Nuclear Plant Control Room Operator Modeling Within the ADS-IDAC, Version 2, Dynamic PRA Environment: Part 1 - General Description and Cognitive Foundations

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Abstract: Dynamic simulation-based approaches for probabilistic risk assessment (PRA) offer several key advantages over traditional “static” techniques such as traditional event tree-fault tree based methods. For example, dynamic simulation approaches can more realistically represent event sequence and timing, provide a better representation of thermal hydraulic success criteria, and permit more detailed modeling of operator response. Version 2.0 of the Accident Dynamics Simulator paired with the Information, Decision, and Action cognitive model in a Crew context (ADS-IDAC) is one such dynamic method that shows promise for supporting nuclear power plant PRAs and other risk-informed applications. By linking a realistic nuclear plant thermal-hydraulic model with a crew behavior model, ADS-IDAC creates a rich simulation environment. The crew behavior model describes the operators’ preferences and tendencies, knowledge, and situation-response rules.

ADS-IDAC generates a discrete dynamic event tree (DDET) by applying simple branching rules that reflect variations in crew responses to plant events and system status changes. Branches can be generated to simulate a variety of operator behaviors, including procedure execution speed and adherence, evolving situational assessments, and variations in plant control preferences. This is the first of two papers in this volume and provides an overview of the ADS-IDAC Version 2.0 simulation platform and a description of the cognitive foundations underpinning the operator human performance model.

Keywords: Dynamic PRA, human reliability analysis, cognitive decision making

1 Introduction

Previous human performance research efforts have found that nuclear plant operators can be induced to commit unsafe actions under certain error forcing situational contexts [1]. Situational context includes factors such as the system state, the operator’s state of mind, and the sequence and timing of events. In particular, four important observations regarding accident analysis have been noted [2]:

1. Plant operators and plant components are interacting parts of an overall system that responds to upset conditions.
2. The actions of operators are governed by their beliefs as to the current state of the plant.
3. The operators have memory; their beliefs at any given point in time are influenced by the past sequence of events and by earlier trains of thought.
4. A number of operators are involved during the accident.

These observations point to the need to develop analysis techniques that can explicitly model the dynamics and feedback of nuclear systems while capturing the cognitive behavior and limitations of operators performing within a crew environment. Although
the dynamic interaction and feedback between human and machine strongly affects the situational context and potential for operator error, these dynamic effects are difficult to capture with current state-of-the-practice human reliability methods such as Cause Based Decision Trees [3] or SPAR-H [4]. Simulation-based HRA methods can address many of the shortcomings of earlier HRA methods. For example, the dynamic interaction and feedback resulting from operator actions can be directly modeled. The time-dependent behavior of performance influencing factors such as stress, fatigue, and work load can also be modeled within a simulation environment. Additionally, the operators evolving understanding of situational context as feedback from previous actions and new information is perceived can be explicitly modeled. Simulation-based methods can augment the data usually derived from time consuming and expensive control room simulator experiments conducted with actual control room crews. A computer simulation model can also explore a wider range of accident conditions than would be possible with actual control room operators in a simulator. Finally, a simulation approach allows a better determination of the consequences of a human error event. By coupling an operator model with a plant system model, one can determine the impact of each error event on the system – thus it becomes a straightforward matter to determine if a human error event has an actual risk impact.

The Accident Dynamics Simulator with the Information, Decision, and Action in a Crew context cognitive model (ADS-IDAC) provides a means to achieve these human error analysis goals. IDAC decomposes the operator’s cognitive flow into three main process: information processing, decision-making, and action execution [5]. The crew is modeled as a team of individuals working on different assigned tasks and communicating with one another. The individuals differ by the content of their memory, by their mental state, and by the goals and strategies they employ. While the domain of applicability of IDAC is currently constrained to environments characterized by high levels of training and explicit requirements to follow procedures [6], this tool is capable of providing useful insights across a range of nuclear power plant human performance issues.

This is the first of two papers and provides an overview of the key elements of this modeling approach, with a focus on modeling elements added under the recently developed for Version 2.0 of the ADS-IDAC code. The second paper describes the dynamic modeling capabilities supported by the ADS-IDAC Version 2.0 simulation platform and provides examples of their application. Section 2 of this paper provides a high level description of the ADS-IDAC code, including the modules needed to simulate a nuclear power plant and generate a discrete dynamic event tree. Section 3 describes the IDAC cognitive model including information processing, decision making, and action execution. Section 4 discusses the development and implementation of the operator knowledge base, which is used to represent the operator’s knowledge, experience, and preferences.

2 Overview of the ADS-IDAC Simulation Platform

The theoretical foundation for ADS-IDAC has been under development for over a decade [6–10]. Early research efforts focused on developing necessary infrastructure to link a dynamic event tree scheduler driver with a thermal hydraulic simulation code capable of adequately representing a nuclear power plant. These early research efforts resulted in the development of the Accident Dynamics Simulator (ADS) approach which linked a thermal hydraulic representation of a nuclear power plant with a scheduling module capable of generating a dynamic event tree [11]. Parallel development of the Information, Decision, and Action (IDA) cognitive model established the theoretical basis for the model-based
human reliability approach used in ADS-IDAC. Later research efforts linked the ADS dynamic event tree scheduler and elements of the IDA cognitive model (extended to include crew interactions) to the RELAP thermal hydraulic nuclear plant analysis code [12]. The key distinction between the current ADS-IDAC research effort and other dynamic methods such as MCDET [13] and ADAPT-MELCOR [14] is the explicit treatment of human performance using an underlying cognitive model. The addition of an expanded knowledge base, implementation of dynamic performance influencing factors, and cognitive elements such as information filtering have culminated in the current Version 2.0 of the ADS-IDAC code [15].

Similar to previous versions, Version 2.0 of the ADS-IDAC simulation platform consists of three major elements: the nuclear plant model, the operations crew model, and a scheduler that controls the generation of the dynamic event tree.

2.1 Nuclear Plant Model

The nuclear power plant (NPP) thermal-hydraulic model in ADS-IDAC provides a rich contextual environment for the analysis and prediction of operator behaviors. The current version of ADS-IDAC utilizes the RELAP5/MOD 3.2 computer code [16] to provide a transient simulation of NPP response. The RELAP5 code can simulate a wide variety of accident initiators and provides the capability to model key safety systems, controls, and instruments. Advantages of RELAP5 include its proven capabilities as a transient analysis tool and the availability of detailed power plant models. However, due to the limitations of the RELAP5 code, it is not currently possible to model core damage states and severe accident scenarios. Therefore, ADS-IDAC is currently limited to the analysis of scenarios up to the start of core damage. However, the capability of ADS-IDAC to provide a reasonable estimate of the start of core damage (i.e., up to a Level 1 end state used in conventional probabilistic risk assessment) has been confirmed for several accident scenarios [17]. More recent efforts have linked the ADS-IDAC model with the MELCOR severe accident thermal hydraulic code to address this limitation [18]. Although ADS-IDAC can interface with any suitable RELAP5 nuclear plant model, it has been successfully integrated with a three-loop, pressurized water reactor (PWR) NPP RELAP model. The ADS-IDAC operator model is linked to the RELAP plant model through a virtual control panel that represent the indicators and controls available to the modeled operations crew. The current plant model includes approximately 90 controls, 200 indicators, and 100 alarms. These control panel elements allow ADS-IDAC to represent most of the significant operator actions included in the emergency operating procedures (i.e., those actions that directly impact reactor plant and front line safety system status or conditions).

2.2 Crew Model

The ADS-IDAC Version 2.0 crew model currently includes a senior reactor operator (SRO) and a reactor operator (RO). Similar to an actual control room, each operator has unique roles and responsibilities within the IDAC model. Each modeled crew member includes a cognitive model that represents information perception, decision-making, and action execution processes. The crew model is capable of representing several decision-making and problem solving strategies, including passive and active information gathering, diagnosis, skill-, rule-, and knowledge-based actions, and procedure following. The model includes a number of dynamic and static performance influencing factors as
part of the set of factors and rules that simulate SRO and RO responses. Each operator also has a unique knowledge base that defines his or her knowledge about nuclear plant systems and operations.

After the first few hours of an accident, the control room decision making structure will change dramatically as emergency response facilities are activated. In general, command and control of the accident response will shift from the control room to an offsite emergency operations facility. The activation of additional onsite emergency response facilities such as a technical support center and an operations support center will further change the control decision making dynamics. For this reason the ADS-IDAC simulation model should only be considered to be valid when the primary decision making responsibility resides in the control room.

2.3 Dynamic Event Tree Scheduler

ADS-IDAC generates a discrete dynamic event tree (DDET) to explore the impact of component failures and operator behaviors on plant safety. The DDET is constructed by allowing changes in plant and operator states at discrete points in time. Plant state changes include component actuations and failures while operator state changes may include decisions and interactions with plant hardware. This approach is categorized as an implicit state transition approach [19] and permits analyst supplied model-based rules to be used to direct plant and operator state changes. A main limitation of this approach is that the computational effort needed to obtain a solution exponentially grows as the number of modeled component and operator states increases. This exponential growth is known as sequence explosion and can limit the practicality of the approach.

The ADS-IDAC scheduler and simulation control module balances solution completeness with computational effort by focusing computational effort on certain sequences. During an ADS-IDAC simulation, component and operator state changes are permitted to occur at discrete branching points. State changes are modeled by generating one or more sequence branches at each branching point. Specific branching points and the number of branches generated at each branching point are defined by a set of analyst-supplied branching rules. Branching rules can be constructed to include sequence initiators, hardware and process variables, operator actions, and software. A set of sequence termination rules are also identified to prevent excessive expansion of the DDET.

3 Cognitive Foundations of ADS-IDAC

The Information, Decision, and Action (IDA) cognitive model provides a framework for modeling individual operator behavior [6]. As the name suggests, the IDA model consists of three main processes – information perception and processing (I), decision-making (D), and action execution (A). The extension of the model to represent a crew of interacting operators is known as IDAC (where C stands for Crew).

3.1 Information Perception and Processing Module

A key feature of the ADS-IDAC simulation model is that all operator behaviors arise from perceived data rather than the direct output from the plant thermal-hydraulic plant model. Information drives all important operator behaviors in the IDAC model and influences goal and strategy selection, formulation of the operator’s event diagnosis and situational assessment, the activation of non-proceduralized actions, and the verification of the impact of recent operator actions. Observations of nuclear plant control room activities have determined that operators actively and passively gather information from a variety of
sources [20]. Active information gathering occurs when the operators specifically seek information about the status of a parameter, alarm, or component state. Active information collection generally refers to two main types of information collection – information gathering directed by procedures and periodic control panel scanning. Since the operator intends to gather and use actively collected information, this information would have a lower likelihood of being filtered. Passive information gathering occurs when the operator receives unanticipated information from another crew member or perceives the actuation of an alarm. All information, regardless of whether is collected actively or passively, is subject to biasing or distortion. If the operator uses this incomplete or inaccurate data to guide their decisions and actions, human error events may occur.

The ADS-IDAC information collection process generally directs the operator toward data that is perceived as most relevant to the current plant state. For example, if the operator has perceived a problem with the feed water system, attention generally will be focused on relevant parameters such as steam generator water levels and feed water flow rates. Because the operator does not possess infinite information processing capabilities, shifting focus to a new area will result in reduced attention to other areas. Therefore the dynamic information collection model causes the operator to spotlight information perceived to be relevant and to ignore information deemed less important. If the operator has developed an accurate situational assessment, this process serves to improve the efficiency of limited information processing capabilities. However, if the operator’s situational assessment is incorrect, the operator is more likely to miss important information and be less likely to mitigate an accident event.

Within the ADS-IDAC model, this focusing process is controlled by the operator’s control panel “scan queue”. The scan queue contains a listing of parameters that the operator monitors on a frequent basis. Scan queue parameters may include instruments, alarms, and component states. The number of items contained in the scan queue is limited by the individual capabilities of the operator, the amount of attention the operator can apply to information gathering, and the operator’s perception of the current plant state. As the number of monitored items in the scan queue increases, the operator improves his or her ability to accurately assess and diagnosis the plant state.

Two main factors determine which items are included in the operator’s scan queue: (1) the maximum size limit of the queue, and (2) the priority level of each item in the queue. The maximum size of the scan queue \( N_{\text{Scan Queue}} \) is determined by Equation 1.

\[
N_{\text{Scan Queue}} = N_{\text{Baseline}} \left( 1 - \gamma_1 PIF_{\text{Info Load}} \right) \left( 1 - \gamma_2 PIF_{\text{System Criticality}} \right)
\]

The constants \( N_{\text{Baseline}}, \gamma_1, \) and \( \gamma_2 \) are set in each operator’s profile and serve to calibrate the model to the desired operator performance level. \( N_{\text{Baseline}} \) establishes the maximum amount of information that can be contained in the scan queue while the \( \gamma \) factors (\( 0 < \gamma_i < 0.1 \)) set the sensitivity of the dynamic scan queue limit to the information load and system criticality. Performance Influencing Factors (PIFs) described in the second paper. Qualitatively, as the information load increases (as indicated by a high value of PIF_{Info Load}), the scan queue size will decrease to prevent an information overload. If there is a significant degradation in the plant level of safety (as indicated by a high value of PIF_{System Criticality}), the size of the scan queue decreases to force the operator to focus limited attention resources on the most serious problems. The relevance of a particular parameter to the perceived situational assessment is driven by the results of the diagnosis module (Section 4.2) and the relationship of the parameter to the diagnosis described in the component functional map (Section 4.3). Therefore the dynamic information collection
model causes the operator to spotlight information perceived to be relevant and to ignore information deemed less important. If the operator has developed an accurate situational assessment, this process serves to improve the efficiency of limited information processing capabilities. However, if the operator’s situational assessment is incorrect, the operator is more likely to miss important information and be less likely to mitigate an accident event.

All perceived information is stored in a memory repository for later use. Information that is available but not perceived is not placed in memory and is not cognitively available for later use. When the operator requires information, the memory is searched to determine if the information has already been perceived. If the information is stored in memory, the operator may use the stored data depending on the preferences and tendencies established in the operator’s profile. Using information already stored in memory can be more efficient for the crew because it is readily available and is not subject to further biasing, filtering, or communication errors. However, depending on the recency of the information, it may no longer accurately represent actual plant conditions.

3.2 Decision-Making Module

The decision-making process immediately follows the information processing stage and is the heart of the ADS-IDAC approach to crew modeling. During the decision-making process each operator assesses current plant conditions, evaluates his or her current high-level goal and associated strategy for achieving the goal in light of his or her situational assessment, identifies specific actions in accordance with the selected problem-solving strategy, and implements memorized skill- and rule-based activities through the activation of mental beliefs. Because the decision-making engine is based on an information-driven architecture, small variations in perceived information may lead significant changes in the output from the decision-making process. For example, biasing or ignoring a critical parameter or other piece of information may lead the crew to initiate inappropriate actions in response to an accident. It is this feature that enables ADS-IDAC to show promise for predicting and analyzing errors of commission.

The decision-making engine used in ADS-IDAC Version 2.0 is based largely on a recognition primed naturalistic decision making (RPD) model [21,22]. The RPD model was formulated to explain how experienced firefighters identify and carry out a course of action without having to compare the merits of alternative actions. This model was based in part on the observations that: (1) rarely did experienced fire ground commanders consider even two options concurrently, and (2) a search for an optimal choice could stall the decision maker long enough to result in loss of control of the operation. In general, decisions are made within the RPD framework by a process of matching the current situation to a familiar or prototypical situation based on experience. The environments where RPD methods have been used are very similar to the nuclear plant control room. Specifically, nuclear operators routinely face uncertain, dynamic situations; have competing goals; time stress; and high stakes. The RPD model places greater emphasis on the operator’s situational assessment. Therefore, factors that influence information perception and evaluation can have a large influence on the potential for error events. However, because the RPD model (as currently implemented in ADS-IDAC, Version 2.0) is unable to capture all reasonable and expected operator behaviors, it was necessary to augment the RPD framework in order to capture the inherent variability in the human decision making process. For example, variations in operator response times and the selection of control values for key plant parameters were simulated with stochastic models.
The ADS-IDAC decision-making engine supports three main functions: (1) selection of a high-level goal, (2) selection of an appropriate strategy to meet the high-level goal, and (3) formulation of mental beliefs, which represent discrete decisions and conclusions that operator has reached about the plant status.

### 3.2.1 Goal Selection

The selection and verification of a high-level goal is the one of the first steps in the decision-making process. ADS-IDAC Version 2.0 supports four high level goals:

- **Maintain normal operation** – a goal associated with normal operation and is the default goal for the operator. This goal is active when the operators perceive that key plant parameters are within a range normally associated with normal, full-power operation.
- **Monitoring** – This goal is activated when the operator has perceived that key plant parameters have diverged from the normal operating range, but the condition has not been diagnosed as an accident condition. This goal normally drives the crew to collect additional information to support a better assessment of plant status and take simple actions to restore normal operation. If key plant parameters return to the normal range, the operator can return to the “maintain normal operation goal”.
- **Troubleshoot abnormal conditions** – This goal is activated when the crew has a high level of confidence that an accident condition is developing, but is biased toward initially implementing knowledge-based actions rather than formal emergency procedures. If knowledge-based actions return key plant parameters to the normal range, the operator can return to the “maintain normal operation goal”.
- **Maintain global safety**.

The selection of a specific goal is based only on information perceived by the operator and information contained in the operator knowledge base.

### 3.2.2 Problem Solving Strategy Selection

The problem solving strategy establishes the overall approach the crew uses to achieve their selected goal. Four problem solving strategies are modeled to support the selected high level goals:

- **Wait and Monitor** – a passive information gathering strategy intended to improve the operator’s situational assessment by either actively or passively gathering additional information.
- **Instinctive Response** – a response strategy used to perform simple skill- or rule-based actions. These actions are activated by matching perceived information to memorized situation-response profiles.
- **Follow Written Procedures** – a strategy used to implement formal written procedures (e.g., abnormal or emergency operating procedures); and
- **Knowledge-Based Reasoning** – a strategy that uses a diagnostic process to guide crew actions in order to balance the flow of mass, momentum and energy within major plant systems.

The main determinant in selecting a strategy is the operator’s high level goal. To ensure that crew actions are coordinated, an order of precedence for problem solving strategies has been developed. The “Wait and Monitor” strategy has the lowest order of precedence and is only activated if no other problem solving strategy is active. The “Knowledge-Based Reasoning” and the “Follow Written Procedure” strategies are mutually exclusive.
and cannot be activated simultaneously. The “Instinctive Response” strategy actions will interrupt all other strategies. However, once the instinctive response actions are complete, the operator will return to the previous strategy.

3.2.3 Mental Beliefs

The implementation of the mental belief model in ADS-IDAC was inspired, in part, by the Recognition Primed Decision (RPD) model [22]. The key observations supporting the RPD model are that experienced decision-makers often use a pattern matching process when selecting an appropriate course of action and that the decision process does not usually involve simultaneous evaluation of multiple action alternatives. Pattern matching allows the decision-maker to relate his or her current situational assessment to a memorized prototypical situation. Consistent with the RPD model, ADS-IDAC mental beliefs are triggered by a pattern matching process that compares the operator’s perceived situational assessment to a set of prerequisites that define the activation conditions for the mental belief. An additional motivating factor for the implementation of mental beliefs is the observation that nuclear plant operators engage in important situational assessment and decision-making activities in parallel with written procedure following [23]. Mental beliefs provide also provide means to overlay decision-making tasks with procedure following in order to obtain more realistic operator behavior. For example, mental beliefs can be used to activate actions that are either not adequately described by plant procedures or may be performed in addition to procedural actions. Additionally, mental beliefs can be used to model continuous activities performed in parallel with written procedures.

Within ADS-IDAC, mental beliefs represent discrete decisions or conclusions that the operators reach based on their situational assessment. Three main types of mental beliefs are used in ADS-IDAC: (1) symptom-related mental beliefs that support the event diagnosis process, (2) rule-based mental beliefs that trigger memorized procedures, and (3) mental beliefs that represent intermediate decisions and are used as prerequisites for building more complex mental beliefs. Mental beliefs include a number of properties that describe the conditions required to activate the belief and resultant actions. Each mental belief is associated with prerequisite conditions that describe the prototypical situation that activates the belief. Prerequisites may include alarms, component states, parameter values, active procedures, and other mental beliefs. A confidence level activation threshold is used to specify how many of the specified prerequisite conditions must be met in order to activate the associated mental belief. An activation time delay and a reset time delay is specified for each belief. The activation time delay specifies the time lag between activation of the mental belief and execution of the associated action while the reset time delay is used to control repeated activations of a mental belief. The activation status of all mental beliefs is updated when the operator perceives new information.

Mental beliefs that are used to trigger memorized actions are linked to memorized procedures (i.e., skill- and rule-based actions typically performed by an operator without reference to a written procedure) within the operator knowledge base. The content of mental procedures is guided by two fundamental principles: (1) the actions can be performed without reference to a written procedure and (2) the procedure can be accomplished within a short time period (generally within a few minutes). The first principle limits mental procedures to relatively simple skill- or rule-based tasks. The second principle prevents a single task from monopolizing the operator’s attention during rapidly changing events. If needed, complex or lengthy tasks can be decomposed into smaller discrete tasks to meet these guiding principles. Upon activation of a mental belief, the associated mental procedure (if one is specified) is added to a queue list in the
operator’s memory. The order that queued mental procedures are executed depends on the specified priority level for the procedure (higher priority procedures are performed first) and the activation time delay.

4 Operator Knowledge Base Model

Within the ADS-IDAC Version 2.0 environment, cognitive processes for each operator are supported by a unique knowledge base. The knowledge base represents the memorized information, skills, and abilities of the operator. Specific items included in the knowledge representation include written and memorized procedures, diagnostic guidance, a functional decomposition model of reactor plant systems, and rules governing the activation mental beliefs.

4.1 Procedures

Two main types of procedures are used in ADS-IDAC: (1) written procedures, and (2) memorized mental procedures. Written procedures represent formal proceduralized guidance contained in normal, abnormal, and emergency operating procedures. As discussed in Section 3.2.3, memorized mental procedures represent the skill- and rule-based actions routinely used by the operators that do not require formal procedure guidance.

ADS-IDAC includes the capability to represent both the structure and content of many types of plant procedures. Procedure step execution follows a standard action-expectation-mitigation format [15]. In this procedure framework, each step specifies the following an operator action, a set of expectations that are anticipated to occur as a result of the action, and a mitigative action if the expectations are not met.

4.2 Diagnosis Model Description

An event-symptom matrix was constructed to specify the probabilistic relationship between a set of plant symptoms and events. The probability values in the matrix can be interpreted as the probability of observing a particular symptom given that a specific event has occurred. During the ADS-IDAC simulation, the operator’s confidence level for each plant symptom is periodically recalculated based on data obtained from the plant thermal-hydraulic model and the operator’s ability to perceive this data. Standard fuzzy-logic mathematical techniques have been used to evaluate the likelihood of plant events given a set of plant symptoms [24–26]. These techniques provide a lower and upper bound for the “membership value” of each event based on perceived symptoms. A limitation of the fuzzy inference method is its inability to discriminate among incompatible events when provided with contradictory symptom information. Additionally, a likely event identified by the method may only explain a subset of the observed symptoms. Consequently, a combination of two or more events may be needed to account for the full spectrum of observed symptoms. Although these limitations reduce the usefulness of this approach as a diagnostic operator aid, they provide an advantage within the ADS-IDAC environment since a larger spectrum of possible misdiagnoses may be examined.

The ADS-IDAC Version 2.0 diagnostic engine supports three functions: (1) the identification of an abnormal event requiring the initiation emergency operating procedures (EOPs), (2) the activation of knowledge-based actions based on the identification of mass, energy, or momentum flow imbalances in the reactor plant, and (3) the determination of a component’s relevance to the operator’s situational assessment.
4.3 Plant Functional Decomposition

Inspired by the Multilevel Flow Modeling technique [27], a functional component categorization based on the flow of energy, mass, and momentum is used in ADS-IDAC. In this modeling scheme, the reactor plant is viewed as a collection of mass, energy, and momentum flow paths, each containing sources and sinks. For example, in a PWR, the reactor core is a source of energy, while each steam generator is considered to be an energy sink. Because the reactor coolant system carries the energy released in the reactor core to the steam generators, any imbalance between energy production and removal will impact the reactor coolant energy state. In general, the following rules are used to identify mass, energy, and momentum imbalances:

- Energy flow imbalances are generally indicated by changes in temperature for subcooled single phase systems and changes in pressure for saturated two phase systems;
- Imbalances between mass sources and sinks are generally related to net inventory measures such as tank or vessel levels; and
- Momentum imbalances are generally indicated by changes in flow rates.

This modeling technique provides a powerful mechanism for linking components within a functional framework.

4.3.1 Identification of Key Plant System Groups and Functions

A key issue for developing a useful component functional mapping is the level of plant system decomposition used to organize energy, mass, and momentum flow paths. If the decomposition level is set too high, there will be insufficient resolution between component functional groups to differentiate key components from less important ones. If the decomposition level is set too low, the model will not represent the integrated plant functional model typically used by operators. Therefore, in order to functionally categorize plant components, it was first necessary to identify the flow path boundaries. Plant system groups are used to represent the boundaries for mass, energy, and momentum flow paths. The strong coupling among nuclear plant systems presents a significant challenge when identifying functional system groups. Within a nuclear plant, energy flow is often carried by moving fluids such as the reactor coolant or main steam systems; therefore, changes in mass flow rate can directly impact energy flow.

Consequently, coupling can result in imbalances in one flow type influencing a second flow type within the same system group or a connected system group. Coupling can also mask the cause of disruption in energy, mass, or momentum flow. For example, changes in reactor coolant system temperature due to an imbalance between reactor core power and turbine load (an energy flow imbalance) can result in variations in system volume due to the expansion or contraction of the coolant (which might be interpreted as a mass flow imbalance). An additional consideration is the diagnostic capability afforded by the system groupings. It is desirable to constrain the system group boundaries such that a flow imbalance within a grouping can be linked to a manageable number of potential causes. In practice, the identification of the system groups requires a balance between maximizing the linkage between plant components, minimizing undesirable coupling, and providing a high level of diagnosticity.

Decomposition into five major sub-systems was found to effectively balance the above objectives. The main PWR subsystems currently modeled are: the reactor coolant system, the pressurizer, steam generators (each considered a separate subsystem), the secondary
system (i.e., the turbine, main steam, main feed, and condenser systems), and the containment. This level of decomposition provides sufficient resolution to differentiate between the functions supported by control panel equipment while maintaining the ability to integrate high level plant functions. The operator’s assessment of the adequacy within each functional group is based on the perceived trends in energy, momentum, and energy flows. Three trend categories are currently used: stable, increasing, and decreasing. During normal, steady-state operation, the trend for all functional flow paths within each group is stable. Departure from a stable condition indicates that a deficiency in the affected flow path has occurred and mitigative measures are required to stabilize the condition.

4.3.2 Component Functional Map

The component map describes the functions associated with every control, indicator, and alarm available to the ADS-IDAC control room crew. Each operator knowledge base includes a unique component functional map in order to match operator behavior to a desired level of knowledge, skills, and abilities. Each component, indicator, and control provided on the ADS-IDAC control panel is assigned one or more functional identifiers that describe the type of balance that is associated with the item (energy, mass, or momentum), the system group that transports the energy, mass, or momentum flow, and how the component affects (or is associated with) the flow balance in the system group.

As an example of the functional coding method, consider the functional decomposition of the following three components: (1) the turbine trip alarm, (2) the reactor coolant system loop average temperature, and (3) the manual reactor scram switch. Each of these components is associated with the flow of energy within the reactor coolant system. Specifically, the turbine trip alarm indicates the possible loss of an energy sink from the reactor coolant system, the manual reactor scram switch can be used to reduce a significant energy source to the RCS, and a change in loop average temperature indicates an imbalance between energy sources and sinks. The component functional map allows each of these components to be meaningfully linked within the operator knowledge base.

5 Conclusions

Recent additions to the ADS-IDAC simulation model have dramatically improved its ability to realistically represent operator knowledge, skills, and problem-solving styles. In particular, improvements to the ADS-IDAC, Version 2, cognitive decision-making model based on Recognition-Primed Decision making have further strengthened the cognitive foundations of the underlying operator model and improved modeling capabilities for a range of problem-solving styles. Extensions of both the operator knowledge base and improvements to the nuclear plant simulation model have also greatly improved the realism and capabilities of this dynamic PRA approach. An example of this increased realism includes an information processing model capable of linking the salience of plant parameters to the operators’ situational assessment. The application of these improvements to nuclear plant operator human performance analysis is further examined in a second paper included in this volume.

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