Heat Mass Transfer, Vol.131, p.1138–1146, 2019.

[5] D.Y. Lim, I.J. Jin, I.C. Bang, CONVOLUTIONAL NEURAL NETWORK-BASED BOILING REGIME DETERMINATION USING ACOUSTIC EMISSION SIGNAL IMAGE, Proceedings of 19th International Topical Meeting Nuclear Reactor Thermal Hydraulics, p.1–10, 2022.

[6] K.M. Kim, I.C. Bang, Design and operation of the transparent integral effect test facility, URI-LO for nuclear innovation platform, Nuclear Engineering Technology, Vol.53, p.776–792, 2021.

[7] J.S.K. He, X. Zhang, S. Ren, Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, p.770–778, 2016