Prediction of Containment Pressure and Hydrogen Concentration in Severe Accidents Using TCN Model with Uncertainty Quantification

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1. Introduction

In Nuclear Power Plants (NPPs), various accidents can cause coolant leaks or losses, further expose the reactor core, and cause safety systems to malfunction [1]. This can prevent the core from cooling, eventually leading to core melting and a severe accident. A severe accident is an accident in which NPPs designed considering Design Basis Accidents (DBA) exceed the design basis and cause the core to melt down.

Since the operator's actions are important in a severe accident, guidelines that provide appropriate instructions to the operators are the Severe Accident Management Guidelines (SAMGs). SAMGs are guidelines that enable the operator of NPPs to identify severe accident symptoms and analyze the cause by severe process variables, and take appropriate mitigation actions when a severe accident occurs. SAMGs suggest variables and thresholds instructing the operator to take mitigation actions when an abnormality occurs. Among them, safety variables were suggested to maintain the integrity of the containment.

The integrity of the containment is a very important factor of safety. In high-pressure accidents such as a small Loss Of Coolant Accident (LOCA), the released corium causes direct containment heating, which directly increases the temperature and pressure of the containment. In addition, the hydrogen gas generated by the chemical reaction of corium increases the temperature and pressure of the containment [1]. As the hydrogen concentration and pressure of the containment reach the threshold, it can become factors that threaten the integrity of the containment. This can reduce the reliability of the information instrumented in NPPs and lead to a potentially explosive situation. Therefore, it is important to provide time for the operator to take actions before each variable reaches the threshold. In this study, the hydrogen concentration and pressure of the containment were selected as targets, and their predictions were conducted to support the operators.

In this study, the Cold-leg LOCA scenario, the Hot-leg LOCA scenario, and the Steam Generator Tube Rupture (SGTR) scenario data were acquired and used through the Modular Accident Analysis Program (MAAP) code. Each scenario considered the break location and the operation of the safety system. The Artificial Intelligence (AI) model, Temporal Convolution Network (TCN) [2] was used to predict the containment pressure and hydrogen concentration. The TCN model was used to predict the targets after 240 minutes from the current time. In addition, the Monte Carlo (MC) dropout method was used to evaluate the uncertainty of the TCN model and obtain a confidence interval.

2. Methods

This section describes the TCN method used for prediction and the MC dropout method for evaluating prediction uncertainty.

2.1 Temporal Convolution Network

In this study, the TCN method is applied to predict the hydrogen concentration and pressure of containment, which are safety variables of the containment.

TCN is a methodology that applies the convolution neural network structure to time series data. It is a model proposed to overcome the limitations of existing recurrent neural network-based models. TCN uses multiple filters to process the input sequence in parallel. This overcomes the low learning rate and long-term dependency problems in recurrent neural network-based models.

TCN can perform detailed tasks using a hierarchy of temporal convolutions [2]. In particular, dilated TCN, including dilated convolution, was used in this study. Dilated convolution adjusts the interval of input data to which the filter is applied, allowing a more comprehensive range of inputs to be accommodated. Eq. (1) shows the equation of dilated convolution.

$$y(t) = \sum_{i=0}^{k-1} f(i) \cdot x(t - r \cdot i) \tag{1}$$

$x(t-i)$ represents the input at time $(t-i)$, $f(i)$ represents the weight of the filter, and k represents the size of the filter. r represents the dilation rate, which means the interval of the kernel. As r increases, it accommodates values located further apart. In addition, adding the output of each layer to the original input through residual connection stabilizes the learning of the network and helps it learn effectively.

In this study, dilated TCN was used, and the dilation rate was set to a range of 1 to 4, enabling learning of time series patterns in various ranges. In addition, residual connections were used to prevent the gradient vanishing problem and increase the stability of the model. Fig. 1 shows the structure of dilated TCN.

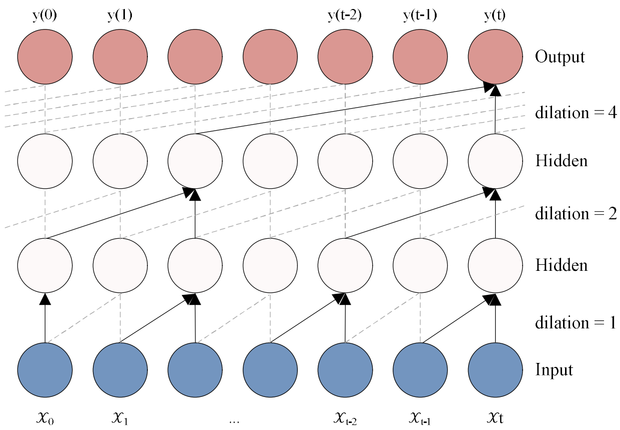

Fig. 1. Structure of dilated TCN model.

2.2 Monte Carlo Dropout

As AI research increases, the need for quantifying uncertainty is emerging [3]. Uncertainty quantification increases the reliability of AI models and can be a safety technology for continued use [4]. In this study, the MC dropout method was used to quantify the uncertainty of the TCN model.

The commonly used dropout method is one of the techniques used to prevent AI models from being overfitted. The MC dropout method used in this study quantifies uncertainty by activating dropout even during the testing process.

In this study, 0.4 was selected as the dropout probability. After the training process, N iterations of prediction are performed in the test step with dropout activated. Different dropout masks are applied to the data set with a specific probability to generate various prediction results in this process. Since 100 iterations were selected, 100 prediction results were generated for each data set.

As a result, the average of the results obtained through N iteration predictions is used as the final prediction value, and the variance of the prediction results expresses the uncertainty of the prediction. The final prediction value and the variance of the prediction results are shown in Eqs. (2) and (3).

$$\hat{y}_{MC} = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_t \quad (2)$$

$$v = \mathrm{Var}(\hat{y}) = \frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t - \hat{y}_{MC})^2 \quad (3)$$

The confidence interval can be calculated using the values derived from Eqs. (2) and (3). It is used as an essential indicator of how confident the model is about the predicted results at a certain confidence level. Eq. (4) expresses the confidence interval.

$$CI = \hat{y}_{MC} \pm Z \cdot \sqrt{v} \quad (4)$$

Z represents the percentile corresponding to a certain confidence level in the standard normal distribution, and in this study, a 95% confidence level was adopted. The confidence interval is derived by multiplying the Z value by the standard deviation, which is the square root of the variance.

The uncertainty of the prediction affects the range of the confidence interval. Therefore, by quantifying the uncertainty in model predictions, the reliability of the model can be evaluated, thereby enhancing safety.

3. Data

In this study, hydrogen concentration and pressure of containment predictions were performed in LOCA and SGTR scenarios. Data were acquired using the MAAP code to make the predictions. The MAAP code is software that can simulate and analyze reactor accident scenarios, model various accident situations, and calculate variables.

Data for each accident scenario was acquired by adjusting the break size at a constant ratio. Specifically, break size, break location, and safety system operation were considered, and data for 86,400 seconds (1 day) were acquired for each scenario through the MAAP code. However, since the collected data was very large, the AI model learning efficiency decreased, so the data in seconds was converted to data in minutes. To this end, the data was grouped at 60-second intervals, and the average value was calculated within each group, converted to minute data, and applied to the model training process.

In this study, the safety system was specified as a high-pressure safety injection system, a low-pressure safety injection system, a containment spray system, and an auxiliary feedwater system. It turned on/off for each scenario (It was assumed that recirculation was impossible). The data were divided into train, validation, and test datasets. During the train and test processes, it was randomly dropped with a probability of 0.4 set arbitrarily by the MC dropout method.

The input variables for the prediction target were selected using the Pearson correlation coefficient analysis. The Pearson correlation coefficient measures the linear relationship between variables and expresses the strength and direction of the relationship as a value between -1 and 1. The closer it is to -1 and 1, the stronger the correlation. In this study, variables with a correlation coefficient value less than -0.4 or greater than 0.4 were selected as input variables. Through this, the predictions of hydrogen concentration and pressure used seven input variables (The seven input variables are different in each predicted target).

4. Results

This study used the TCN model to predict the hydrogen concentration and pressure of the containment in LOCA and SGTR scenarios. The predictions were conducted 240 minutes (4 hours) ahead of the current time, and the uncertainty was quantified using the MC dropout method. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) were used as model performance evaluation metrics for the prediction results. The evaluation indices are shown in Eqs. (5) to (7).

$$RMSE = \sqrt{\frac{\Sigma(y-\hat{y})^2}{n}} \tag{5}$$

$$MAE = \frac{\Sigma|y-\hat{y}|}{n} \tag{6}$$

$$R^2 = 1 - \frac{\Sigma(y-\hat{y})^2}{\Sigma(y-y_{mean})^2} \tag{7}$$

In the equation, y represents the actual value of the prediction target, $\hat{y}$ represents the predicted value, and y_{mean} represents the average of the predicted values. The lower the error values, and the closer R^2 is to 1, the better the performance of the model.

Figs. 2 to 7 show the results of predicting the hydrogen concentration and pressure of the containment for each scenario and calculating the uncertainty. In the graph, the blue line represents the actual value of the prediction target, and the red line represents the value predicted by the model 240 minutes ahead of the current value. In addition, the area around the predicted value represents the confidence interval indicating the uncertainty of the model, and in this study, it means a 95% confidence level. The green line is when the core exit temperature reaches 649℃, which is the SAMGs entry condition and is the estimated point when a severe accident will occur. The two purple lines in the prediction of pressure results are the pressure thresholds that require containment condition control suggested by SAMGs. Threshold 1 is approximately 392,975 Pa , which is the threshold that may threaten the containment, and threshold 2 is approximately 841,142 Pa , which is the threshold that requires immediate implementation of containment condition control. Additionally, the purple line in the prediction of hydrogen concentration results is the hydrogen concentration threshold that requires hydrogen control inside the containment, which is 0.05%.

The prediction results show that the TCN model is highly accurate in each scenario, even when predicting the future with a long time-step of 240 minutes. In the case of pressure prediction, it generally showed high accuracy. All of them show a trend of exceeding threshold 1 and approaching threshold 2 due to the accident progression (Among the test results, there are cases where threshold 2 was reached). Pressure prediction performs better than hydrogen concentration prediction but has a wider confidence interval.

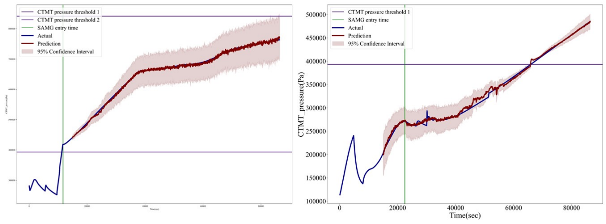

Fig. 2. Prediction of pressure results for Cold-leg LOCA scenario (Left: safety system inactivating, Right: safety system activating).

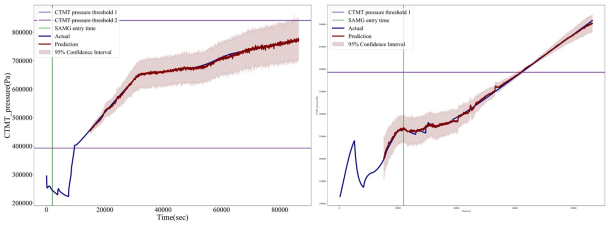

Fig. 3. Prediction of pressure results for Hot-leg LOCA scenario (Left: safety system inactivating, Right: safety system activating).

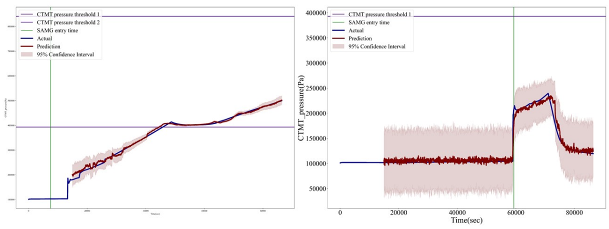

Fig. 4. Prediction of pressure results for SGTR scenario (Left: safety system inactivating, Right: safety system activating).

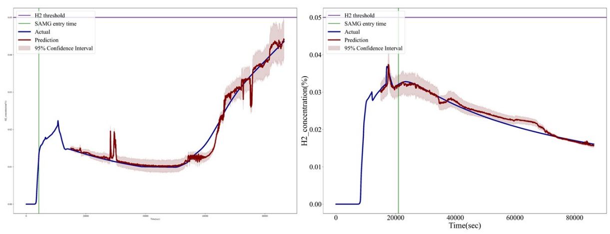

Fig. 5. Prediction of hydrogen concentration results for Cold-leg LOCA scenario (Left: safety system inactivating, Right: safety system activating).

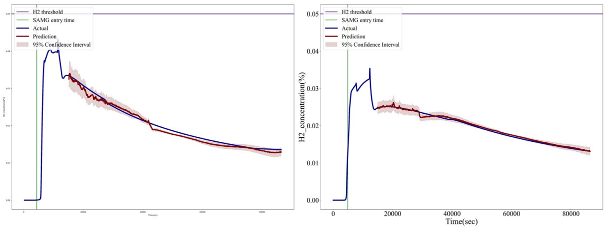

Fig. 6. Prediction of hydrogen concentration results for Hot-leg LOCA scenario (Left: safety system inactivating, Right: safety system activating).

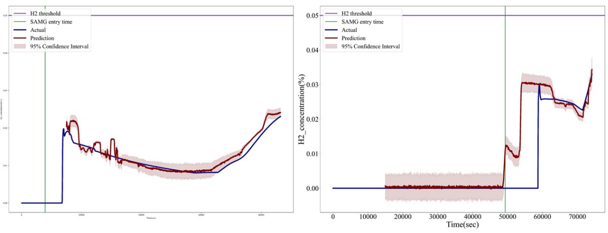

Fig. 7. Prediction of hydrogen concentration results for SGTR scenario (Left: safety system inactivating, Right: safety system activating).

The accuracy of the hydrogen concentration prediction result is slightly lower than that of the pressure prediction. This is because hydrogen is affected by various factors in the reactor and shows complex chemical reactions. In addition, it is difficult to accurately predict the hydrogen concentration because the process of removing hydrogen by passive auto-catalytic recombiner is sensitive to various environmental variables. These factors affect the prediction of hydrogen concentration. Table I shows the performance evaluation results for each scenario of the prediction model.

Table I: Prediction performance of TCN model

Predicted targets	Scenario	Safety system	RMSE	MAE	R^2
Containment pressure	Cold-leg LOCA	On	0.0054	0.0039	0.99
		Off	0.0043	0.0035	0.99
	Hot-leg LOCA	On	0.0039	0.0030	0.99
		Off	0.0047	0.0037	0.99
	SGTR	On	0.0086	0.0056	0.97
		Off	0.0081	0.0056	0.99
Containment hydrogen concentration	Cold-leg LOCA	On	0.0172	0.0129	0.96
		Off	0.0253	0.0152	0.97
	Hot-leg LOCA	On	0.0057	0.0047	0.99
		Off	0.0124	0.0108	0.98
	SGTR	On	0.1435	0.0621	0.31
		Off	0.0263	0.0184	0.80

In terms of pressure prediction, we need to reduce the uncertainty of the model to increase its reliability. In terms of hydrogen concentration prediction, the prediction performance of the model should be increased. Based on this information, performance improvement is needed in this study.

5. Conclusions

This study aims to support operators in responding appropriately when a severe accident occurs by predicting the hydrogen concentration and pressure of the containment. To this end, the TCN model, which is effective in analyzing time series data, was used, and the uncertainty was quantified using the MC dropout method to increase the reliability of the prediction.

As a result, the TCN model was confirmed to predict key variables with high accuracy and especially showed high performance even when predicting time steps further than the present. In addition, the reliability of the prediction results was verified through uncertainty quantification, and it was implied that it could provide important information for effective response in case of a severe accident.

This technology allows operators to predict hydrogen concentration and pressure in real-time and take proactive actions to maintain the integrity of the containment. It can also be applied to various accident scenarios, and it will be an important key to increasing the reliability of AI and enabling continuous use through uncertainty quantification.

The results of this study can be utilized as part of the operation support system, such as the early warning system of NPPs. This would allow for a proactive response before reaching the threshold, helping to prevent or mitigate accidents effectively.

In future studies, various accident scenarios and data should be used, and the performance of the model should be improved. In addition, improved methods should be sought to narrow the confidence interval to increase the reliability of the model. Furthermore, the optimal prediction model can be selected through performance comparison with other AI techniques. This will further enhance the reliability and efficiency of severe accident management.

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