Use of Corrective Action Programs at Nuclear Plants for Knowledge Management

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Abstract: Due to the uncertainty of many of the factors that influence the performance of the humans in nuclear power plant maintenance activities, we propose using Bayesian networks to model this kind of system. In this study, several models are built from the information contained in the Condition Reports from the Corrective Action Program at a nuclear power plant. This first study, using actual nuclear power plant data, includes a method for data processing and highlights some potential uses of Bayesian networks for improving organizational effectiveness in the nuclear power industry. The tool described in this paper is designed to provide a systematic approach to assist in managing an organization's knowledge base and support improvements in organizational performance. This paper describes the utilization of cause codes recorded in the Corrective Action Program for determining their effect on consequential events.

Keywords: Bayesian Networks, Corrective Action Program, Knowledge Management, Organizational Performance.

1. INTRODUCTION

Almost every organization manages data in some way. Data is a major corporate resource; however it is frequently poorly documented. Descriptions of data and other resources are metadata, which are part of the corporate memory for the organization, and preserving corporate memory is one of the basic features of knowledge management. At present, many countries are experiencing a large percentage of the personnel at nuclear power plants reaching retirement age. As a result, recording the memories of these workers, including the meaning of data, is increasingly important. Preserving metadata is crucial for understanding data years after the data were created. Human error and organizational performance is of special interest in any industry, and the nuclear industry has developed methods for performing Human Reliability Analysis (HRA) to calculate the contribution of human error to accidents. 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 US Nuclear Regulatory Commission's Human Event Repository and Analysis (HERA) system [2] and the UK's CORE Database [3]. However, many experts in HRA have related the opinion that there should have been more effort on collecting human error data for the purpose of quantifying the probabilities of human error [4]; however, there does exist a wealth of information in the Condition Reports (CRs), products of the Corrective Action Programs (CAPs), at most nuclear plants. The corrective action process includes formal mechanisms to report, capture, assess, and correct organizational failures or shortcomings. Typically the focus is placed on identifying root causes and implementing corrective actions to ensure organizational learning and improvement [5].

In fact, in the nuclear industry, we asseverate that the CAPs are a source of this metadata. The information contained in the CRs at every nuclear power plant is invaluable, and while the reports for each event may be lengthy, there should be 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

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presents a model to include this wealth of information in a structure that furthers the knowledge management about human errors in nuclear power plants.

The cause coding together with study of written descriptions in the failure and repair work orders helps to identify candidates of human errors related to maintenance activities from the failure and maintenance history. From a sample containing thousands of human related labeled condition reports it was possible to define a model of the factors that influence the occurrence of these events. The model provides the structure of the information necessary in the database to be able to utilize it for knowledge management. Once validated, the model can serve to predict events as well as risk-inform the procedures to reduce the reoccurrence of the events as well as avoid consequential events.

2. DEVELOPING A MODEL FROM STATISTICS

While some of the HRA methods have made attempts to collect data to inform quantification of HRA, these efforts have not been completely successful in being able to provide useful and complete data for human error quantification. Even if we were to be able to derive the quantitative HRA data, which focus entirely on the human error probability (HEP), this does not necessarily provide the information about the performance measures that can be used to track weakness in human factors. For example, knowing the error likelihood does not actually tell the human factors researcher the expected performance or the level of performance degradation that may precede an actual error. One of the principal motivations for this research is the lack of data in the human as well as organizational areas.

In order to obtain the information necessary to quantify the human errors and obtain the performance measures necessary to identify risk significant process steps for frequently performed activities (e.g., surveillance procedures) and interpret the degraded barriers at a nuclear plant, it is necessary to study and understand the events that actually occur at the plants. In the United States, the Nuclear Regulatory Commission requires a Problem Identification and Reporting program. Compliance with this requirement is performed through station specific Corrective Action Programs. These Corrective Action Programs generally use a reporting mechanism that is available to the general station employee population to identify and record problems, issues, or actions that need to be performed to accomplish the station's business and operational missions. Typically, a standard Condition Report form is used to document and enter this information into station databases. Thus, the CRs are significant and objective source of events and metadata. The information contained in the Condition reports is invaluable and while the reports can be lengthy and be highly variable from CR to CR due to the many "authors" at a plant for a CR, it is important that the CR information be processed and evaluated to generate important data and analyses relative to plant and human performance. This offers a significant opportunity to associate consequential station events to those processes and activities that were being performed by station personnel at the time of the event as well as their associated causes. This provides important opportunities to develop human performance models from objective plant specific data that has the potential to reveal organizational weaknesses and those station activities that are risk significant relative to consequential human failures (not just core damaging events). There needs to be a process model that provides an efficient and consistent way to record the data, store it, and have it provide the basis for follow-on technical analyses related to human performance. 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 and uncertain. For this reason, the cause coding was reviewed at a pilot plant in order to use the data to develop a model.

2.1 Factor Analysis

A Factor Analysis (FA) was conducted on the database from the pilot plant to test the methodology described in the work reported in Groth [6]. In particular, the Factor Analysis in the XLSTAT computer program [7] was applied in order to extract the factors and determine the grouping of the variables for the causal model network that was developed. A sample size of 95 events was used, which are the significant events reported in the seven year period from 2004 - 2011. While strict rules regarding sample size for exploratory factor analysis have mostly disappeared, studies have revealed that adequate sample size is partly determined by the nature of the data. It is considered adequate to have 5 or 10 times the number of samples as variables, thus the 95:11 ratio of samples to variables is considered sufficient for the analysis [8].

Factor analysis is one of a family of techniques for taking high-dimensional data, and using the dependencies between the variables to represent it in a more tractable, lower-dimensional form, without losing too much information. FA is one of the simplest and most robust ways of doing such dimensionality reduction.

The variables considered in this study were taken from the causes indicated for each event reported in the Condition Reports and are listed in Table 1. We can observe the name and the description of the cause code variables, with some examples to demonstrate the types of causes considered in this study. Table 2 presents a sample of the first 10 lines of the data used for the FA; there are 95 entries in the complete matrix. In order to conduct the FA, the data was converted to binary, which means that the 0 represents "*Adequate*" for that variable, and a 1 means "*Less than Adequate*" for that variable. And, in this way a binary matrix is formed for the data for the significant events reported in the Condition Reports.

Table 1: Variables Considered

Variable	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 Assessment/Corrective Action	Organization Not Sufficiently Self-Critical, 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

Table 2: Binary Matrix for 11 Variable FA

Condition Report	DE	HF	LS	MA	MC	MP	MR	PA	WI	WP	TR
1	0	0	1	0	0	1	0	0	0	0	0
2	1	0	0	0	1	0	0	0	0	0	0
3	1	0	0	1	0	0	0	0	1	1	0
4	0	0	0	0	0	0	0	0	1	0	0
5	0	0	0	0	1	0	0	0	1	0	0
6	1	0	0	0	0	0	0	0	0	0	0
7	0	0	1	1	0	1	0	0	0	1	0
8	1	0	0	0	0	0	0	0	0	0	0
9	1	0	1	1	0	1	0	0	1	0	1
10	0	0	1	1	0	1	1	0	0	1	0

The default in most statistical software packages is to retain all factors with eigenvalues greater than 1.0, corresponding to the first five factors in our analysis; however, there is broad consensus in the literature that this is among the least accurate methods for selecting the number of factors to retain [8]. Many researchers describe that the best choice for researchers is the scree test. This method is described in every textbook discussion of factor analysis. The scree test involves examining the graph of the eigenvalues and looking for the natural bend or break point in the data where the curve flattens out. The number of data points above the "break" (i.e., not including the point at which the break occurs) is usually the number of factors to retain. Figure 1 presents the Scree plot where we can see that the first four factors explain almost 60% of the variance.

Figure 1: Scree Plot

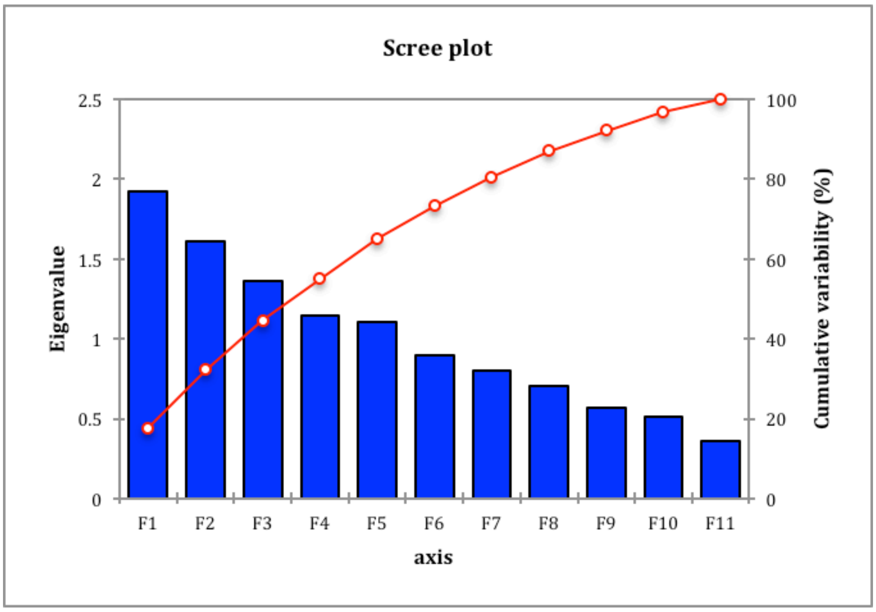


Table 3 illustrates the loading of the variables on the four extracted factors. As we can see, DE loads on F1, while the management variables load on F2 (MA, MC, MP, MR), etc. We can interpret this by observing that the factors divide the human performance difficulties into four categories: maintenance programs, management issues, work practices and supervision, and training, procedures and instructions.

Table 3: Factor Loadings

Variables	F1	F2	F3	F4
DE	0.871			
HF		0.436		
LS			0.366	
MA		0.436		
MC		0.456		
MP		0.504		
MR		0.276		
PA				0.583
WI				0.415
WP			0.538	
TR				0.736

Table 4 shows the correlations among the variables, which in turn are used to define the links or arcs between the variables in the causal model that was developed and is presented in Section 4.

Table 4: Correlations among Variables

Variables	DE	HF	LS	MA	MC	MP	MR	PA	WI	WP	TR
DE	**1**	0.216	-0.147	-0.001	-0.184	-0.248	-0.197	-0.137	-0.155	**-0.297**	0.008
HF	0.216	**1**	0.156	0.106	0.164	0.201	-0.062	-0.043	-0.131	-0.127	-0.072
LS	-0.147	0.156	**1**	0.075	0.044	**0.369**	0.243	0.086	0.034	0.254	-0.029
MA	-0.001	0.106	0.075	**1**	0.129	0.199	0.152	-0.143	0.030	-0.107	0.152
MC	-0.184	0.164	0.044	0.129	**1**	0.091	0.123	-0.115	-0.073	-0.228	-0.025
MP	-0.248	0.201	**0.369**	0.199	0.091	**1**	0.152	0.106	0.040	0.060	0.153
MR	-0.197	-0.062	**0.243**	0.152	0.123	0.152	**1**	-0.047	0.061	-0.036	0.076
PA	-0.137	-0.043	0.086	-0.143	-0.115	0.106	-0.047	**1**	0.043	-0.097	-0.055
WI	-0.155	-0.131	0.034	0.030	-0.073	0.040	0.061	0.043	**1**	0.126	**0.282**
WP	**-0.297**	-0.127	**0.254**	-0.107	-0.228	0.060	-0.036	-0.097	0.126	**1**	-0.072
TR	0.008	-0.072	-0.029	0.152	-0.025	0.153	0.076	-0.055	**0.282**	-0.072	**1**

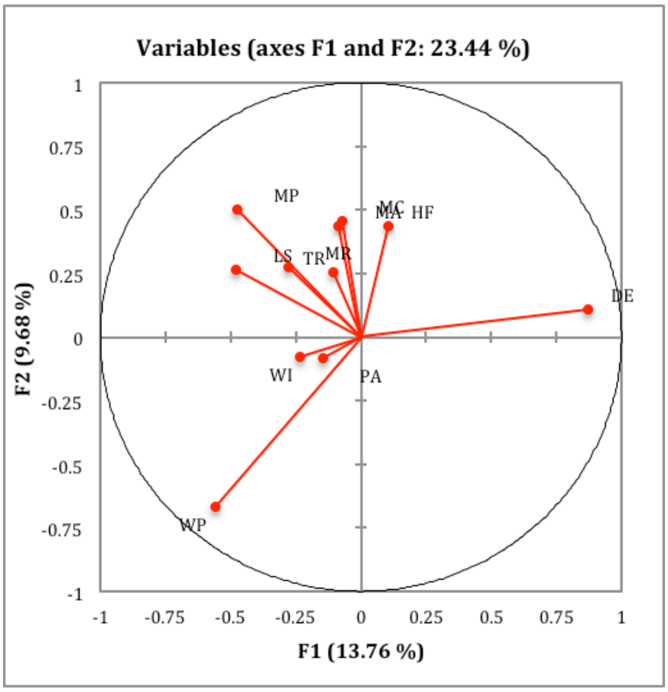
Another result from the Factor Analysis is a biplot, as shown in Figure 2. As used in FA, the axes of a biplot are a pair of extracted factors. These axes are drawn in black and are labeled F1, F2 in this case. There is another plot for F2, F3, etc. which are not shown here.

A biplot uses vectors to represent the coefficients of the variables on the factors. Both the direction and length of the vectors can be interpreted. Vectors point away from the origin in some direction. A vector points in the direction that is most like the variable represented by the vector. This is the direction which has the highest squared multiple correlation with the factors. The length of the vector is proportional to the squared multiple correlation between the fitted values for the variable and the variable itself. For example, in Table 3 DE is loaded on Factor 1 with 0.871, thus the vector representing the DE variable has a value of 0.871 on the F1 axis in Figure 2.

The fitted values for a variable are the result of projecting the points in the space orthogonally onto the variable's vector (to do this, you must imagine extending the vector in both directions). The observations whose points project furthest in the direction in which the vector points are the observations that have the most of whatever the variable measures. Those points that project at the other end have the least. Those projecting in the middle have an average amount. For example, the perpendicular line from MP to the F2-axis intersects in 0.541, while MR in 0.276.

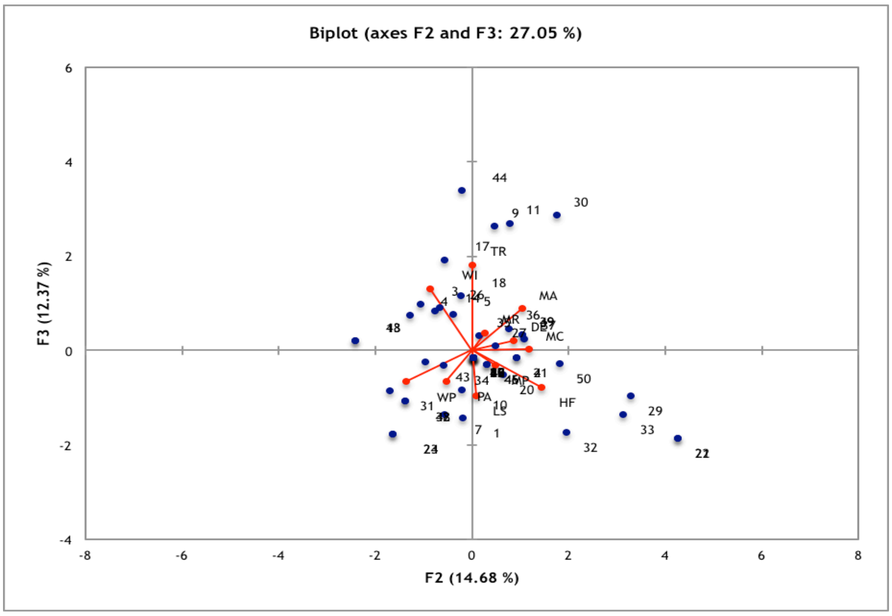
Thus, vectors that point in the same direction correspond to variables that have similar response profiles, and can be interpreted as having similar meaning in the context set by the data.

Figure 2: Biplot Vectors



The biplot uses points to represent the scores of observations on the factors, and in Figure 3, each numbered point represents one of the condition reports, and the vectors represent the causes (variables). The relative location of the points can be interpreted in the following manner: points that are close together correspond to observations that have similar scores on the factors displayed in the plot. To the extent that these factors fit the data well, the points also correspond to observations that have similar values on the variables. In this example, events that are close together are ones that have similar profiles of causes.

Figure 3: Scatter Plot of Significant CAP Events



3. GRAPHICAL MODELS

3.1 Causal Models

A causal model can be used as an estimating approach based on the assumption that future value of a variable is a mathematical function of the values of other variable(s). It is used where sufficient historical data is available, and the relationship (correlation) between the dependent variable to be forecasted and associated independent variable(s) is well known [9]. Sufficient data can be considered as having ten times the data samples as the number of variables that describe the samples, as mentioned in Section 2.1.

Among the different data mining algorithms, probabilistic graphical models, in particular Bayesian Networks (BN) is a sound and powerful methodology grounded on probability and statistics, which allows building tractable joint probabilistic models that represent the relevant dependencies among a set of variables. The resulting models allow for efficient probabilistic inference. In this work, a BN represents the probabilistic relationships between the causes and the incidents reported at a nuclear power plant during routine maintenance and surveillance activities, providing a new methodology for probabilistic downscaling: i.e. allowing to compute the probability of a certain type of event, including reactor trip: Pr (reactor trip | a certain cause combination), as well as the decreased probability given a decrease in the probability of a given cause. For instance, the improvement in procedures (in this case, we assume perfect procedures) can decrease the probability of reactor trip.

Formally, BNs are directed acyclic graphs (DAGs) whose nodes represent variables, and whose arcs encode conditional independencies between the variables. The graph provides an intuitive description of the dependency model and defines a simple factorization of the joint probability distribution leading to a tractable model that is compatible with the encoded dependencies. Here we present two models derived from the same set of data, with two purposes: (1) to predict types of events, given different less than adequate performance in different areas, (2) to predict the probability of undesired consequences in routine operation at a nuclear power plant. Efficient algorithms exist to learn[†] both the graphical and the probabilistic models from data, thus allowing for the automatic application of this methodology in complex problems. Generalizations of Bayesian networks that can represent and solve decision problems under uncertainty are called influence diagrams, an example of which is presented in Section 4.

3.1.1 Probabilistic Networks

A Bayesian network is a graphical model that encodes probabilistic relationships among variables of interest. Bayesian networks can be used to learn causal relationships and be used to gain understanding about an area of interest and to predict the consequences of intervention.

Building a probabilistic network for a domain of application involves three tasks:

- Identify variables that are of importance and their possible values

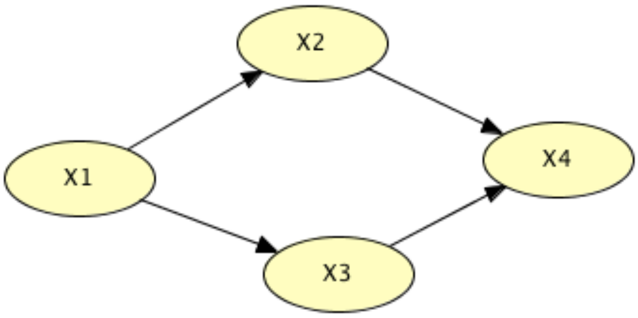
- Identify the relationships between variables and express in a graphical structure

-Obtain the probabilities that are required for the quantitative part

Basically we can understand how a Bayesian network is used for quantification by observing the following simple example in Figure 4. If we have four variables that are used to describe cases, we can derive the graphical model from the data and quantify the probability of the network from the following equation 1.

[†] The verb *learn* is used to mean build the graphical model and calculate the conditional probability table directly from the data, in the computer science lexicon.

Figure 4: Example Bayesian Network



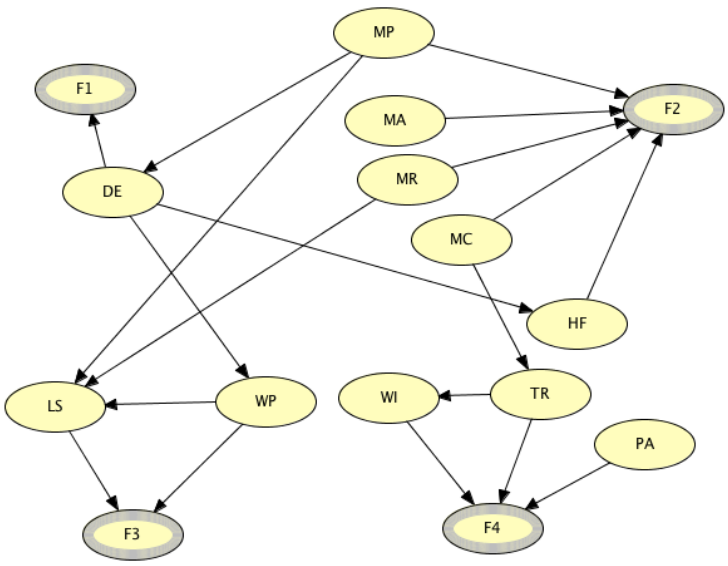
$$Pr\ (X1,X2,X3,X4) = Pr\ (X1) * Pr\ (X2|X1) * Pr\ (X3|X1) * Pr\ (X4|X2,X3) \quad (1)$$

There are two approaches to developing a BN: using the factor analysis results, as described in the previous section or learning the graphical structure from data. The graphical model resulting from the first approach is presented in Figure 5, while the learned structure is presented in Figure 6. Once the graphical structure has been established, assessing required probabilities is straightforward and involves studying subsets of data that satisfy various conditions [10].

Concentrating on the task of obtaining the probabilities, the most common sources are statistical data, literature, and human experts. Although there is abundant information, these sources seldom provide all the numbers required for a real application; however, we propose that the use of the data available in the Corrective Action Programs, once put into ontological terms, could provide the statistics necessary for producing extremely accurate probabilistic models for human error, including organizational influence.

Figure 5 illustrates the model created from the data analyzed in the Section 2.1. From the factor analysis, four factors were maintained. Thus, we can observe that the model identifies the variables loaded on the four factors, previously identified in the factor loadings and the arcs represent the correlations (greater than 0.240) between the variables. The arc between MC and TR was added, since the author has seen cases of correlation, despite the low correlation found in the FA.

Figure 5: Bayesian Network Designed from Pilot Plant CAP Data



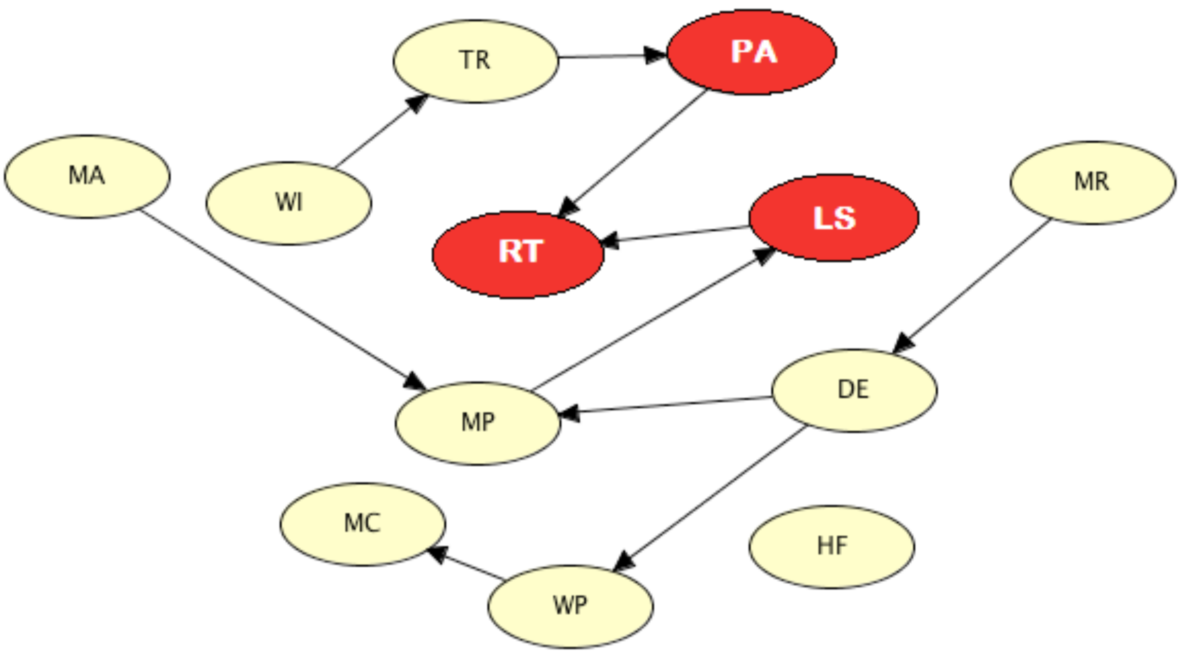
From this BN it is possible to determine how to reduce the probability of the four types of events (F1, F2, F3, F4 as described in Section 2.1) by reducing the probability of a less than adequate performance of the variable (considered to be one of the causes of the event). These shadowed nodes can also be considered as error forcing contexts, as described by Groth [6]; however, for the purpose of this study we use the former definition because it enables us to calculate the probability of an F3 type event given less than adequate performance in WP and LS, for example.

3.2. Predicting Reactor Trip

The next step is to add the undesirable consequences as nodes to the model. For this paper, we add only one node, in this case, reactor trip (RT), to simplify the explanation of the method. We will use pink boxes to represent "treatments" or "aids" in order to reduce the probability of the undesired event. These treatments are considered barriers or defenses used in nuclear power plants to aid human performance, such as 3-way communication, process and procedure approvals, pre-job brief, etc. However, before we can get develop the influence diagram, we must develop the graphical representation of the relationship between the variables and the consequences, defined as reactor trip in this example.

We can also correlate the causes or variables to the occurrence of consequential events, such as reactor trip. The structure of this next model was learned directly from the data. While the sample size is sufficient for the statistical analysis, it may scarce to directly determine all the arcs (correlations between the variables) directly using the HUGIN [11] program. The node HF that is not linked in this model evidences this effect. A column was added to the data table for another variable called RT (reactor trip) and the 1 indicates when the event caused or terminated in reactor trip. Thus, this BN is used to determine the effect of reducing adverse impacts of the underlying causes of the events on the probability of reactor trip. One result shows that the elimination of procedural adherence errors would decrease the probability of reactor trip by one third. This BN was learned using the Greedy algorithm [12] and is presented in Figure 6.

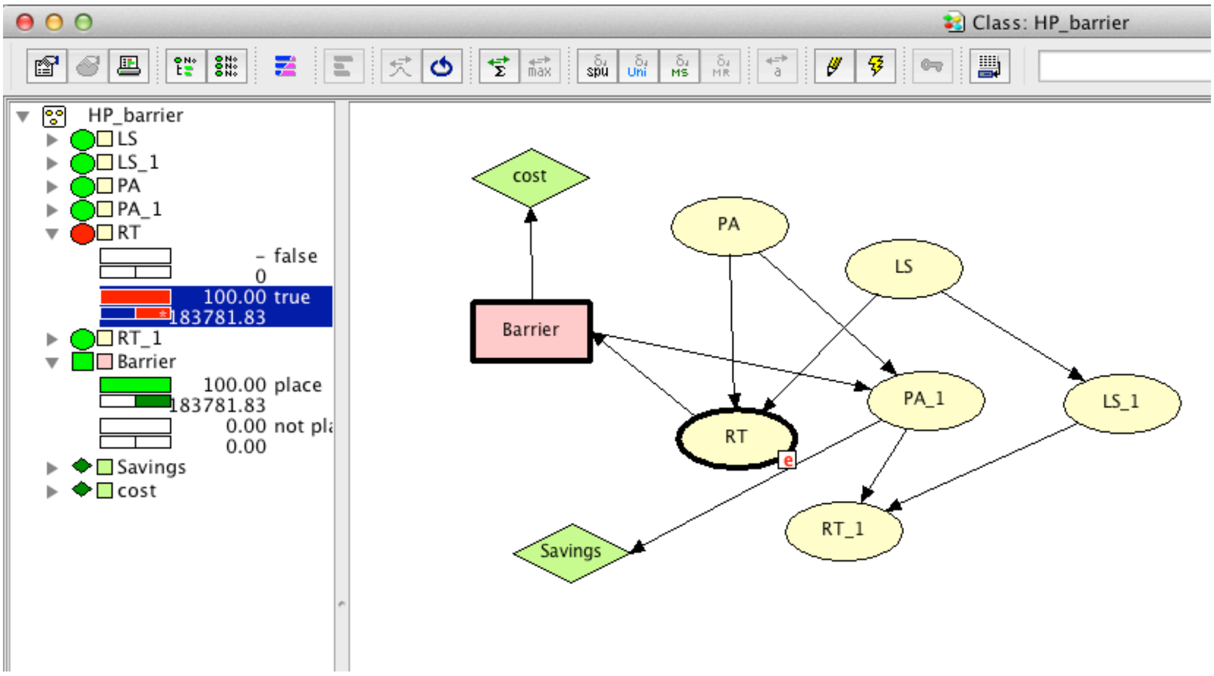
Figure 6: Learned Structure of the BN



4. RESULTS

Now we have the information necessary to be able to construct the influence diagram; however for the purposes of this paper, we shall concentrate on only one part of the diagram. The probability of reactor trip (RT) depends directly on procedure adherence (PA) and on Supervision (LS), as shown in Figure 6 (nodes in red). So, we will amplify this section of the network. We add a decision node, that is, should plant management implement a human performance barrier to reduce the probability of reactor trip from these cause sources. In this case we are referring to human factors/organizational barriers, not actual physical barriers. The pink box in Figure 7 represents this decision node. We can also add a cost node and a utility node (savings acquired from avoiding a reactor trip), represented by the green diamonds in this same figure.

Figure 7: The Influence Diagram Propagated with RT=100%



For this paper it is postulated that operating experience has shown an unacceptable level in the occurrence of reactor trips due to human errors. The model indicates that procedure adherence (PA) and supervision (LS) are key contributors to reactor trip, thus for this example, we propose implementing a barrier to PA (e.g., additional procedure approvals). The process shown in this paper allows the proposed barrier to be evaluated in terms of cost and savings to determine its viability and, also provides a means to determine its effectiveness in reducing the occurrence of future reactor trips. In this hypothetical situation, the barrier was determined to have an expected utility of 183,781.83 (i.e., benefit) and an associated organizational implementation cost of 40,000. Thus, due to high value relative to cost, the analysis indicates it is advantageous to implement the barrier. This demonstrates a key benefit of this approach in that focused barriers can be specifically structured to target and improve specific human and organizational performance activities relative to consequential historical plant events such as reactor trips.

5. CONCLUSIONS

Since a small set of data was used for the development of the models relative to the amount of data contained in Corrective Action Programs, the quantitative results are preliminary. However, the models developed in this paper are functional and the results are promising for several reasons: (1) the methodology enables the incorporation of operational experience into the model by using information from the Corrective Action Programs at nuclear power plants; (2) the models make it possible to identify and incorporate organizational factors into the probabilities of human error in a meaningful way; and (3) the influence diagrams, developed from the Bayesian networks, enable the user to evaluate the utility of adding human performance barriers or other organizational effectiveness initiatives and calculate their effect on undesirable consequences in a nuclear power plant caused by human error during routine operation and maintenance activities.

It is important to emphasize that the purpose of these models is to illustrate the type of insights that can be gathered through the model development process and data collection effort, as well as to provide a road map for future model development and data collection process improvements. Despite the many limitations of the data, the models are useful and the uncertainty in the results will be reduced by additional data collection and associated screening. Additional work will be performed to develop a more comprehensive model and data screening process to support the development of a database and associated data processing specification (e.g., to define the fields necessary, etc.) for Corrective Action Programs that would further support and facilitate an analysis such as described in this paper. This work will contribute to the development of a method for trending and tracking human and organizational performance events, as well as associated causes to support efforts in improving knowledge management and organizational effectiveness.

Acknowledgements

We would like to acknowledge the participating plant personnel for spending time to perform the searches we requested, without which, this work would not be possible.

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