USE OF OPERATIONAL DATA FOR REDUCING CONSEQUENTIAL EVENTS AT NUCLEAR POWER PLANTS

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The integration of human and organizational factors into risk management is necessary and has become evident after the accident at the Fukushima nuclear power plant. It is crucial to be able to identify human and organizational factors that can increase the likelihood of errors. The objective of this paper is to describe a tool to incorporate these factors into a quantifiable approach. The tool is used to determine what measures should be taken to avoid errors that can occur due to increased organizational stress at the station. First, the human and organizational factors associated with causes of consequential events were identified from the incident reports at the plant. Then a Bayesian Belief Network (BBN) was used to determine the best defense or barrier against further weakening of the organization. The methodology developed in the paper to build and evaluate the BBN is based on the interactions among causes identified in the reporting system for incidents at the stations, usually in a Corrective Action Program database. The resulting model is expanded to be able to analyze how the causes affect the probability of a consequential event, as well as to carry out evidential reasoning in order to study the types of deficiencies we can expect to find in the case of a consequential event. These causes translate into plant-specific compensatory measures that can be utilized by station management or personnel to offset reduced organizational resilience margins. Future work upon this basic model will allow a comparison of barriers based on their costs and savings in order to aid the plant in choosing the most appropriate barrier.

I. INTRODUCTION

The occurrence of consequential events during normal operation and outages, such as a reactor trip at a nuclear power plant, are inevitable at any power plant. In general, in the nuclear industry, this type of information is recorded in the Condition Reports (CRs) of the Corrective Action Programs (CAPs). Human error is almost always involved in one way or another in accidents in any industry, and the nuclear industry is not an exception. While it is possible to refer to the major accidents that have occurred and investigate the causes, many times the blame remains on the sharp end, where the last action occurred, and fails to consider the blunt end, that is, the organizational factors, such as management practices and resources that shape the way operation and maintenance is carried out. The database created from the events in the CAP is used in this study to investigate the relationships between the causes and their effect on consequential event frequency.

Human error and organizational performance is of special interest in the nuclear industry; analysts have developed many methods for performing Human Reliability Analysis (HRA). There have been attempts to collect data to inform quantification in HRA, starting with the work done for the THERP methodology by Swain.[1] These efforts have continued to the present time, with efforts like the U.S. Nuclear Regulatory Commission's Human Event Repository and Analysis (HERA) system,[2] the UK's CORE Database,[3] However, due to still little appropriate and sufficient human performance data, the Scenario Authoring, Characterization, and Debriefing Application (SACADA)[4] database was developed by the U.S. Nuclear Regulatory Commission (NRC) and a similar effort was undertaken by the Korea Atomic Energy Research Institute (KAERI)[5] to address this data need, which will most probably prove very useful in the future, once more data can be collected. The IDHEAS[6] project is also looking for useful as well as practical ways to conduct HRA.

Notably, one source of information that is not often exploited in the HRA world is the CAP data. There is a wealth of information in the Condition Reports at most nuclear plants, as the corrective action process includes formal mechanisms to report, capture, assess, and correct organizational failures or shortcomings. Appropriately the focus is placed on identifying root causes and implementing corrective actions to ensure organizational learning and improvement. However, we have found that there is additional, HRA-focused, value to be extracted.

The concern about human errors is not only that they can impact initiating event frequency, but also that they can cause unexpected failures in the plant that can cause plant downtime or worker injury (which also affects the safety of the plant). For example, human errors in test and maintenance activities of NPPs have the potential for inducing unplanned reactor trips. Korea's regulatory organization for nuclear and radiological systems, the Korea Institute of Nuclear Safety (KINS), provides a list of the major events, including unplanned reactor trips and unplanned initiations of safety systems that have occurred in Korean nuclear power plants, on a public website, the Operational Performance Information System (OPIS).[7] According to OPIS, there were 150 trip events from 2004-2013, 32 of which (21%) were designated as due to human error. In data from the Licensee Event Reports (LERs) in the United States, the contribution to unplanned SCRAMs during maintenance and surveillance activities was shown to be almost 40%.[8] INPO also issued several Significant Operating Event Reports (SOERs) that further point to declining human performance. Interest in analyzing and reducing the human-induced or human-related unplanned reactor trip events has been increasing gradually in response to the increased number of human-induced unplanned reactor trip events.[9] Additionally, the term human-related includes everything from design error, and slips and lapses to lack of supervision, management decisions, and priorities. In some CAP databases, even when the event is not flagged as human related, it can be argued that there is a human/organizational aspect related to the occurrence in some way, shape or form.

The majority of the events are related to test and maintenance activities performed in nuclear power plants. These activities are essential for sustaining the safety of the power plant and maintaining the reliability of plant systems and components. However, the potential of human errors during test and maintenance activities also has the possibility of inducing unplanned reactor trips or power derate in an active error mode, or inducing latent failures that render safety-related systems or functions unavailable when they are demanded for incidents/accidents.[10] Often, human errors are related to problems in establishing the maintenance or testing boundaries (i.e., equipment clearances) to allow these activities to be performed in a safe manner without inadvertent actuations of equipment or endangering plant personnel.

Since large amounts of plant event data exist from nuclear power plant Corrective Action Programs (CAP), this information can, and we argue should, be used to improve safety in many ways: for knowledge management,[11] leading performance indicators, to decrease repetition of events, reduce core melt frequency, and to aid in selecting defenses against human and organizational weaknesses, the latter of which is presented in this paper. These corrective action programs are the primary mechanism through which station employees and contractors identify problems and issues that need to be addressed.

Because the information contained in the CRs at every nuclear power plant is invaluable, and while the reports for each event may be lengthy, we should identify an efficient way to record, store and retrieve data and feedback continually. The statistics of the data can tell us much about the trends in failures, whether system or human failures; however, if the information is not codified to work for the intended database, the results may be inaccurate. For this reason, this paper describes the review and work done to extract benefit from the root cause analysis done on any abnormal occurrence at a nuclear plant, and presents a model to include this wealth of information in a structure that furthers the ability to put barriers in place to reduce consequential events in nuclear power plants.

From a sample containing thousands of Condition Reports it was possible build a Bayesian Network to evaluate the reduction in consequential events depending on where the defense or barrier is implemented. A barrier can be placed at the organization, supervision or individual performer level. A barrier can be a training improvement, better use of management resources, increased supervision or stricter procedure adherence, among others, as described in the next section.

II. THE MODEL

At a nuclear power station the organization, supervisor and individual performer are all involved in the everyday processes and at each step, there are defenses or barriers established, such as procedural adherence, work practices, management practices and supervision. However, these established barriers might have defects or holes, as represented in Fig. 1. This figure is adapted from James Reason's Swiss Cheese Model[12] and is applied in this study to demonstrate the concept of "barriers." When a work package, such as a large maintenance effort, is to be carried out, the entire organization is involved, in that each level of the organization has defenses in place to prevent undesired events (represented by the slices of Swiss cheese in the figure).

For example, the organization as a whole has in place a safety culture policy, a safety-conscious working environment, and procedures to follow in order to guarantee a safe environment at the station. The supervisor has the function of briefing the worker on the risks and ensuring that the work is done according to procedures. The individual performer has been briefed, has the procedure in hand, has received the training, and has the knowledge and skills to perform successfully.

However, as Reason explains and accident analysis shows repeatedly, consequential events occur when there is an alignment of holes in these defenses. In order to reduce such occurrences, we must plug these holes, which can be accomplished by installing or implementing barriers. This can be considered as filling the hole in the defenses against consequential events and accidents.

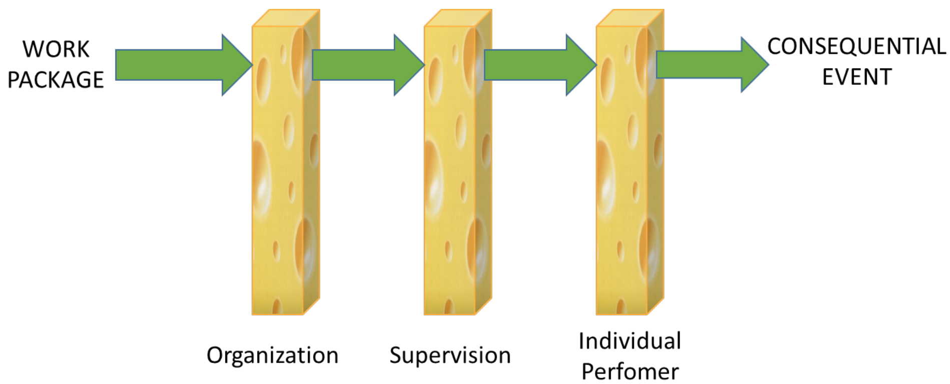

Fig. 1. Adapted from James Reason's Swiss Cheese Model.[12]

There are many types of barriers, which include anything from placing a hold point or warning in the corresponding procedure, or requiring a photograph of the aligned system after the test or maintenance activity, to hiring another person dedicated to conducting independent verifications. Obviously each of these has its costs and benefits, and models for this level of detail are in process, but not presented here. For the sake of this paper, we concentrate on the cause categories and propose them as the barriers, that is, as a means to reduce the occurrence of the cause of the events. For example, by improving training, the occurrence of consequential events should be reduced; by improving procedure adherence, again, the occurrence of consequential events should be reduced; and so on.

II.A. The Data

The causes that can be extracted from the CAP data are assigned to each event. Plants develop their own cause categories. For this reason, until more is done to develop industry wide databases, development continues to be plant-specific. The cause categories that will be considered in this study were taken from the causes indicated for each event reported in the Condition Reports and are listed in Table I. For each category, we have its code (abbreviation), description, and examples causes. These are the major categories; each category has up to ten subcategories, breaking the causes into 64 more specific types of causes. Analysis has begun on the 64 variables and will be included in future publications, but only the 11 major causes are considered here. The CAP database, covering from 2005-2014, includes 149,572 events, 99% of which are rated in the lower two levels of significance (67% CNAQ, 32% CAQ-D). Only 17,050 entries include cause codes. This subset includes all of the events with the highest significance level (SCAQ), 99% of the events with the second highest significance level (CAQ-S), 28% of the CAQ-D events, and only 2% of the CNAQs. A matrix was developed which is 17,050 rows (i.e., the number of events with cause codes) by 11 columns (i.e., the 11 cause code categories from Table I). The matrix contains 0's and 1's, a 1 indicating that the cause code is attributed, and 0 indicating that is it not, to the specific event. This data was used to construct the Bayesian Networks, as discussed in the next section.

TABLE I. Cause Categories

Code	Description	Examples
DE	Equipment Design/Manufacture/Performance Monitoring	Predictive Maintenance Program Inadequacy, Preventive Maintenance Program Inadequacy
HF	Human Factors/Work Environment	Human Factors Not Properly Addressed in Work Area/Equipment
LS	Job Leader/Supervisory Methods	Pre-job Preparation or Briefing Inadequate, Prioritization of Work Activities Inadequate
MA	Management	Organization Not Sufficiently Self-Critical,

	Assessment/Corrective Action	Cause Analysis for Known Problem Inadequate
MC	Change Management	Need for Change Not Recognized, Change Not Implemented in a Timely Manner
MP	Management Practices	Communication Within an Organization Inadequate/Untimely, Communication Between Organizations Inadequate/Untimely, Management Practices Promote/Allow Unacceptable Behaviors
MR	Management Resources	Prioritization/Scheduling of Activities Inadequate (Management level)
PA	Procedure Adherence	Procedure/Instruction/Step Implemented Incorrectly (Intent Not Met)
TR	Training	Necessary Initial/Refresher Training Not Provided
WI	Work Instructions	Document Contents Incorrect or Missing
WP	Work Practices	Slip or Lapse

II.B. The Bayesian Belief Networks

Formally, BNs are directed acyclic graphs (DAGs) whose nodes represent variables (event cause categories in this study) and whose arcs encode conditional interdependencies between the variables. The graph provides a simple description of the dependency model and defines a simple factorization of the joint probability distribution leading to a model that encodes the dependencies between variables. Here we present a model to predict the probability of undesired consequences in routine operation at a nuclear power plant. The objective of this knowledge base (Bayesian Network) is to predict a reactor trip and identify patterns in organizational behavior impacting its occurrence. While algorithms exist to learn both the graphical and the probabilistic models from data, and in this way automate the application of this methodology in complex problems, this will not be covered in this paper; preliminary results of automating the BN building are briefly discussed in the future work section. For this paper, the variables are joined in a network that describes relations between reactor trip and different characteristics of the organization, which are considered as predictors for a reactor trip. The trip relates directly to all predictors in the model.

A Bayesian Network can be used to evaluate two types of conditional probabilities, which can be shown through the Bayes' Theorem Equation:

$$P(A/B) = \frac{P(B/A)P(A)}{P(B)}. \tag{1}$$

Bayes' Theorem enables the evaluation of the conditional probability of A given B from the conditional probability of B given A, as well as the other way around. This makes it possible to determine a causal relationship from A to B as well as to use evidence to determine the outcome. That is, for all practical purposes we can calculate the conditional probability of an outcome given its causes as well as the conditional probability of the causes given the outcome. In this study, we use knowledge about the causes to determine the probability of the outcome (a reactor trip). However, it is also useful to be able to identify which variables are the ones that are more likely to have caused the event that has occurred. In this way, the BN can be used to provide insight into which areas to improve or which barriers to implement in order to reduce consequential events.

III. BAYESIAN NETWORK FOR PREDICTION

The Bayesian Network is constructed to reflect, in a simple graphical manner, the fact that causes are assigned to consequential events after the root cause analysis is carried out. While it can be argued that these cause codes are subjective, the more than 17,000 cases analyzed show that there is a basis for the assigned cause codes, and the evaluation team assures that the analysis is done to the best of everyone's knowledge.

As can be observed in Fig. 2, the causes attributed to consequential events can be divided into three general categories: organizational factors, supervision, and individual factors. The organizational factors are management resources (MR), management practices (MP), management assessment (MA), change management (MC), and performance monitoring (DE), as defined in Table I. For example, an inadequate maintenance program (DE) can result in a consequential event if a component is left in the wrong position and the maintenance program does not require post-maintenance testing. This would need to be changed on a management level in order for the individual to perform the post-maintenance test, due to the requirements at a nuclear power plant (and probably any other plant) that all actions are derived from applicable procedures. The change management cause (MC) indicates that there was a need for change, yet it was not implemented, thus forcing the organization to look to higher levels for instituting the changes required in a timely manner. This attribute is especially seen in cases where an error is repeated; the natural conclusion would be to blame the individual, yet the actual responsibility lies with the organization's management to identify ways to prevent repeats.

The causes codes related to faults in or lack of supervision are: inadequate or lack of training on a specific activity (TR), inadequate work instructions (WI), and deficiencies in leadership and supervision (LS). There are many cases in which the main cause of the event is attributed to the fact that a procedure was not explained properly or completely in the pre-meeting before the work was to be carried out. Due to this lack of supervision, the worker did not realize the risk and did not place the necessary importance on the precautionary notes of the procedure, or in other cases, to the special equipment or clothing. For example, he did not take the extra time to fetch gloves, and the result was an electrocution. What is to be emphasized here is that while the easiest path to take is to blame the worker for not gathering the protective gloves, the real source of this lapse was the lack of properly informing the individual of the danger involved.

Finally, the individual performer certainly is at fault sometimes, and the causes most related to this fact are: inadequate adherence to procedures (PA); a fault in work practices (WP), which is mostly observed as a slip or lapse or a lack of skill required by the worker to perform the activity; and not following the directions required by human factors' requirements (HF), such as the STAR procedure, which instructs the worker to stop, think, act, and review before carrying out a risky activity.

Since each of the 11 causes directly impacts the probability of a consequential event occurrence, arcs are drawn from each of the causes to the reactor trip (RT) node of the Bayesian Network (Fig. 2), which was created using HUGIN.[13] For the sake of this paper, we will treat the causes as independent of one another. Due to this independence, there are no causal arcs between any of the causes in the model. This follows the logic applied by Groth in the modeling of the SPAR-H model using a BN.[14] While this model was constructed based on the premise that the causes are independent, there is evidence that there are dependencies among the causes, and it is possible to identify causal relations between the variables using techniques such as factor analysis, as discussed by several authors.[15,16] In fact, the grouping of the causes in the boxes as shown on Fig. 2 was based on a factor analysis performed on the matrix described in Section II.A. Further work is being carried out to determine the underlying dependencies and discussed in the future work section.

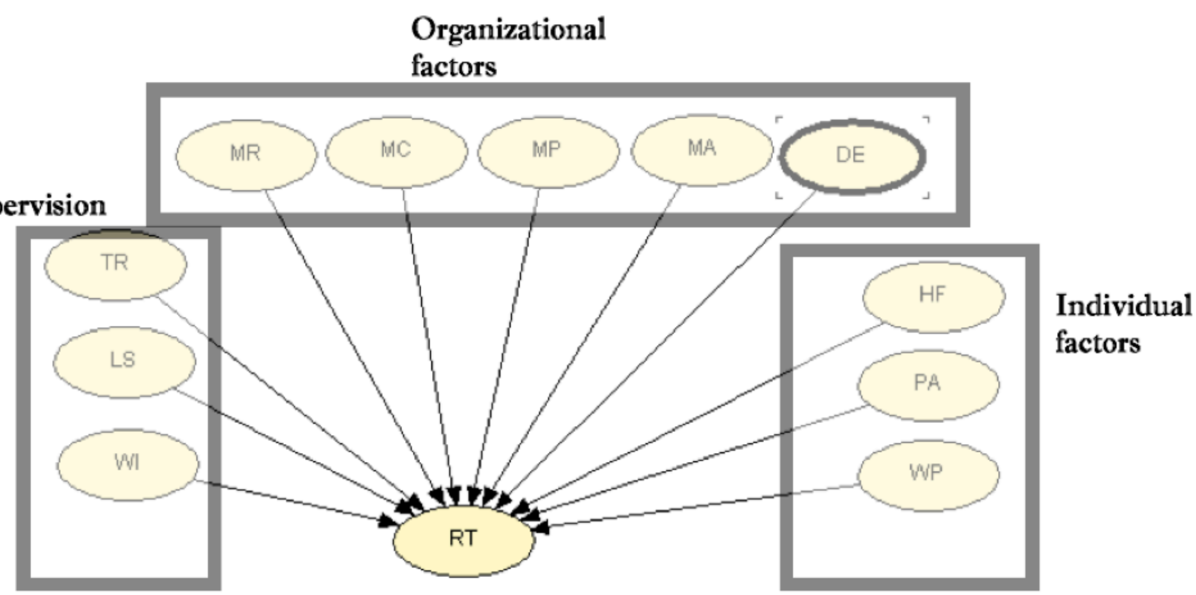

Figure 2. Bayesian Network for Reactor Trip (RT) Prediction.

IV. RESULTS

Once the initial BN is complete, software programs such as HUGIN can also perform the Bayesian updating. HUGIN was used for the work presented here. The analyst's role is to add evidence to the model and to interpret the posterior model. By adding evidence, an analyst is providing the model with new information about the state of the causes (which is expressed by the nodes in the BN). The evidence would be newly collected data or observations (about one or more of the causes and/or about the occurrence of reactor trip). The evidence is automatically propagated through the network to produce an updated joint probability distribution for the model. Another useful aspect of the BN is that the joint probability distribution can be expressed as the conditional probability of the child node given the parent nodes. In this case, the conditional probability of a reactor trip is expressed by the probabilities of the causes and can be updated as evidence is gathered.

Each variable in the CAP knowledge base may take several values that are specific to the plant in question (in this example we are only considering binary values, that is, there is a deficiency or not). It is important to note that the system does not need information about all the characteristics of the plant to be useful. However, the more that is known about a plant, the more accurate the risk assessment will be. For this reason, we start the system with the statistical values found in the database, i.e., the frequency of the inadequacies found in the cases analyzed through the root cause analysis.

IV.A. Bayesian Network Probabilities

We have included the reactor trip node to calculate the probability of a trip, and be able to calculate the conditional probability of a reactor trip given the probabilities of the causes present originally and by inputting new evidence to the network as it becomes available. We can load the prior probabilities based on the CAP database (the 17,050 events with cause codes). There were only six reactor trips in the 10 years studied, corresponding to 0.04% of those events. However, when this information is combined with the prior probabilities of the 11 causes and the Bayesian Network in Figure 2, the likelihood of a reactor trip is found to be 0.79%. Because this is a simplified model, the variations in the probability of reactor trip are more informative than the actual values. Thus, we proceed to analyze the effect of introducing organizational changes at the plant.

If we increase the probability of not adhering to procedure (PA) to 100%, from its prior probability of 5.62%, the probability of a reactor trip increases by an order of magnitude to 8.20%. Similarly, when the LS node is increased to a complete lack of supervision (100% probability), the probability of a reactor trip increases to 2.96%. While this is less than the effect of not adhering to procedures, it is still a significant increase.

Just as we use importance measures in PRA, such as risk achievement worth and Fussel Vesely, to determine important equipment, we use a similar concept to determine important deficiencies or areas for improvement in an organization. If we were to reduce the probability of not adhering to procedures to 0 (i.e., a problem with procedure adherence were never to occur), we would obtain the probability of the reactor trip as 0.35, which represents a reduction by one half. The same analysis was performed for each cause, setting the probability to 100%, as well as artificially setting the probability of the cause to 0%. These values are substituted for the evidence-based probability distribution in the second column of Table II, and the resulting probabilities of a reactor trip are shown in columns 3 and 4, respectively. Again, these values should be compared with the original likelihood of RT = 0.79.

TABLE II. Probabilities

Cause	Prior Probability of cause (%)	RT when cause=100% (%)	RT when cause=0% (%)
DE	23.11	2.74	0.20
HF	1.98	5.19	0.57
LS	3.14	2.96	0.71
MA	2.98	2.03	0.75
MC	3.67	4.15	0.66
MP	3.38	3.11	0.71
MR	0.79	16.57	0.66
PA	5.62	8.20	0.35
TR	0.94	4.51	0.75
WI	8.41	2.07	0.67
WP	50.45	1.10	0.47

We can observe that the elimination of performance monitoring problems (DE) and of procedure adherence problems (PA) reduce the probability of the consequential event the most, to 0.20% and 0.35%, respectively. In contrast, increasing inadequate management of resources (MR) to 100% produces the greatest increase in RT, even though it is the least probable cause according to the data. An increase in procedure adherence problems (PA) increases the probability of reactor trip more than any other cause, after management resources. As we add evidence to the BN, the probabilities are updated, and when a decision must be made as to the best barrier to install, we can consider the decrease in the probability of a consequential event with the new data.

In the previous examples, we focused on the ability of the BN to perform causal reasoning or prediction, where we use knowledge of the variable nodes (causes) to determine the probability of a reactor trip (effect). As mentioned earlier, the BN also makes it possible to reason from effects back to causes; that is, knowing something about the reactor trip also tells us something about the causes. This is again due to the conditional dependencies in the model: the causes are marginally independent, but given information about the state of the RT node, the causes are not conditionally independent. This ability to perform evidential reasoning can be informative in that it helps us to determine which causes are likely to be present when we know there is a reactor trip. In this example, we set as evidence that P(RT) = 1. This evidence adjusts the marginal probability distribution for P(RT), from its uninformed value of 0.79 that it occurred to P(RT) =1, and then propagates this information through the model. The second column in Table III contains the results of this change. The probability distributions change for all of the causes. This provides us with diagnostic insight into the root causes of reactor trip. This also provides insight into how to proactively prevent errors under different scenarios. In this way it appears that it may be most effective to reduce inadequacies in maintenance practice (DE), work practices (WP), and procedure adherence (PA). These results correlate well, but not perfectly, with setting the cause probability to 0% in Table II.

TABLE III. Evidential Reasoning

Cause	**Probability cause exists given RT occurred (%)**
DE	80.45
HF	13.06
LS	12.81
MA	7.68
MC	19.36
MP	13.36
MR	16.66
PA	58.47
TR	5.37
WI	22.12
WP	70.31

V. CONCLUSIONS AND FUTURE WORK

This paper presents a simple Bayesian Network that is built to observe the effects of changing the probabilities of different causes of consequential events. An importance measure type test was done to determine which areas would have the most effect on the occurrence of consequential events; in this paper reactor trip was the consequential event.

The decision as to where to strengthen or implement a barrier becomes important when the organization is under increased stress, as discussed in an article published by the authors.[17] Especially when there is an upcoming major maintenance activity or maneuver, a well-selected barrier can be extremely useful in avoiding consequential events in an already stressful situation, and even more so with the added load. However, it is one thing to understand where to focus attention – on management, supervision or individuals – and quite another to determine the most cost effective barrier to implement. The analysis proposed in an article presented by the authors at the 2014 PSAM conference[14] is being extended to be able to more effectively decide what barrier to implement and guarantee reduction in the probability of a consequential event. Also, the use of the expanded BN, that is, using the 64 nodes representing the specific causes is being developed to more precisely identify where errors can be reduced.

Future work includes the development of BNs that can discover the interdependencies between the causes of events. As more analysis is conducted, we hope to be able to learn the structure from the data and validate it through expert judgment, and with more data, through actual validation using that new data. That is, one part of the data is used to build the BN, and the next part is processed through the network, enabling it to learn from the new evidence.

ACKNOWLEDGMENTS

We are grateful to the nuclear power plant organizations that were willing and able to provide information to conduct this research.

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