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Diagnosis of Severe Accident Conditions and Prediction of Radioactive Material Release Using Deep Learning Models in Nuclear Power Plants

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1. Introduction

During a severe accident, radioactive materials emitted from a damaged reactor core can be rapidly and/or massively released into the environment due to containment leakage and rupture throughout the progression of the accident. To minimize the release of radioactive materials into the environment, an accurate diagnosis of the initial accident state and appropriate decision making for mitigation action are required.

Traditionally, procedures for accident diagnosis and computational code for severe accidents analysis can be used to predict the progression of accident. However, using computational codes for accident prediction requires a significant amount of time.

In this study, the artificial intelligence (AI) models for rapid diagnosis and prediction during severe accident state are developed using Convolutional Transformer (ConvTran)[1] and ensemble Quantile RNN (eQRNN)[2].

2. Methods and Results

The model used in this study is structured as shown in Fig 1. It is divided into an encoder part that 'understands' the input time series data and diagnoses the accident state, and a decoder part that 'predicts' which mitigate measure will result in the lowest amount of radioactive material emissions by injecting the corresponding mitigate measure for the accident. This approach allows us to rapidly diagnose the state of severe accident and quickly determine the most suitable mitigation strategy.

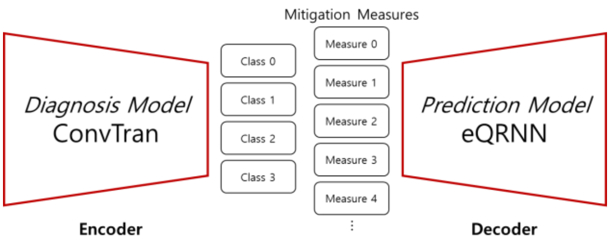

Fig 1. Artificial Intelligence Model Concept Map

2.1 Training Dataset

A large amount of data is required to train AI models, but because severe accidents are extremely rare event, it is difficult to obtain real data of the severe accident, postulated accident data generated through computational codes are utilized. In this study, AI models are trained using datasets generated through the Modular Accident Analysis Program v5 (MAAP5)[4].

The postulated accidents are generated by assuming a Large Loss-of-Coolant Accident (LLOCA) as an initial event in APR1400. Time series data are obtained for a total 208 scenarios by applying various mitigation action and strategies.

2.2 Diagnosis Model

We use ConvTran as a model to diagnose accident states. The ConvTran model has the advantage of effectively learning temporal and spatial data patterns by combining the advantages of Convolutional Neural Network and Transformer architectures. Since the purpose of this study is to extract and analyze accident features from various variable occurring in nuclear power plants, we used ConvTran as a model to diagnose accident conditions.

Table I. Input and output data of ConvTran

Input data of ConvTran			
Symbol	Definition	Symbol	Definition
PPZ	PZR pressure	ZWDC2SG (1, 2)	SG water level
ZWPZ	PZR water level	PSGGEN	SG pressure
TSUBCORE	Subcooling margin	WFWSGE (1, 2)	SG injection rate
RCSINFLOW	RCS injection flow	PEX0(9)	Containment pressure
TWRCS (10, 15, 20, 25, 30, 40)	Hot/Cold leg temperature	TGRB(9)	Containment temperature
TCREXIT	CET temperature	WSPAXX WSPBXX WSPCXX	Containment spray rate
RCSLEAK	RCS leak rate	ZWRB(1)	Cavity water level
ZWV	Reactor water level	-	

Output of ConvTran		
Classification	Break size	Sequence
Class 0	20	Condition 0
Class 1	DEGB	Condition 0
Class 2	20	Condition 1
Class 3	DEGB	Condition 1

Table II. The sequence of event used for analysis

Severe Accident Sequence of Event		
	SIT	SIP
Condition 0	O	X
Condition 1	X	-

The input variables used in the ConvTran model include 25 variables, such as the pressure and water level of the pressurizer and the steam generator, and shown in Table I. The output of the model is a four-term classification, with two severe accident sequence of event such as Safety Injection Tank (SIT) injection and Safety Injection Pump (SIP), for two fracture sizes, that is 20 inch and Double-Ended Guillotine Break (DEGB) shown in Table I.

Performance evaluation of the classification model is based on 'Precision', 'Recall', and 'F1-score'. Precision measures the proportion of correctly predicted positive classifications, while Recall assesses the proportion of actual positives correctly predicted by the model. The F1-score is the harmonic mean of Precision and Recall, used to balance their performance. We evaluate the model's performance primarily based on F1-score.

The number of time steps used for classification in time series data referred to as the window size. For instance, if a classification model is configured with a window size of 12 for data sampled at 300-second intervals, it analyzes data patterns over a 1 hour period. To diagnose accident conditions, we experimented with window sizes of 4, 6 and 12, corresponding 20, 30 and 60 minutes post incident, respectively.

For learning the diagnostic model, we used data created by shifting time series data for 208 scenarios with 52 different operator actions per 4 classes as listed in Table 2. by a set of window size. For example, when the window size is 12, 208 data with 300 second intervals over 72 hours are shifted with a window size of 12, generating 891,310 window data for ConvTran input. The total of 891,310 data was divided into train, validation, test ratios of 8:1:1, and the train dataset was 713,048, the validation dataset was 89,131, and the test dataset was also 89,131 to conduct learning and inference.

Table III. ConvTran results according to window size

Window size	4	6	12
Precision	0.861	0.901	**0.995**
Recall	0.851	0.899	**0.995**
F1-score	0.856	0.900	**0.995**

Table IV. Confusion Matrix for ConvTran

True | Pred	Class 0	Class 1	Class 2	Class 3
Class 0	22503	0	0	0
Class 1	92	21909	123	5
Class 2	115	0	22017	67
Class 3	0	0	1	22299

The experimental results indicate that the window size 12 yields the highest Precision, Recall, and F1-score values. This suggests that the diagnosing the accident status can be performed with high accuracy using data from 60 minutes after the initial incident. Additionally, when the window size is reduced to 6, meaning that the accident status is diagnosed using data from 30 minutes after the initial incident, the F1-score remains relatively high at 0.9.

2.3 Prediction Model

The eQRNN model is used as a model to predict the release of radioactive materials. The eQRNN model has strengths in handling nonlinear time series data and is very useful in predicting the release of radioactive materials over time. Likewise, when radioactive materials are released or reduced, they do not always follow a linear pattern, but rather a nonlinear time series. Therefore, we judged that the eQRNN model is suitable for predicting the amount of radioactive materials released. Additionally, to increase the reliability of the prediction, we used quantile loss to indicate the confidence range of the prediction. The input of the model is defined as an accident number that can represent the current status of the power plant and mitigate measures, and is used together with an 8-dimensional position encoding vector. The output of the model was configured to predict the mass fraction of Cs or I in the Dome area and the Upper Compartment area with 720 time steps.

Performance evaluation of the prediction model uses the R2-score. The R2 score calculated as 1 minus the ratio of the sum of squared residuals to the sum of squared differences from the mean of the actual values. It measures how well the model's predictions match the actual data. The R2-score ranges from 0 to 1, with higher values indicating a better fit of the model to the data.

We use the eQRNN model to predict mass fraction changes of Cs and I in the containment building for 208 scenarios of LLOCA. However, we judged that 208 data were not enough to train the prediction model, so we added Gaussian noise to the data. The noise was injected 20 times in different ways for each data. Therefore, the data used for training was 4160 data with added noise, and the original data without noise was used for inference.

The R2-scores are all above 0.98, indicating excellent prediction performance. Given that the model predicts 720 steps with a time step interval of 300 seconds, it is capable of forecasting changes for approximately 60 hours after the implementation of response measures.

Fig2. below show the change in the mass fraction of Cs or I when a specific mitigation measures, such as the combination SIP operation, Cavity Flooding System (CFS) valve opening, Containment Spray Pump (CSP) startup, and action time, are injected into each class classified by ConvTran.

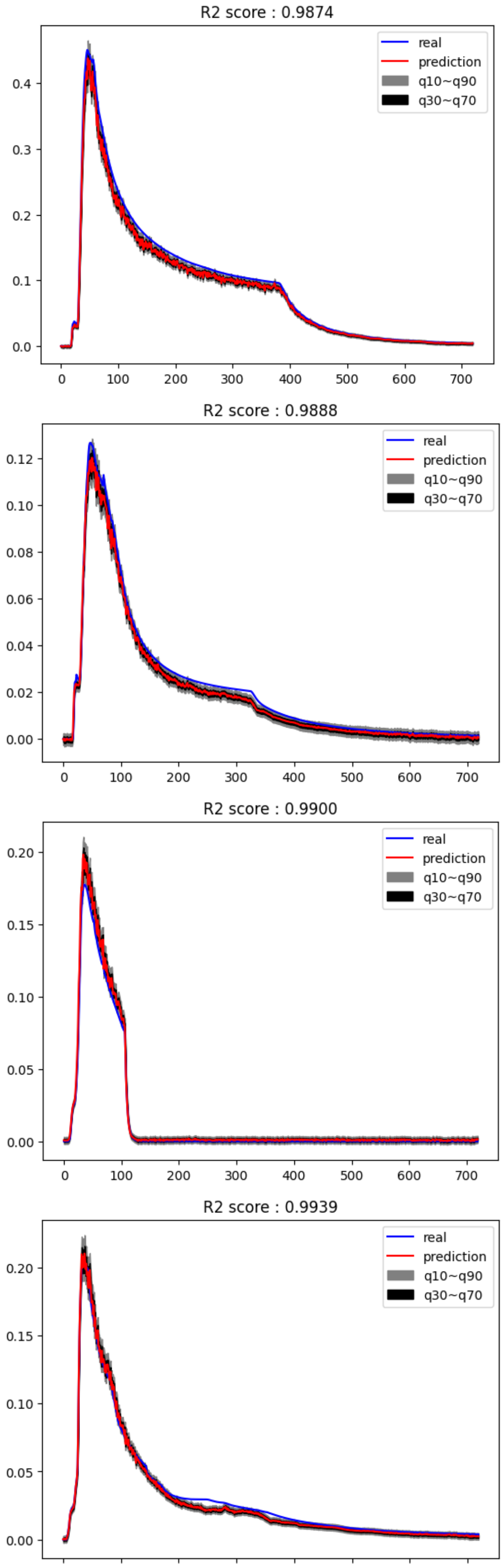

Fig 2. eQRNN prediction results

3. Conclusions

In this study, the performance of two models was evaluated by simulating four scenarios during the initial phase of LLOCA. The ConvTran model demonstrated high accuracy in diagnosing the state of the plant in the early stage of the accident, and the eQRNN model excelled in predicting the mass fractions of Cs and I within the containment. Combining these two models could significantly enhance the reliability of both diagnosing and predicting the accident conditions.

These results can contribute to shortening the accident response time and minimizing the potential release of radioactive materials by providing rapid and accurate plant status information to nuclear power plant operators by enabling optimal mitigation measures.

We diagnosed and predicted the optimal mitigation measures for the LLOCA accident sequence. If further research is conducted to diagnose and predict not only LLOCA but also various type of initial accident, the reliability of selecting mitigation measures to reduce the release of radioactive materials in the event of a severe accident can be improved.

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