Development of a Proactive Alarm Prediction Model to Enhance Operator Situation Awareness

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1. Introduction

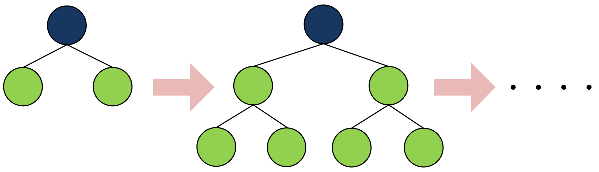
Alarm systems in Nuclear Power Plants (NPPs) are critical components that enable operators to maintain safe plant operations. In the event of emergency or abnormal conditions during plant operation, alarms are triggered to provide critical information to operators. However, existing alarm systems in NPPs are based on logic that triggers as soon as individual instrument signals, such as pressure or temperature, exceed predefined thresholds. While this method provides clear criteria, it has limitations in that operators find it difficult to perceive subtle anomalies before thresholds are reached [1]. Additionally, the occurrence of alarm flooding, where numerous alarms are triggered simultaneously within a short period, causes severe information overload for operators, hindering their ability to make prompt judgments and take appropriate actions [2].

To overcome these limitations, this study proposes a proactive alarm prediction model that provides operators with information on alarms occurring during emergency and abnormal conditions in advance. Proactive alarm prediction technology enables the early recognition of state changes in NPPs, helping operators perform more prompt and effective judgments and actions. By utilizing Light Gradient Boosting Machine (LightGBM), this model estimates the time remaining until alarm onset in seconds and utilizes an Intelligent Alarm Optimization mechanism to filter the predicted data, ensuring that only key alarms are delivered to the operators. For the model development, the data used to train and test this model were collected through the Compact Nuclear Simulator (CNS).

This study offers quantitative forecasts on the timing of specific alarms in seconds, rather than merely notifying operators of the alarm's occurrences. Furthermore, it optimizes core information among the numerous alarms occurring during abnormal situations, providing operators with a practical basis for effective judgment. This helps ensure plant safety by improving the operator's situational awareness during the initial stages of an accident and enabling the proactive execution of high-priority actions, even in alarm flooding scenarios.

2. Light Gradient Boosting Machine

In this study, the LightGBM algorithm was employed to proactively predict the timing of alarm occurrences [3]. LightGBM is a tree-based learning algorithm rooted in the gradient boosting framework; it maximizes learning efficiency for large-scale simulation datasets through Gradient-based One-Side Sampling (GOSS), a technique that optimizes computational load by prioritizing samples with larger gradients. Specifically, by adopting the leaf-wise tree growth strategy, which is more efficient than the conventional level-wise approach, the model precisely captures the complex non-linear relationships between physical variables. This simultaneously achieves faster training speeds and reduced memory consumption. Fig. 1 illustrates the structural differences between the level-wise and leaf-wise methods.



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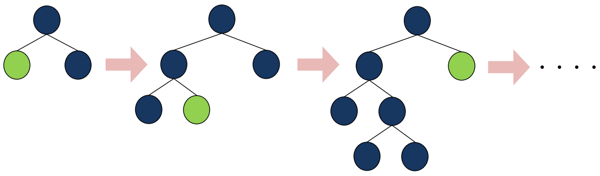

<Leaf-wise trees growth>

Fig. 1. The structure of level-wise and leaf-wise tree methods

In addition, Ensemble Uncertainty Quantification was employed to address the inherent bias of single models and to satisfy the stringent reliability requirements of the nuclear domain. By quantifying uncertainty through the standard deviation of the predicted values among the models, it provides operators with a 95% uncertainty band rather than a simple point estimate. This approach has the effect of enhancing decision-making stability by visually presenting the statistical reliability of the model's predictive results. To summarize, LightGBM demonstrates a distinct advantage in providing high predictive accuracy with low computational costs, making it ideal for real-time inference environments aimed at ensuring the safety of NPP operations.

3. Data

3.1 Data Collection

For model development, the data were collected based on simulated abnormal scenarios in NPPs. The dataset was generated using the CNS, which was modeled for a Westinghouse-type 3-loop pressurized water reactor system [4]. To proactively predict precursor signs before the onset of abnormal conditions, eight abnormal scenarios were established based on Abnormal Operating Procedures (AOPs) and simulator-based experiments. The abnormal scenarios used in this study are presented in Table 1. Additionally, alarms that could occur in various abnormal scenarios were collected based on CNS and AOPs. Alarms within the CNS are linked to specific process variables, serving as critical information that inform system anomalies to the operator.

Table I: List of abnormal scenarios

No.	Scenario name
Automatic logic and instrument errors	
1	Pressurizer level channel failure (Low)
2	Steam generator level channel failure (Low)
Abnormal equipment status	
3	PRZ Safety valve failure
4	PRZ spray valve failure – open
5	PRZ PORV open
6	Continuous insertion of control rod
Pipe leakage	
7	RCS to CCW system leakage
8	CVCS to CCW system leakage

3.2 Data Pre-Processing

Data pre-processing was performed to reduce bias in the model training process and improve overall learning efficiency. The selected data were normalized to values between 0 and 1 using the min-max scaling technique. This normalization process adjusts the scale of data with different units and ranges to maintain data consistency and improve model performance.

Among the total of 86 alarms monitored by operators in real-time via the CNS alarm display, 27 alarms that significantly represent system anomalies within the established scenarios were selected as the prediction targets. To select the target alarms, we first defined the core alarms for each individual scenario by deriving the union of alarms that repeatedly occurred across various abnormal scenarios. Subsequently, by taking the intersection of the alarms derived from all eight abnormal scenarios, we selected the core alarms capable of encompassing a wide range of accident types. The selected alarms are closely associated with the major instrumented variables of the NPP, and their specific alarm tag names and corresponding descriptions are detailed in Table 2.

Table II: Alarm variables description

No.	Alarm variables description
1	Control bank low-low limit
2	Two or more rod at bottom
3	Axial power distribution limit
4	L/D HX outlet flow low
5	L/D HX outlet temp high
6	Charging flow control flow low
7	Charging flow control flow high
8	PWR range high flux rate RX trip
9	RCS flow low at high PWR RP trip
10	Rad high alert
11	VCT level high
12	RCS 1,2,3 TAVG high
13	RCS 1,2,3 low flow
14	PRZ press high alert
15	PRZ press low alert
16	PRZ PORV opening
17	PRZ control level high heater on
18	PRZ press low back-up heater on
19	TAVG deviation high
20	PRZ low press & P-7 RX trip
21	PRT temp high
22	PRT press high
23	SG 1,2,3 STM/FW flow deviation
24	MSL 1,2,3 press rate high
25	AFW actuated
26	FW pump trip
27	TBN trip P-4

4. Results

To quantitatively evaluate the performance of the proposed LightGBM model in predicting the remaining alarm time, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were utilized as key metrics. RMSE represents the square root of the average of squared differences between predicted and actual observations, indicating the overall deviation of the model. MAE is the average of the absolute differences between predicted and actual values, providing a straightforward measure of the average error magnitude. These evaluation indices are shown in Eqs. (1) and (2). In the equations, y and $\hat{y}$ represents the actual value, the predicted value, respectively. Table III shows the prediction performance metrics for each scenario.

$$RMSE = \sqrt{\frac{\sum (y-\hat{y})^2}{n}} \tag{1}$$

$$MAE = \frac{\sum |y-\hat{y}|}{n} \tag{2}$$

Table III: Prediction Performance Metrics

Scenario No.	RMSE	MAE
1	0.0665	0.0482
2	0.0124	0.0044
3	0.0759	0.0391
4	0.0628	0.0222
5	0.0450	0.0182
6	0.0595	0.0494
7	0.0882	0.0576
8	0.0251	0.0099

Figs. 2 and 3 show the results of predicting the timing of alarm occurrences within the abnormal scenarios [5]. In the graph, the actual timing of alarms is indicated by a blue solid line, while the predicted timing from the model is depicted as a yellow dotted line. The green shading surrounding the predicted values represents the 95% uncertainty band, reflecting both model uncertainty and the inherent variability of the data to indicate a reliable range for future predictions. Across all eight scenarios, it was confirmed that the model successfully predicted the trends of actual alarm occurrences. Fig. 2 illustrates the prediction results for Alarms No. 7 and No. 20 occurring in the PRZ PORV Opening scenario, while Fig. 3 shows the prediction results for Alarms No. 6 and No. 18 in the CVCS to CCW system leakage scenario.

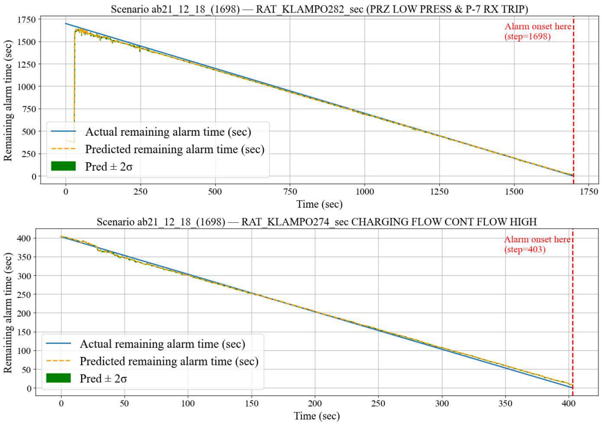

Fig. 2. Alarm prediction for PRZ PORV opening scenario (No. 7 and No. 20)

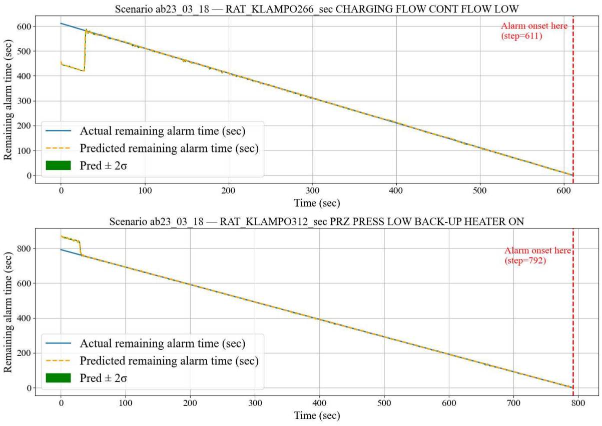

Fig. 3. Alarm prediction for CVCS to CCW system leakage scenario (No. 6 and No. 18)

To prevent information overload and human errors that may occur when a large volume of multi-alarm data is delivered to operators, this study introduced an Intelligent Alarm Optimization process. Rather than operating independently, alarms in an NPP follow physical principles, where a single initiating event triggers a cascade of numerous secondary alarms. To address this hierarchical complexity and support operators' proactive decision-making, this study performed a stepwise optimization process. First, by comprehensively evaluating the predicted remaining time, model reliability, and inherent importance of each alarm, the process extracted alarm information predicted to occur within a 60-second time horizon. Subsequently, causal modeling was performed by integrating data-driven correlation analysis with the physical interconnectedness of the system. Information hierarchy was achieved by grouping multiple derivative alarms expected to occur due to the same physical perturbation. Finally, within this structured architecture, the process prioritizd the identification of the alarm that serves as both a key indicator of accident progression and the physical basis for the observed change. Through this process, the system was configured to select and display the trends of up to five key predicted alarms, thereby considering the operator's cognitive limits.

Based on these filtered alarms, a comparative analysis was performed between the actual remaining alarm time and the predicted remaining alarm time. Figs. 4 and 5 present plots comparing the actual and predicted alarm onset times for alarms within the abnormal scenarios. The timeline plots are color-coded to indicate the proximity of predicted alarm occurrences: orange represents alarms expected to fire imminently, yellow indicates alarms with a medium-term lead time, and green denotes alarms with a relatively longer time margin. The gray bar plotted behind the colored bars represents the actual time the alarm fires. By overlaying these two elements, the plot facilitates a direct comparison between the actual and predicted alarm occurrence times, highlighting the precision of the model. The comparison confirmed that the predicted alarm onset times were closely aligned with the actual times within an error margin of approximately 10 seconds. This suggests that the proposed model achieves a level of accuracy that is practically useful for operator decision support. Furthermore, by providing minimal and essential information, it is possible to both prevent human errors and ensure consistency in operator responses.

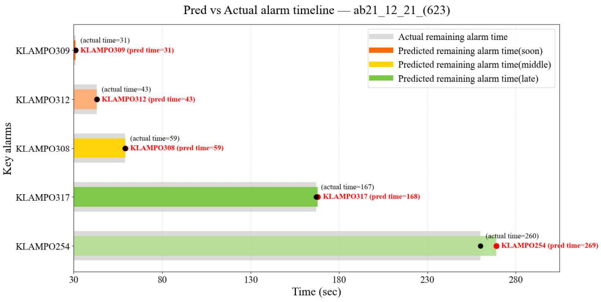

Fig. 4. Comparison of actual and predicted alarm onset times (PRZ PORV opening scenario)

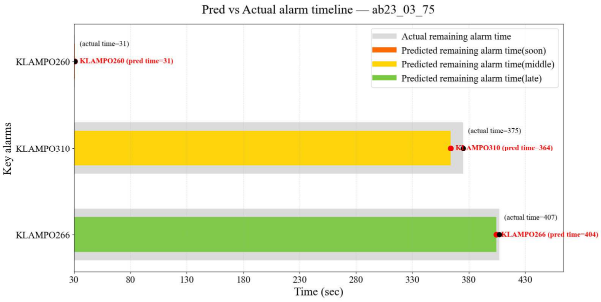

Fig. 5. Comparison of actual and predicted alarm onset times (CVCS to CCW system leakage scenario)

5. Conclusions

To support operators' proactive situational awareness and prevent human errors during abnormal conditions in NPPs, this study proposed a LightGBM-based remaining alarm time prediction model and validated its performance.

Experimental results demonstrated that the proposed LightGBM model effectively captured complex physical causal relationships and achieved superior predictive precision with lower computational costs compared to existing deep learning models. Additionally, in the nuclear domain where high reliability is paramount, this study quantitatively presented the statistical confidence of the prediction results. Furthermore, through the intelligent alarm optimization proposed in this study, only core information with high predictive confidence and alarm importance was filtered and provided. This can significantly reduce information overload and the potential for human error during alarm flooding scenarios.

However, as this study was conducted within a CNS environment, there is a limitation in fully validating the robustness against various noises and unexpected, unknown accident scenarios that may occur in actual NPPs. In future works, efforts will be made to enhance model robustness and generalization by incorporating diverse abnormal datasets and real-world plant history. Furthermore, the scope of performance verification will be extended to next-generation nuclear technologies, including SMR.

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