Deep Learning Model for Predicting Future Trends of NPP Parameters with Accident Trend Predictor and Operator Action Impact Evaluator

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Abstract: Operators in the main control room (MCR) of a nuclear power plant (NPP) play a crucial role in monitoring plant status and controlling safety devices during emergency operations. To support operators and prevent potential errors that could jeopardize plant safety, it is essential to provide predictive insights into key parameter trends following their actions. Traditional thermal-hydraulic system codes, while accurate, are too slow for real-time validation. Hence, this study explores a data-driven approach using deep learning to predict NPP parameter trends in real time. We propose a novel two-step deep learning model consisting of an Accident Trend Predictor and an Operator Action Impact Evaluator. The Accident Trend Predictor estimates the base trends of parameters, assuming no operator actions are taken, while the Operator Action Impact Evaluator learns the residuals between these base trends and the actual future trends, reflecting the impact of operator actions. This dual-trend output allows operators to intuitively understand the effects of their last actions by comparing the base and future trends. Our case study demonstrated that the proposed model shows a high level of accuracy comparable to previous models, such as the Long Short-Term Memory networks using Multiple-Input Multiple-Output strategies, in predicting future trends. Additionally, we present a preliminary user interface that can be seamlessly integrated into digital MCR systems, enhancing real-time decision support for operators. Future work will focus on incorporating explainable AI techniques to further improve the interpretability of the model and developing optimal action selection algorithms based on the model's evaluations.

Keywords: Nuclear Power Plant, Deep Learning, Prediction, Operator action

1. INTRODUCTION

When an accident occurs at a nuclear power plant (NPP), the role of operators becomes more crucial. They continuously monitor numerous parameters such as sensor values, signals, valve status, and component status. Following appropriate Emergency Operating Procedures (EOP), they diagnose the type of accident and take proper mitigation actions. However, improper actions and delays can lead to core damage, as seen in the TMI-2 accident [1]. This potential can burden operators performing complex tasks. For this reason, research on operator-supporting technology is necessary to reduce human errors.

As part of supporting technology, real-time prediction of NPP parameter trends helps operators better understand the plant states. Operators can anticipate potential issues by evaluating the future trends of key parameters. Additionally, predicting how operator actions will alter these trends allows them to verify if the trends change as intended. As illustrated in Figure 1, the prediction system serves as a tool to predict the future trends of key parameters. If an operator performs an action, the system provides real-time feedback on the trends, allowing the operator to monitor whether the trends align with expectations. This study focuses solely on the prediction system and does not include proposals for correction or additional mitigation actions.

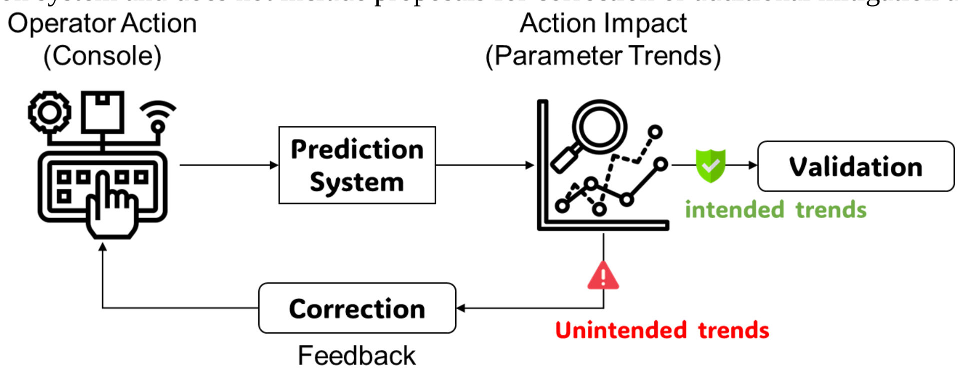

Figure 1. Function of the NPP Parameter Trend Prediction System

Therefore, extensive research on predicting NPP parameter trends has been conducted. One reliable method involves using thermal-hydraulic system code (TH code), which simulates the physical and thermodynamic behaviors of fluid and heat transfer within the plant. These simulations employ mathematical models to replicate interactions under various operational conditions. However, in the full plant scope, the TH code requires too much computation time to predict parameter trends in real time.

Recently, deep learning has been widely studied as an alternative method. NPP is a complex system that deals with many parameters and involves their rapid changes. So deep learning, which is good at processing multivariate time series data and has fast calculation speeds, is suitable for real-time prediction. There are various parameter prediction studies using deep learning. Ryu et al. (2022) developed a surrogate prediction model using bi-directional long short-term memory (Bi-LSTM), positional encoding, quantile method, and model ensemble to assist TH code simulations [2]. Kim et al. (2023) used Bi-LSTM and attention mechanisms for long-term safety parameter prediction during NPP emergencies [3]. Song et al. (2024) used the MELCOR simulator to model the Fukushima Daiichi Unit 3 accident progression, predicting parameters like nuclear aerosol amounts and core levels with long short-term memory (LSTM) [4]. However, these studies did not consider the possible improper operator actions that rapidly change the parameters.

Bae et al. (2021) performed real-time prediction of NPP key parameter trends following operator actions, by combining artificial neural networks and prediction strategies [5]. Their LSTM model using a multi-input multi-output strategy (MIMO-LSTM model) showed the best performance in future trend prediction [5]. However, the model did not distinguish by what factors future trends are determined. Especially in the case of unintended future trends, it is difficult to determine what effect operator actions had based on future trends alone.

More intuitive judgments can be made if the operator can simultaneously check the future trend assuming the action was not taken and the future trend after the action was taken. In this paper, we proposed a deep-learning model that independently predicts accident trends and operator action impacts. This model distinguishes between these effects and achieves sufficiently high accuracy. To show feasibility, We evaluated the proposed model using simulator data. Additionally, we proposed a preliminary user interface for the model application.

2. METHODS

In this section, a prediction framework of the proposed model and the structure of each stage are described. The model consists of Accident Trend Predictor and Operator Action Impact Evaluator. The suitable training strategies and processes are explained.

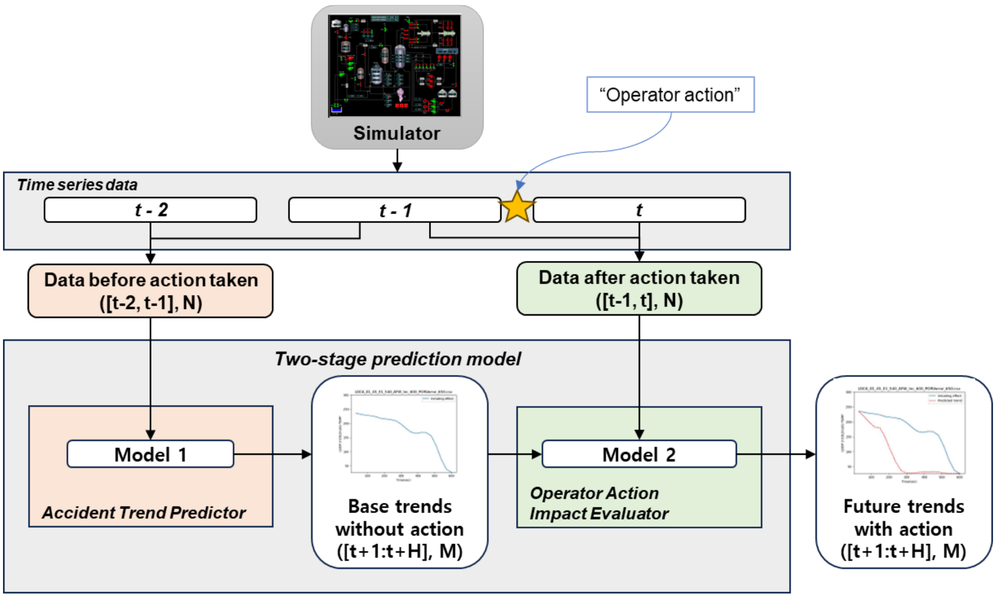

Figure 2. Prediction framework of the proposed model

2.1. Prediction Framework

The prediction model predicts future trends based on past values of plant parameters. Figure 2 illustrates the prediction framework of the proposed model. In this study, we use two models to provide two trends. One predicts the base trends assuming that the operator action is not taken by using data from the time before the operator action was taken. The other predicts future trends using data before and after operator action.

The model uses the past three time steps with N input parameters to obtain H time steps with M target parameters in the future. For time series data extracted from the simulator, the action starts after $t-1$ step and is completed at t step. Since the input parameter values of the $t-2$ step and the $t-1$ step do not include the operator action information, Accident Trend Predictor provides base trends ($[t+1:t+H]$, M) by using them as input data. The input parameter values of $t-1$ step and t step include the action information, Operator Action Impact Evaluator provides future trends by using them and base trends as input data. This explains how operator intervention and accident progression are integrated. Operators will be able to more intuitively check impacts of the accident and the action through the two trends.

2.2 Accident Trend Predictor

Accident Trend Predictor predicts base trends assuming that no action was taken at the last time step. Therefore, the impacts of accident, several automatic actions of the instrument and control (I&C) system, and previous actions are evaluated, excluding only the impact of action at the last time step.

To reflect these properties, it uses an independent deep-learning model. The training dataset includes scenarios in which operator actions were performed. This is because, considering the multi-action scenario, there is a possibility that another operator action was taken between the $t-2$ step and the $t-1$ step. Afterward, the sliding window method is used to move and index the time window and train the plant dynamics in the overall time domain after the action. This work helps predict future trends for actions taken at untrained time points after an accident occurs. The model used LSTM layers with MIMO strategy, and a dropout layer was added to prevent overfitting and increase robustness.

Figure 3 shows the training workflow of the proposed model. The red part on the left is the Accident Trend Predictor area. As shown, the trained model is used to output base trends for the next stage, Operator Action Impact Evaluator. These base trends are used as one of the inputs in the next model.

2.3 Operator Action Impact Evaluator

Operator Action Impact Evaluator predicts final future trends after the action was taken at the last time step. The difference from the Accident Trend Predictor is that it reflects the impact of the last action. To reflect this property, the model's input is split into two parts.

The green area on the right of Figure 3 is the Operator Action Impact Evaluator area. The values of $t-2$ step and $t-1$ step constitute input(a) in which the influence of the last action is not reflected. This input(a) is used to Accident Trend Predictor's pre-trained model and outputs base trends. To clearly distinguish what to learn, the pre-trained layers of Accident Trend Predictor are set as non-trainable during the training of Operator Action Impact Evaluator.

The values of $t-1$ step and t step constitute input(b), which reflects the influence of the last action. This input (b) is used as input to the Operator Action Impact Evaluator along with base trends to output final future trends. Because base trends are input together, the trainable parameters are used to calculate the residual between base trends and future trends. Since base trends and future trends differ in the impact of the last action, this model explicitly performs the function of evaluating operator action impact.

The sliding window method was used equally. When dealing with the part that does not contain action in the area between $t-1$ step and t step, there is no residual because the base trends and future trends are the same, which is helpful for testing no-action scenarios. This model also used LSTM layers with MIMO strategy, and a dropout layer was added to prevent overfitting and increase robustness.

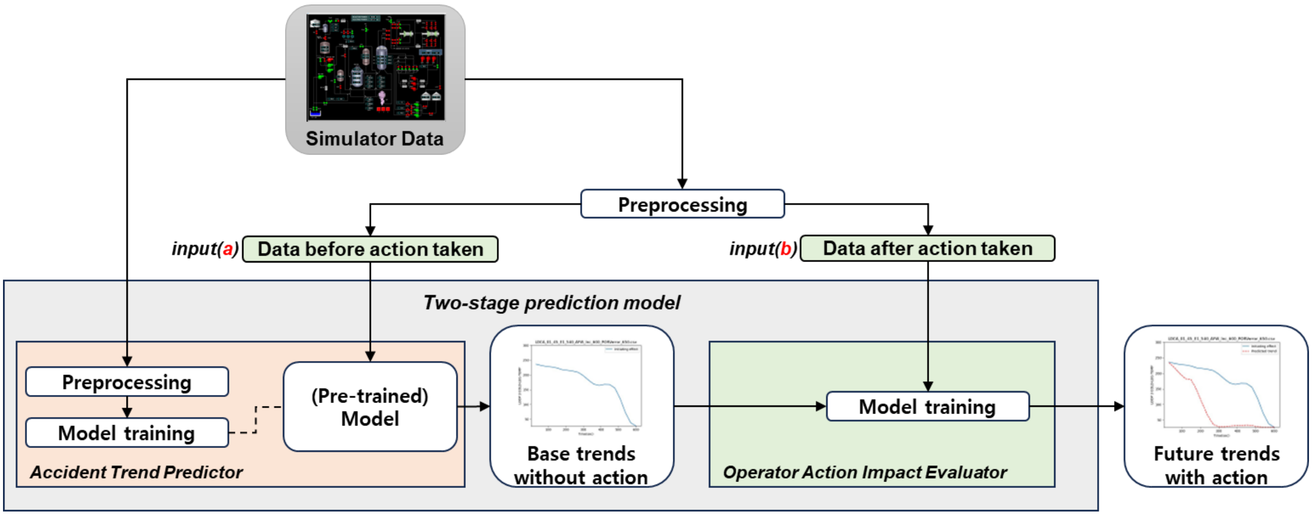

Figure 3. Training workflow of the proposed model

3. CASE STUDY

We conducted a case study to demonstrate the high accuracy of the proposed model. The same data from the previous study was used, which has the advantage of using emergency operation scenarios in which possible human errors were well selected through EOP analysis [5]. We aimed to demonstrate the feasibility of the proposed model by comparing its performance with the MIMO+LSTM model, which showed the highest performance in previous studies [5].

In addition, we presented a preliminary user interface including prediction results using the model characteristic of outputting both base trends and future trends. We qualitatively evaluated whether operators can intuitively check action impact.

Table 1. Target parameters from the Compact Nuclear Simulator [5]

	Plant Parameters (units)
1	POWER RANGE PERCENT POWER (%)
2	INTERMEDIATE RANGE START-UP RATE (DPM)
3	INTERMEDIATE RANGE NEUTRON LEVEL (A)
4	SOURCE RANGE START-UP RATE (DPM)
5	CORE OUTLET TEMPERATURE (◦C)
6	LOOP 1 HOT-LEG TEMPERATURE (◦C)
7	LOOP 2 HOT-LEG TEMPERATURE (◦C)
8	LOOP 3 HOT-LEG TEMPERATURE (◦C)
9	PRESSURIZER PRESSURE (kg/cm2)
10	STEAM GENERATOR #1 NARROW LEVEL (%)
11	STEAM GENERATOR #2 NARROW LEVEL (%)
12	STEAM GENERATOR #3 NARROW LEVEL (%)
13	FEEDWATER #1 FLOW (m3 /hr)
14	FEEDWATER #2 FLOW (m3 /hr)
15	FEEDWATER #3 FLOW (m3 /hr)
16	STEAM GENERATOR #1 PRESSURE (kg/cm2)
17	STEAM GENERATOR #2 PRESSURE (kg/cm2)
18	STEAM GENERATOR #3 PRESSURE (kg/cm2)
19	LOOP 1 COLD-LEG TEMPERATURE (◦C)
20	LOOP 2 COLD-LEG TEMPERATURE (◦C)
21	LOOP 3 COLD-LEG TEMPERATURE (◦C)
22	CONTAINMENT PRESSURE (kg/cm2)
23	CONTAINMENT SUMP WATER LEVEL (m)
24	CONTAINMENT RADIATION (mRem/hr)
25	PRESSURIZER LEVEL (%)

3.1. Data Description

Data were extracted from the Compact Nuclear Simulator (CNS), a simplified simulator of a Westinghouse 1000MWe 3-loop plant [6]. Table 1 lists the 25 target parameters. They were selected as monitoring parameters of the CNS EOP critical safety function (CSF) tree. Input parameters were selected as 109 parameters, including 25 target parameters and 84 parameters consisting of valve state, component state, sensor instrument values, and important signals.

To extract NPP emergency operation data, the following three accidents were assumed: loss of coolant accident (LOCA), a steam generator tube rupture (SGTR), and a spurious reactor trip. Table 2 is a list of a total of 1153 training datasets. For a given accident situation, various operator action timing and degrees were reflected, and multi-action scenarios were also included. Table 3 is a list of a total of 35 test datasets. Unlike the training dataset, the accident scale (break size) was adjusted, and scenarios with different action timing were selected. Additional data was produced to evaluate the performance of the Accident Trend Evaluator of the proposed model. It consisted of data excluding the last actions for the existing 35 test datasets. Regarding the Accident Trend Evaluator, an evaluation was conducted to predict the base trends of new data using the values of the *t-2* and *t-1* steps of the existing test dataset.

Table 2. Emergency operation scenario of the training datasets [5]

Accident	Accident Details	Operator Action
LOCA (865 scenarios)	Leak of reactor coolant due to $10cm^2$, $20cm^2$, $30cm^2$, $40cm^2$, $50cm^2$ break in the cold leg	1. Auxiliary feedwater flow control 2. Reactor coolant pump stop 3. PORV shut-off valve open 4. PORV open 5. Safety injection signal reset 6. Safety injection pump stop 7. No action
SGTR (200 scenarios)	Single-tube or double-tube ruptures in a steam generator	1. Auxiliary feedwater flow control 2. PORV shut-off valve open 3. PORV open 4. Reactor coolant pump stop 5. Main steam line isolation 6. Secondary side relief valve manual open 7. Contaminated steam line isolation 8. No action
Spurious Trip (98 scenarios)	Unintended reactor trip due to a malfunction of the reactor protection system	1. Auxiliary feedwater flow control 2. PORV shut-off valve open 3. PORV open 4. Reactor coolant pump stop 5. No action

3.2. Model Configuration

We evaluated three models on existing test datasets: Operator Action Impact Evaluator from the proposed model, MIMO+LSTM from previous work, and MIMO+MLP as a generic model. Additionally, we evaluated two models on new test datasets: Accident Trend Evaluator from the proposed model, and MIMO+MLP for base trends as a generic model.

The models predict a total of 21 time steps (including the current time step *t*) with a time interval of 30s. MIMO+LSTM and MIMO+MLP predict 25 target parameters of [*t* : *t+20*] steps with 109 input parameters of [*t-1*, *t*] steps. Operator Action Impact Evaluator predicts [*t* : *t+20*] steps with the input of [*t-2*, *t-1*, *t*] steps. Accident Trend Evaluator and MIMO+MLP for base trends predict the base trends of [*t* : *t+20*] steps with the input of [*t-2*, *t-1*] steps.

Table 3. Emergency operation scenario of the test datasets [5]

Accident	Operator Action
LOCA ($25cm^2$, $35cm^2$, $45cm^2$)	1. Auxiliary feedwater flow control 2. Reactor coolant pump stop 3. PORV open 4. Safety injection signal reset 5. Safety injection pump stop
LOCA ($60cm^{2)}$	1. No action
SGTR (single-tube rupture)	1. Auxiliary feedwater flow control 2. Reactor coolant pump stop 3. Main steam line isolation 4. Secondary side relief valve manual open 5. No action
SGTR (double-tube rupture)	1. Auxiliary feedwater flow control 2. PORV shut-off valve open 3. PORV open 4. No action
SGTR (triple-tube rupture)	1. Auxiliary feedwater flow control 2. Reactor coolant pump stop 3 PORV shut-off valve open 4 No action
Spurious Trip	1. Auxiliary feedwater flow control 2. PORV shut-off valve open 3. PORV open 4. Reactor coolant pump stop 5. No action

Table 4 describes the ANN structures of the 5 models. The number of trainable parameters was set as similar as possible for each dataset group. Accident Trend Predictor predicts relatively simple trends without considering operator actions. Therefore, Accident Trend Predictor and MIMO+MLP for base trends predict 25 target parameters at once with 1 ANN, and the other models use 1 ANN for each parameter, for a total of 25 ANNs to predict future trends. To implement them, we utilized Python and its libraries including Keras API and TensorFlow 2.11.0.

In the case of the proposed model, it is difficult to understand the structure because it is constructed as a non-sequential model using the Keras API, so the structure is not accurate based on the information in Table 4. Instead, the input/output structure of the layer can be understood through the architecture of the proposed model illustrated in Figure 4.

Table 4. ANN structures of the 5 models

	ANNs	Input shape	Hidden layers	Cells per hidden layer	Output shape	Trainable parameters
MIMO+MLP	25	(218,)	10	200	(21,)	409,821
MIMO+LSTM	25	(2, 109)	5	100	(21,)	407,721
Operator Action Impact Evaluator	25	(3, 109)	5	100	(21,)	370,642
Accident Trend Predictor	1	(2, 109)	3	218	(21, 25)	2,124,566
MIMO+MLP for base trends	1	(2, 109)	9	525	(21, 25)	2,324,175

3.3. Evaluation Metric

In this study, we evaluated the performance of our time series prediction models using four metrics: Dynamic Time Warping (DTW), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

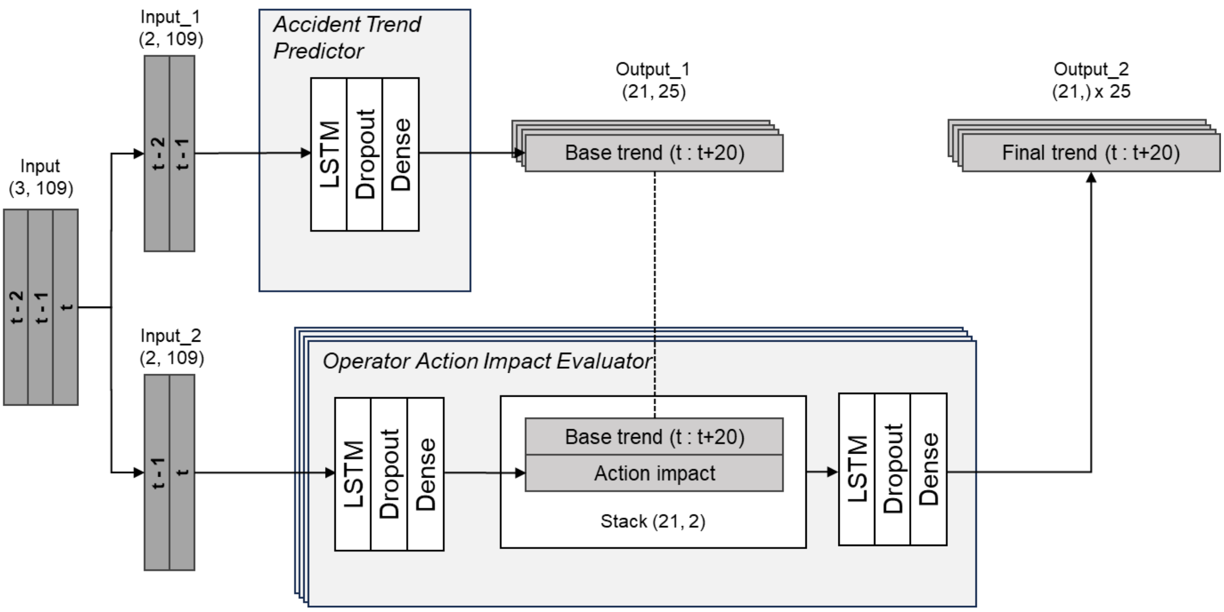

Figure 4. The architecture of the proposed model

Dynamic Time Warping (DTW)

DTW is a technique that measures the similarity between two time series. It aligns the time series by warping the time axis to find the optimal match between the sequences. For each predicted time series $\hat{Y}_i$ and the corresponding actual time series Y_i, the DTW distance is computed as follows:

$$DTW(X, Y) = \min\left(\sum_{k=1}^{K} d(x_{ik}, y_{jk}\right) \tag{1}$$

where $d(x_i, y_j)$ represents the distance between points x_i and y_j. The average DTW distance $\overline{DTW}$ across n pairs of time series is calculated as:

$$\overline{DTW} = \frac{1}{n}\sum_{i=1}^{n} DTW(X_i, Y_i) \tag{2}$$

A smaller DTW distance indicates a higher similarity between the predicted and actual time series, reflecting better model performance.

Other Metrics

MSE measures the average squared difference between predicted and actual values. It is sensitive to large errors due to the squaring of differences, making it useful for emphasizing larger deviations. RMSE is the square root of MSE and provides a measure of the average magnitude of errors. It retains the same units as the original data, making it more interpretable in practical terms. Lastly, MAE calculates the average absolute difference between predicted and actual values, providing a straightforward measure of prediction accuracy. It is less sensitive to outliers compared to MSE and RMSE, offering a balanced view of model performance across all errors. They are calculated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2 \tag{3}$$

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{Y}_i - Y_i\right| \tag{5}$$

Results

By combining these four metrics, we obtain a comprehensive evaluation of the prediction model's performance. DTW captures the temporal alignment of time series, while MSE, RMSE, and MAE provide insights into the magnitude and nature of prediction errors. This multi-faceted approach ensures a thorough assessment of the model's accuracy and reliability in forecasting time series data.

We calculated 21 points for each of the 25 parameters in 35 test scenarios, for a total of 18,375 points, and listed them in Table 5. The actual and predicted values used for these calculations were min-max normalized, resulting in values between 0 and 1. The DTW, MSE, and RMSE of the Operator Action Impact Evaluator scored the lowest at 70.6198, 0.00037, and 0.01931, respectively. However, in the case of MAE, the MIMO+LSTM model scored the lowest error at 0.00548. Because MAE is less sensitive to outliers compared to MSE and RMSE, we can assume that the existing model predicts outliers more robustly than MIMO+LSTM. In conclusion, the proposed model has similar or higher accuracy to the previous best model, MIMO+LSTM.

Table 5. Evaluation metrics of 3 models for test datasets

	MIMO+MLP	**MIMO+LSTM**	**Operator Action Impact Evaluator**
DTW	2432.79	71.8989	**70.6198**
MSE	0.04031	0.00038	**0.00037**
RMSE	0.20078	0.01948	**0.01931**
MAE	0.13532	**0.00548**	0.00562

Accident Trend Predictor and MIMO+MLP for base trends were also evaluated using new test datasets. We also calculated 21 points for each of the 25 parameters in 35 test scenarios, for a total of 18,375 points, and listed them in Table 6. Accident Trend Predictor's DTW, MSE, RMSE, and MAE all received the lowest scores at 104.673, 0.00085, 0.02912, and 0.00939, respectively.

Table 6. Evaluation metrics of 2 models for new test datasets

	MIMO+MLP for base trends	**Accident Trend Predictor**
DTW	135.058	**104.673**
MSE	0.00099	**0.00085**
RMSE	0.03149	**0.02912**
MAE	0.01209	**0.00939**

3.4. Preliminary User Interface

In this section, the overall accuracy of the model was checked by qualitatively evaluating the base trends and future trends provided by the proposed prediction model. We discussed the need for an NPP parameter trends prediction system to provide operators with base trends. Lastly, we presented a preliminary user interface for the application.

Figure 5 shows the NPP parameter trends prediction results of the proposed model. The blue solid line is the real trend, the green dotted line is the base trend, and the red dotted line is the future trend. The three trends on the left below in (a) are Accident Trend Predictor's predictions of base trends assuming there is no last action. The three trends on the right below in (b) are future trends predicted by the Operator Action Impact Evaluator. It can be qualitatively confirmed that all real trends were successfully predicted. Also, we can calculate allowable time by measuring the time for trip variables to reach the set point by base trends. Then, we can verify whether the appropriate response was made by checking the response time and result of actual action performed.

Through Figure 5, we can see the need to predict base trends along with future trends. Figure 5 reflects a scenario in which a human error occurs in a LOCA with a 35cm2 break size, entering the E1 procedure at 540s, and then opening the PORV as the last action in a situation where the auxiliary supply is increased at 600s. If we check (1a) and (1b), we can see that the Cold-Leg Temperature decreases in both. We can see from the difference between the green and red lines that the human error called PORV open accelerates the temperature decrease. If only the red line is given, it is difficult for us to determine whether the temperature decrease is the effect of PORV open or Accident. For this reason, prediction of the base trend is necessary to understand the effect of the operator's intuitive action.

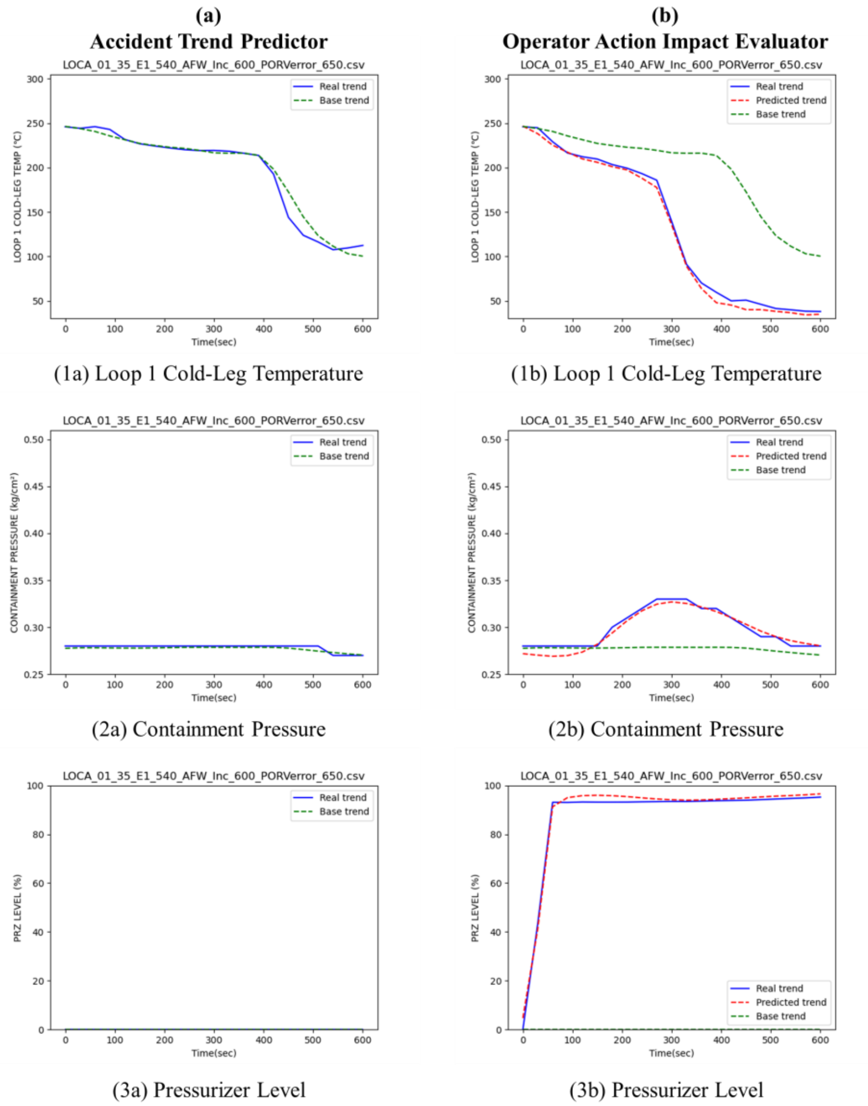

Figure 5. Prediction results of the proposed model

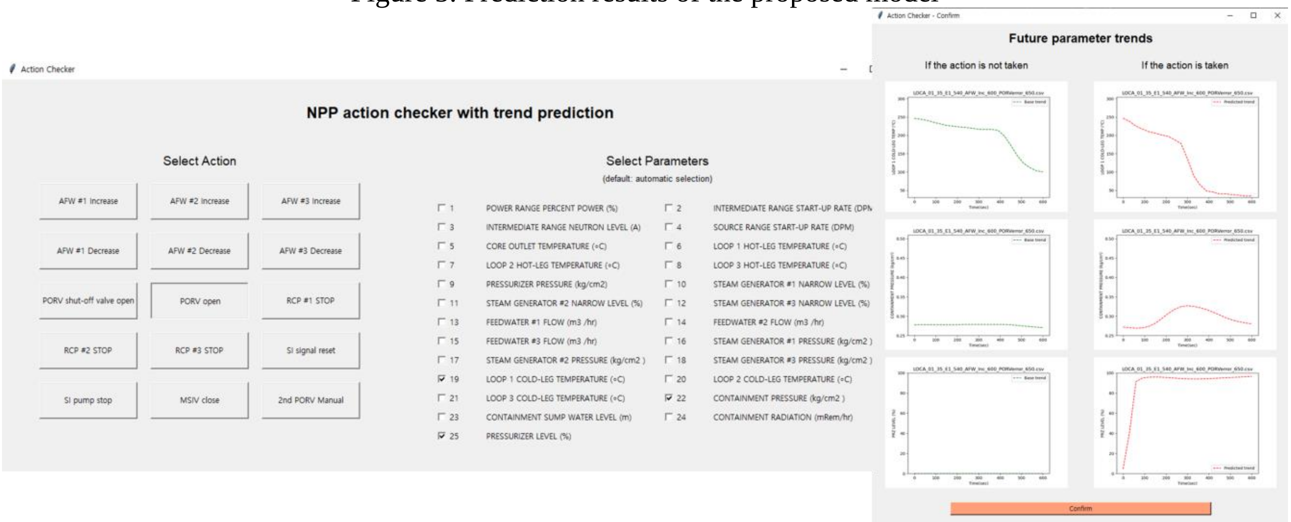

Figure 6. Preliminary user interface

Next-generation NPPs are often attempting to transition to a digital main control room (MCR). There are already cases of soft control of plant devices using a personal computer, mouse, keyboard, etc. For example, there is a digital MCR of APR1400 (Advanced Power Reactor with 1400 MWe) designed by the Korea Electric Power Corporation [7]. As one of the display systems, engineered safety component control system (ESF-CCS) soft control module (ESCM) provides a means of manual control of critical components. PORV open, such as the case in Figure 5, is also controlled through ESCM. However, one study showed that in emergency operating conditions, ESCM works causing higher tension and stress to operators [8]. Therefore, it is worth attempting to show the impact of the action by presenting the gap between the base trend and future trend of NPP key parameters at the final confirmation stage of the action.

Figure 6 is a preliminary user interface. The operator can select a candidate action on the left side of the main screen and select the NPP key parameters they want to see on the right side. (The default is to select parameters with a large gap.) Then, a pop-up window will open and operators will be able to check the left and right graphs as auxiliary indicators for the final confirmation.

4. CONCLUSION

Deep learning is increasingly being used as a valuable tool for predicting NPP parameter trends. These parameter trends aid in the validation of operator human factors. Previous studies have demonstrated that models combining MIMO strategies and LSTM layers excel at predicting parameter trends based on operator actions. However, in certain cases, understanding the impact of actions based solely on future trends proved to be challenging for operators. To address this, we propose a two-step prediction model that outputs two distinct trends. Each step is divided into the Accident Trend Predictor and the Operator Action Impact Evaluator. The Accident Trend Predictor generates a base trend assuming the operator's last action is excluded. The Operator Action Impact Evaluator learns the residuals between the base trend and the future trend to produce a future trend that reflects the impact of the last action. By comparing the base trend and the future trend, operators can intuitively grasp the impact of their last action. Given the ongoing research on digital MCR, we have also proposed a preliminary user interface that can be easily implemented as software.

It is evident that the proposed model's Operator Action Impact Evaluator learns the impact of the last action. For future work, applying explainable AI (XAI) techniques could enhance model interpretability, providing operators with more intuitive and useful information. Additionally, as the proposed model evaluates the impact of actions, it could also contribute to the development of optimal action selection algorithms through scoring.

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