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Prediction of Small-Scale Leak Flow in Nuclear Power Plants Using Bidirectional LSTM

Hye Seon Jo, Sang Hyun Lee, Man Gyun Na*
Department of Nuclear Engr., Chosun Univ., 10, Chosundae 1-gil, Dong-gu, Gwangju, 61452
**Corresponding author:* magyna@chosun.ac.kr

1. Introduction

Nuclear Power Plants (NPPs) are composed of many valves and pipes, and leakage can occur due to deterioration as the operating period increases. In particular, the probability of leakage is high in areas vulnerable to leakage such as welded parts, small pipes, and so on. Currently, in NPPs, it is possible to check whether or not leakage occurs through changes in humidity, radiation, and the sump level of the containment. However, for small-scale leakage, their change rate is not large; so, after a long period of time has elapsed since the leakage occurred, leakage can be detected. In other words, if a small-scale leakage occurs, it is difficult to detect it quickly. Accordingly, the Korea Atomic Energy Research Institute is currently conducting a research on the development of a detection system for unidentified RCS small leakage [1]. The system consists of a suction loop, transfer loop, and measurement area. Humid air in the leakage area is collected through the suction loop and transferred to the measurement area through the transfer loop; finally, leakage detection is performed by measuring relative humidity and radiation changes in the measurement area. It can detect not only whether or not leakage has occurred but also the amount of leakage.

As a part of the study for quantifying leakage, this study aims to confirm the possibility of quantifying leakage in the case of small-scale leakage. In this study, small leak flow prediction was performed using artificial intelligence in Loss-Of-Coolant Accident (LOCA) situations. An existing study [2] has shown high prediction performance by predicting leak flow in case of large leakage situations. Since the purpose of this study is to predict the leak flow for small-scale leakage situations, data for leakage situations with very small break sizes were used. The data were obtained for hot-leg and cold-leg LOCA scenarios through a Modular Accident Analysis Program (MAAP) [3]. Bidirectional Long Short-Term Memory (BiLSTM) was used to predict the leak flow, and the hyperparameter optimization method was applied to build an optimal model.

2. Methods

2.1 BiLSTM

BiLSTM consists of a forward LSTM network and a backward LSTM network [4]. Basic LSTM networks learn only sequence information from the past to the present for an input sequence. This causes the limitation that the results of LSTM are mainly determined based on past information [4]. To solve this problem, BiLSTM was proposed. BiLSTM learns not only forward, but also backward sequence information from future to past. In other words, better performance than basic LSTM networks can be expected because it learns forward and backward sequence information for the input data. Fig. 1 shows the structure of BiLSTM.

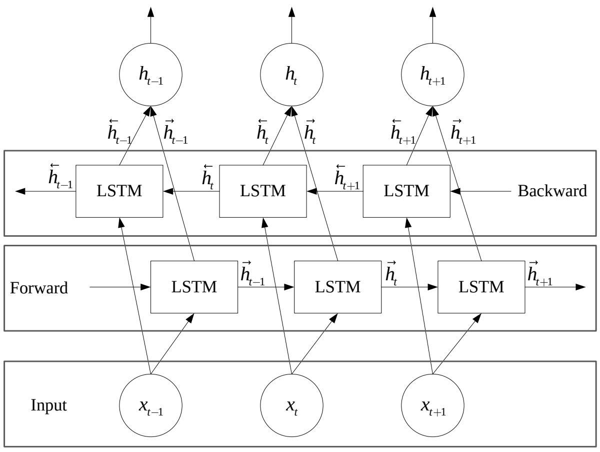

Fig. 1. Structure of BiLSTM [4].

In Fig. 1, $\overrightarrow{h}$ and $\overleftarrow{h}$ are hidden states of forward and backward layers, respectively. And h is hidden states of BiLSTM. The final hidden states of BiLSTM can be derived by merging the hidden states of forward and backward LSTM networks. Merging methods include simply concatenating, summing, and averaging them. In this study, the final hidden states were derived by concatenating the hidden states of forward and backward LSTM networks.

2.2 Optimization of BiLSTM model

To develop a BiLSTM model for leak flow prediction, we optimized the hyperparameters using Keras Tuner. There are various hyperparameters that users need to decide when developing an artificial intelligence model. In this study, four parameters were optimized through Keras Tuner. Table I shows the hyperparameters and search spaces for each hyperparameter. Here, units of hidden layer decrease by two times as the number of layers increases. (e.g., when the number of layers is 3 and units of the hidden layer are 128, the units per hidden layer are 128, 64, and 32.)

After randomly determining the hyperparameters through the combination of each search space, the optimal hyperparameters are selected according to the loss value of validation datasets. The loss function is the mean squared error.

Table I: Search space for hyperparameter optimization

No.	Hyperparameters	Search space
1	Number of layers	[2, 3]
2	Units of hidden layer	[64, 128, 256, 512]
3	Learning rate	[0.001, 0.005, 0.01]
4	Batch size	[64, 128, 256]

3. Data preprocessing

Data were obtained using the MAAP code that simulates the condition of the OPR-1000 power plants. The obtained data were hot-leg and cold-leg LOCA scenarios. In order to simulate small leakage situations, the break sizes of about 2.0×10^{-7} to 6.0×10^{-6} times the double-ended guillotine break were applied. These are scenarios in which a leakage of about 0.03 to 1 gpm occurs, and data for 30 minutes after the event. Table II shows the postulated scenarios and the number of datasets. To develop the prediction model, nine variables that are affected by leakage were applied as input variables. In addition, the data were normalized to a value between 0 and 1 for effective model training.

Table II: Postulated scenarios

Scenario types	Range of leak flow (10^{-2} kg/sec)	Range of leak flow (gpm)	No. of train/val/test datasets
Hot leg LOCA	0.17~5.1	0.039~1.184	24/3/3
Cold leg LOCA	0.14~4.7	0.031~1.011	27/3/3

4. Leak flow prediction results using BiLSTM

The leak flow prediction models using BiLSTM were developed separately for hot-leg and cold-leg LOCA scenarios. Also, the models were developed by changing the input sequence to check the prediction performance according to the input sequence. Here, the input sequence is a 1-second interval: if the input sequence is 5, it means data for 5 seconds. When developing the model according to the input sequence change, the optimal hyperparameters were determined using Keras Tuner.

The performance of the developed models was evaluated through Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Each evaluation metric is calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}(y^i_{real} - y^i_{pred})^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left|y^i_{real} - y^i_{pred}\right| \tag{2}$$

$$\mathrm{MAPE} = \frac{100\%}{N_t}\sum_{i=1}^{N_t}\left|\frac{y^i_{real} - y^i_{pred}}{y^i_{real}}\right| \tag{3}$$

where, y_{real} and y_{pred} are real and predicted values, respectively. N_t is the total number of datasets.

Table III shows the performance of the developed leak flow prediction model on test datasets. In both hot-leg and cold-leg LOCA scenarios, prediction errors in all evaluation metrics decrease as the input sequence increases. This means that past long-time information has a positive effect on prediction performance when predicting leak flow. However, long input sequences are limited because the purpose of this study is to check the leak flow in a short time. Therefore, input sequence of 10 was selected as best because the MAPE is within 10% in both scenarios. Table IV shows the hyperparameters of the model developed at input sequence 10.

Table III: Leak flow prediction results

Scenario types	Input sequence	Test datasets		
		RMSE	MAE	MAPE (%)
Hot-leg LOCA	2	0.0048	0.0029	11.00
	5	0.0039	0.0024	9.04
	10	0.0032	0.0020	7.48
	20	0.0024	0.0015	5.86
Cold-leg LOCA	2	0.0044	0.0027	12.06
	5	0.0037	0.0025	11.48
	10	0.0026	0.0017	8.00
	20	0.0023	0.0015	7.18

Table IV: Hyperparameters of the developed model in case of input sequence 10

No.	Hyperparameters	Scenario types	
		Hot-leg LOCA	Cold-leg LOCA
1	Number of layers	3	3
2	Units of hidden layer	128	128
3	Learning rate	0.005	0.001

4	Batch size	64	256

Fig. 2 shows the MAPE values according to break sizes in hot-leg and cold-leg LOCA scenarios; as the case number increases, the break size (i.e., leak flow) increases. In Fig. 2, the black dotted horizontal line represents the MAPE of 10%, showing an error of less than 10% from about the 10th break size in all scenarios. It is a scenario with a leakage of about 0.4 gpm, meaning that leak flow can be predicted somewhat exactly in larger leakage situations. However, it is difficult to predict the leak flow below 0.4 gpm. It is thought to be because the plant states do not change significantly at very small-scale leakage.

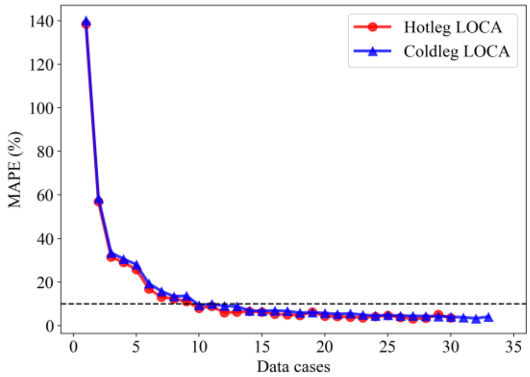

Fig. 2. MAPE values according to break sizes (in case of input sequence 10).

Figs. 3 and 4 show the prediction results using the prediction model when the input sequence is 10. The prediction error is rather large at the beginning of the leakage, but the prediction model predicts accurately overall over time.

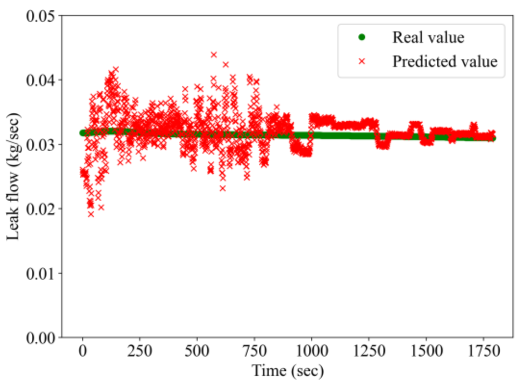

Fig. 3. Prediction results in the hot-leg LOCA scenario (for leak flow of 0.75 gpm).

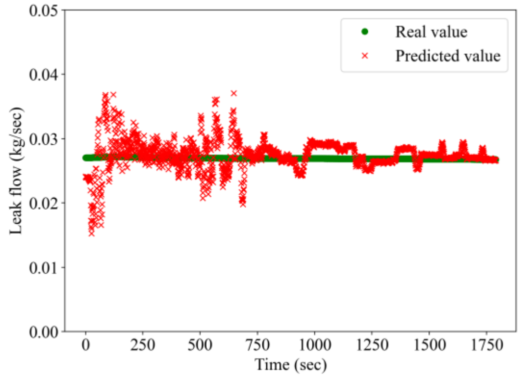

Fig. 4. Prediction results in the cold-leg LOCA scenario (for leak flow of 0.58 gpm).

5. Conclusions

In this study, leak flow prediction was performed to quantify the small-scale leakage. BiLSTM, an artificial intelligence method, was used to predict the leak flow. Data applied for model development were the hot-leg and cold-leg LOCA scenarios, where leakage of 0.03 to 1 gpm occurs. The leak flow prediction model was developed by changing the input sequence of BiLSTM. The optimal input sequence was determined to be 10 based on the prediction performance and the purpose of this study (i.e., leakage detection and quantification in a short time). The results of the developed model showed that the prediction error decreased as the break sizes increased, and the MAPE was within 10% above a certain break size. The leak flow at the break size is approximately 0.4 gpm, and it was accurately predicted in scenarios with leakage between 0.4 and 1 gpm. However, the prediction error in the leakage scenarios below 0.4 gpm is very high and it was difficult to confirm the leak flow in a short time in the case of a very small-scale leakage.

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