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Human reliability modeling for the Next Generation System Code

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ABSTRACT

This paper derives the human reliability model requirements for the Next Generation System Code which will be utilized to determine risk-informed safety margins for nuclear power plants through dynamic probabilistic risk analysis. The proposed model is flexible, with the facility to apply a coarse-grain or a fine-grain structure based on the desired resolution level. The varying resolution is achieved by employing human reliability analysis methods with the demonstrated capability of handling human errors that occur during the execution of procedural activities for the coarse-grain structure and the advanced cognitive IDA/IDAC method for the fine-grain structure. The paper proposes improvements to the existing IDA/IDAC model to incorporate functionalities demanded by the NGSC. The improvements are derived for four modules of IDA/IDAC. A Bayesian belief network is constructed for the performance-shaping factors and the conditional probability for existence of each factor is computed from data collected from aviation and nuclear accidents. The influence of the performance-shaping factors on the strategy-selection process of the operator is also depicted. A foundation is laid for the development of mental models with a focus on NPP operation. The research lists the modifications/additions required for the IDA/IDAC method to enable the incorporation of Human Reliability Analysis (HRA) into the Next Generation System Code.

1. Introduction

Nuclear power plant simulators such as RELAP (Fletcher and Schultz, 1992), TRACE (Odar et al., 2004), and MELCOR (Gauntt et al., 2005) have been used widely for research, development, and training purposes. The scope of simulation in these simulators is limited by their efficacy and level of fidelity. These limitations include the lack of consideration of uncertainties in modeling the behavior of structures, systems, and components (SSCs); the dynamics of operations; and the human performance. There is also a rising need to upgrade the existing codes to the level of performance enabled by contemporary simulation research. The simulations are vital in understanding risks, training operators, and preparing ourselves for the future.

The Next Generation Simulator Code (NGSC) project is funded by Idaho National Laboratory (INL) and focuses on the development of capabilities to develop, demonstrate, and validate the next generation of system simulation and safety analysis codes. These included fluid flow homogenization, high-order-accurate solution scheme, validation, and uncertainty quantification. The prediction of human performance stands as one of the sources of uncertainty because it is highly dynamic and significantly varies with changing conditions—unlike the SSCs where the reliability has been realistically quantified. Human performance can be quantitatively represented in terms of Human Error Probability (HEP). The dynamic nature of operator performance is understood from the fact that the HEP can vary over a very broad range. For example, the probability of error of commission can be 0.0005 (when the man–machine interface is very clear and user friendly) to as high as 0.5 (under unclear man–machine interface designs and high-stress conditions) (Swain and Guttmann, 1983). The extent of this probability range depends on the diversity of contexts in which operators perform actions. The incorporation of a human performance model in the simulation will provide a major development towards reducing the uncertainty margins. This paper focuses on the selection of efficient Human Reliability Analysis (HRA) methods and on adapting them according to the needs of a simulation environment.

We propose a model for the human performance component of the NGSC code. This component is designed with a layered structure, with a complex (fine-grain) and simple (coarse-grain) model. The methodology adopted to achieve the above objective is as follows:

- Review existing HRA methods to identify the method suitable for NGSC.
- Propose improvements in the selected HRA method for incorporation in NGSC.
- List the requirements to integrate the improvements in existing NGSC code.

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2. Coarse-grain and fine-grain model

The coarse-grain model needs to satisfy three major requirements: (1) be less resource intensive in terms of volume of data and memory usage, (2) analyze the scenarios to an acceptable degree of resolution, and (3) be consistent with the fine-grain model. Consistent results should be obtained using both fine-grain and coarse-grain models (for definition of consistency, see Appendix A).

The proposed layered structure of HRA is targeted towards facilitating detailed simulations of nuclear accident scenarios. A task performed by the operator can be subdivided into several subtasks. For example, consider the task of starting a furnace and heating it up to 800 °C. This task is composed of a number of subtasks as shown in Table 1 (Hollnagel, 1998).

Each of the subtasks involves a human action that must be evaluated for probability of error occurrence. The errors can be categorized into errors of commission, errors of omission, and diagnosis errors. Errors of commission and omission that occur during procedural tasks will be handled by the coarse-grain structure of the HRA model while the diagnosis errors will be handled by the fine-grain structure. The design of a layered HRA model requires the following: (1) classification of the human action into the error category (Smidts et al., 1995; Shen et al., 1997) (based on this, the complexity can be evaluated and selection of the coarse/fine-grain HRA structure can be made), (2) interface to regulate switching between the two layers, (3) the computation of HEP in the two layers, and (4) an interface to assimilate the results obtained from each layer.

The first step towards building this layered structure is to select the HRA methods that would provide results to the required degree of resolution at the coarse- and fine-grain level. The methods must also be reliable, possessing characteristics to support their suitability, or have a proven record from past applications. For a standardized comparison, the necessary features of these methods were identified as (1) context importance, (2) standalone function-ability, (3) cognitive reasoning, (4) proven application, (5) repeatability and reproducibility, (6) available time importance, and (7) resource intensiveness.

The importance of the above characteristics is different for the coarse- and fine-grain model. The fine-grain model is focused on providing a detailed HRA analysis while the coarse-grain model is aimed at minimizing resources while providing a reliable HRA analysis. HRA methods that do well on context importance, cognitive reasoning, and available time importance will be favorable as fine-grain model methods. HRA methods that feature resource intensiveness, proven application, and repeatability will be preferred for building the coarse-grain model. The evaluation of the methods is done by comparing their functional and non-functional characteristics with the ideal HRA method which is suitable for comprehensive and dynamic HRA simulation.

The "context" is a significant factor in high-fidelity modeling of human error. The context can be considered to encompass the situational characteristics and human factor features of a plant. Performance Shaping Factors (PSFs) govern the major features of a context. This implies that a change in PSF status results in changes in the context. The ideal HRA method would closely model the context for both cognitive and procedural tasks. The degree of representation of the context increases with an increase in the number of PSFs in the model. The HCR (Moieni et al., 1994) method uses just three PSFs (operator experience, stress level, man–machine interface) while the IDA/IDAC method uses 50 PSFs (Chang and Mosleh, 2007a, 2007b, 2007c, 2007d, 2007e). Additionally, IDA/IDAC (Smidts et al., 1996; Chang and Mosleh, 1999) is highly applicable to modeling cognitive contexts. The ATHEANA method (Forester et al., 2007) does not have a defined realm of PSFs, but is oriented towards identifying the conditions/contexts that give rise to operators' unsafe acts. Thus, IDA/IDAC and ATHEANA are ranked high in their "context importance" characteristic. The THERP method (Swain and Guttmann, 1983), similar to ATHEANA, uses a broad range of PSFs under four major categories (external PSFs, stressor PSFs, and internal PSFs), however, it is restricted to only procedural tasks. Thus, its representation of cognitive contexts is limited. The SPAR-H (Gertman et al., 2005) method is similar to THERP with an improved application to cognitive contexts. However, it stills falls short of ATHEANA and IDA/IDAC in the "context importance" characteristic.

The "standalone function-ability" is the ability of an HRA method to cover the range of human activities to be analyzed without the support of another HRA method. An ideal HRA method for simulation entails high-fidelity modeling of the context and quantification of the HEP. ATHEANA is unable to meet these requirements and therefore ranks low on standalone function-ability. Likewise, the HCR method computes only a non-response probability and, as such, would need to be supplemented by other HRA methods. THERP, SPAR-H, and CREAM (Hollnagel, 1998) allow the representation of the context through PSFs and also possess a mechanism to quantify the HEP. IDA/IDAC depicts the cognitive context in detail but does not quantify the HEP. However, recent research on IDA/IDAC has lead to the development of ADS-IDAC. The ADS code generates event trees and helps in estimating accident scenarios based on the probabilities of each event. This probability is a reflection of the human error involvement at each event. For this to be feasible the ADS must be supported by a strong cognitive mechanism and IDA/IDAC provides it. Thus, IDA/IDAC shows potential as a standalone-functional method that could be used for simulation purposes.

The "cognitive reasoning" characteristic of an HRA method refers to its ability to replicate human thought and decision-making processes. This factor is very important in fine-grain analysis of HEP. In situations such as the following of Emergency Operation Procedures (EOPs) or Severe Accident Management Guidances (SAMGs), the cognitive reasoning of an operator is limited and not as important. The HCR method is not designed to capture an operator's cognitive thinking and therefore ranks very low in this characteristic. On the other extreme, the IDA/IDAC method is provided with modules that portray the information processing of an operator. Thus, it is ranked high in cognitive reasoning. The CREAM and ATHEANA methods analyze cognitive activities but fail to provide a robust cognitive mechanism to perform the analysis. THERP is suited for procedural tasks that have negligible cognitive reasoning. SPAR-H has a higher capability for representing cognitive reasoning compared to THERP.

The factor "proven application" provides evidence about the effectiveness of a method. The effectiveness of an HRA method can be gauged, in part, from previous benchmarking exercises. A comparison of the predictions made by HRA methods with results obtained from the Halden simulator data was performed in a recent benchmark exercise to understand the respective strengths

Table 1
Subtasks in starting a furnace. *Source*: extract from Hollnagel (1998).

Goal	Task step or activity
Prepare plant and services	Ensure plant is in a ready state Ensure that gas–oil supply is available Ensure that oxygen analysis system is working
Start air blower	Start air blower
Start oil pump	Start air pump
Heat to 800 °C	Increase temperature controller as per chart Monitor oxygen Monitor temperature When temperature reaches 800 °C, switch furnace to automatic control

and weaknesses of these methods (Lois et al., 2009). Results from this comparison follow. The positive influencing factors[1] (PIFs) identified by THERP matched the Halden simulator data. However, there were a few factors such as procedural guidance and task complexity which were not adequately identified in the THERP analysis for the Steam Generation Tube Rupture (SGTR) scenario studied. In addition to these benchmark results for THERP, it should be noted that the THERP method has been validated with a fair degree of accuracy in Brune et al. (1983) and Kirwan (1988, 1996). In the benchmark exercise, the ATHEANA method identified three out of the five PSFs observed to be important in the simulator study (Lois et al., 2009). It was noted that ATHEANA is capable of accurately deriving error-producing conditions from which insights for error reduction can be obtained. The application of ATHEANA in research is limited due to its high input requirements in the form of detailed context information. The CREAM method analyzed in Lois et al. (2009) provided a fair agreement to the simulator results. The SPAR-H method was found to be consistent with the results of the simulator study in Lois et al. (2009). In addition, it has been successfully applied for risk informed regulatory activities (Bell and Holroyd, 2009). The CREAM, SPRA-H and THERP methods have been implemented in software codes and can be found at http://www.ews.uiuc.edu/~serwy/cream/v0.6beta/ and http://scientech.cwfc.com/software/spokes/03_HRAcalculator.htm. The implementation makes these methods readily accessible. Based on this discussion, one can conclude that the THERP, SPAR-H, and CREAM methods should be placed in the high "proven application" category while ATHEANA should be placed in the moderate category.

The HCR method has been used in a benchmark exercise which preceded the Halden simulator data benchmark exercise along with THERP and other HRA methods such as the SLIM and the HEART methods (Poucet, 1988). The HCR method was found to perform well for diagnostic tasks that involved a time constraint. Its usage for tasks in the absence of time constraint is not recommended due to high variability in the results. Hence, HCR fares low on "proven application". The IDA/IDAC method has been used in dynamic probabilistic risk assessment to predict human error events. ADS-IDA has been utilized to study the SGTR accident (Shukri, 1997) while ADS-IDAC has been implemented in simulating a basic Loss of Feedwater Accident (LOFW) accident (Coyne, 2009). For the LOFW accident being studied, Coyne weighed the existing PSFs on a ten point scale. Weightage for factors was used to compute probabilities using equations/rules. These probabilities were in turn used to predict crew performance such as procedure execution, procedure skipping, and utilization of mental beliefs. The IDAC human performance model was successfully integrated with a nuclear power plant model for simulation purposes. The prior application of IDA/IDAC to simulation studies provides confidence in its application to HRA simulation research. Consequently, it ranks high in proven application.

"Repeatability and Reproducibility" (R&R) – repeatability is the ability of the HRA method to produce the same result when exercised by the same individual at different times (the conditions are maintained). Reproducibility is the ability of the HRA method to deliver the same result when used by different personnel at the same time. The prediction of human error through the use of expert opinion is known to produce varied results. This is because the opinion varies from person to person. Thus, methods using expert elicitation as a means of quantifying the HEP will rank low on reproducibility. Due to the low number of PSFs in the HCR method, information about the context is not captured in its entirety. This leads to multiple assumptions and variability in assessment from person to person. The same person may also provide varied results at different times because the assumptions may become distorted over time. This is observed in the benchmark study performed using HCR (Poucet, 1988). This gives HCR a low rating in R&R. Methods such as THERP and SPAR-H deal largely with procedural tasks and do not require as many assumptions as HCR. The CREAM method uses a broad HEP range for its control modes. The broader ranges will ensure that there is sufficient leeway for HEP computation. Thus, variations in analyst assumptions will not distort the final HEP to a great extent. Thus, THERP/SPAR-H and CREAM are ranked high on R&R. The ATHEANA method features more PSFs. This improves its "context importance" but introduces a large volume of deviation due to analysts' assumptions. The IDA/IDAC method is similar to ATHEANA due to the qualitative assessment of a large number of PSFs. Thus, ATHEANA and IDA/IDAC are considered to rank moderately in repeatability and reproducibility.

"Available time" refers to the time that the operator has to make decisions during accident-like events. Time constraint is considered a major factor in restricting the clear cognitive thinking process of the operator. The HCR method is based on estimating the non-response probability solely from time available to the operator to complete a diagnosis/task. Thus, the HCR method is rated high on "available time importance". A limited availability of time has psychological effects on the operator and THERP does not model such influence. However, SPAR-H, CREAM, and ATHEANA consider "available time" as one of the PSFs. The IDA/IDAC method captures the influence of "available time" through the "time constraint load" PSF. These methods give an almost equal importance to time availability and to the other PSFs they consider. Therefore, the rating is assigned as "moderate".

"Resource intensiveness" refers to the usage of software resources such as storage and computation time. The need for real-time simulation necessitates fast execution of the HRA methods. However, the greater the detail required in the HRA methods, the greater will be the use of these resources. The simplified structure of the HCR method causes it to have low resource requirements. The IDA method functions through three modules and the interaction between them. IDAC increases the complexity with analysis of scenarios with multiple operators. It is estimated that the resources to store data and accomplish interaction between modules to perform a detailed context analysis (as done by IDA/IDAC) will surpass the requirements for THERP, SPAR-H, CREAM, and ATHEANA. This is attributed to the fact that the level to which they model cognitive mechanisms is significantly less than IDA/IDAC's.

A comparison between the existing HRA methods is required to make an informed selection of the appropriate method for the fine-grain and coarse-grain structures. The characteristics and the pros/cons of the HRA methods discussed are shown in Table 2. Table 3 provides an overview of the suitability of the HRA methods with respect to the necessary features discussed above.

It is observed that the IDA/IDAC method satisfies the major requirements for a fine-grain structure model. Likewise, the THERP/SPAR-H models are apt for usage as the coarse-grain models. For analyses where the economy of computational requirements is more important than the resolution level of simulation, the THERP method can be used to handle the procedural tasks, while the SPAR-H method can be used to compute the HEP for the diagnostic tasks. Once again, the results can be assimilated using an interface component. Such an entirely coarse-grain approach could be considered as a pre-processing phase. The coarse/fine-grain approach could then be used on scenarios deemed important and which would necessitate further refined analysis.

[1] PIFs and PSFs are interchangeable denominations for the concept of performance shaping factor.

Table 2
Comparison of HRA methods. *Source*: adapted from Forester et al. (2006).

Methods	Characteristics	Pros/cons
HCR	Uses simulator measurements for estimating the operator response time	Simulator efficacy influences results
	HCR curves are used to estimate the nominal likelihood that the operator will take correct action	It is not a standalone method
	Uses simulator data and expert judgment	Requires several simulations to construct a dataset for analysis
	Used as a supporting tool with other quantification methods	Expert judgment can induce analyst-to-analyst variability
		Does not adequately represent the context
THERP	Quantification of pre-initiator and post-initiator Human Failure Events (HFEs)	Large number of PSFs covers all contexts
	Nominal HEPs calculated and modified by PSF multipliers	Widely applied, large data available
	Large range of potential PSFs used	Convenient for use in PRA
	Time reliability correlation (TRC) used to factor in the influence of time available	Suitable for HEP evaluation of errors of commission
	Expert judgment used wherever shortage of data	Resource intensive
		Analyst-to-analyst variability in evaluation
		Cognitive context is not given importance
		Does not account for the dependency of human performance reliability with time, uses generic TRC
SPAR-H	Uses eight broad PSFs	Simpler to use compared to THERP. Less resource intensive
	Simpler HRA method based on THERP	PSF resolution is inadequate
	Nominal error rates available for both diagnosis and action errors	Has a theoretical model that factors the cognitive reasoning in the analysis
		Does not consider the context to the extent of IDA method
		Does not account for the dependency of human performance reliability with time, uses generic TRC
		Chronologically new method, low usage until date
CREAM	Quantification is based on identifying the control mode of operator based on context	Considers the context of the analysis
	Considers the cognitive aspect of operator performance	Broad ranges of nominal HEP
	Nominal HEPs and PSF multipliers arrived at through documented literature tables	Analyst to analyst variability on making expert judgments exists
ATHEANA	The context is not tailored to fit pre-established PSFs as is done in many HRA methods	Gives importance to context. Focuses on the identification of error-forcing contexts
	Focused on analysis of post-initiator HFEs	Time will be considered if important in the context. Time is given due importance
	Expert judgment used for quantification since there are no established PSFs	ATHEANA framework fits the standard PRA framework for incorporating HFEs into PRA model
		Expert based quantification leads to variability
		Currently, applications of ATHEANA are limited
IDA/IDAC	Considers the human cognitive behavior through modules	Gives importance to the context
	Qualitative reasoning of human behavior	Framework not suitable for use with classical PRA
	Reasons operator behavior through goals, strategies, and information flow	Considers the mental/memory storage, overlooked in other HRA methods
	Considers the information storage process	Modular format of method is advantageous
		Quantification is unclear
		Lack of real-time data
		Benchmark study exists
		Extended to crew scenarios

3. IDA/IDAC

IDA is an HRA method that functions by modeling the cognitive aspect of operator performance. Its functioning is based on communication between three modules: the information module, the problem solving/decision making module, and the action module. The functioning of a nuclear reactor is supervised and controlled by a crew of specialists. The number of crew members can vary from four to ten with varying functions (Chang and Mosleh, 1999). For example, a nuclear reactor control room can have a shift supervisor, a control room supervisor, a primary operator, a secondary operator, a technical advisor, and an emergency communicator (Chang and Mosleh, 1999). During performance, each role imposes different cognitive loads on each individual. For simplicity, the roles of each of the crew members can be segregated into three broad categories: "decision maker", "action taker", or "consultant". The supervisors fall under the decision maker category when they make critical decisions. The plant operators function primarily as action takers. They become decision makers while performing routine diagnosis and troubleshooting activities. The technical advisors are grouped together under the consultant category.

Studies on IDA have enabled its application to scenarios that involve crew members with roles spread across all three categories (Chang and Mosleh, 1999, 2007a). The research led to the development of IDA-Crew. Previous simulations had been performed using ADS (Chang and Mosleh, 1998) which is a dynamic PRA software. ADS has been used over the years for risk analysis and its features have been constantly improved. ADS began with a simple NPP thermal–hydraulic model and handled primarily EOP-based operator responses. Several enhancements later, it now includes the ability to handle crew performance and graphical user interfaces. However, due to a lack of content in the knowledge base of the existing IDAC model, these studies had limitations in replicating operator behavior in accident simulations. Therefore, there is a need to introduce a mental model which will behave as a repertoire of the operator's knowledge. The mental model depicts the organization of data that an operator uses to make important decisions; the memory model depicts how that information is used by describing its movement across the internal divisions of the memory. Barring the depleted knowledge base drawback, studies have demonstrated the ability to use IDA/IDAC in simulating accidents to an acceptable degree (Coyne, 2009). The shortcomings can be overcome by improving the existing IDA/IDAC modules, develop-

Table 3
Compatibility of HRA methods.

Criteria	Levels	HCR	THERP	SPAR-H	CREAM	ATHEANA	IDA/IDAC
Context importance	Low	×					
	Moderate		×	×	×		
	High					×	×
Standalone function-ability	Low	×				×	
	Moderate						
	High		×	×	×		×
Cognitive reasoning	Very Low	×	×				
	Low			×			
	Moderate				×	×	
	High						×
Proven application	Low	×					
	Moderate					×	×
	High		×	×	×		
Repeatability and reproducibility	Low	×					
	Moderate					×	×
	High		×	×	×		
Available time importance	Low		×				
	Moderate			×	×	×	×
	High	×					
Resource intensiveness/resource requirements	Low	×					
	Moderate		×	×	×	×	
	High						×

ing the operator memory and mental models, and integrating the modules. The aforementioned studies make IDA/IDAC an appealing candidate to be used for the fine-grain structure component of the NGSC. The improved IDAC module will be designated IDAC-I (the "I" stands for "improved"). The following sections introduce and discuss the IDAC-I structure in detail and aim to derive the requirements for NGSC to facilitate its use.

4. IDAC-I architecture

The modules for the IDAC-I architecture are denoted as (1) the PS/DM module, (2) the PSF module, (3) the mental module, and (4) the memory module. Thus IDAC-I covers the Information and Decision Making modules of IDA. The action module will be handled by the coarse grain method used for the HRA analysis. Fig. 1 represents the interaction between the modules; the arrows indicate the direction of information flow. The operator is considered the central component of the architecture. The cognitive aspect of the operator is represented in the model through the interaction between the four modules mentioned above. The architecture does not consider the physical properties of the system (such as spatial location of the system components or an operator's physical abilities/disabilities) unless this information is also available in the operator's knowledge base. The functioning of the IDAC-I model is based on the processing of data in each individual module before being passed over to the next module in the connected sequence.

Earlier work on IDA (Smidts et al., 1996) considered the operator's memory to be divided into three categories: Working Memory

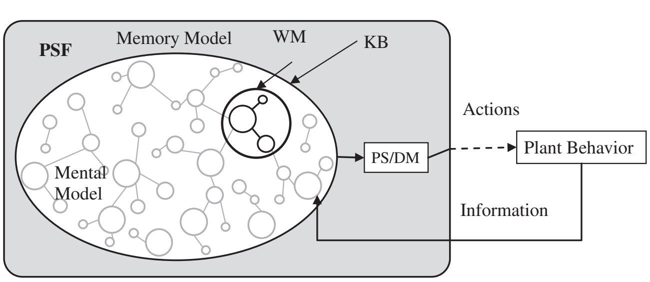

Fig. 1. IDA-I architecture.

(WM), Intermediate Memory (IM), and Knowledge Base (KB). The WM would store active information, the IM would contain the passive information ("back of the mind" information), and the KB would contain details acquired through experience and practice. The proposed architecture of IDAC-I does not model the intermediate memory. As per the existing IDA model, when new information enters the WM, the existing information is sent to IM. In IDAC-I, this information is time tagged and as time progresses, the information gradually moves back into the KB or is lost due to attrition. The longer the elapsed period of time since the usage of a piece of information, the longer it takes to retrieve that information from the operator's memory. The IM can be considered a subset of the KB in IDAC-I.

The plant behavior is described by system outputs that are noticeable by the operator (such as sensor readings, alarms, and indicators)—trends of physical variable variations. The information coming from the plant is altered by the existing PSF conditions (see Fig. 1). For example, the operator fatigue level or high time constraint may lead to incomplete assimilation of the sensor readings. These PSFs and their influences are discussed in greater detail in the next section of this paper. The IDAC-I model does not factor the sensory and physical disabilities of the operator as separate PSFs in its analysis. However, these PSFs are valid and could be incorporated after further research on the IDAC-I. Hearing impairment and visual disability are some of the operator's sensory PSFs that will influence the perceived information. This distorted information is temporarily stored in the operator's WM, while relevant information is retrieved from his KB for further processing. The KB is composed of a collection of mental models and these enable the operator to make rationalized decisions—an activity represented by the PS/DM module. The mental models discussed in Section 4.3 are represented as a knowledge web. Variables such as pressure, temperature, and equipment status form the nodes of this web and their relationships represent concepts. The operator's KB is replete with concepts learned through his training and experience. It is a repertoire of concepts and ideas of the operator from all domains of life. This includes his knowledge in plant operations as well as something completely different such as swimming skills. The actions are chosen based on the decisions made and the influence of the action is modulated due to the existing PSFs. For example, a "poor man machine interface design" can lead to an error of commission while executing a sequence of operations. Thus, the operator might have correctly diagnosed the problem but may commit an error due to the influence of PSFs. As per the current composition of IDAC-I, the action module is handled using well established HRA methods. The errors committed during actions are omission or commission errors and can be handled by simpler methods such as THERP/SPAR-H.

4.1. PSF causal graph

PSFs influence an operator's perception of information and modulate his diagnosis and decisions. Therefore, it is important to understand and model the PSFs and their influence. The intensity of a PSF depends on the existence of the other PSFs. Relationships between them can be positive, negative, or inconsequential. For example, Time Constraint Load (TCL) and Task Related Load (TRL) have a positive relationship with stress. An increase in either TCL or TRL will subsequently lead to an increase in an operator's stress level. On the other hand, higher operator ascendency can reduce stress levels because an operator with more experience is more capable of handling demanding situations (refer Chang and Mosleh, 1999 for PSF definitions). It is necessary to understand these relationships in order to decipher the PSF influence on the operator. This is done by constructing causal graphs.

4.1.1. Causal graph

Causal graphs are used to understand complex systems. They provide an analyst with the ability to identify and display relationships and root causes. An entity that functions to achieve an objective while interacting with the surroundings is defined as a system. It is comprised of several dynamic components which interact with the surroundings. For example, an eco-system's objective is to maintain a balance between available resources. Consider an example where variable *A* can affect variable *B* and variable *B* can in turn influence variable *C*. The causal graph is used to graphically represent these influences and a scrutiny of the completed causal graph can reveal the overall system behavior.

Table 4
IDAC performance shaping factors.

Criteria	Intrinsic	Extrinsic
Static	(perceived) Operator ascendancy (perceived) Complexity of strategy (perceived) Group cohesiveness (perceived) Operator group status (perceived) Decision maker ascendancy Decision responsibility load Favorable operating schedule	Procedure quality Team training Safety culture Man–machine interface[a]
Dynamic	**Time constraint load** **Task related load** **Passive information load** Perceived alarm importance Perceived number of alarms **Global condition assessment** Number of failed diagnosis Number of failed strategies Attention to current task Stress Confidence in action package Confidence in current diagnosis Perceived consequence severity of diagnosis	Alarm occurrence rate[a] Number of activated alarms[a] Control room distraction Importance of activated alarms[a]

Bold font: Major PSFs.
[a] System dependent factors.

Table 5
Supporting factors.

Actual number of alarms	Strategy selection	Action package
Sensor value	Succeeded actions to total actions ratio	Total expectation number
Actual value of physical parameter	Actual time taken to solve a problem	Diagnosis
Perceived physical parameter importance	Operator response	Strategy selection
Trends (increasing, decreasing: state high, low)	Reference value/safe value	Action cost/ consequences
EOP entry point		

Table 6
Decision factors.

Is strategy follow procedure/follow instruction?	Is sub-goal "Decide Action Package and Perform Recovery Action (DAP)?"	Is sub-goal find root cause and diagnosis?

A causal graph is composed of arrows connecting the variables indicating the influence of one variable on another. The variables are indicated in bubbles/nodes at the end of each arrow. The relationship between the variables is expressed in terms of statistical correlation calculated from data. A positive correlation indicates a direct relationship, i.e., both variables increase and decrease together. For instance, economy and the stock market are directly related. A negative correlation indicates an inverse relationship, i.e., if one variable increases then the other decreases and vice versa. For example, increase in gas mileage of a car decreases the number of fuel stops required.

PSFs are variously defined depending on the field of application. Groth arrived at a hierarchical PSF set with orthogonally defined PSFs that can be used for modeling based on the required resolution level. This paper's dynamic model is derived from IDAC and therefore, to maintain consistency with the previous research, the IDAC PSF set is used. The PSF categories can be collapsed or expanded depending on the level of data available for analysis (Groth, 2009). In this paper, the causal graph is formed from the rules in the IDAC framework (Chang and Mosleh, 1999) and is validated using the data collected from nuclear and aviation accidents.

The IDAC-I PSF set is represented in Table 4, adopted from the ADS-IDA Crew technical research report (Chang and Mosleh, 1999) which contains 28 of the 50 PSFs mentioned in Chang and Mosleh (2007b). The PSFs are organized according to two dimensions: the "intrinsic and extrinsic" and the "static and dynamic". The 28 PSFs are considered in addition to the 17 supporting factors and three decision factors. The supporting factors and decision factors are shown in Tables 5 and 6. Supporting factors are not identified as PSFs in the IDAC literature and they have been derived

$$10-\text{Score}=\left(\begin{array}{l}0.5\times\dfrac{10-\text{Perceived Alarm Number}}{10}\\+0.5\times\dfrac{10-\text{Perceived Alarm Importance}}{10}\end{array}\right)\times\left[\begin{array}{l}0.2\times(10-\text{Number of Activated Alarms})\\+0.2\times(10-\text{Total Importance of Activated Alarms})\\+0.4\times(10-\text{Maximum Alarm Occurrence Rate})\\+0.2\times\text{Operator Ascendancy}\end{array}\right]$$

Fig. 2. Passive information load score (Chang and Mosleh, 1999).

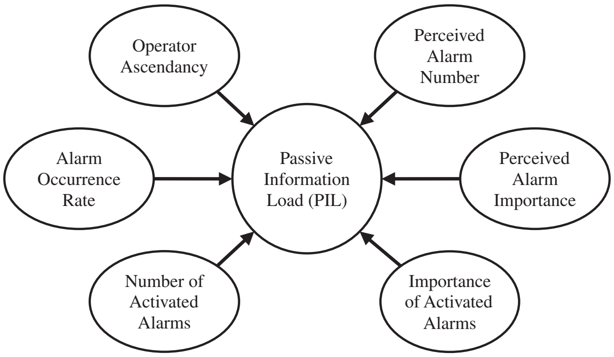

Fig. 3. Causal graph for "Passive Information Load".

from Chang and Mosleh (1999). They contain reference values that the operator records such as actual number of alarms activated, flow sensor values, and EOP entry point. They are also composed of details such as the current strategy selected and the current diagnosis. They have high significance in simulation because they connect the PSFs to observations and information directly related to the reactor and operator performance. The decision factors are ones that direct the influence of one PSF on another depending on criteria such as the "current strategy selected" or the "diagnosis made". Thus, these factors act like conditional statements in an algorithm and enable deciding the direction in which the influence of one PSF to other PSFs is to be extended.

Having classified the PSFs into static versus dynamic, intrinsic versus extrinsic, and identified the supporting factors and the decision factors, one can next build a causal graph from the rules linking these various concepts as defined in Chang and Mosleh (1999). As an example, consider the following rule extracted from Chang and Mosleh (1999) (see Fig. 2). The rule specifies how to calculate a score for "Passive Information Load". This score varies between 0 and 10. When the score is equal to "0", the passive information load is deemed minimum. It is maximum when the score is equal to "10". From Fig. 2, it can be seen that the score, and hence "Passive Information Load", depends on the "Perceived Alarm Number", "Perceived Alarm Importance", "Number of Activated Alarms", "Total Importance of Activated Alarm", "Maximum Alarm Occurrence Rate", and "Operator Ascendancy".

The causal relations extracted from the rules in Chang and Mosleh (1999) are then translated into the partial causal graph depicted in Fig. 3. Presence of a PSF or supporting factor in the rule is translated into a directed edge of the causal graph.

The rule for attention to current task also extracted from Chang and Mosleh (1999) is shown in Fig. 4.

The causal graph constructed from the attention to current task rule is shown in Fig. 5 and illustrates the use of decision nodes representing conditions such as "If strategy is FP or FI" or "If Strategy is Neither FP nor FI".

$$\text{Score} = \begin{cases} \text{if strategy is neither FP nor FI} & \begin{pmatrix} 0.2\times\text{Perceived Consequence/Severity Associate with Current Diagnosis} \\ +0.1\times\text{Confidence in Current Diagnosis} \\ +0.1\times\text{Perceived Strategy Complexity} \\ +0.2\times\text{Confidence in Current Action Package} \\ +0.1\times\text{Decision Responsibility Load of Current Strategy} \\ +0.3\times(\text{OF}) \end{pmatrix} \\ \text{if strategy is FP or FI} & \begin{pmatrix} 0.2\times\text{Procedure Importance} \\ +0.1\times\text{Complexity of Current Strategy} \\ +0.1\times\text{Decision Responsibility Load of Current Strategy} \\ +0.6\times(\text{OF}) \end{pmatrix} \end{cases}$$

where:

$$\begin{aligned} \text{OF} = {} & 0.4\times\text{Time Constraint Load in Problem Solving} \\ & +0.4\times\text{Task Related Load} \\ & +0.2\times\text{Passive Information Load} \end{aligned}$$

Fig. 4. Attention to current task score (Chang and Mosleh, 1999).

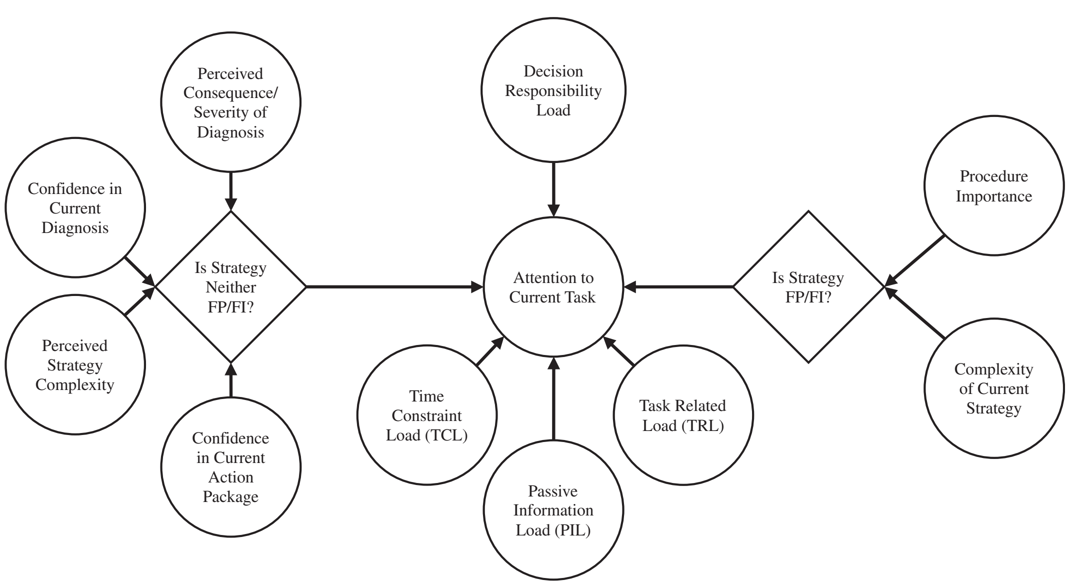

Fig. 5. Causal graph for "Attention to Current Task".

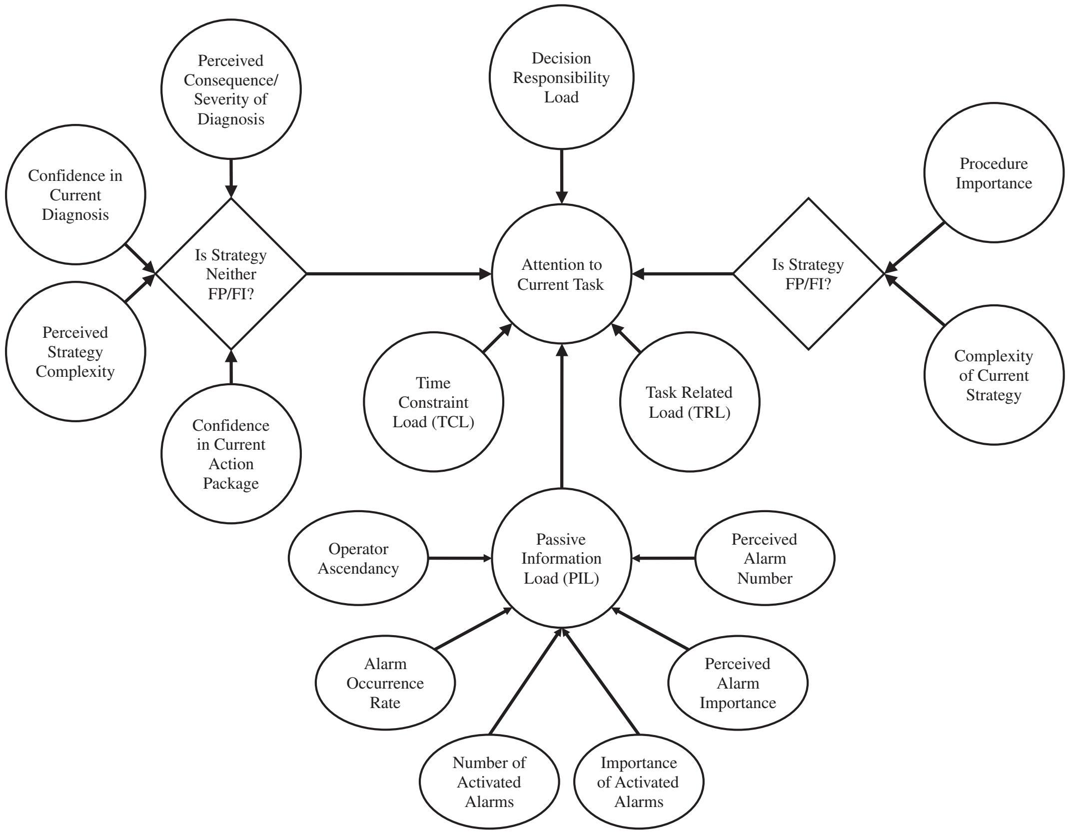

Fig. 6. Assembling the two partial casual graphs corresponding to “Passive Information Load” and “Attention to Current Task”.

Chang and Mosleh (1999) contains 14 rules. Each rule is transformed through this procedure into a corresponding partial causal graph. The partial causal graphs are then easily assembled as shown in Fig. 6. Fig. 7 displays the overlay of the partial causal graphs for “Passive Information Load” and “Attention to Current Task” onto the complete causal graph.

Fig. 8 shows the complete causal graph. The causal graph can be used to identify the system-dependent factors. To achieve this, the hierarchical relationship between factors needs to be traced. For example, the stress level is influenced by the passive information load—which is dependent on the number of alarms that may be activated at an instant. The number of activated alarms can be retrieved from data collected from the simulation code. Thus, the system-dependent variables form an important part of the interface between the simulation code and the PSF module.

From the causal graph, we can infer that certain PSFs seem to be more heavily influenced by other factors. These include the TCL, TRL, Passive Information Load (PIL), attention to task, global condition assessment, and stress level. These are referred to as the major PSFs. The large influence is inferred from the larger number of “incoming links” to these PSFs as compared to non-major PSFs. From a simulation perspective, the non-major PSFs and supporting factors that influence the major PSFs are important because they represent important inputs read from the system (reactor). The non-major PSFs such as “number of failed strategies” and “number of failed diagnosis” are a measure of the operator’s effectiveness and are significant for HEP assessment. These non-major PSFs describe actual scenario information and are tied to major PSFs through the causal graph.

The decision factors are represented in the graph by diamond-shaped blocks. For example, according to the causal graph, if the sub-goal is in DAP mode, then the confidence of the operator in the current diagnosis will influence the TCL.

The strength of relationships between factors in the causal graph must be quantified to render them usable for the NGSC simulation code. Two metrics are used towards the quantification process: (1) the amount of positive or negative correlation (the strength of the links in the causal graph) and (2) the probability of existence of a PSF in an accident scenario. Calculation of the aforementioned metrics requires application of statistical procedures to data collected from real-life scenarios. The study was performed with data collected from two sources: nuclear accidents and aviation accidents. Due to confidentiality reasons, the availability of data from nuclear accidents is limited and data is difficult to access. Aviation accident data are more abundant and easier to access. The study was performed using the nuclear accident data collected by Groth (2009). This paper presents a methodology to create a Bayesian Belief Network (BBN) using data collected from human error events and the causal graph in Fig. 8.

4.1.2. Bayesian belief network

The choice of a model for the representation of the relationships between PSFs is largely based on which machine learning method can most accurately model the causal graph structure. Prospective models include decision trees, artificial neural networks (NNs), support vector machines (SVMs), and BBNs. Decision trees are created by splitting source data based on some characteristic of the data. They are best used in instances of attribute–value pairs and therefore do not accurately model the causal graph structure (Mitchell, 1997). Conversely, the NN structure is applicable because NN nodes can be branched as necessary to model complex relationships. Also, these relationships can be based on statistical probabilities, useful in risk analysis (Specht, 1990). However, in most NN methods, information can only flow in one direction and it is impossible to insert dynamic behavior (Zio, 2007). Some work on recurrent neural networks (RNNs) has been performed,

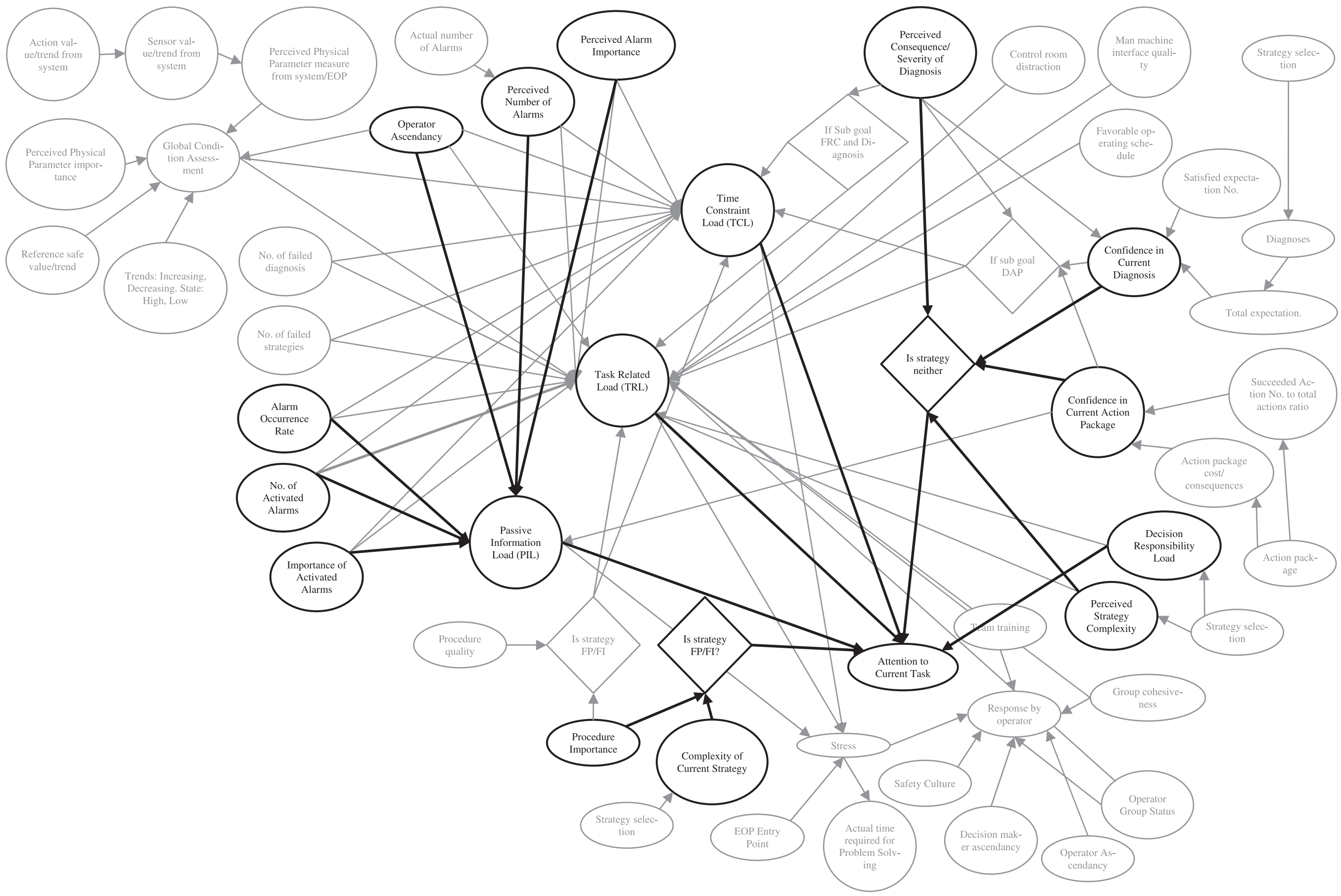

Fig. 7. Relationship between partial casual graphs and complete graph.

where the relationships between nodes are formed in a way that allows the model to exhibit dynamic behavior and process an arbitrary sequence of events. However, this method cannot be scaled to large datasets and has yet to be adopted into widespread practice (Zio, 2007). Finally, due to their inherent flexibility, SVMs can generate a model with the structure of the causal graph, but similar to RNNs, SVMs do not scale well to large datasets (Bennett and Campbell, 2000).

Of these four types, both BBNs and RNNs have been used in PRA (Modarres et al., 1999; Zio, 2007). Both BBNs and NNs are useful in HRA because new data can be added to the model as it becomes available. This is an especially important characteristic for HRA because data can originate from multiple, simultaneously unavailable sources. Unlike SVMs, BBNs can be used to study the behavior of systems where multiple factors simultaneously exist while providing conditional probabilities of occurrence for each factor in the network. The usefulness of a BBN increases with an increasing amount of data, rendering them meaningless for limited datasets. However, BBNs can expand geometrically and become difficult to read with an increasing number of factors. BBNs were chosen because they can accurately model the causal graph structure, the number of factors to be modeled is limited, they are able to quantitatively correlate factors within the model, and because they are able to process large amounts of data.

A BBN is a directed graph that is widely used to represent abstract concepts and to reason on uncertainties. BBNs are used across various fields such as medical research, network risk-propagation assessment, and socio-ecological research. Abramson developed a knowledge-based system called ARCO1 that modeled the market for crude oil in the form of a belief network (Abramson, 1994). Scenario generation along with Monte Carlo analysis was used for predicting oil prices. BBNs have been used to study the population variations of endangered species. This has been done by modeling the habitat and the growth patterns of the subject species (Abramson, 1994). The study involved the construction of a causal graph and subsequent quantification. Trucco developed a novel method towards combining the human organizational factors and risk analysis. This study has been applied in a case study and can be expanded to other fields. The behavior of the Maritime Transport System is studied by modeling the influence between different factors using BBNs (Trucco et al., 2008).

BBN has been used in Groth (2009) to build the “6 bubble model”, “9 bubble model”, and the “mixed expert/data model”. These models were developed based on the level and sources of data used. The “6 bubble model” used the data obtained from an NRC workshop to construct the model while the “mixed expert/data model” used a large set of over 30 PSFs. The “9 bubble model” was an intermediate model aimed at the identification of error contexts.

The BBN provides a probability table for each node/factor in the network that represents the state probability of the corresponding node/factor. The BBNs can be constructed using mathematical techniques (Groth, 2009). These mathematical concepts have been implemented in commercial software that facilitate efficient creation of BBNs. The GeNIe 2.0 software developed at the Decision Systems Laboratory at the University of Pittsburgh (Druzdzel, 1999) has been used to generate the BBN for this paper. It is open source software implemented in Visual C++. The procedure used to create the BBN is explained in the following paragraphs.

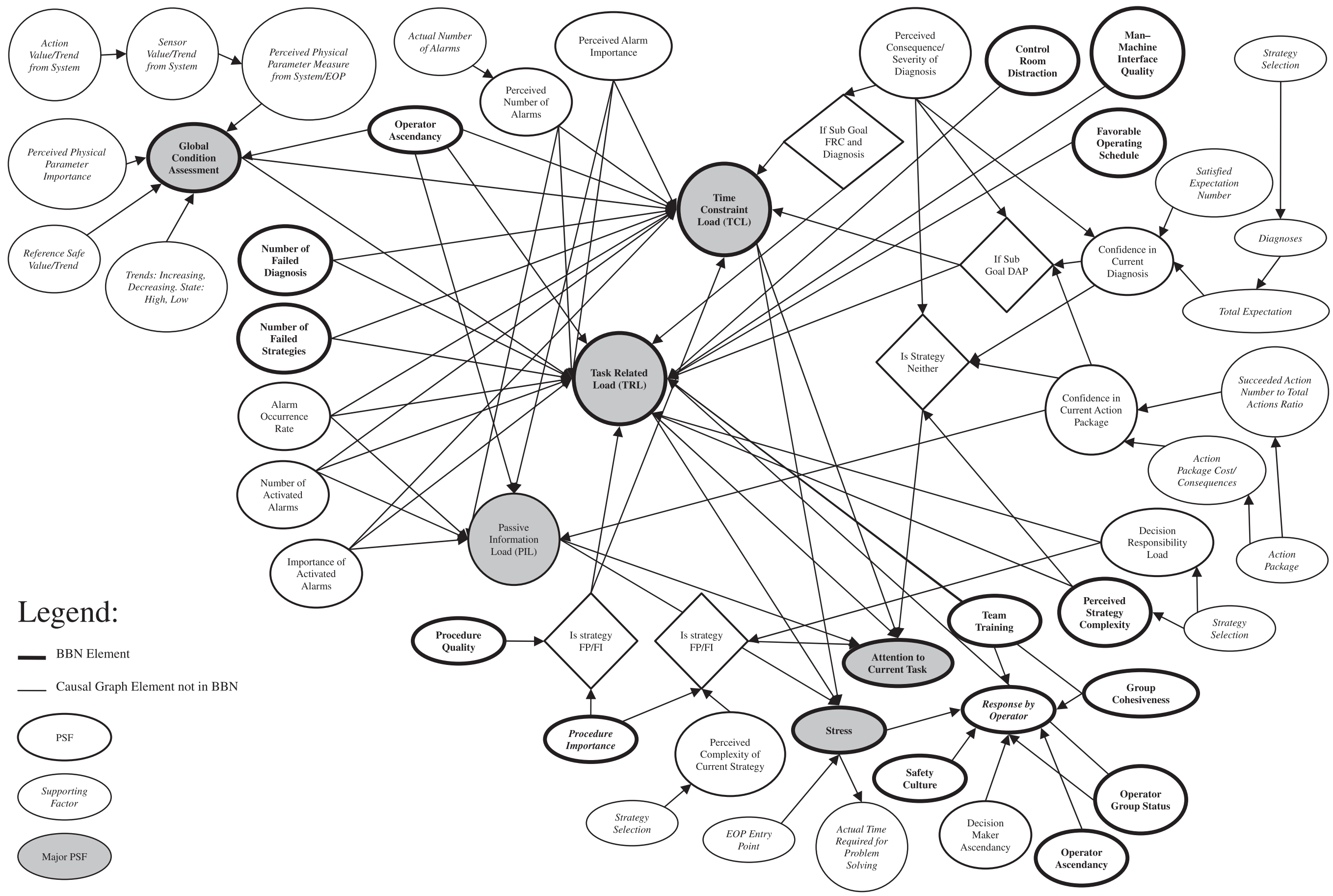

Fig. 8. PSF causal graph.

4.1.2.1. Simplification of the causal graph. The causal graph in Fig. 8 provides the initial structure of the BBN. The final BBN structure is represented by the simplified causal graph in Fig. 9. The simplified causal graph incorporates only those PSFs that are observable in the nuclear and aviation data discussed in Sections 4.1.2.2 and 4.1.2.3. The simplified causal graph includes five of the six "Major PSFs". Unfortunately, there is not enough data related to "Passive Information Load" to include this major PSF in the simplified network. Supporting factors and various minor PSFs are not included in the simplified causal graph, again because of inadequate data. Our experience shows that such detailed information is currently not being recorded in the description of the events examined. Additionally, the simplified network combines "Procedure Quality" and "Procedure Importance" into one PSF because the two factors cannot be distinguished in the available data. Figs. 8 and 9 show the full causal graph and the resulting simplified causal graph that is based on the available data and is used for BBN analysis. It should be noted that more detailed records would allow us to retain a final BBN structure that would be closer to the full causal graph.

4.1.2.2. Bayesian belief network for nuclear accidents. Having obtained the structure of the BBN, we next calculate the node probabilities and the conditional probabilities for BBN nodes using nuclear accident data.

4.1.2.2.1. Nuclear accident data collection. To populate the BBN, the first step is to identify relevant data sources. Possible nuclear data sources include the Human Event Repository and Analysis (HERA) (Hallbert et al., 2006, 2007), Licensee Event Reports (LERs), Inspection Reports (IRs), and Augmented Inspection Team reports (AITs). In this paper, the data was borrowed directly from the research in Groth (2009). Groth (2009) used mostly data extracted from the HERA event repository.

The goal during the data-collection process is to identify the existence and the magnitude of PSFs during accidents. Existence of a PSF is defined as a condition where its presence has a detrimental or positive effect on the operator performance. Hence, while reviewing scenarios, conditions such as excessive TCL and excessive TRL will signify presence of the corresponding PSFs. Groth identified the presence or absence of symptoms of events in 144 nuclear accident scenarios involving human error. However, the varying intensities of the symptoms were not identified in her study.

4.1.2.2.2. Mapping the data to the IDAC PSF set. Given that Groth had encoded the nuclear accident data using a set of observed symptoms, the encoded data from Groth (2009) had to be translated in terms of the IDAC PSF set. This translation was performed using a translation key which expresses the underlying symptoms in terms of IDAC PSFs. A portion of the translation key is presented in Table 7. A resulting sample of nuclear events reanalyzed in terms of IDAC PSFs is presented in Table 8.

4.1.2.2.3. Calculation of BBN conditional probabilities and node probabilities from IDAC PSF data. The node probabilities and strength of the relationships between PSFs was established using the data thus obtained and the GeNIe and Minitab software. The GeNIe software learned the mapped data to calculate the conditional probabilities of the PSFs. The GeNIe input file was prepared from the mapped data and fed into the software. The "learn parameter" feature of the GeNIe software allows the input data to get assigned to their respective parameters (nodes) on the causal graph.

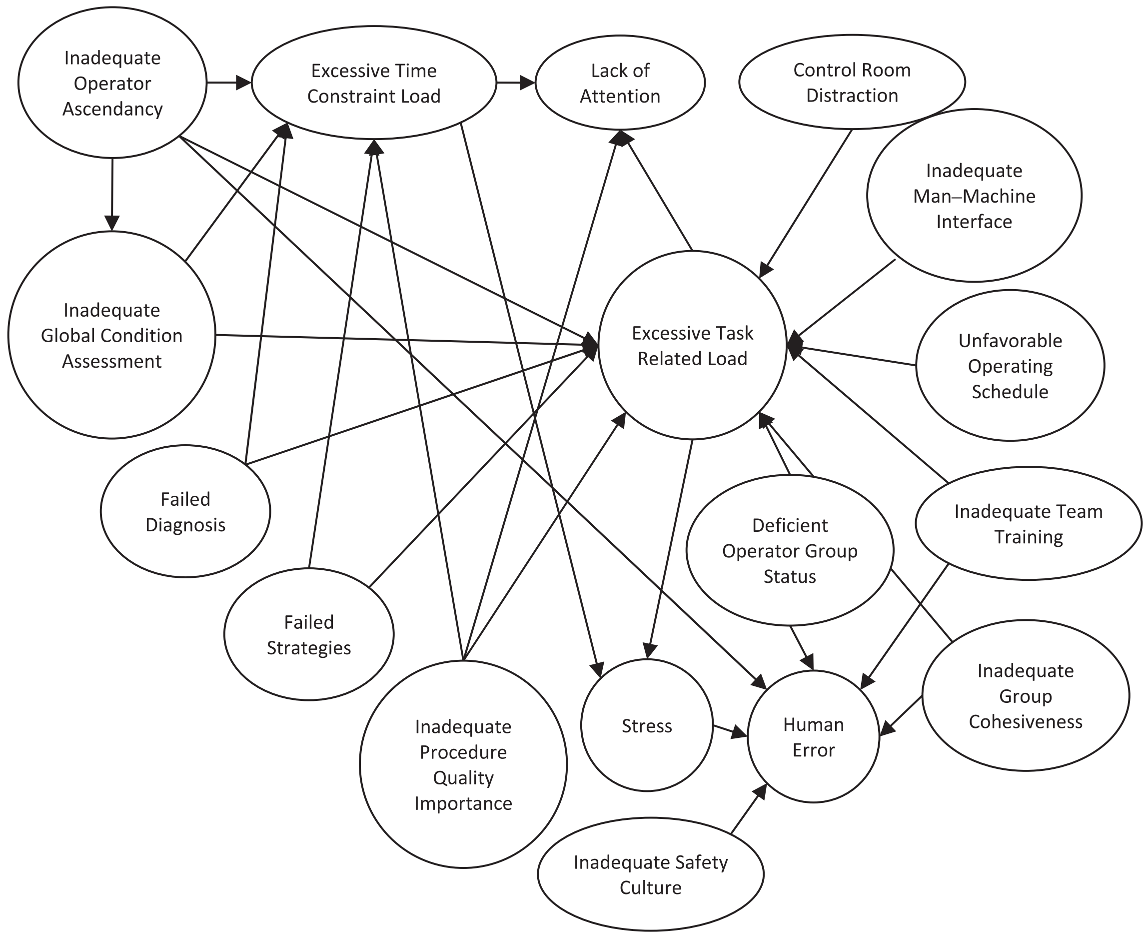

Fig. 9. Causal Graph for BBN analysis.

Table 7
Sample of PSF dataset for nuclear accidents.

IDAC PSFs	Symptoms observed in events
Time constraint load	Limited time to focus on events Time pressure to complete task
Stress	High stress
Task-related load	Demands that the operator combine information from different parts of the process Demands to track and memorize information Simultaneous tasks with high attention demands Simultaneous maintenance tasks
...	...

Table 8
Sample of PSF dataset for nuclear accidents (where S. No. signifies the scenario number).

S. no.	Time constraint load	Stress	Task-related loading	Training	Group cohesiveness	MMI	Control room distractions	...
1	1	1	0	1	1	0	0	...
2	0	1	1	1	1	0	0	...
3	0	1	0	1	1	0	0	...
4	0	0	0	0	1	0	0	...
...	...	...	...	...	...	...	...	...

Simultaneously, the conditional probabilities of each of the factors are also calculated. Fig. 10 shows the probability of occurrence of the PSFs in two states: present and absent. The PSFs are reworded in the BBN to make the chart more self-explanatory. For example, procedure quality importance, safety culture, operating schedule, etc. are replaced by inadequate procedure quality importance, inadequate safety culture, and unfavorable operating schedule, respectively. It is noticed that inadequacies in team training, safety culture, operator ascendancy, and high stress have a greater than 50% probability of being present in cases where a human error has occurred. It must be remembered that the status of a PSF is captured under two categories: present and absent. Therefore, while recording the data, the presence of a PSF is acknowledged in the "present" category while cases in which the evidence is inconclusive are classified under the "absent" category. Fig. 10 also shows the strength of influence between the individual PSFs. This can be validated against the correlation between the factors calculated from the statistical software Minitab. The correlation of Stress with Excessive Time Constraint Load is 0.49, and the correlation of Stress with Excessive Task Related Load is 0.48. These relationships are represented by thick lines in Fig. 10.

The representation using BBN helps to identify the primary PSFs that prominently occur in nuclear accidents involving human error. This information can be used in training to simulate scenarios where these PSFs are prevalent, observe human performance, and devise training methods accordingly.

4.1.2.3. Bayesian belief network for aviation data.

The building of a BBN for aviation required the following stages.

4.1.2.3.1. Collection of data. The data was collected from Aviation Accident Reports (AARs). A total of 81 aviation accidents

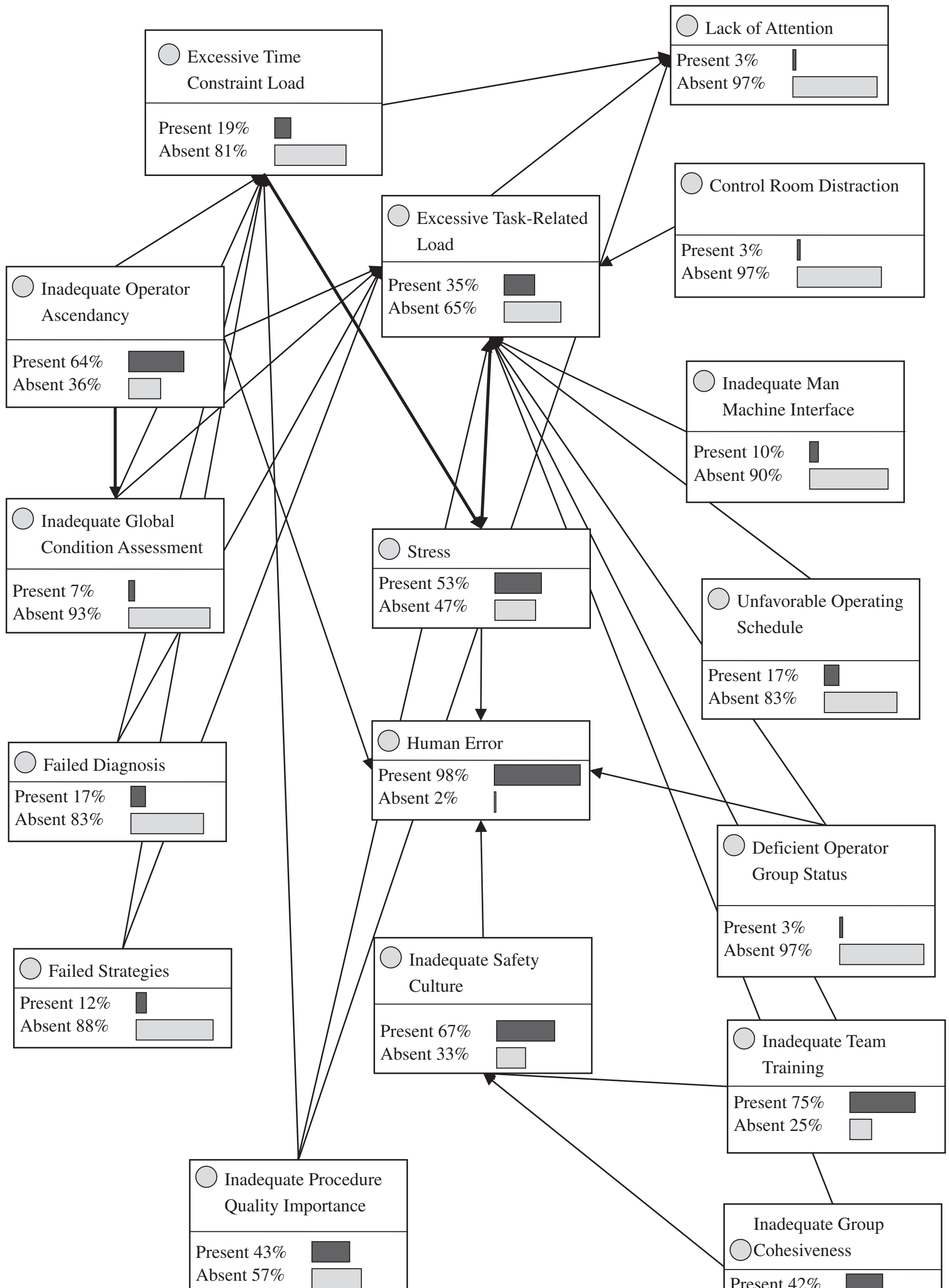

Fig. 10. PSFs BBN for nuclear accidents.

that involved human error were reviewed. These featured human errors either at the "sharp end" (errors in which pilots were directly involved) or the "blunt end" (errors in which indirect factors such as organization culture and machine interface design were involved). The database of reports of the accidents is available at http://www.ntsb.gov/investigations/reports_aviation.html.

4.1.2.3.2. Identification of the IDAC PSF values. Because the data was being directly collected from the literature, the reviewed data was captured to the desired IDAC PSF set and no mapping was necessary. An example is shown below, taken from an aircraft accident report (National Transportation Safety Board, 2008).

Table 9
Sample mapping of aviation data to IDAC PSF set.

Time constraint load	Stress	Task-related load	Training	Group cohesiveness	Safety culture	...
0	0	0	1	1	1	...

"The National Transportation Safety Board determined that the probable cause of this accident was the pilots' mismanagement of an abnormal flight control situation through improper actions, including failing to control airspeed and to prioritize control of the airplane, and **lack of crew coordination**.

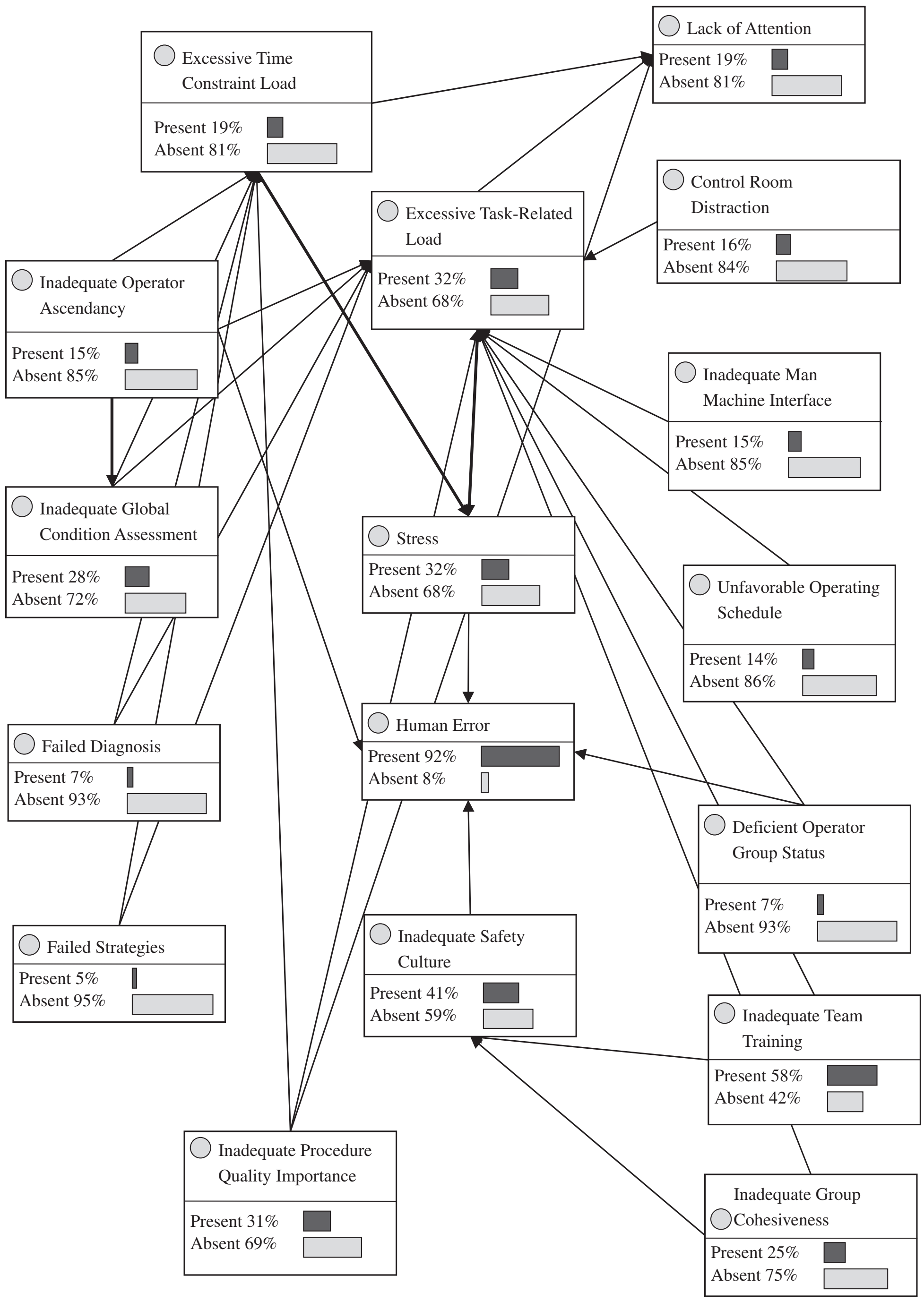

Fig. 11. PSFs BBN for aviation accidents.

Contributing to the accident were [the airline's] operational safety deficiencies, including the **inadequate checkrides** administered by [the airline's] chief pilot/check airman, and the [regulatory agency's] failure to detect and correct those deficiencies, which placed a pilot who **inadequately emphasized safety** in the position of company chief pilot and designated check airman and placed an **ill-prepared pilot** in the first officer's seat." [emphasis added]

This was mapped to the PSF set as shown in Table 9.

4.1.2.3.3. Calculation of BBN conditional probabilities and node probabilities from IDAC PSF data. The BBN structure built in Section 4.1.2.1 was reused. The statistical analysis was then performed on the encoded aviation data. Similar, to the case of the nuclear data, the node probabilities and the strength of the relationships were developed using GeNIe software (for conditional probabilities and node probabilities) and Minitab (for correlation coefficients). The BBN constructed for the aviation data is shown in Fig. 11. The correlation of Stress with Excessive Time Constraint Load is 0.67, and the correlation of Stress with Excessive Task Related Load is 0.56. These relationships are represented by thick lines in Fig. 11.

Inferences were deduced from a comparison of the analysis of the two data sets. The general pattern of PSF state probabilities and the strength-of-influence pattern for both nuclear and aviation BBNs is in many cases similar, indicating similar interaction between the PSFs in both cases.

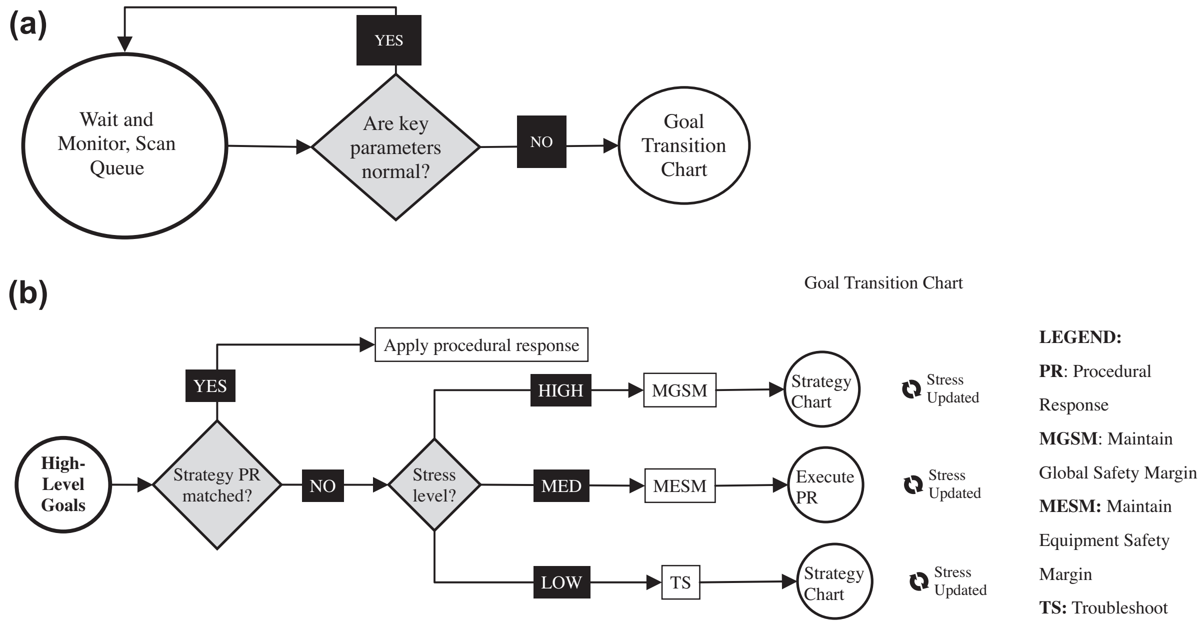

Fig. 12. Strategy selection model (a).

In nuclear accidents, events can unfold over several hours, enabling an operator to demonstrate his/her ascendancy qualities. For example, the Chernobyl accident lasted over 28 h. The initiating act (at 1:06 am on April 25, 1986) was the beginning of a test procedure to check if one of the turbines could supply power to feedwater pumps until standby diesel generators came online in case of a power failure. The fires resulting from an explosion during the course of the accident were finally brought under control at 5:00 am on April 26, 1986. However, in aviation, the accident span is only a few minutes. The ascendancy qualities are either not recorded in the accident reports or not even demonstrated in the first place. This could explain the dissimilarity in the operator ascendancy state probability between the nuclear and aviation BBNs. Another limitation noticed in the BBN is that in both cases the observations of deficient operator group status are low. This is mainly due to inconclusive evidence from the literature reviews of the existence of this inadequacy. More informative BBNs can be constructed as and when more data becomes available. Once an appreciable amount of data is available, more reliable conditional probabilities of the PSFs can be arrived at. The BBN will enable the HRA model to compare existing conditions in the simulated scenario and identify error-likely scenarios based on the database of conditional probabilities.

In this paper, software is used to construct the BBN. However, to make the model suitable for NGSC, the BBN development code has to be built into the model by coupling it with the source code of the IDAC-I. Alternatively, the same external software can be coupled with the IDAC-I source code.

The requirements to incorporate the PSF causal model in NGSC are:

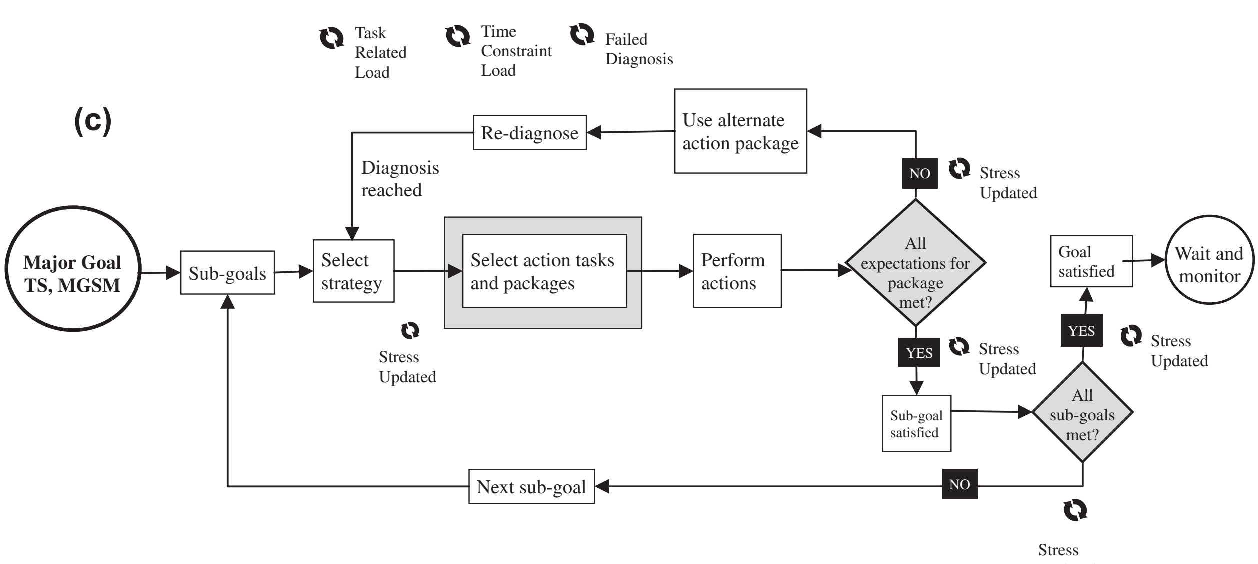

Fig. 13. Strategy selection model (b).

- Creating a larger database of accidents through simulator experiments, analyzing licensee event reports, augmented investigation reports, etc. using the IDAC PSF set. Data for supporting factors and non-major PSFs need to be recorded to eliminate the uncertainty related to these portions of the BBN.
- Incorporating a BBN building code in the IDAC-I code.
- Updating the BBN with data discovered during its usage.

4.2. PS/DM

In the control room, an operator's main functions are to monitor plant performance and ensure the management objectives are constantly met. Operating the nuclear power plant within prescribed safety guidelines is an ever-present objective. Depending on the instantaneous situation in the plant, an operator can have four major goals for safe functioning: Normal Operation (NO), Trouble Shooting (TS), Maintain Equipment Safety Margin (MESM), and Maintain Global Safety Margin (MGSM). These four major goals govern the choice of sub-goals and strategies to fulfill those sub-goals. An operator's strategies can be divided into eight types based on the involved cognitive level: Wait and Monitor, Programmed Response, Direct Matching, Follow Procedure, Follow Instruction, Trial and Error, Limited Logical Expansion, and Logical Expansion (Smidts et al., 1996). Fig. 12a describes the strategy selection model when the plant is in normal operation. By default, an operator uses the Wait and Monitor strategy when the plant is in normal operation mode. When an abnormal condition is detected in the system, the operator becomes alert and revises his major goal. His/her selection depends on the time available, the criticality of the abnormal condition, and the plant's mode of operation (such as start up, shut down, steady-state operation and maintenance). These factors influence the stress level of the operator. It is expected that under high-stress conditions, an operator will be inclined to maintain the overall plant safety while under low-stress conditions, an operator will attempt to troubleshoot problems. In the event of equipment breakdown, an operator will apply an instinctive response from his/her professional training; for example, isolate the equipment or switch to a backup. The instinctive response is driven by the MESM goal.

The strategy-selection process begins depending on the selected high-level goal (see Figs. 12 and 13). An operator attempts to fulfill the major goal by dividing it into sub-goals and then attempts to satisfy each by consecutively adopting the aforementioned strategies. During this iterative process, an operator's psychological status is affected based on feedback from the plant. A negative response from the plant can increase the operator's stress level and increase related PSFs such as TCL and TRL. The PSFs are updated at instances that demand verification from the operator based on plant feedback. If the stress level crosses a threshold into a higher or lower level, a change in the major goal is necessary. Thus, the major goal is revised according to the earlier description and, again, the strategy selection model is executed. The strategy selection module and the PSFs dynamically interact with each other and this can be made possible by choosing the necessary interface to link the two modules together. In the existing IDAC literature (Chang and Mosleh, 1999), the interaction between the strategy selection and the PSFs is captured through equations. The selection of the next strategy that the operator is willing to adopt is determined by the strength of PSF factors such as stress, operator ascendancy, and perceived complexity of strategy. In the IDAC-I model, the strength of PSFs will be derived from their instantaneous probabilities in the BBN. The selection of the strategies in IDAC-I will be achieved by employing these probabilities in the transition rules mentioned in Chang and Mosleh (1999). Thus, a bidirectional influence is established between the PSF and PS/DM modules.

The proposed requirements to include the above improvements to the existing IDA/IDAC PS/DM module are (1) linking the major PSFs to the PS/DM module, (2) parallel updating of the PSFs during the PS/DM execution, and (3) enabling updates of the goals and strategies based on existing PSFs.

4.3. Mental model

The knowledge base of an operator is a repository of mental models. These models are dynamically constructed, modified, and expanded by an operator as s/he interacts with and learns from the environment. This learning pertains not only to the plant operation but also to daily activities including commuting, equipment use, communication, and so on. Each activity is represented in an operator's mind in a format similar to its existence in the real world. This representation is the mental model that an operator uses to rationalize, assimilate information, make decisions, and take further action. These models are not replicas of reality but a generalization that efficiently utilizes an operator's memory resources. The major purposes of the models are to allow an individual to quickly recall ideas upon demand and enable a quick rationalization to allow prompt action. Thus, in a control room, an operator will build mental models of the spatial location of the controls s/he monitors, the work culture in his/her organization, the typical communication/coordination between crew members, and so on. Each mental model has a defined theme and is accessed as and when a scenario demands. Thus, there can be a very large number of such mental models commensurate with the number of scenarios that can develop and it is impractical to model every one. Further research is required to classify scenarios into categories for which a parent mental model can be constructed. The models of scenarios in each category can be generated from the information available for the scenario.

4.3.1. Structure of mental models

The mental model approach is based on the premise that people make deductions by working through models in their minds. While

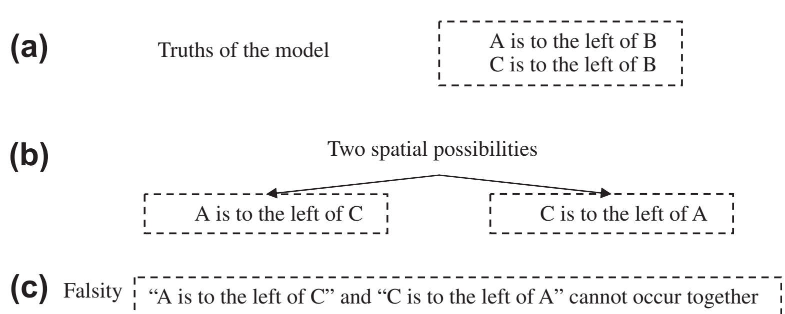

Fig. 14. Example of falsity.

there are a variety of methods for representing an operator's mental processes, research suggests that mental models are a better representation of how people actually process information and make decisions than purely rule-based models, for example Byrne (1992). Rather than modeling the world as it exists, or the world as we articulate it with language, mental models represent our perceptions of the world (Byrne writes, "Rule theories rely on mental representations that are close to the structure of language, whereas mental models are close to the structure of the world as we perceive it"). A credible mental model captures mental shortcuts, prioritized information, and knowledge gaps.

In order to construct workable external mental models, we will consider three constraints that are essential characteristics of mental models:

(1) Mental models are computable. This is also a requirement if we consider coding and simulating an operator's ability to make decisions based on assimilation of information.
(2) Mental models are finite in size.
(3) Mental models are represented using "tokens" (symbols) for entities and relationships between entities.

The key to simulating mental models is to use a method that imitates the phenomenon of perception, understanding, and choice but is easy to represent and simulate (Laird, 1983). Examples have been widely noticed in the scientific literature. For example, certain behaviors of micro-organisms that appear to be the result of cognitive understanding and action can be explained using basic scientific rules. The movement of *E. coli* away from toxins can be represented as movement based on detection of chemical gradients and movement in a direction of decreasing concentration. Likewise, rules can be defined to explain and represent human mental models and simulate them.

The mental models largely retain assertive information perceived by an operator. An important concept discussed in Laird (1983) with respect to mental models is the notion of "Falsity". Falsities are guidelines which are given in the form of negative statements. These include statements such as:

- "Action X does not lead to symptoms Y and Z."
- "Symptoms P and Q do not imply diagnosis 1."

An operator may either read these guidelines in manuals or infer them from other existing instructions and experience. Falsities' important characteristic is that they are easily forgotten unless frequently revised. Falsities are required to guarantee the completeness of an instruction set and assist in the human reasoning process. Their absence may lead to the development of fallacies, which are specious beliefs of a person.

Consider a situation where an operator is learning to use a set of knobs (i.e., parameters): A, B, and C. The manual describes the knob positions using the statements "Knob A is to the left of Knob B" and "Knob C is to the left of Knob B".

Fig. 14a is a representation of the mental model of the operator. Instructions are stored as truths in the operator's memory. Given these truths two possible spatial arrangements of the knobs exist which are displayed in Fig. 14b. However, only one of the spatial models is correct and therefore the inference is that the two spatial arrangements cannot co-exist. This is a falsity and operators tend to forget such inferences especially when the number of parameters involved is higher. The consequences of being unaware of such a falsity can be severe depending on the context. For instance, the operator may perform an erroneous action (such as switching off an emergency pump) without being aware of having committed a mistake.

The spatial models can be visualized in Fig. 15b and c.

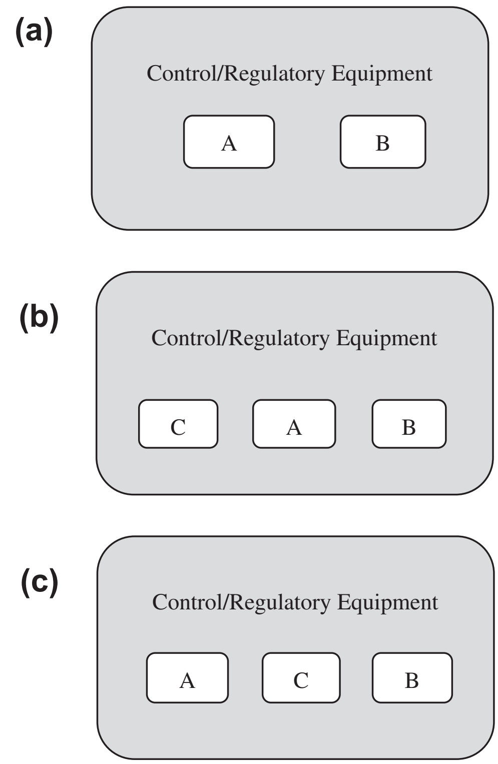

Fig. 15. Mental model falsity example.

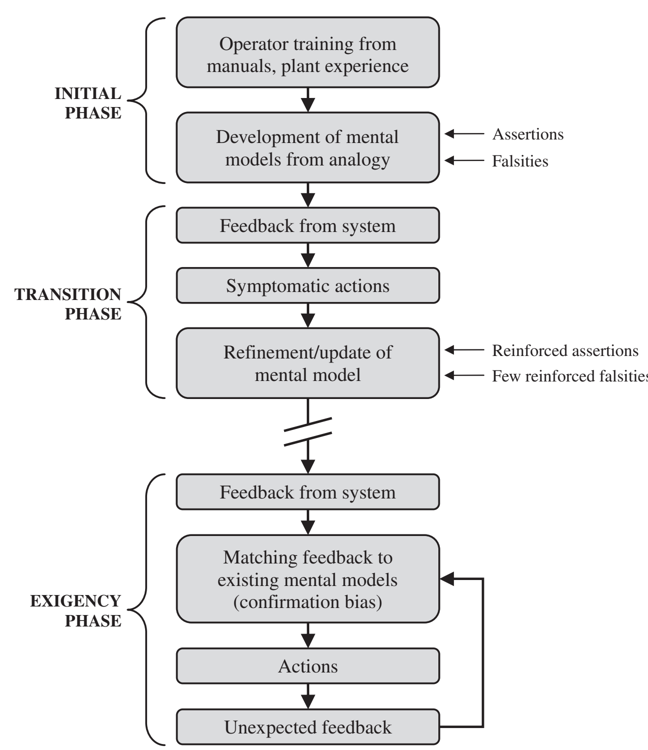

Fig. 16. Structure of mental models.

4.3.2. Mental model behavior

The mental model passes through three phases during its development process: initial, transition, and exigency. The phases differ in their duration; the demarcation is dependent on the scenario in which the operator is functioning.

The initial stage is the infancy stage when development and growth of the model is rapid as shown in Fig. 16. Newer concepts are learned and related data that are easily linkable to new information are tied together. The length of the infancy stage is brief but the stage is very dynamic. The relevant data for the model originates from the operator's hands-on experience in the control room and knowledge gained from training manuals. As the initial model grows in size, the model becomes increasingly stable. This is due to the increase in the cognitive requirements to further build the model due to the increasing difficulty in making new connections by finding relevant information.

The next stage is the transition phase. It is difficult to demarcate this phase from the initial phase because the change is gradual. It can be assumed that there is an overlapping region (called the "semi-transition phase") where both phases exist. In this phase, the transition phase becomes predominant and the initial phase fades out over time. An initial mental model can be considered the smallest segment of the mental model that is usable for rationalizing and arriving at decisions. The transition phase is a long drawn out phase and is the main phase where errors can appear in the mental model. During this phase, multiple changes and revisions are made to the initial model. The operator learns the operation of the plant and understands provided instructions through assertions and falsities. The assertions are easier to remember. However, the falsities are temporary and are easily forgotten unless frequently revised. Further construction of the mental model during the transition stage with infrequent recollection of the falsities leads to the encroachment of errors in the mental model.

The final stage is the exigency stage. The mental model transforms to the exigency stage during accident-like situations. In such scenarios, depending on the situation severity, the operator makes little or no updates to the mental model. This stage persists for the entire duration of the emergency situation. In fact, the transition stage can coexist with the exigency stage provided the mental model is being updated. Once high-stress and high-time-constraint conditions are met, the operator's mental model freezes and s/he attempts to address the situation with the available mental model. If the operator has a faulty mental model in this scenario, then s/he would try to make sense of the situation by fitting the symptoms into the existing mental model. The phenomenon is called "confirmation bias".

The necessary mental models will vary according to the scenario considered. Based on our experience, we expect that in any given situation, an operator's mental model may include the following: (1) Relevant procedures. (2) A high-level model of the plant's primary systems. (3) A mental mapping of the control panels and their connections to the plant systems. (4) A model of the plant's failure modes and success paths.

Each situation will probably also require: (1) A detailed model of the systems related to the current activity. (2) Higher fidelity models for the essential elements of the systems in use. (3) A model of the alarms in their current state.

To truly understand which models are appropriate and to understand how many models are sufficient for a particular scenario, further research is necessary. Methods for understanding the properties/structure of mental models are the methods used to elicit mental models (Rogers et al., 1992): (1) Interviews with operators, often reviewing previous experiences and discussing the decision-making process. (2) Questionnaires given to operators. (3) Group discussions, often walking through case studies or reviewing scenarios. (4) Thinking-aloud protocols: operators are asked to explain their thought process as they work through a procedure, ideally in a high-fidelity simulator. (5) Constructive interaction: an operator teaches a novice about a system, process, or situation. Alternatively, two experienced operators may work together to solve a problem. (6) Simulator experiments: researchers may use eye-tracking tools, etc., to follow an operator's thought process.

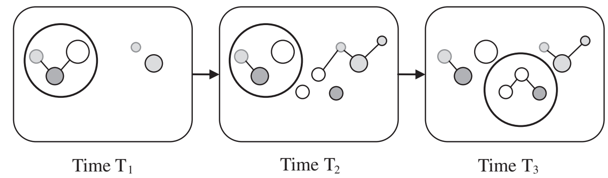

Fig. 17. Dynamic mental model formation.

Using a combination of these methods, researchers will be able to identify the common elements in a mental model and acquire a better understanding of how extensive models must be to capture the operators' thought processes. Mental models required will then be based on this scientific research rather than being dependent on a particular analyst's or implementer's knowledge.

It is expected that the number of mental models will be restricted by the scope of a particular scenario and the level of detail required to handle the situation be limited. It is also expected that mental models are organized hierarchically with levels of detail dependent upon the particular focus of the scenario considered. The realm of knowledge necessary is also typically limited to the technical field under study: nuclear, aviation, etc. These elements should restrict the number of mental models and prevent combinatorial explosion. When different scenarios are investigated, it is expected that portions of already established mental models could be reused.

Requirements:

- Development of mental models through data collected from simulator experiments or through interviews with operators.
- Developing the ability to select the appropriate mental model based on data perceived by operator, information present in the WM or KB.
- Coupling the PS/DM with the mental models.
- Allow updates of mental models—initially, basic mental models can be tested. When the simulation provides desirable results, manipulation of the mental models to mimic human learning should be explored. This will require knowledge of artificial intelligence.

4.4. Memory model

The memory model is comprised of the Working Memory (WM) and the Knowledge Base (KB) (Smidts et al., 1996). The WM is the short-term memory where active information is temporarily stored for processing. To assist the processing, relevant data is retrieved from the KB. The KB, as previously discussed, houses the mental model. At any instant, single or multiple mental models can be accessed from the KB. Thus, the WM content continues to vary with time. Fig. 17 shows the changing content of the WM over time. Initially, only a few ideas (represented as circles) are present in the operator's KB. Over time, with further information gathered, newer relationships are established between the ideas (entities). With the passage of time, the mental model dynamically changes and the assimilation of information into the mental model is proposed to follow a pattern similar to the power law of learning[2] (Anderson, 2000). Thus, with time, the rate of growth of a particular

[2] Rapid improvement in performance followed by lesser and lesser improvements with further practice. Such learning curves are described by power functions. Mathematically, $T = a/Pb$ where, T, time to complete a task. P, the number of practice trials, a and b are non-negative constants.

mental model becomes increasingly gradual. This implies the rate of learning gradually decreases with time with regard to a particular task. Similarly, the transfer of information from the KB to the WM is quick when the information has been recently added to the mental model. Thus, among information that is accessed, older information requires more time to be retrieved into the WM. The retrieval of information to the WM is represented in Fig. 17, indicating that different sections of the mental model are in focus at different instances of time. The mental models can be imagined to be clusters of data interlinked with each other and representing learned concepts. During functioning, the operator retrieves necessary information from the KB to the WM. It is essential to determine the segments of data that must be transferred to the WM and this presents an opportunity for future research in the field of HRA.

Requirements:

- Further research is required to mimic the loss of information from WM and also the transfer of information to KB over time.
- Research is required to determine which portions of the mental model will be retrieved from the KB as a function of the information present in the WM that triggers the retrieval.

5. Interface

The constructed IDAC-I HRA models can be rendered ineffective if the functionalities exhibited by them are not transferred to the simulator code through a potent interface. The interface is used to switch control between a coarse-grain and fine-grain structure (depending on the analysis requirements) and it carries the necessary information between the modules/components at the desired rate to simulate human performance. The human actions are identified and categorized into procedural and diagnosis tasks. The procedural tasks are handled by the coarse-grain HRA method (THERP or SPAR-H) while the diagnosis tasks are dealt with by the fine-grain HRA method (IDAC-I). The PSF sets differ between THERP, SPAR-H, and IDAC-I methods. Therefore, the PSF sets in each HRA method must be continuously updated.

The IDAC-I models/modules are designed to interact with simulator codes and dynamic event tree codes used to mimic nuclear accident scenarios. The simulator codes provide data about the component states and the physical variables (pressure, temperature, flow rate, status of equipment, etc.). The memory model/module of the operator interacts with the simulator code by storing the critical information (such as the instantaneous values of physical parameters monitored by the operator in the WM). This information is used to diagnose problems in the PS/DM module. The mental models are called from the operator KB to simulate process, rationalize decisions, etc. The final decisions made in the PS/DM module are transformed to actions. The PS/DM interacts again with the simulator code through these actions.

The interactions are performed by the interface at predefined rates across the modules. There is a time delay between the symptoms being read from the plant and the operator taking necessary actions against it. This time delay must be included in the HRA evaluation to provide a reliable assessment. With the knowledge of these response times, the HRA model IDAC-I is run with a time lag behind the simulator code. The response time of the operator is close to 1.4 min for scenarios where a clear diagnosis exists. When multiple parameters are required to be verified for diagnosis, the response time is increased to approximately 3.8 min. If the operator is misled by false indicators, the diagnosis process can take approximately 10.5 min (Dougherty and Fragola, 1988).

The requirements derived for the development of the NGSC simulation code are:

- Identification of the nature of human action and classification into procedural or diagnosis-oriented action.
- The PSF sets of THERP/SPAR-H and IDAC-I methods vary and therefore must be continuously updated.
- The switching between the coarse- and fine-grain structures must be quick to reduce the processing time.
- Timing behavior must be added to IDAC-I.
- Quick integration of the results from the layered structure to provide a single HEP value.

6. Future work

The development of the mental model and memory model is in the infancy stage and no method exists yet to validate them. However, the reliability of the model can be increased by collecting data through surveys from nuclear power plant operators and experienced professionals. The surveys will elicit details about operator behavior by various means. The participants can be asked to pictorially represent their answers or demonstrate their response to devised scenarios. Studies can be performed using simulators that can replicate nuclear power plant conditions. The data obtained from such experiments will offer insights into modeling the mental models and would greatly increase the accuracy of the model. The Ohio State University's Risk and Reliability Laboratory is currently establishing a facility to run these experiments and thus real-time data will become available in the near future.

In order to have a high-fidelity representation, the mental model must be populated with data similar to the one an operator frequently encounters in a control room. Usually the data is in the form of trends, charts, and signals. Images as viewed by an operator can be subjected to parsing techniques that convert the pictorial data to textual data. Studies such as image parsing (Yao et al., 2010) are being performed towards achieving this task. The technique discovers spatial location, temporal, and functional details from images fed into it. These details will greatly assist in constructing the operator KB which is essential for simulation purposes. The PSF set in this paper is derived from the IDAC PSF set in ADS-IDA Crew technical research report (Chang and Mosleh, 1999). The IDAC method (Chang and Mosleh, 2007a, 2007b, 2007c, 2007d, 2007e) contains a more comprehensive PSF set that includes additional PSFs not modeled in this paper. The existing model can be further improved by expanding the causal graph/BBN with the additional PSFs through further research.

The human reliability model discussed in this paper requires a dataset for computation of the strength of PSFs. The larger the dataset, the greater the fidelity of the model to real-life scenarios. Aviation and nuclear data were collected in this study resulting in 225 data points. The dataset can be expanded by conducting simulator experiments with operators on selected scenarios of a NPP. The operators can be categorized based on their experience levels and the study can be used to compare experience-wise operator performances. In addition, it would be beneficial to perform a repeatability and reproducibility analysis on the definition of the PSFs to ensure that there would be limited variability in the dataset created by the analysts from accident reports. Also, the incident logs should be expanded to capture all the PSFs. Once the model's algorithm has been coded, it can be coupled to the NGSC simulator through an interface and initiated using the dataset collected.

The dataset obtained is an array of 0's and 1's for each PSF with "1" signifying the presence of that PSF in a scenario. The conditional probabilities and correlation are calculated from this data. With an increase in the size of the dataset, the computational requirements will increase due to the expansion in the size of the arrays. A larger dataset can be used as per the level of resolution that is required from the human reliability model. The IDA/

IDAC methods help in understanding how an accident progresses over time. They do not provide a HEP for the scenarios discovered. The PSF strengths, decisions, and actions were deterministic in the LOFW simulation performed using IDAC (Chang and Mosleh, 1999). The utilization of a BBN in IDAC-I provides a foundation for probabilistically calculating the PSF strengths. Further research can help in extending the probabilistic nature to the other modules and enable the computation of a HEP.

7. Conclusion

This paper has identified requirements for a coarse grain/fine grain human reliability model to be integrated with NGSC. The IDAC-I HRA model is targeted for the fine grain analysis while the SPAR-H and THERP methods have been identified to be suitable for the coarse grain analysis. This paper suggests reserving the use of fine grain analysis for critical scenarios to reduce the computation resources. Improvements to the IDA method's modules in order to create the IDAC-I method are defined. A foundation has been laid for probabilistic HEP analysis through IDAC-I, by developing a BBN for modeling the causal interactions of PSFs. Furthermore, the knowledge base of the existing IDA/IDAC methods is strengthened with the development of mental models. The PS/DM module is designed with identification of interactions points with the other modules. Finally, the NGSC requirements to integrate the modules together are derived and listed. A prioritization of these requirements should be developed to create a defined path for its implementation. In addition areas worthy of research must be identified and prioritized.

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Appendix A

In the framework of the coarse-grain/fine-grain structure, let us assume that the description of the system at time t is given by:

$$(\vec{x}(t), \vec{i}_{\bar{O}}(t), \vec{i}_{O}(t))$$

where $\vec{x}(t)$ is the vector of physical variables at time t, $\vec{i}_{\bar{O}}(t)$ is the state of non-operator related components at time t, and $\vec{i}_{O}(t)$ is the state of operator-related components at time t. If the fine-grain model of the operator is used, $\vec{i}_{O}(t)$ is denoted $\vec{i}_{OF}(t)$ If the coarse-grain model of the operator is used, $\vec{i}_{O}(t)$ is denoted $\vec{i}_{OC}(t)$. The dimensions of $\vec{i}_{OF}$ and $\vec{i}_{OC}$ are n_F and n_C, respectively.

During simulation, we will transition from fine-grain to coarse-grain model (F → C) and from coarse-grain to fine-grain model (C → F). Consistency between coarse-grain and fine-grain models will require that defined mapping relationships exist such that:

Condition 1. Given that a switch between fine-grain model and coarse-grain model occurs at time t, let $T_{C\to F}$ be the time at which the fine-grain model was entered, then:

$$\forall k = 1, n_C, \exists M^{(k)}_{F\to C} | i_{OC}(t,k) = M^{(k)}_{F\to C}(\vec{i}_{OF}(t), \vec{i}_{OC}(T_{C\to F}), \vec{x}(t), \vec{i}_{\bar{O}}(t))$$

where $i_{OC}(t,k)$ is the kth component of state vector $\vec{i}_{OC}(t)$, $T_{C\to F} < t$ and $M^{(k)}_{F\to C}$ is the kth mapping relation from F → C.

Condition 2. Given that a switch between coarse-grain and fine-grain model occurs at time t, let $T_{F\to C}$ be the time at which the coarse-grain model was entered, then:

$$\forall k = 1, n_F, \exists M^{(k)}_{C\to F} | i_{OF}(t,k) = M^{(k)}_{C\to F}(\vec{i}_{OC}(t), \vec{i}_{OF}(T_{F\to C}), \vec{x}(t), \vec{i}_{\bar{O}}(t))$$

where $i_{OF}(t, k)$ is the kth component of state vector $\vec{i}_{OF}(t)$, $T_{F\to C} < t$ and $M^{(k)}_{C\to F}$ is the kth mapping relation from C → F.

Coarse-grain and fine-grain models are consistent if such relationships can be established, inconsistent otherwise.

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