Cognitive-Based State Diagnosis Module for Operator Decision Support in Nuclear Power Plants

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Abstract: Timely state diagnosis is essential for supporting operators during abnormal situations in nuclear power plants. Although artificial intelligence–based diagnostic models have achieved strong performance, discussion on how their results should be provided to operators remains limited. This study focuses on the design of an operator-centered state diagnosis module that determines what diagnostic information should be presented and how it should be structured to support operator decision-making. Based on an analysis of operator cognitive activities during abnormal situations, the required diagnostic information is identified and organized in a sequential manner reflecting the operator reasoning process. Diagnostic results, diagnostic reasons, abnormal operating procedure entry condition consistency, and time margin information are hierarchically structured to reduce cognitive burden while supporting situation assessment. The proposed module illustrates how AI-based diagnostic outputs can be presented to assist operators in judging plant conditions and determining appropriate abnormal operating procedure entry.

1. INTRODUCTION

Nuclear power plants (NPPs) are highly complex systems composed of many interconnected structures, systems, and components that must operate in a coordinated manner to ensure safe operation. In digitalized main control rooms (MCRs), abnormal situations are typically first recognized through alarms, after which operators assess plant conditions and determine whether to enter an appropriate abnormal operating procedure (AOP). In large pressurized water reactors, the number and complexity of AOPs make correct procedural selection challenging, particularly under time pressure, stress, and high system complexity. Delayed or inappropriate diagnosis and procedure entry can escalate abnormal situations into emergency conditions, increasing the risk of human error. During abnormal situations, operators must interpret alarms and plant behaviors to understand the underlying causes of plant disturbances and judge whether procedural entry is required. However, current operational environments primarily provide alarms and raw plant data, offering limited support for organizing information in a way that aids operator understanding and procedural decision-making. As a result, operators must rely heavily on their own cognitive integration of disparate information sources.

Recent studies have explored artificial intelligence (AI)–based diagnostic methods for NPPs, demonstrating promising performance in classifying predefined abnormal events from plant data [1, 2]. While these approaches improve diagnostic accuracy, most focus on producing a single diagnostic result and give limited consideration to how diagnostic information should be structured and presented to support operator judgment during abnormal situation management.

Despite these advances, several barriers limit the field application of AI-based diagnosis in NPPs. Diagnostic models may behave unpredictably for scenarios outside their training distribution, are sensitive to anomalous signals arising from instrument faults, and can suffer performance degradation due to discrepancies between simulator-generated training data and actual plant data. Because of these issues, raising the field applicability of AI in NPPs is widely regarded as a long-term effort in which trust must be established incrementally. In this context, how diagnostic information is delivered to operators becomes as important as the underlying model accuracy: the value of an AI diagnosis is realized only when an operator can interpret it, judge its credibility, and act on it within the limited time available during an abnormal situation.

From an operator-centered perspective, effective diagnosis support should help operators compare possible abnormal conditions, recognize related systems and components, and assess the appropriateness of entering a specific AOP. This paper presents an operator-centered state diagnosis module for nuclear power plants, focusing on the design of a user interface that supports operator understanding and decision-making during abnormal situations. Rather than providing a single confirmed diagnosis, the proposed interface presents diagnostic candidates along with structured supporting information, including diagnostic reasons, entry condition consistency, and trip margin information. By supporting operator judgment rather than automated decision-making, the proposed interface aims to assist operators in determining whether and when to enter the appropriate AOP. The scope of this work is limited to the design and implementation of the state diagnosis interface.

The contributions of this paper are twofold. First, we analyze operator cognitive activities during abnormal situations and derive diagnostic information requirements that a state diagnosis module must satisfy prior to response planning. Second, we structure these requirements into hierarchical information architecture and realize them in an operator-centered state diagnosis interface for a plant. The remainder of this paper is organized as follows. Section 2 reviews related work, Section 3 presents the cognitive framework, Section 4 describes the interface design, and Section 5 concludes.

2. RELATED WORK

A large body of work has applied machine learning to fault detection and abnormal event classification in NPPs, generally reporting high classification accuracy on predefined event sets [1-3]. These studies primarily target diagnostic performance and treat the diagnostic output as a single classification result, paying comparatively little attention to how such outputs should be organized and presented so that operators can use them during abnormal operations.

More recent research has begun to integrate AI into operator support systems with explicit attention to the human–machine interface. Sethu et al. [3] reviewed how AI has been introduced into various operator support systems—including decision support, sensor-fault detection, operation validation, and operator monitoring systems—to mitigate human errors in nuclear power plants. Rather than pursuing fully automated diagnosis, Shin et al. [4] proposed an interpretable deep-learning approach that improves the existing abnormal state diagnosis process by providing operators with insights from the model while preserving operator autonomy and reducing cognitive burden. More broadly, national programs on small modular reactors have begun developing HMIs for high-level autonomous monitoring, diagnosis, and mitigation. These efforts confirm a growing interest in AI-assisted operator support but generally stop short of specifying, from the operator's cognitive perspective, what diagnostic information should be shown and how it should be structured. This gap is increasingly relevant from a regulatory standpoint as well: the U.S. Nuclear Regulatory Commission's Artificial Intelligence Strategic Plan (NUREG-2661) anticipates the growing use of AI in nuclear applications and emphasizes the systematic review of AI tools, underscoring the importance of transparent, interpretable presentation of AI outputs in safety-critical settings [5].

In contrast to prior work centered on model accuracy, this paper focuses on the presentation layer: it derives diagnostic information requirements from operator cognition and realizes them in a verifiable HSI, bridging AI diagnostic output and operator decision-making.

3. COGNITIVE FRAMEWORK FOR OPERATOR DECISION SUPPORT

3.1. 2.1Operator Cognitive Processes in Abnormal Situations

Figure 1 presents the major cognitive activities underlying NPP operator performance during abnormal situations, as defined in the A Technique for Human Error Analysis (ATHEANA) methodology developed by the U.S. Nuclear Regulatory Commission [6]. ATHEANA categorizes operator performance into a sequence of cognitive activities that occur when plant conditions deviate from normal operation, providing a structured basis for analyzing operator cognition during abnormal situations. According to ATHEANA, operator cognitive activities during abnormal situations can be broadly classified into four stages: monitoring and detection, situation assessment, response planning, and response implementation. Monitoring and detection refer to the process by which operators recognize deviations from normal operation through alarms and observed plant behaviors. Situation assessment involves interpreting these observations to develop an understanding of the current plant condition. Response planning and response implementation follow situation assessment and involve selecting and executing operational actions and procedures.

Within this cognitive sequence, abnormal state diagnosis is primarily associated with the monitoring and detection stage and the situation assessment stage, both of which occur prior to response planning. During these stages, operators first determine whether an abnormal situation has occurred, then assess whether the observed plant condition corresponds to an abnormal state, and interpret the characteristics of the abnormality based on available information. ATHEANA explicitly distinguishes these diagnosis-related cognitive activities from subsequent decision-making and action execution processes. Therefore, analyzing operator cognitive activities during monitoring and detection and situation assessment under abnormal situations provides a necessary basis for defining the diagnostic information required to support abnormal state diagnosis before response planning.

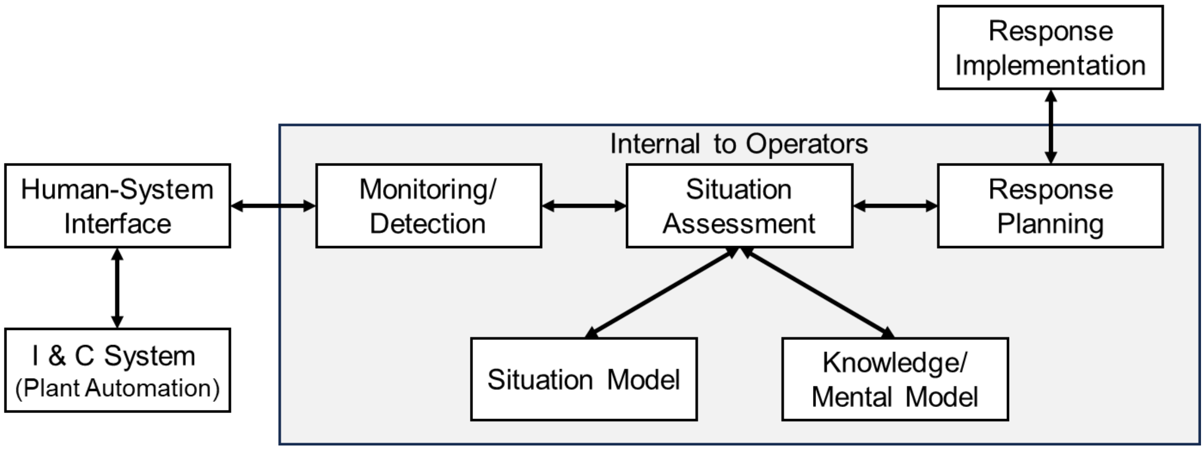

Figure 1. Major cognitive activities underlying NPP operator performance

Table 1. Potential human errors and corresponding decision-support information by cognitive activity

Cognitive activity	Potential human error	Decision-support information
Monitoring / Detection	Missing a critical alarm under alarm overload, misjudging sensor-fault readings	AOP entry-condition satisfaction, signal validation results
Situation Assessment	Confusing the cause of the abnormal event	Diagnostic results and reasons
Response Planning	Delayed response from misjudging available time	Trip margin time; key-variable progression prediction
Response Implementation	Procedure omission, wrong manipulation, delayed response	Procedure-based and function-recovery-based action support

3.2. Cognitive Task Analysis for Decision Support Design

Within the monitoring and detection and situation assessment stages described in the previous section, operators perform several diagnosis-related cognitive tasks during abnormal situations. These tasks include recognizing whether an abnormal situation has occurred, interpreting alarm information and plant behaviors, and determining whether the observed condition corresponds to a specific abnormal state associated with an AOP. Rather than being a single decision, abnormal state diagnosis is a progressive cognitive process in which operators continuously interpret and refine their understanding of plant conditions based on available information. This section focuses on identifying these diagnosis-related cognitive tasks as a basis for defining the information requirements of a state diagnosis module.

3.2.1 Decision Ladder–Based Cognitive Modeling

To identify the diagnostic information required for abnormal state diagnosis, this study adopts the decision ladder framework proposed by Jens Rasmussen, which describes how operators transform observed information into decisions and actions under time pressure [7]. The decision ladder represents operator cognition as a sequence of information processing stages, ranging from the perception of alerts and observations to the identification of system states and the selection of appropriate actions. In abnormal situations, operators do not directly select procedures upon receiving alarms. Instead, they progress through intermediate cognitive steps, including interpreting observed plant behaviors, identifying the current plant state, and evaluating alternative diagnostic hypotheses. Based on this reasoning process, the decision ladder highlights that effective diagnosis requires explicit support for intermediate cognitive states, rather than only providing final decisions or actions.

Based on the decision ladder and the ATHEANA-based classification of operator cognitive activities, the diagnostic information required during abnormal situations can be structured into two primary stages: monitoring and detection and situation assessment. During monitoring and detection, operators require information that supports the recognition of abnormal occurrences, such as alarm status, signal validity, and observable deviations from normal behavior. During situation assessment, operators require information that supports state identification and hypothesis evaluation, including diagnostic candidates, diagnostic reasons, entry condition consistency, and indicators related to plant safety margins. Accordingly, Figure 2 illustrates the diagnostic information elements required for abnormal state diagnosis, mapped onto the operator cognitive processes described by the decision ladder and ATHEANA. This structured representation serves as the basis for defining the information to be presented by the state diagnosis module prior to response planning. In the figure, rectangular blocks represent cognitive states formed by operators during abnormal situation management, while circular nodes represent cognitive activities through which operators transition between these states. This distinction is used to explicitly separate cognitive processing activities from the resulting diagnostic states.

Applying the decision ladder to abnormal operation makes the information flow explicit. In the monitoring-and-detection stage, an abnormal event generates an ALERT, prompting operator observation of the plant state; here the module provides alarm presentation and observation of key process variables. In the situation-assessment stage, the observed data are presented as INFORMATION in the form of trip margin time and diagnostic results and reasons, which serve as inputs to state identification. After identification, signal validation and AOP entry conditions are checked and diagnostic candidates are derived; the operator then predicts consequences and evaluates candidates to confirm the appropriate AOP. The subsequent response-planning and response-implementation rungs lie beyond the scope of state diagnosis and are addressed by separate planning and action-support functions. This decomposition shows that effective diagnostic support must populate the intermediate rungs of the ladder—identification, candidate generation, and candidate evaluation—rather than only delivering a final result.

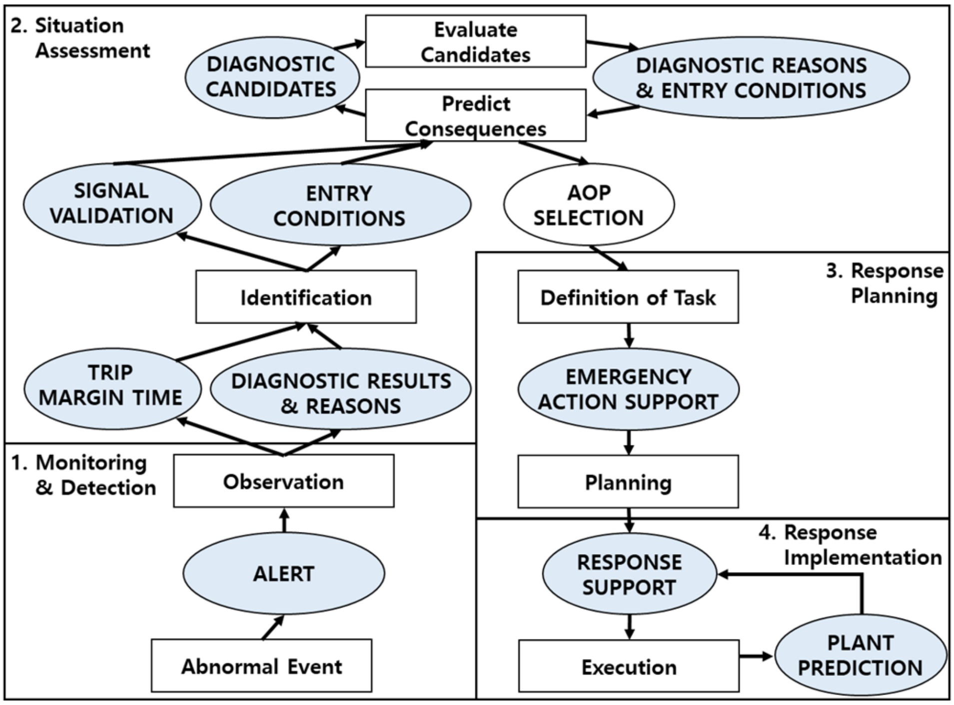

Figure 2. Diagnostic information requirements for abnormal state diagnosis based on operator cognitive processes

3.2.2 Use Case–Based Operator–System Interaction Analysis

Based on the cognitive tasks identified in the previous subsection, this study structures the diagnostic information required for abnormal state diagnosis using a use case diagram [8]. The use case diagram is employed to clarify what diagnostic information is provided by the state diagnosis module and how that information is made available to operators during abnormal situations.

In the use case diagram, diagnostic information is classified into information that is continuously presented and information that is selectively presented based on operator interaction, corresponding to the include and extend relationships, respectively. Information represented by include corresponds to essential diagnostic information that must always be available to support monitoring and detection and initial situation assessment. This includes plant state information, abnormal occurrence alarms, top-level diagnostic results, and AOP entry condition consistency. These information elements provide a baseline understanding of plant conditions and support the early recognition of abnormal situations. In contrast, information represented by extend is provided upon operator request and supports deeper cognitive processing during situation assessment. This includes diagnostic candidates with confidence, trends of relevant variables, contribution information related to diagnostic causes, detailed signal validation results, and trip-related margin information. Such information supports operator inference by allowing operators to examine the rationale behind diagnostic results and to refine their understanding of the abnormal state.

Using the AOP decision ladder and the use-case relationships, the diagnostic information required during abnormal situations was classified into seven categories: Alert, Diagnostic Results, Diagnostic Candidates, Diagnostic Reasons, Trip Margin Time, Entry Conditions, and Signal Validation. Alert and Diagnostic Results support the monitoring-and-detection stage, while the remaining categories support hypothesis evaluation and state identification during situation assessment. The inclusion and extension relationships among these categories define both the content and the disclosure order of information in the interface.

Each diagnostic information element in the use case diagram is associated with an artificial intelligence model that generates or supports the corresponding information. These models do not replace operator decision-making or execute operational actions; instead, they present diagnostic inferences and supporting evidence, thereby assisting operators in making informed decisions during abnormal situations. Figure 3 presents the use case diagram describing the diagnostic information structure and the relationship of the cognitive requirements of monitoring and detection and situation assessment.

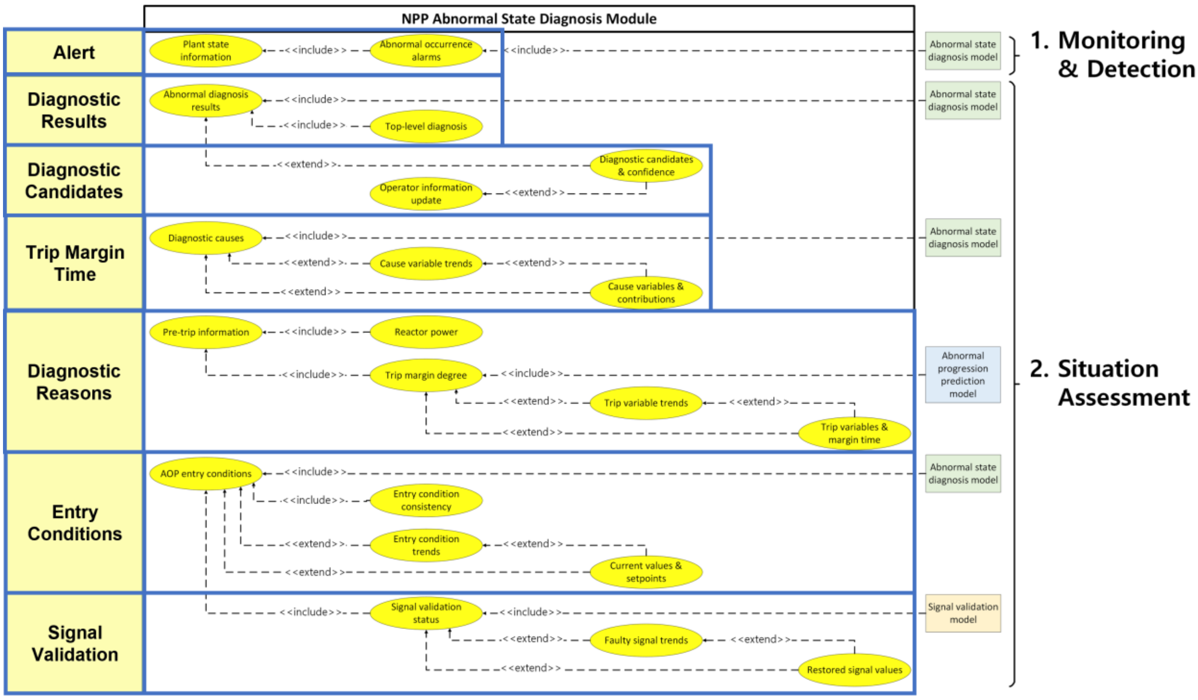

Figure 3. Diagnostic information structure mapped to operator cognitive processes

3.2.3 Integrated Operator–DSS Interaction Flow

Figure 5 illustrates the information flow of the proposed abnormal state diagnosis module, organized according to operator cognitive activities during abnormal situations. The figure integrates the monitoring and detection stage with the situation assessment stage, which together form the cognitive basis for abnormal state diagnosis prior to response planning. In the monitoring and detection stage, abnormal situations are recognized either through abnormal occurrence alarms generated from real-time plant instrumentation data or through proactive indications provided by the abnormal state diagnosis model, which identifies deviations from normal operating behavior before explicit alarm activation.

Following abnormal detection, the situation assessment stage focuses on identifying and evaluating possible abnormal states. The state diagnosis module presents diagnostic results in the form of candidate abnormal states with associated confidence levels, rather than a single confirmed diagnosis. This candidate-based representation reflects the inherent uncertainty and overlap among abnormal symptoms in nuclear power plants and allows operators to compare multiple plausible interpretations of the observed plant behavior. To support operator inference, the module provides diagnostic reasons by presenting related plant systems, causal variables, and their contributions, along with corresponding trend information. In addition, pre-trip information, including reactor power, trip-related variables, and trip margin time, is presented to support operator judgment regarding the urgency of the diagnosed abnormal state. The module also supports procedural decision-making by evaluating the consistency between the diagnosed abnormal state and the entry conditions of candidate AOPs. Entry condition variables, their current values, setpoints, and trends are provided to help operators assess whether procedural entry is appropriate. Signal validation results are simultaneously presented to indicate whether observed symptoms may be influenced by faulty instrumentation, thereby supporting the credibility of the diagnostic inference.

Overall, the information flow shown in Figure 4 demonstrates how the proposed state diagnosis module organizes AI-derived information to support operator inference and decision-making during abnormal situations. Rather than prescribing actions, the module assists operators by presenting diagnostic candidates and their underlying reasoning in a structured manner, forming a cognitive bridge between abnormal event detection and response planning.

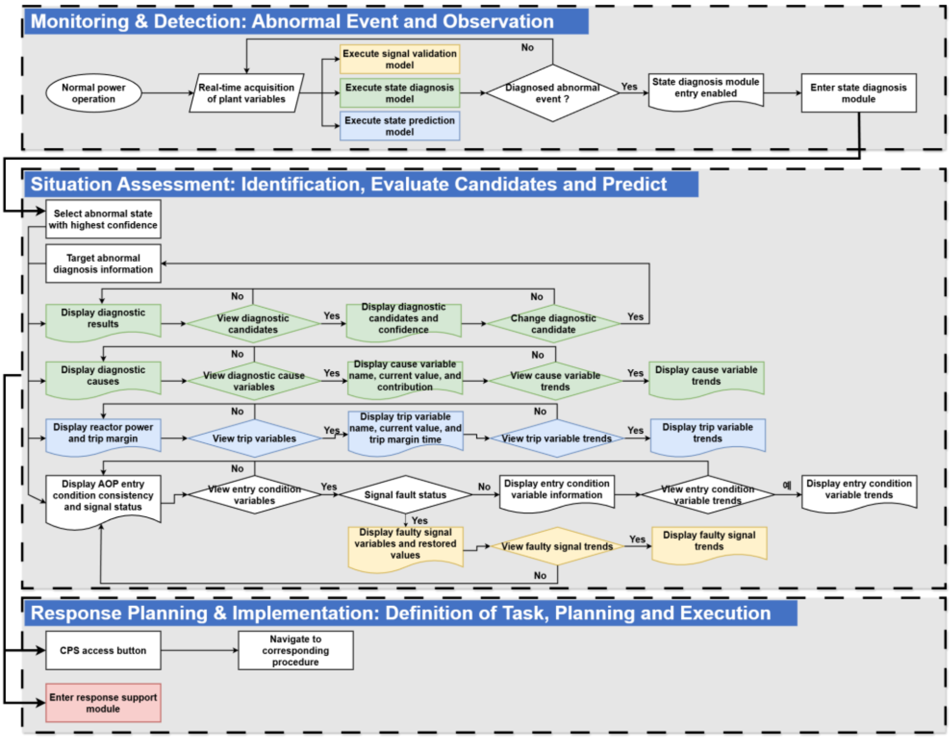

Figure 4. Information flow from monitoring and detection to situation assessment for abnormal state diagnosis

4. COGNITIVE-BASED STATE DIAGNOSIS INTERFACE

Following the information flow concept, the proposed state diagnosis interface is designed to align with operator cognitive processes by organizing diagnostic information in a top-to-bottom and left-to-right manner. The interface organizes diagnostic information into three hierarchical levels of detail—primary information, variable information, and variable detail—so that operators can move from broad situation recognition to detailed evidence without leaving the screen. The module is designed for deployment within the distributed control system (DCS) of a commercial plant and is rendered at a 1280×1064 resolution consistent with the plant operating displays.

The interface is composed of seven functional areas (Figure 5):

(1) DCS navigation bar. Located at the top, it shows the current time and operating mode and provides buttons to major displays (DSS, Pri, Sec, BI, Aid, CPS, Alarm). When an abnormal condition is detected, the DSS button is illuminated to draw the operator's attention, and selecting it opens the diagnostic display while preserving the current context.

(2) Decision-support-system navigation bar. Fixed at the top of the DSS display, it lets the operator switch between the State Diagnosis (S/D) module and the Response Support (R/S) module.

(3) State diagnosis result panel. The top-level diagnostic result—an AOP number and state name—is presented in a yellow panel for at-a-glance recognition. Selecting the result reveals diagnostic candidates with their confidence levels, allowing the operator to compare multiple plausible interpretations and select one; the module then updates to the chosen candidate. A CPS button is co-located so the operator can jump directly to the corresponding procedure display.

(4) Trip margin time panel. The time remaining until a trip is color-coded so that risk level can be judged intuitively; selecting the item lists the trip-related variables and their margins to support response planning.
(5) System-based diagnostic-contribution panel. Diagnostic contributions are visualized on a plant system diagram, with high-, medium-, and low-contribution systems shown in red, orange, and yellow, respectively, so that operators can prioritize cause analysis. Selecting a system links its key variables and real-time data to the variable-detail panel.
(6) Diagnostic-result verification panel. To establish the reliability of the diagnosis, the satisfaction of AOP entry conditions is shown as a true/false table, and signal validation items are displayed only when a fault exists (shown in gray). Selecting an item links the relevant variables, real-time values, and setpoints to the variable-detail panel, supporting verification of the diagnostic basis.
(7) Variable-detail panel. Shared by panels 3–6, it provides on-demand detail for whichever item the operator selects: it lists the relevant variables with real-time values, and selecting a variable displays its trend graph so the operator can analyze temporal behavior.

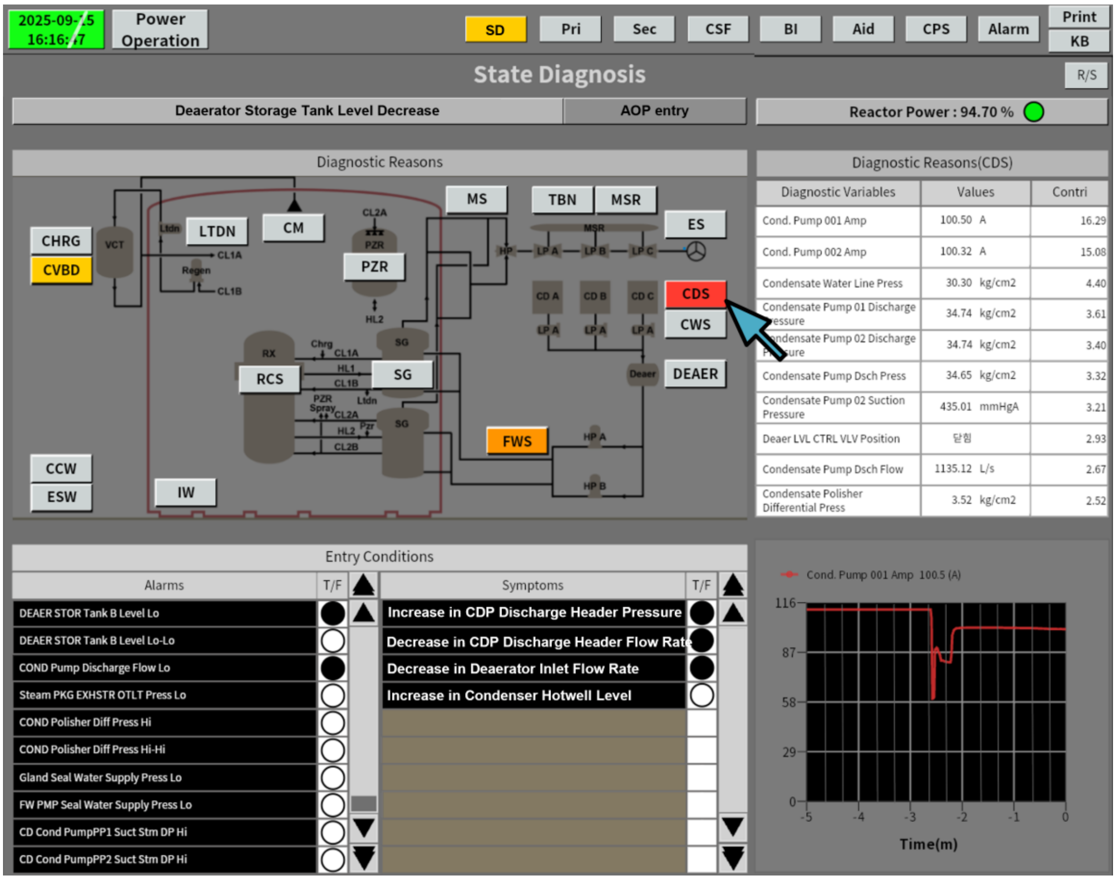

Figure 5. State diagnosis module human-system interface

Taken together, the layout enforces a cognitive diagnostic workflow that proceeds from overall state recognition (panel 3), through urgency assessment (panel 4) and cause identification (panel 5), to verification of the diagnostic basis (panel 6). At each of these stages, the variable-detail panel (panel 7) serves as a shared inspection area: whenever the operator selects an item in panels 3–6, its associated variables, real-time values, setpoints, and trends are displayed there on demand. Because these information stages and their supporting details are co-located on a single screen, the operator can traverse them without display switching, reducing cognitive load and supporting faster, more accurate judgment during abnormal situations.

5. CONCLUSION

This study presented an operator-centered state diagnosis module that focuses on how AI-derived diagnostic information should be organized and presented to support operators during abnormal situations in nuclear power plants. Rather than treating diagnosis as an automated decision, the work analyzed operator cognitive activities during the monitoring-and-detection and situation-assessment stages using the ATHEANA framework and Rasmussen's decision ladder, derived the diagnostic information requirements that must be satisfied prior to response planning, and structured them into a hierarchical information architecture through a use-case-based analysis. This architecture was realized as a state diagnosis interface for a plant, in which diagnostic results, diagnostic candidates with confidence, causal systems and variables, entry-condition consistency, and trip margin time are arranged according to the operator reasoning process.

By presenting diagnostic candidates and their underlying reasoning rather than a single confirmed result, and by co-locating the diagnostic result, its causal systems, verification evidence, and a shared variable-detail panel on a single screen, the interface allows operators to interrogate and validate AI output while progressing from high-level state recognition to detailed variable inspection without display switching. This design supports operator judgment, reduces cognitive load, and strengthens situation awareness during abnormal operation, forming a cognitive bridge between abnormal event detection and response planning. Future work will integrate the state diagnosis module into a unified decision-support prototype connected to a plant simulator and evaluate it with operators to quantify gains in situation awareness, response time, and diagnostic accuracy.

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