Development of Expert System with Bayesian Networks for Application in Nuclear Power Plants

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ABSTRACT

A nuclear power plant (npp) is a complex special system that requires detailed health monitoring for improving performance assessment and reliability. This fact brings the application of *on-line diagnosis* and *prognosis* on the modules, systems and components existing in the npp's. In order to apply on-line health monitoring effectively and efficiently, it is necessary to use techniques that can quantify certain issues. The primary issue is quantifying both *the expected performance and the uncertainties* of the system reliability, which is reasoning under uncertainty . In doing this, it is beneficial to know the probability values associated with each possible system state; its availability, reliability and its dependence upon a possible action. The system states and the actions are associated with cost or benefit to the operating system, which is handled by the *utility* concept. Actions represent the content of the *decision making* in the relevant system. An action causes a change of state probability density function (pdf) from a *prior* to a *posterior* distribution. *Bayesian Networks (BN),* which are able to handle these challenges in complex environments, are appropriate for application in on-line health monitoring, fault diagnosis and predictive maintenance in the nuclear power plants.

The objective of our work is using the *knowledge engineering* techniques to introduce the *smart expert systems* to nuclear power plant operations. The scope of our project is predicting the behavior of the system under operation and providing advisory information about the possible actions and the net beneficial consequence of these actions. Predictive modeling of the failure progression and diagnosis, as well as the advice concerning maintenance actions for the monitored system is being established by the help of experts' judgements. The knowledge elicited from the experts is necessary in defining the behavior of the system under all possible conditions within the operational domain. This primarily involves three major parts. First part is constructing the functional hierarchy in the monitored system. The second part is providing the state subjective probability distributions. The final part is estimating the relative utility values associated with the states and the actions. The software tool that has been employed in this study as the expert system shell is the HUGIN Prof ™, which uses the Bayesian and decision theories in its inference engine in accomplishing the assessments. The modeling of the systems are made by using the *causal directed acyclic graphs (DAG)* in this tool. This developing product is initially being applied to a high energy, horizontal, centrifugal pump lubrication system mock-up for validation. Our project is funded by USDOE-NERI program.

I. INTRODUCTION

The purpose of this report is to present the concept and development of a prototype expert system to serve as a decision support system for the reliability improvement and maintenance planning in future and currents nuclear power plants. This study is a part of the USDOE-NERI program, “Smart equipment and systems design to improve reliability and safety in future nuclear power plant operations”. A nuclear power plant must be maintained to satisfy the Technical Specifications and other rules and regulations during all operating phases, including normal and unscheduled operations. Adherence to these requirements leads to handling a large information database involving numerous plant components. Prediction of the possible fault occurrences, diagnosis of failures to identify which component(s) to maintain is usually time-consuming and it is vulnerable to human errors and omission due to the large scale of information to be handled. Another problem is to determine whether taking a plant component out of service to repair or to apply on-line maintenance to the component is the most beneficial decision. To this effect, a reliable expert system is necessary for sound decision support, on-line diagnosis and predictive maintenance in the nuclear plants. For this, the knowledge of the experts in the relevant area, needs to be assimilated for implementation within the technical information database, that is to say, within the knowledge base of the expert system.

The proposed and developed expert system, within the scope of this paper, focuses on the bearings of the charging pumps in the pressurized water nuclear power plants. The initial task of the USDOE-NERI Smart program has been to:

- Develop a methodology for evaluating plant structures, systems and components (SSCs) to identify those that would benefit most from application of Smart program concepts.
- Select a demonstration component.
- Determine an optimum health monitoring plan for the selected component, including identification of its failure modes.

The main selection criteria included:

- High failure rate.
- Sufficiently long repair time to cause significant lost generation.
- Well-known failure modes.

- Availability of accessible locations allowing sensor installation and data acquisition.

A study of failure rates and modes has been done to analyze data of SSC contributions to forced outages, using the NRC MORP2 database for monthly reports between 1990 and 1999 for 14 PWR and 13 BWR units. The most significant result was the identification of rotating machinery, including pumps, as the primary contributors to forced outages in LWRs. Along with their application in both charging and feedwater systems, this result led to the selection of a high energy, horizontal, centrifugal pump as the demonstration component for the project. From the same study, it has been found that the bearings are the components in the relevant pumps, which serve as one of the most frequent cause of pump failure. Hence, the expert system, which is involved in this part of our project is called the "Smart-Bearings".

Therefore, the examples in this paper are concentrated around the bearing failure diagnosis and attack the maintenance issues of the bearings with the expert system approach. The computer programs constructed in the modeling of expertise is called *expert systems*. The goal of an expert system is to develop a software tool that achieves a high level of performance on problems that are difficult enough to require significant human expertise and understanding for their solution. The knowledge representation and reasoning paradigm that are adopted for our project are based on Bayesian Theory and Bayesian Networks. The software tool, which is used in preparing the expert system has been Hugin Prof-5.6, which is attained by PhD license from Hugin Expert.

II. KNOWLEDGE BASE

The knowledge base of the expert system is structured with three major modules: (1) the functional hierarchy in operation of the component, along with causal relations, (2) possible set of action decisions, (3) the conditional probability values within the state, and the utility functions for the actions and state changes. These modules, altogether, define the behavior of the component under all defined sequences of operation. The modules (1) and (2) comprise the qualitative information in the knowledge base. The module (3) represent the quantitative information in the technical information database.

1. Functional Hierarchy and Causal Relations

The *functional hierarchy* in the bearings system is composed of the following:

- Top event (failure mode) of bearing-seizure

- Faults that would cause the top event in order of functional relation
- At successive states of the hierarchy, faults that would cause the previous layer of faults in the hierarchy
- Features, which are measured to get information on the status of the relevant component.

The functional hierarchy is an efficient and organizational way of expressing the pre-structure of the system on which the expert system will be applied. Table 1 shows the functional hierarchy that is adopted for this experts system. It also reflects the range of problems that the expert system is expected to solve.

Table 1: Faults and features related to the Bearing Seizure (Failure Mode)

BEARING-SEIZURE	**Bearing Seizure (Failure Mode)**
BE-CLR	Improper Clearances (Fault)
CLR-TGT	Clearances Too Tight (Fault)
BRG-LUB-TMP	Bearing Oil Temperature (Feature)
BABBIT-TMP	Babbit Temperature (Feature)
CLR-LSE	Clearances Too Loose (Fault)
RATIO-HARM	Ratio of Harmonic Vibrations (Feature)
NUM-HARM	Number of Harmonics (Feature)
CLR-ASY	Axial Asymmetry (Fault)
BRG-LUB-TMP	Bearing Oil Temperature (Feature)
1X-PHASE	1X Phase
2X-SHAFT-VIB	2X Shaft Vibration
BE-LOAD	Improper Loading (Fault)
LOAD-STO	Static Overload (Fault)
BRG-LUB-TMP	Bearing Oil Temperature (Feature)
BABBIT-TMP	Babbit Temperature (Feature)
RATIO-ORBIT-AXES	Ratio of Orbit Axes (Feature)
SHAFT-ECCY	Shaft Eccentricity (Feature)
LOAD-STU	Static Underload (Fault)
RATIO-ORBIT-AXES	Ratio of Orbit Axes (Feature)
ENERGY-BAL	Energy Balance (Feature)
SHAFT-ECCY	Shaft Eccentricity (Feature)
SUB-SYNC-VIB	Subsynch. Vibration (Feature)
LOAD-DYO	Dynamic Overload (Fault)
BABBIT-TMP	Babbit Temperature (Feature)
2X-VANE-PASS	2X Vane Pass (Feature)
SHAFT-VIB	Shaft Vibration (Feature)
VISCOSITY	Oil Viscosity (Feature)
BE-LU	Improper Lubrication (Fault)
LU-PRE	Bad Oil Pressure (Fault)
LU-TMP	Bad Oil Temperature (Fault)
BRG-LUB-TMP	Bearing Oil Temperature (Feature)
LU-QUAL	Inadequate Oil Quality (Fault)
QUAL-CHM	Chemical Contamination of Oil (Fault)
CONCENTRATION LEVEL	Infrared Spectroscopy (Feature)
VISCOSITY	Viscosity (Feature)
QUAL-DRT	Dirt/Debris in Oil

PART-COUNT	Particle Count (Feature)
BABBIT-MASS	Babbit Mass (Feature)
QUAL-DEG	Oil Degradation
VISCOSITY	Viscosity (Feature)

Color Code in the Table 2: Failure Mode, Fault, Sensor Feature

The *causal relations* are derived from the functional hierarchy in this physical system. However, the hierarchy itself is not enough to specify all the causal links among the variables of the bearing system failure. For instance, the cases of improper clearances and improper load are possible cause to yield bearing seizure independently. However, it is also possible to have improper clearances due to improper load, hence this is an extra relation, which cannot be displayed with a simple fault tree or functional hierarchy. Such links, which are suggested by the domain experts, are implemented to the structure of the model.

Each of the variables at this stage of causal-relations-structure, which are the failure mode, faults and features, are associated with discrete states. The states that characterize the faults and failure mode are most of the time *normal*, *intermediate* and *severe.* There are a few exceptions to this format, where defining a different set of states has been more appropriate.

The states that characterize the features are most of the time denoted as *low*, *normal* and *high*, which also corresponds to the measurements of these features. There are some exceptions to this format, as in the case of the faults. This is due to the fact that, there are situations where the readings from the features are not considered as "normal" when the magnitude of the measurement is normal. A "low" reading is rather preferred as the healthy measurement at such situations. Then, the states are redescribed as *low, medium,* and *high,* and the consideration is made accordingly.

2. Action Decisions

The module, or the portion of the expert system, which covers the possible maintenance actions, consists of decision-making options. The expert system is aimed to have the ability to draw conclusions and to advise for an appropriate maintenance action based on two concerns. The first concern is the state of the fault/failure mode, which is not known perfectly. The second one is the existence of uncertain predictions of future changes that might follow a particular action. In the way to comply with this aim, action variables are incorporated into the expert system structure. The action variables embed the *trip, maintenance* and *no-action* options. *Trip* corresponds to taking the unit out of service, and maintenance is done when the component is off-line. *Maintenance* corresponds to the situation where service is given to the component when the unit is still on-line operating. *No-action* corresponds to the situation where no service is given to the component either on-line or off-line. The consequences of these options are considered in short time intervals following the actions.

In decision making on the probable actions, the model considers taking the most beneficial option based on the net utility joined with each relevant variable (fault or failure mode) in the structure. The details of the utility concept are presented in Section III .

At this stage in building the knowledge base of the expert system, the overall structure is as in Figure 2a-e. This is an influence diagram of the smart-bearings. The influence diagram shown in Figure 2a-e includes the directed acyclic graph of the causal relations, the decision nodes for the actions and the relevant utility representation. The meanings and the functions of these terms will be presented in Section III. At this point, it is sufficient and informative to lay out the basic structure in the knowledge base of the expert system.

III. HOW THE EXPERT SYSTEM TOOL WORKS

There are two main components of the expert system. These are the knowledge representation, and the reasoning paradigm.

The knowledge representation is made of two sources:

- *qualitative part:* the graph representation,
- *quantitative part:* the associated probability model,

where each part is constructed by knowledge elicitation from the domain experts for this project. The graph representation covers the *directed acyclic graphs* and *the influence diagrams.* The associated probability model, for reasoning under uncertainty, for the quantitative analysis in the solution is *Bayesian* and *decision theories.*

1. Graph Representation

The qualitative representation of the causal relations is handled with the use of the *directed acyclic graphs (DAGs).* The graph determines the structure and the semantics of the reasoning. The variables (the failure modes, the faults and the features in the structure) together with the directed edges (the casual directions) form the DAGs. Each variable in the DAG has a finite set of mutually exclusive states. These were explained in Section II, as for instance, *low,* *normal, high* for the feature variable states, *normal, intermediate, severe* for the fault or failure mode states, etc.

The DAGs are complemented with the decision and utility concepts, and the relevant nodes, in this study. Therefore, in fact, the DAG is extended over the chance nodes (for the variables: the failure modes, the faults and the features), decision nodes (for the actions: trip, maintenance, no-action) and the utility nodes (for the cost/benefit). The extended version of the graphical representation, which cover the decision trees along with the causal relations between the variables, is the final *influence diagram.* The requirement on the influence diagrams is that there is a directed path comprising all decision nodes. This is to indicate the order of decisions taking place in the structure. However, until this part of our study, the order of decision has not been an important point. Therefore, the connections are made to comply with the theoretical and computational requirement.

2. Probability Model

The reasoning under uncertainty is handled by using the Bayesian Theory and the decision theory, as the probability models. Hence, in the diagrams, to each variable *A* (fault C_, failure mode F_, feature S_) with other parent variables, ($B_1, B_2, \ldots , B_n$), there is attached the potential table, or the conditional probability table $P(A| B_1, B_2, \ldots , B_n)$. This brings the definition of the graphs to *Bayesian Networks.*

The probabilities over the unobserved variables, given the setting of the observed variables (i.e. evidence) should be computed. This is *diagnostic* reasoning task, where effects are made known and the causes are inferred. The computations involved in this inference are spent on making the relevant pieces of gathered information explicit. That is to start with the measured features, and to infer to the possible fault or failure modes, which would be the causes to the changes in the feature readings. This is the propagation in the opposite direction of the causal arrows, and the computations are held with the Bayesian theory.

The basics behind the Bayesian theory is summarized as follows:

Conditional Probability: The basic concept in the Bayesian treatment of certainties in causal networks is *conditional probability.* A conditional probability statement is of the following kind:

"Given the event b, the probability of the event a is x"; P(a|b)=x

Fundamental rule: P(a|b)P(b) = P(a,b);

where *P(a,b)* is the joint of the event *a* and *b*.

Bayes rule: $P(b \mid a) = \frac{P(a \mid b)P(b)}{P(a)}$,

where the probabilities can be based on frequencies or may also be subjective estimates of the certainty of an event.

In the current calculations, the tool adopts the chain rule for Bayesian Networks, which is stated as:

The chain rule for Bayesian networks: Let BN be a Bayesian network over the set of variables $U = \{A_1, \dots, A_n\}$. Then the joint probability distribution P(U) is the product of all conditional probabilities specifies in BN

$$P(U) = \prod_i P(A_i \mid pa(A_i)),$$

where $pa(A_i)$ is the parents of A_i. Let $\underline{e}_1, \dots, \underline{e}_n$ be findings - evidence -, then

$$P(U, e) = \prod_i P(A_i \mid pa(A_i)) \prod_j \underline{e}_j,$$

and,

$$P(A \mid e) = \frac{\sum_{U \setminus \{A\}} P(U, e)}{P(e)}.$$

The task of determining the actions to take on the faults are computed on the criterion to have the highest expected utility. The usefulness of a decision or the usefulness of the state of a variable can be measured on the utility scale. Since there are several kinds of utilities in this problem (as the utility of an action, which is the relevant cost, and the utility of a state, which is the beneficial availability of the component), these scales are assigned a common unit. This assumption may seem dubious but has a sound reasoning. Then, this optimization is managed as in the decision tree solutions, with the concept of expected utility. For each set of actions, D, (which are left the same for this part of the project: trip, maintenance, no-action), the expected utility, EU, is calculated over the domains $X_1, X_2, \dots, X_n$ (the states of the faults or the failure modes in this study), with the utility functions (or values) U_1, U_2, ... , U_n, given the evidence, *e*, (which is collected from the measured features).

$$EU(D \mid e) = \sum_{X_1} U_1(X_1)P(X_1 \mid D, e) + ... + \sum_{X_n} U_n(X_n)P(X_n \mid D, e)$$

and a decision action, *d*, from the set D, maximizing EU(D|e) is chosen as an optimal action.

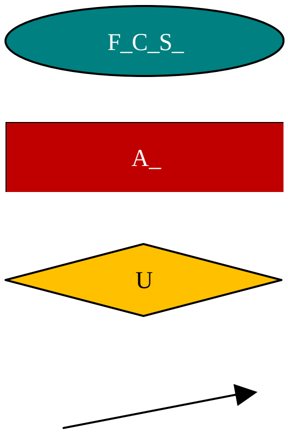
In the structure of this problem, there are three utility function sets related to each fault. First is the utility of the action, second is the utility of the states of a fault before an action is taken, and the last is the utility of the states of a fault after an action is taken.

During the course of this study, the utility values have not been elicited from the experts, yet. Therefore this task is not completed. However, it will be done in the future work.

Table 2: Nomenclature in Expert System Structure

F_xxx	Discrete chance node representing a *failure mode xxx* from Table 1
C_xxx	Discrete chance node representing the *fault xxx* from Table 1
y_xxx*	Discrete chance node representing the *fault or failure mode, y, of xxx* from Table 1, after an action is taken
A_xxx	Decision node representing the decision on actions to *fault or failure mode of xxx*
U_xxx	Utility node representing the value of the *state of the fault or failure mode of xxx*
U_A_xxx	Utility node representing the cost of *an action on the fault or failure mode of xxx*
MED_xxx_#	Discrete chance node representing the *mediating variable for the failure mode, fault or feature xxx, appearing #th time*

Figure 1: Variables that are used in the Expert System



Discrete chance node for failure mode, fault or feature, associated with a conditional probability table in the input

Decision node, associated with a set of actions

Utility node for cost/benefit/expected utility analysis, associated with a set of values.

Causal relation link between the cause and the consequence

Figure 2-a: Top Part of the Complete Structure – Influence Diagram – of the Smart Bearings

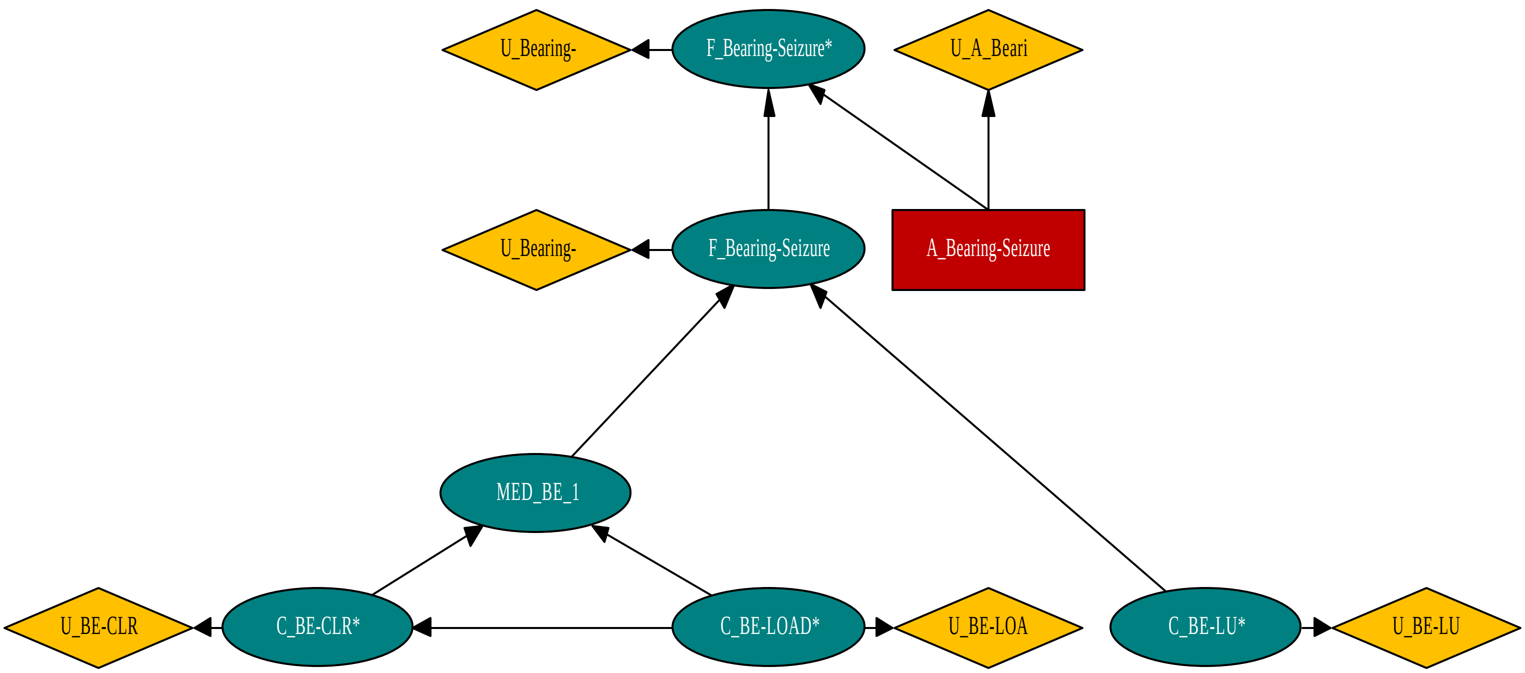


Figure 2-b: Complete Structure – Influence Diagram - of the Smart-Bearings

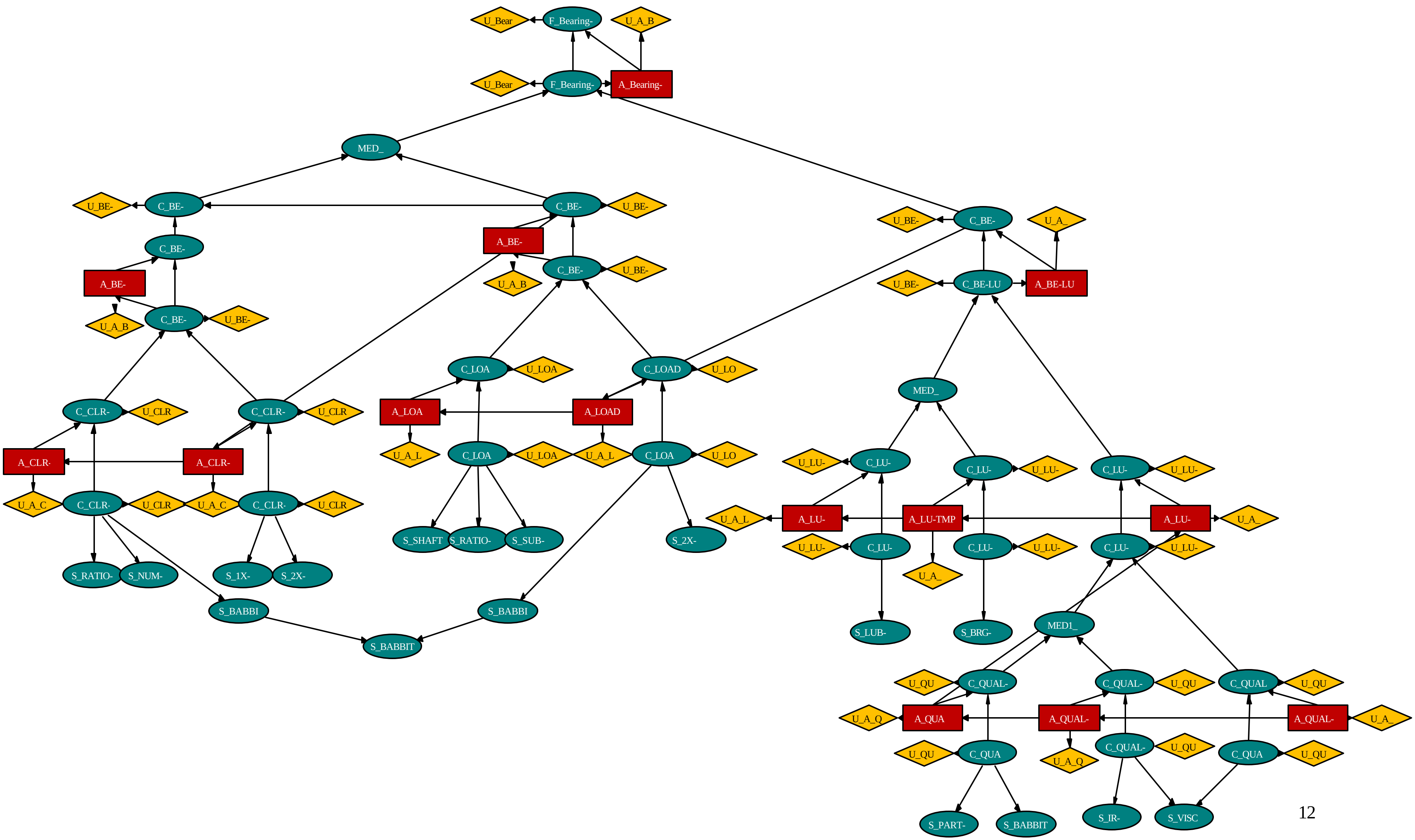


Figure 2-c: The Branch Related to Improper Clearances in the Complete Structure – Influence Diagram – of the Smart Bearings

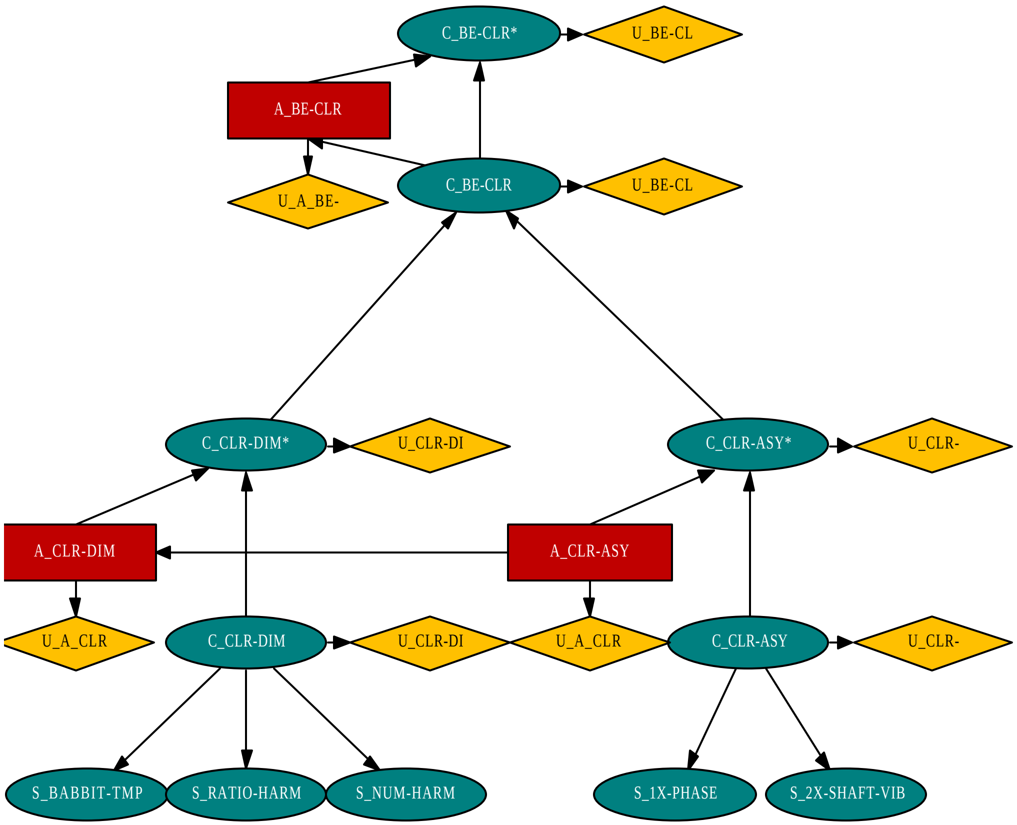


Figure 2-d: The Branch Related to Improper Load in the Complete Structure – Influence Diagram – of the Smart Bearings

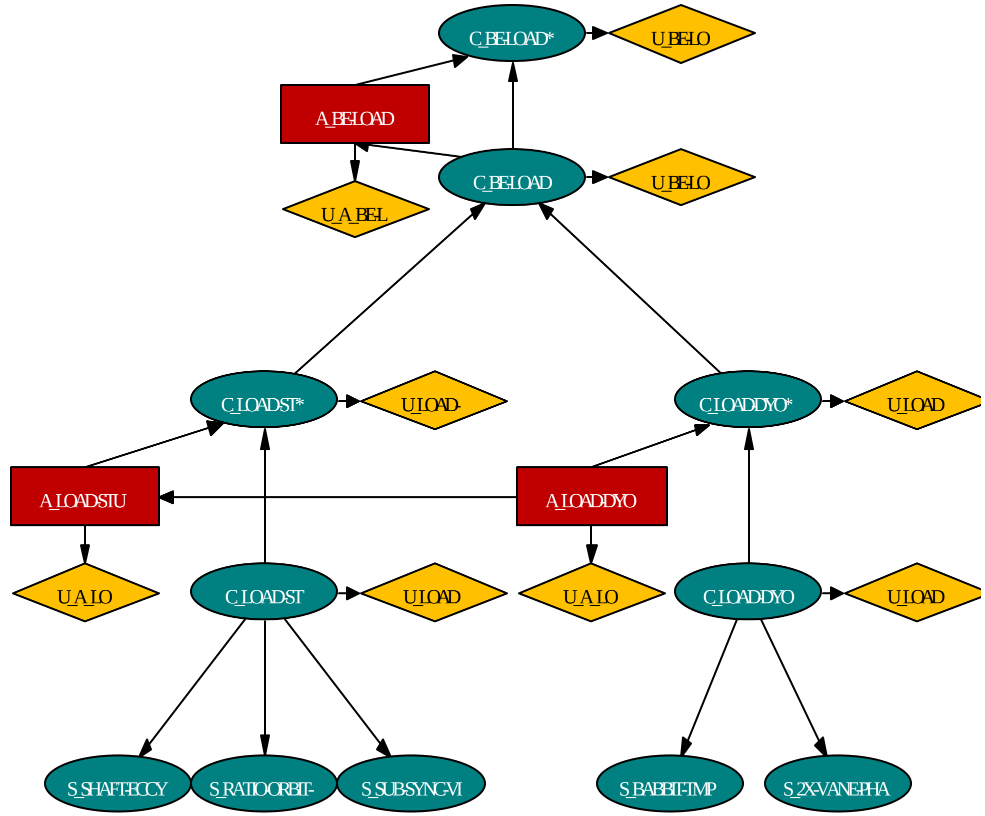
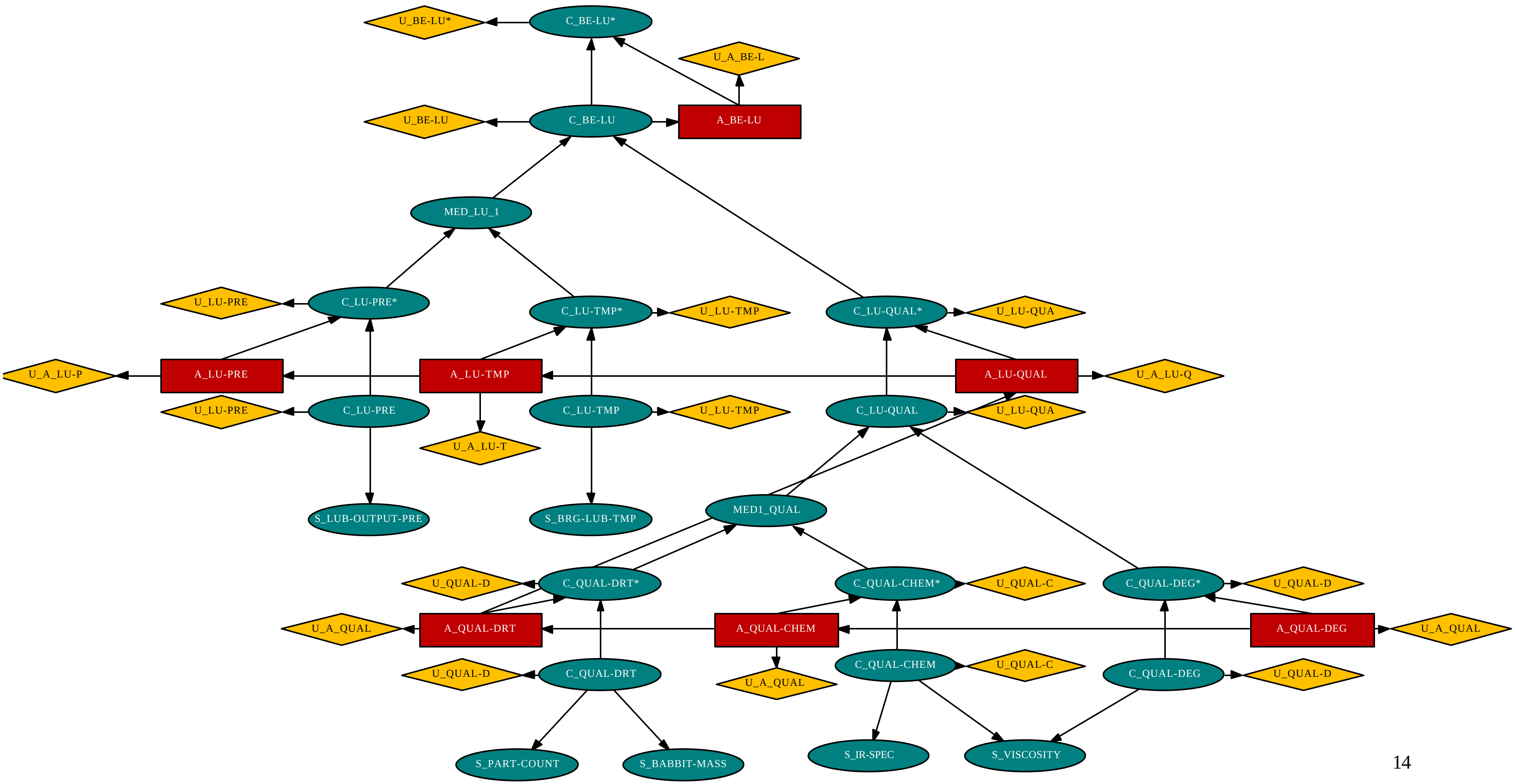


Figure 2-e: The Branch Related to Improper Lubricant Properties
in the Complete Structure – Influence Diagram – of the Smart Bearings



3. The Conditional Probability and Utility Values

The quantitative information embedded in the knowledge base is composed of the conditional probability input values and the utility function values.

The basic concept in the treatment of uncertainties in the above causal networks is conditional probabilities. This is the probability of an event in the model (the event at the end of the arrow = child), given the evidential event (the event at the beginning of the arrow = parent). However, there is lack of sufficient data to derive the conditional probabilities in terms of frequencies. Therefore, these probabilities are elicited from the experts in terms of subjective estimates of the certainty of events modeled in the structure of the expert system.

The second part of the quantitative information in the data base is the utility values associated with the state changes, and with the actions. The need for this is due to the treatment of the decision problem embedded in this structure, with the utility theory. The decisions are evaluated on the basis of the usefulness of their consequences. The usefulness is measured on the numerical scale called *utility scale* in the scope of this project. However, the utility values have not yet been elicited from the experts. This is a near future work to be completed for activating the decision making ability of this developing tool.

IV. THE TASK OF SMART BEARINGS -ILLUSTRATION

The experts system designed for the bearings in the charging pumps is able to comply two tasks. The first one is to diagnose possible faults associated with the operation of the bearings given the measurements on the features, which are the eventual symptoms. The second is to predict how the measurements could change at certain faulty operation. Another feature of the system, which has been one of the purposes but which couldn’t be finished is its ability to make decision about taking maintenance actions. This is not possible, yet, because the part in the knowledge base which helps to make the decisions is not completed. This is one of the future work on this system. For instance; for “high” readings on the measurements of the features “ratio of harmonics” and “number of harmonics”, the system indicates that the possible failure is in the clearances of the bearings. However, clearances could fail due to dimensional fault or asymmetry. The system especially diagnoses that the failure is in the dimensional failure of the clearances rather than the asymmetry failure. This is a very reasonable finding, validated by the domain experts.

Example:

The set of measurement readings are on 1X-Phase and 2X-Shaft-Vibr. The reading for 1X-Phase shows “high” and reading for 2X-Shaft-Vibr shows “medium”. These are to be entered by the user, by clicking on the high and low states of these variables in the run mode of the program. In the run mode, all the state probabilities of all the variables are available to the user to be accessed through the graphical user interface. The evidence entry is now by the user, however, in actual operation it should be with no user interface, where data should be fed to the entries directly. The readings of the measurements, which are entered to the program, are the new evidence of the expert system. The next step is to propagate the new evidence through the structure. This initiates the mathematics of the tool (as explained in Section III). The new probability distributions for all the states of all the variables are displayed to the user. The new evidence shows its effect by changing the probability distribution on the states of the relevant faults only. In this case, the system indicates that:

Table 3: Example problem

States	Asymmetry		Clearances	
	Initial Probability Distribution	Final Probability Distribution	Initial Probability Distribution	Final Probability Distribution
Normal	0.7	0.488	0.361	0.331
Intermediate	0.2	0.233	0.309	0.304
Severe	0.1	0.279	0.33	0.365

No other state probability changes are observed in the resulting list, therefore the indication is that the likely failure is from the clearances of the bearings, and specifically due to asymmetry.

Range of problems: At this stage, the expert system can handle the range of problems, which are listed in Table 1. These are all the faulty operation states that the bearings can face. The system can accomplish the diagnosis task with discretely given measurements in discrete states. When a new module based on rule base is added to the lower level of the system, the readings can be categorized rather continuously, and the system can handle more uncertainty by different ranges of feature measurements.

In addition, when there are multiple symptoms of different fault states, it is rather easy for the system to determine the faults, because almost all the features that are relevant to each fault are separate. In the course of this study, this has been accomplished by providing as much different features as possible for each fault.

The currently lacking part of the system is the inability to give sound advice on the maintenance actions. This will become possible after eliciting the relevant utility values from the domain experts.

V. CONCLUSIONS

The designed expert system is able to well handle various diagnosis aims given the collected evidence by entries in the run-mode. This is propagation in the opposite direction of the causal relation arrows. The evidence collected refers to the state of the features. It is also able to well predict what the behavior of the features, or of another fault, which are connected to the current fault variable, will be. This is propagation in the direction of the causal relation arrows in the graphs.

The knowledge presentation, which covers both the qualitative and quantitative information in the form of graphical representation, has been found very useful and convenient. The software tool to utilize these features was also very well serving.

The knowledge and reasoning related to the functional hierarchy and to the causal relations was rather easily elicited from the domain experts, and translated to the graphical representation and solution. There have been iterations and changes in the overall structure during the development, but this is an expected consequence due to the nature of the task.

The quantitative information, which is the conditional probability tables associated with each variable in the structure, was very hard to elicit and complete. This is due mainly to two reasons. The first is the complex structure of the physical system. The second is the depth in which the expert has to think while providing his subjective assessment of the probability values. Eventually, once this level was overcome, the result was quite strong and efficient in complying with the task..

The system, at the moment, cannot give accurate advice on the actions because the utility values have not been provided by the domain experts, yet. However, this does not mean that the system cannot do it. It is designed and structured to be capable of handling this task, too. This aim will be accomplished in the following studies.

The conditional probability tables associated with each variable in the structure, was very hard to capture, due to the reasons that were mentioned in the previous section. This is a built in problem in Bayesian techniques, due to exponentially growing amount of information, which becomes necessary as one increases the number of parent nodes. This is a burden on the experts while trying to yield their knowledge. This problem has been overcome by adding mediating variables to the Bayesian networks. These mediating variables do not represent any physical variables related to the bearings system itself. But they combine two parent nodes at a time, to carry the information form them. Then, the mediating variable itself is combined with the other nodes to the common child node. This changes the resulting probability distributions slightly, but doesn't change the set of possible diagnosis options much, because the mediating variables have the similar set of states as faults, and the tables relevant to them are completed appropriately, too.

There have been several issues that have been noticed during the course of this study. The main points are:

- It is difficult to get hold of the domain real experts. Though, when they are available, they are very helpful and efficient with the correct approaching manner. There is need to the experts yet to complete the quantitative knowledge base, to have the system work more thoroughly.
- It is almost impossible to get the knowledge correct at once. Iterations have been necessary to the structure of the model and to the quantitative knowledge base during the development of the expert system.

Both points are the main issues which are being dealt with in expert system design in the field of artificial intelligence applications in the industry.

This approach to handling on-line diagnosis and predictive maintenance with expert system design will allow plant designers to simplify designs without comprising reliability and safety. It is taken as another step to move towards a risk-based regulatory concept and application. In addition, this methodology provides a blueprint for creating the capability to predict the mean time to failure of the SSCs, therefore becomes an aid to decrease the operations and maintenance costs, while enhancing the reliability.