AI-Based Framework for Assessing Operator Mitigation Actions During Abnormal Conditions in Nuclear Power Plants

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1. Introduction

During transient conditions in nuclear power plants (NPPs), operators follow a series of procedures to restore the plant to a safe and stable state. These procedures consist of situation awareness, diagnosis, and mitigation actions. When properly executed, they contribute to maintaining the safety of the NPP. However, if human errors occur during the execution of these procedures, the situation may worsen. Past incidents, such as the Three Mile Island accident, have demonstrated that operator errors can exacerbate accidents. Therefore, preventing operator errors is essential for ensuring the safety of NPPs.

Although human error can have various causes, one of the most significant is operator workload. In recent years, research on artificial intelligence (AI)-based operator support systems has been actively conducted to reduce such workload [1, 2]. Most AI-based support technologies focus on improving operators' situation awareness and diagnostic capabilities. However, the potential for human error during mitigation actions should not be underestimated, as inappropriate mitigation actions have been identified as critical factors contributing to the escalation of past accidents.

This study proposes a framework aimed at reducing human errors that may occur during mitigation actions taken by operators under transient conditions in NPPs. The proposed framework monitors these mitigation actions, evaluates their impact, and provides feedback to the operator. This study focuses specifically on the impact evaluation component. The evaluation is implemented using an artificial intelligence technique called the temporal fusion transformer (TFT). The TFT-based model quantitatively assesses mitigation actions based on the plant’s critical safety functions (CSFs). The data required for developing the AI model is generated using the compact nuclear simulator (CNS).

Consequently, the impact evaluation function within this framework is divided into two components: mitigation appropriateness evaluation and mitigation golden time estimation. The mitigation appropriateness evaluation analyzes the impact of executed mitigation actions and provides feedback on whether the actions were appropriate or inappropriate. The mitigation golden time estimation offers feedback on the optimal timing for executing mitigation actions to achieve the most stable plant state. This information can help minimize human errors during the mitigation process and ultimately enhance the overall safety of NPPs.

2. Conceptual Framework

This paper presents a framework designed to minimize human errors occurring during operator mitigation actions in abnormal conditions of NPPs. The framework consists of three main functions: monitoring, impact evaluation, and feedback, as illustrated in Fig. 1. This framework continuously provides feedback to operators, assisting them in making real-time, informed decisions. The provided information offers operators an opportunity to reconsider their mitigation actions. For instance, it allows them to gain confidence in correctly executed actions while prompting a reassessment and adjustment of erroneous actions.

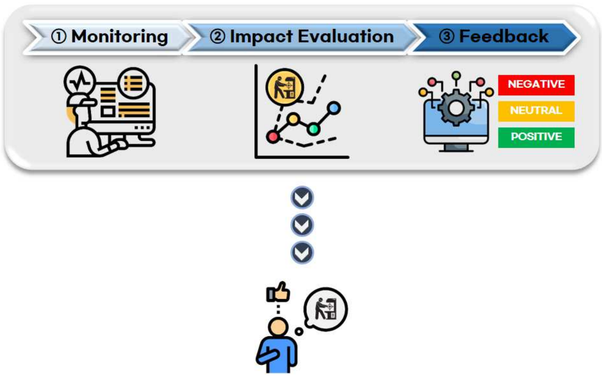

Fig. 1. Conceptual framework for a mitigation action monitoring and support system.

2.1 Mitigation Appropriateness Evaluation

The appropriateness of mitigation actions is evaluated based on CSFs. As shown in Table I, CSFs consist of nine safety functions [3]. Each CSF has specific variables for monitoring. For instance, the RCS pressure control function monitors the pressurizer (PRZ) pressure. To evaluate the appropriateness of mitigation actions, these variables are predicted. However, it is crucial to ensure that the predictions adequately reflect the characteristics of the mitigation actions. The prediction results reflecting mitigation actions are evaluated using various metrics. For instance, in the case of PRZ pressure, multiple alarms are used for assessment: (1) PRZ press high alert, (2) PRZ press low alert, (3) PRZ high press reactor trip, and (4) PRZ low press reactor trip. The evaluation metrics for PRZ pressure are illustrated in Fig. 2.

Table I: List of CSFs

	Safety function
1	Reactivity control
2	Reactor coolant system (RCS) inventory control
3	RCS pressure control
4	RCS heat removal
5	Core heat removal
6	Containment isolation
7	Containment pressure and temperature control
8	Hydrogen control
9	Maintenance of vital auxiliaries

Fig. 2 illustrates the PRZ pressure during an abnormal scenario in which the PRZ spray valve is improperly opened. Due to the improperly opened PRZ spray valve, the PRZ pressure decreases over time, eventually leading to a reactor trip caused by low PRZ pressure. In this study, one of the evaluation metrics can be chosen to verify whether a specific mitigation action maintains the pressure between the "PRZ Press High Alert" and the "PRZ Press Low Alert". Additionally, factors such as the rate of pressure change and gradient of PRZ pressure are also considered.

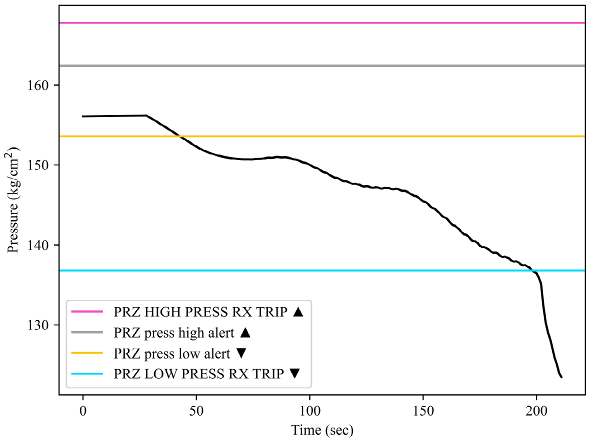

Fig. 2. Indicators for the appropriateness evaluation of PRZ pressure.

2.2 Mitigation Golden Time Estimation

The golden time of mitigation actions is evaluated based on the aforementioned assessment metrics. For example, in the previously mentioned PRZ spray valve opening scenario, the mitigation action involves closing the spray valve. The optimal timing for closing the spray valve is immediately after the abnormal event occurs. However, if operators are informed of the available time window before the system stability is compromised, they can make decisions without being pressured into hasty actions. Fig. 3 illustrates the results of performing the mitigation action at different times in the PRZ spray valve opening scenario.

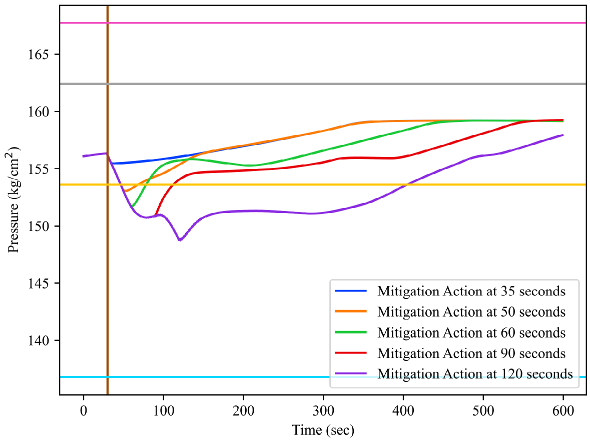

Fig. 3. PRZ pressure response to different mitigation action timings.

If "PRZ Press Low Alert" is adopted as the appropriateness criterion for PRZ pressure, the mitigation action at 35 seconds can be considered appropriate, whereas the action at 50 seconds may be inappropriate. In other words, providing such results to operators can emphasize the urgency of performing the mitigation action within 50 seconds at the latest.

3. Temporal Fusion Transformer

In this study, the TFT method [4] is employed to implement the two aforementioned functions. TFT is a deep learning architecture tailored for time-series forecasting, effectively modeling both short-term and long-term dependencies. Unlike conventional recurrent neural network-based models such as long short-term memory, TFT integrates both gated recurrent units for sequential processing and self-attention mechanisms [5] for capturing long-range dependencies. This hybrid architecture enables TFT to dynamically highlight critical features in time-series data while preserving sequential information. Fig. 4 presents the overall architecture of the TFT model.

Moreover, TFT incorporates a variable selection network, allowing the model to automatically identify and prioritize the most relevant input features for prediction. This enhances the interpretability of the model, providing insights into which factors contribute significantly to the forecasting process.

In this study, the TFT model is trained using historical data related to PRZ pressure and other CSF parameters. The trained model predicts future system states based on operator actions and evaluates the appropriateness of mitigation actions. By analyzing these predictions, the model provides real-time feedback, ensuring that mitigation actions maintain system stability within predefined safety thresholds.

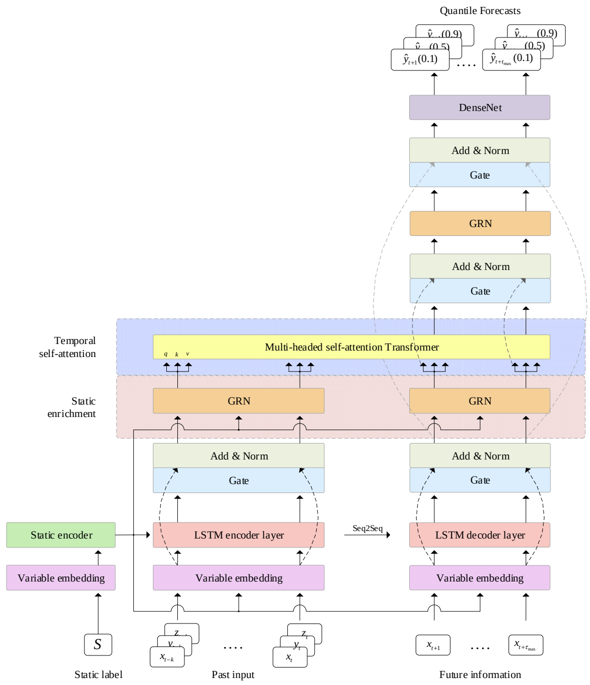

Fig. 4. Structure of the TFT method.

4. Data Collection and Preprocessing

The data were collected using the CNS, developed by the Korea Atomic Energy Research Institute. The CNS can simulate normal, abnormal, and emergency operations. In this study, we focus on abnormal operation simulations. Data from an abnormal scenario in which the PRZ spray valve failed in the open position were collected. Fig. 5 illustrates the RCS, with the red box indicating the PRZ spray valve.

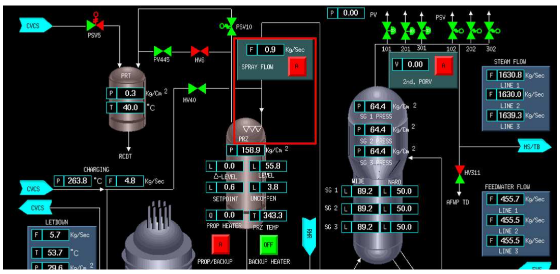

Fig. 5. Overview of the RCS in CNS.

The data were collected based on two factors: (1) the degree of spray valve opening and (2) the timing of the mitigation action. First, the degree of spray valve opening was collected in 5% increments, ranging from 0% (fully closed) to 100% (fully open). Second, the timing of the mitigation action was considered at 5, 20, 30, 60, and 90 seconds after the malfunction injection. Additionally, no mitigation actions were applied in the 0% opening state (normal condition). Furthermore, for opening states above 5%, cases without mitigation actions were also collected. As a result, a total of 120 cases were collected, with 80% used for training and 10% each allocated for validation and testing.

Data preprocessing involved feature selection and normalization. Feature selection was performed using the Pearson correlation coefficient, while normalization was conducted using the min-max normalization method.

5. Experiment

In this study, the TFT method is utilized to predict specific variables for evaluating the appropriateness and golden time of mitigation actions. These variables are safety-related parameters associated with CSFs, as listed in Table II.

Table II: List of target variables

	Target variable
1	PRZ water level
2	RCS subcooling margin
3	PRZ pressure
4	Steam generator (SG) water level
5	SG Pressure
6	Containment radiation
7	Containment temperature
8	Containment pressure

Since the PRZ spray valve opening scenario has minimal impact on containment-related parameters (6-8 in Table II), they are not discussed in this study. The PRZ pressure is associated with RCS pressure control among the CSFs, while the PRZ water level is related to RCS inventory control. Since the PRZ spray valve opening scenario significantly affects RCS pressure control and RCS inventory control, this study focuses on PRZ water level and pressure.

As PRZ pressure has already been described in Figs 2 and 3, this section focuses on experiments related to PRZ water level. Fig. 6 presents the predicted changes in PRZ water level based on the timing of the mitigation actions. In the cases of 5 seconds (mitigation action at 35 seconds) and 20 seconds (mitigation action at 50 seconds) after the abnormal event, the PRZ water level remains relatively stable. In contrast, at 30 (mitigation action at 60 seconds), 60 (mitigation action at 90 seconds), and 90 seconds (mitigation action at 120 seconds) after the abnormal event, unstable variations in the PRZ water level are observed. These results indicate that operators should execute mitigation actions within 20 seconds to ensure system stability. Furthermore, this study highlights the necessity of considering multiple CSFs simultaneously. From the perspective of RCS inventory control, the mitigation action can be performed within 50 seconds. However, from the perspective of RCS pressure control, it must be executed earlier.

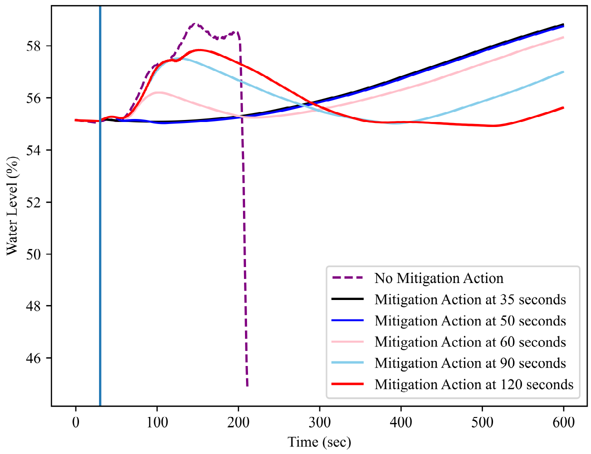

Fig. 6. Prediction results of PRZ water level based on mitigation action timing.

6. Conclusion

This study proposes a framework designed to reduce human errors that may occur during mitigation actions taken by operators under transient conditions in NPPs. The focus of this study is on evaluating the impact of mitigation actions. This evaluation is critical to ensuring that operator responses do not exacerbate the situation but instead contribute to system stability.

To implement the framework, we adopted the TFT, a method capable of handling multivariate time-series data while maintaining interpretability. The TFT-based evaluation model utilizes CSFs to provide quantitative assessments of mitigation actions in terms of both adequacy and timing, thereby offering real-time feedback to operators.

The training dataset was generated using the CNS, developed by the Korea Atomic Energy Research Institute. Data collection focused on abnormal scenarios involving PRZ spray valve failures, in which the degree of valve opening and the timing of mitigation actions varied. A total of 120 cases were collected, including scenarios with and without mitigation actions. Feature selection was performed using Pearson correlation coefficients, and the data were normalized using min-max scaling.

The proposed framework supports informed decision-making by providing critical feedback on the effectiveness and timing of mitigation actions, helping operators avoid unnecessary urgency. This approach has the potential to enhance the overall safety and reliability of nuclear power plants by reducing the likelihood of inappropriate actions. Future work will aim to improve the predictive accuracy of the model and extend its applicability to a broader range of abnormal scenarios in NPP operations.

However, while the effectiveness of the proposed approach was validated in a simulated environment, it has not yet been verified under real-world conditions in an actual NPP. Therefore, pilot testing under realistic conditions is essential to confirm the experimental results and assess practical feasibility.

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