Initial Relative Humidity Prediction for Quantifying Small Leakage at Nuclear Power Plants

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

1. Introduction

In nuclear power plants (NPPs), events occur due to various pattern (i.e., station blackout, loss of coolant accident, etc.). Among the numerous events, leaks are serious accidents. Leakage can be caused by deterioration of NPPs, material deterioration at welds between pipes, or rupture due to vibration of equipment. If the small leakage accident by these causes is not identified quickly by the operator and the leakage accident worsens, the NPPs is shut down or if it worsens, it may lead to casualties, leading to a dangerous situation. To prevent the above dangerous situation, it is important to detect leaks quickly and quantify leakages. This is even more essential in NPPs where safety is of more importance. Therefore, it is important to predict the initial humidity required to quantify leakage [1, 2]. In this paper, we present a system for predicting initial relative humidity through artificial intelligence (AI) to quantify small leakage. In this study, the regression method is used among the learning fields of AI to predict the initial relative humidity. Among the AI methods, long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM) were used for AI learning. And the data used for AI learning is the CUPID thermal hydrostatic code. After AI learning, performance was evaluated through three performance evaluation indicators. The best method was Bi-LSTM with superior results. In the future, it is expected to help predict the initial relative humidity for early detection and quantifying leakages in NPPs.

2. Methods

2.1 LSTM

LSTM is known as a time series-based AI method. In the conventional recurrent neural network method, there is no long-term dependence on storing old information, and LSTM is a method that overcomes the disadvantage of not being able to remember as it gets later from the output of the recurrent neural network [3]. The structure of LSTM is shown in Fig. 1. LSTM has four characteristic layers. 1) Cell state, 2) Forget gate, 3) Input gate, 4) Output gate.

First, the cell state is divided into a long-term state c_t and a short-term state h_t.

Second, the forget gate is a gate that decides whether to selectively forget information. It is calculated through the sigmoid function. The forget gate is shown in Eq. (1).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

Third, the input gate plays a role in determining the input information to be stored in the cell state among the input information. After that, a new vector is formed on the tanh layer. The input gate is shown in Eq. (2).

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

Finally, the output gate proceeds to the next cell by updating the output value in the cell state. Thereafter, the same process is performed in the next cell. The output gate is shown in Eq. (3).

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3}$$

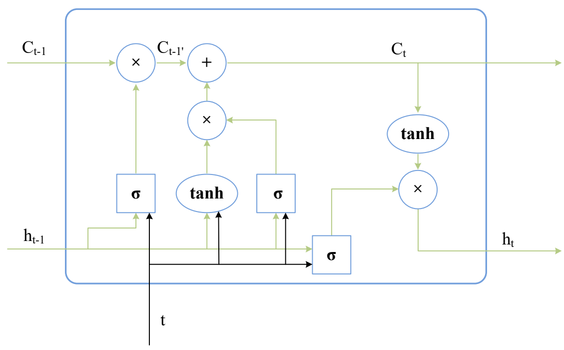

Fig. 1. Structure of LSTM [4].

2.2 Bi-LSTM

The Bi-LSTM is a method that adds an LSTM layer that proceeds in the reverse direction to the existing LSTM structure. The final hidden state outputs a vector linking the hidden states of two LSTMs. Because LSTMs are input sequentially, there is a gradient vanishing problem in which the output tends to converge based on the previous pattern. To solve this problem, Bi-LSTM has the advantage that past information is not lost even if the layer is deep by adding backward propagation to the forward propagation [5]. The Bi-LSTM structure is shown in Fig. 2.

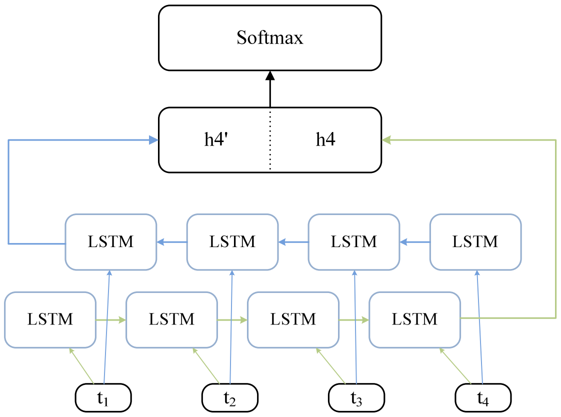

Fig. 2. Structure of Bi-LSTM [6].

3. Data Processing

CUPID code is a code for reactor equipment analysis at Korea Atomic Energy Research Institute (KAERI). It is a three-dimensional high precision thermal hydraulic analysis code that can describe two-phase flow by adopting a 2 fluid, 3 field model to analyze two-phase flow [7]. In this study, data simulating a small leakage using the CUPID code was used. The figure of the simulated pipe is shown in Fig. 3.

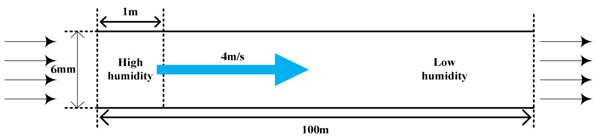

Fig. 3. Structure of simulated small pipe for AI learning.

The data simulated in the CUPID code was preprocessed and utilized for AI learning data.

Data preprocessing proceeds with 1) variable selection, 2) normalization, and 3) time series processing using sliding window technique.

First, the important variables were selected to facilitate the AI learning of CUPID code data. This process has a positive impact on performance by eliminating unnecessary variables.

Second, through normalization, the value of the data is adjusted to a value between 0 and 1. The normalization reduces the range of high changes and acts as good input for AI learning in a specific range. This is because when carrying out predictions, a large amount of specific data can negatively affect the prediction.

Finally, the CUPID code data simulated in this study is data representing the humidity spread inside the pipe over time. Accordingly, it was classified into time series using the sliding window technique. For data with all three procedures above, the temperature was simulated in units of 5°C from 60 to 100°C and the initial humidity was simulated by 5% from 60 to 90%.

Table I shows the data length when relative humidity is fixed and temperature changes among many simulated cases.

Table I: Data construction

Input relative humidity (%)	Temperature (°C)	Data length
60	60	26,658
	65	
	70	
	75	
	80	
	85	
	90	
	95	
	100	

4. Prediction Result

In this study, the initial humidity prediction for quantifying leakage was performed using AI learning. The initial relative humidity prediction performance was compared using LSTM and Bi-LSTM AI methods, and AI learning was conducted using CUPID code data. To compare prediction performance, each layer of each AI model is set up with the same form. And, in general, the larger the batch size, the faster the learning rate, but the learning instability may increase relatively. Therefore, the batch size was adopted as 32. In addition, the number of epochs for each method used the early stop method to prevent overfitting. And, patience was set to 20 to prevent underfitting due to early stopping. When evaluating the prediction performance, mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE) were used as evaluation indicators. The error for the predictive performance for each method is shown in Table II. Each indicator is calculated as Eq. (4), (5) and (6).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2 \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_i - x\right| \tag{5}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum(\hat{Y} - Y)^2}{n}} \tag{6}$$

Figs. 4 and 5 show the graph showing the prediction results by pulling out an untrained case. In the case taken in the figure, the initial relative humidity was fixed at 90 percent and the initial temperature was adjusted. In the graph, the blue dot indicates the initial humidity for the actual initial humidity, and the red dot indicates the initial humidity as a result of the prediction model.

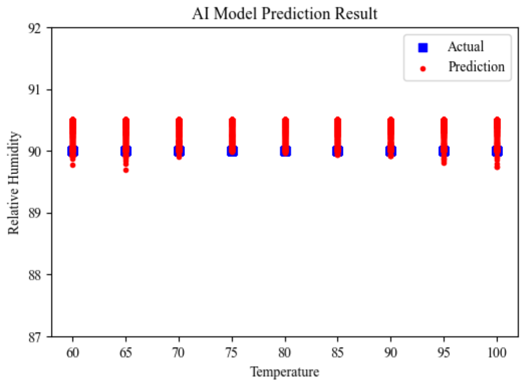

Fig. 4. Initial relative humidity prediction result of LSTM method.

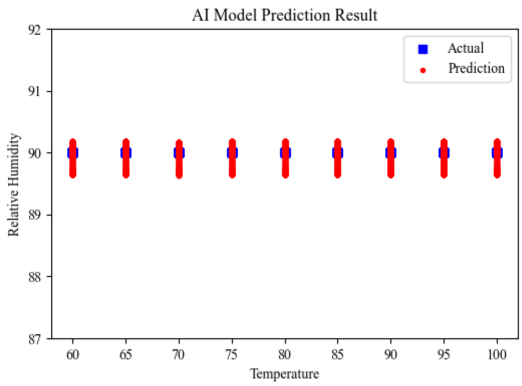

Fig. 5. Initial relative humidity prediction result of Bi-LSTM method.

Table II: AI method prediction result

	Result	
	LSTM	Bi-LSTM
MAE (%)	0.8423	0.7351
MSE (%)	0.8151	0.6978
RMSE (%)	0.8566	0.7475

5. Conclusion

In this study, the prediction of initial humidity for quantifying leakage was conducted using AI methods. The used AI methods are LSTM and Bi-LSTM. As a result of the prediction, Bi-LSTM learning using not only forward propagation but also backpropagation showed superior performance. In the future, it is expected that the performance will be further improved by applying the attention mechanism to the Bi-LSTM structure.

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