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Decision Support System for Predictive Maintenance

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Abstract
Predictive maintenance (PdM) is having vital importance in achieving optimum business objectives in industrial processes. Adapting to appropriate maintenance system is the necessity of today's corporate world in view of cutthroat competitions for maximizing profits. A decision support system (DSS) added with PdM activities helps achieve organizational goals in structured manner. Bayesian Networks (BN) and Influence Diagrams (ID) have got unique features to be used in DSS. The present work uses these tools to develop a DSS for PdM of industrial equipment.

Key Words: Bayesian Network, Decision Support System, Influence Diagram, Predictive Maintenance

1. Introduction

There is a wide gamut of industrial maintenance problems that requires the analysis of uncertain and imprecise information. Usually, an incomplete understanding of the problem domain further compounds the problem of generating models used to explain past behaviors or predict the future ones. These problems present a great opportunity for application of BN, which offers a methodological framework, and mathematical concepts for modeling various domains having inherent uncertainty. This approach focuses on using conditional probability theory to generate an accurate model and helps in fault diagnosis for complex systems. BN offers the ability of discovering cause-effect with uncertainties. It is a probabilistic graphical model for reasoning under uncertainty. In industries, the uncertainty may originate from incomplete understanding of the problem domain in process condition when maintenance actions are required to be performed.

Industry is built upon critical equipment that are vital to the smooth and safe operation of business. Appropriate maintenance is required to keep them operational for as long as possible, and as economicallyas possible, without sacrificing reliability or safety. If this task is neglected, equipment are likely to deteriorate, leading to unscheduled downtime and loss of production or more seriously, catastrophic failure that impacts on health, environment and safety. When schedules are tight, the effects of these equipment failures can cascade well beyond any individual system. However, a rigorous maintenance plan can be damaging to profits, with financial overheads of unnecessary maintenance and downtime quickly mounting up. In the interest of maximizing the profit margins, service should only be performed when required.

Maintenance is expensive and critical in most systems. Unexpected breakdowns are not tolerable. That is why planning activities intelligently using PdM system is an important issue since it saves money, service time and also lost production time.

Bayesian Statistics was developed several hundred years ago [1]. Now BN is a fast expanding technology in many areas where decision aids are needed in a context of uncertain knowledge about the real world [2]. It is a powerful tool to represent the causal relationships among the symptoms and possible faults [3]. It has been significantly used in fault diagnosis because of its ability of reasoning with uncertainty, discovering causal relationship, dealing with incomplete data set and incorporates with human knowledge [4]. If only a classification of the failure type is required, neural networks or statistical classifiers are more appropriate, but the neuro-fuzzy approach does not provide causal interpretation of diagnostic conclusions [5]. However, if DSS is needed, BN can be used for probabilistic reasoning in intelligent systems and the posterior probabilities can be calculated [6]. There is also another advantage that BN has the ability to adapt to changes [7]. The Bayesian method focuses on the combination of current probabilistic information of an event with newly found information for the same event, resulting in updated information [8]. [9] first applied the principles of Bayesian Statistics to decision theory. [10] used the concept of utility functions in decision theory. [11] introduced utility functions in Bayesian approach to decision theory. [12] used BN in decision-theoretic troubleshooting to balance between costs and likelihoods for the best action. [13] provides a formalism that combines the methodologies used in reliability analysis and decision theoretic troubleshooting. [14] presents a generic decision-theoretic troubleshooter to handle troubleshooting tasks incorporating questions, dependent actions, conditional costs, and any combinations of these. Decision-theoretic troubleshooting has always been studied as a static problem and with an objective to reach a minimum-cost action plan. The framework of ID is tailored to decision-making. It provides formalism for capturing the various types of knowledge involved in a decision problem and offers algorithms for computing preferred decisions [15]. ID provides a natural representation for capturing the semantics of decision making with a minimum of clutter and confusion for the decision maker [16]. BN and ID are especially suitable for DSS, since they incorporate probabilistic reasoning and can provide causal explanations [17]. Decision Analysis based on financial implications is very well suitable for maintenance decision making because of the uncertainty of trying to maintain equipment during the aging part of its life cycle [18]. The term that the decision maker is most concerned with is not whether a component will fail, but what this failure will mean to the health of the company [19].

However, with all the above efforts it is not possible to address problems such as (i) a fault showing multiple symptoms, (ii) different faults showing similar symptoms and (iii) faults leading to multiple failures. The diagnosis process may not get its guidance when unknown faults happen in the field, as it is not possible to enumerate all possible fault-circumstances for the training set in the learning phase.

The objective of the study is to develop a DSS for PdM based on processing a set of measured variables by using BN to sense changes in condition of equipment occurring due to a single fault with multiple symptoms or different faults with similar symptoms; having features to adapt to new faults, multiple failures and dynamically update maintenance schedules in response. Such activities will result in drastically reducing maintenance costs, while ensuring that production and services are reliable and efficient.

2. Decision Support System

The purpose of DSS is to gain insight into a decision and not to obtain a recommendation only. There are two types of DSS, such as data-driven and model-driven. Data-driven DSS is more suitable in online analytical processing (OLAP) and data mining applications. Users in OLAP applications think of a database as having multiple dimensions and query those dimensions in various combinations. Users use those queries to analyze relationships among the various dimensions and their associated data elements and present data in multiple formats. But such queries cannot reveal the patterns associated in databases used in data mining applications. In such cases one or more algorithms based on neural network, tree induction and/or clustering is used to identify the hidden patterns in the data.

Model-driven DSS allows the users to apply quantitative and/or qualitative models to data in order to solve semi-structured and unstructured problems. Users interact with a DSS and can perform sensitivity analysis to gain more insight into the problem and its potential solutions. Generally, this DSS contains three components: a data management system, which is a database; a model management system, which contains one or more models that are pertinent to the problem under investigation and an interrogation mechanism, which portrays various options, allows users to enter and change inputs, and provides access to the data and model management systems. Traditional DSS, which incorporates operations research models, has evolved over time. Some DSS includes knowledge models, which support the other components or act as an independent component to provide inference capabilities. The knowledge modules can use rules, BN, or some other formalism.

Model-driven DSS using BN and ID is most suitable for PdM systems. The model management contains one (or more) qualitative, quantitative, or knowledge model(s). The nature of the problem, objectives of decision maker, available data, and/or availability of implementation procedure would determine the number and types of models in the DSS. These models should support 'sensitivity' analyses. The data management module would contain data to be analyzed by the model(s). If an empirical model appears in the model management module, it is highly likely that the data management module would also have to support the database on which the empirical model is based. Model builders would have to update the empirical models to account for changes in technology and implementation practices over time. Finally the DSS would require a user interface that would facilitate the application of the model(s) to the data and provide practical recommendations for users to consider. Structure of the DSS for PdM is shown in Figure 1.

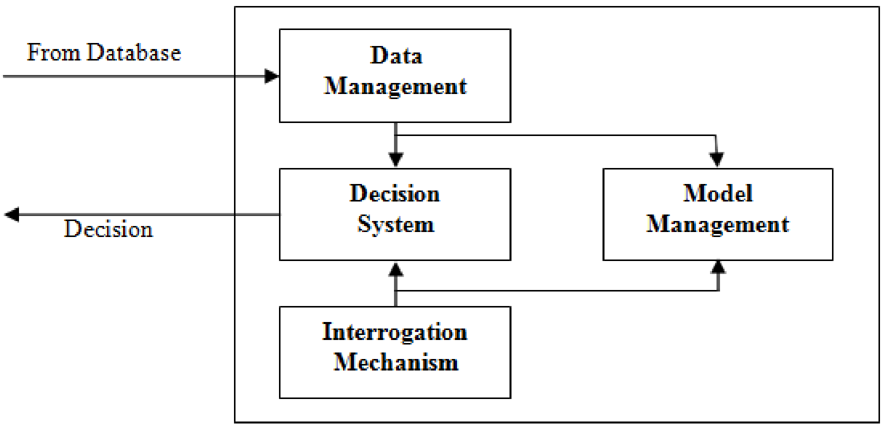


Figure 1: DSS for PdM

Figure 2: Proposed DSS

In the context of PdM, the DSS takes information about the status of equipment and query the database in order to respond to the situation in best possible way. The database holds information about the conditions that lead to an equipment failure, how these conditions evolve and interact, and how best to resolve problems. Having an appropriate DSS is critical for the success of the whole PdM system. It involves gathering data from a variety of sources, mining and analyzing this data, and deciding the best way to carry out maintenance activities. Clearly this is a complex task. However, a well-implemented DSS results in an efficient PdM system.

3. BN AND ID FOR DSS

BN is a graphical model that combines elements of graph theory and probability theory. It is one of the primary research topics in machine learning and data mining applications. For a DSS, BN and ID are most suitable as these can be used to calculate posterior probabilities and have the ability to adapt to changes. BN is a directed acyclic graph (DAG) in which nodes represent random variables and arcs represent direct probabilistic dependences among them. Each node has discrete states. The probability of a particular node taking its each state, given the states of its parent nodes, is defined using a Conditional Probability Distribution (CPD). The structure of a BN is a graphical, qualitative illustration of the interactions among the set of variables. It models a problem by mapping out cause-effect relationships among key variables and assigning to them probabilities that represent the extent to which one variable is likely to affect another. It gives a useful, modular insight into the interactions among the variables and allows for prediction of effects of external manipulation. It can also provide causal interpretation of diagnostic conclusions, which is one of the main system requirements for explanatory decision support. It can be used to generate optimal predictions / decisions even when key pieces of information are missing.

To some extent it is possible to construct a model for decision making with a pure BN but the concepts of utility and decisions are not explicitly covered in it. Therefore ID is used to bridge this gap. An ID can be also viewed as a BN extended by decision and utility nodes. The goal of ID is to choose a decision alternative that has the highest expected gain. The visual arrangement provides a convenient knowledge representation. The real power of the network manifests itself when applies the rules of Bayesian inference to propagate the impact of evidence on the probabilities of selected outcomes. An ID can thus be thought of as a probabilistic inference engine that can answer queries about the variables that appear in the network. Such queries may include calculation of conditional probabilities or the determination of independence between two variables. When used in this way, ID has the potential of making inferences under uncertain conditions.

BN is used to quantify uncertain interactions among random variables and this quantification helps to determine the impact of observations. ID is used to quantify a decision maker's decision options and preferences, which determines the optimal decision policy. In order to build a decision model, a decision maker has to clearly frame both the problem and the decision to be made.

Decision analysis rests on an empirically verified assumption that while it is relatively easy for humans to specify elements of decisions, such as available decision options, relevant factors, and payoffs; but it is much harder to combine these elements into an optimal decision. This assumption suggests strongly that decisions be modeled. A model supports a decision by computing the expected utility (value) of each decision alternative. The decision alternative with the highest expected gain is by default optimal and is chosen by the decision maker.

4. Methodology

The method of study for this work is done in the following steps:

Data acquisition – Status of equipment is monitored on regular intervals using Machinery Analyzer CSI2120

Updating Database – The above data are fed into a central database.

Analyzing Data – From the acquired data the current states of the equipment are assessed and their future states are predicted with the help of the software RBMWare Rev4.31 supplied by M/s Emerson Process Management Ltd.

Decision support – A course of action based upon the analyzed data is decided by using the DSS developed with the help of the software GeNIe 2.0 developed by Decision Systems Laboratory, University of Pittsburgh.

Updating Maintenance Schedule –As per the decision, maintenance schedules are updated usingthe maintenance package supplied by RAMCO Systems.

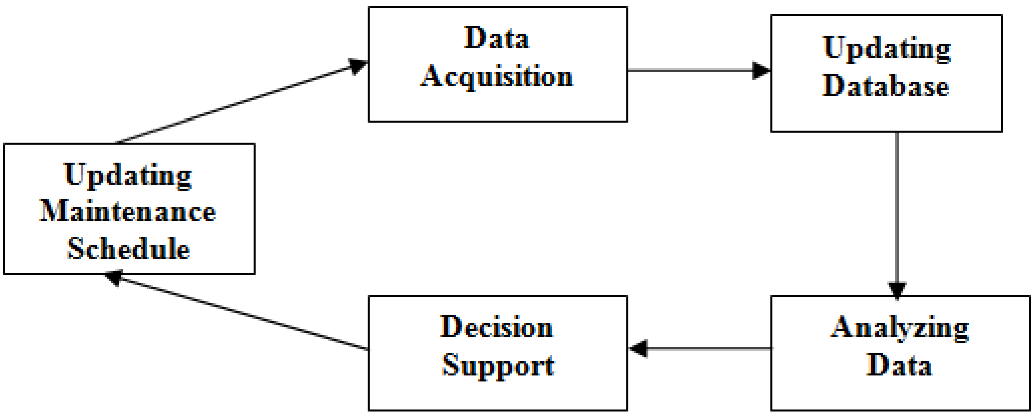


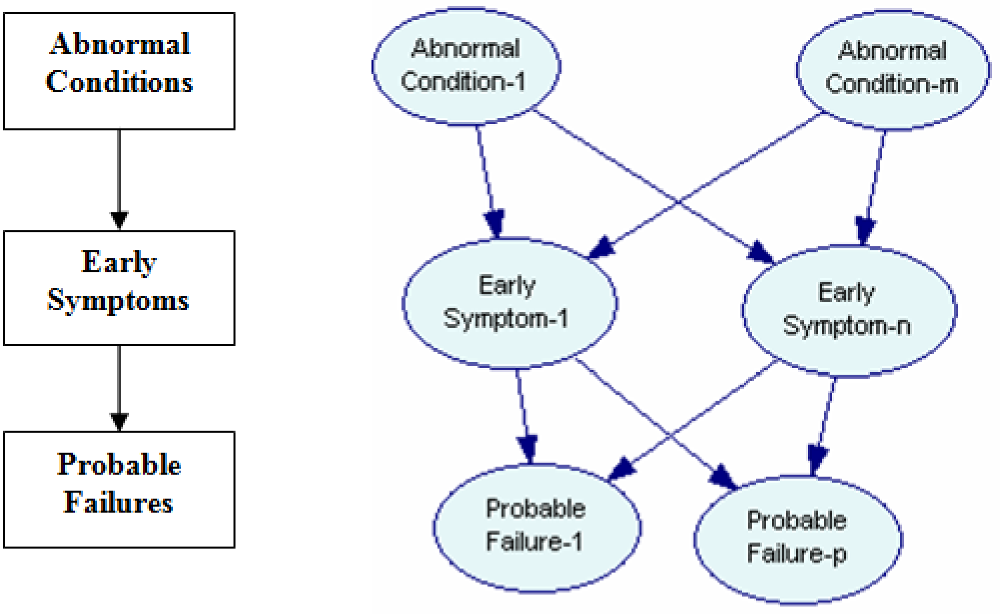
Figure 2: DSS in PdM System

The PdM system combines these steps in an integrated way as shown in Figure 2. There will always be some monitoring that can be best achieved manually, but this can be evaluated in combination with more automated monitoring to provide a comprehensive picture of all related equipment and consequences across the entire business.

The core of the PdM system is the DSS. Based on current state of equipment the DSS suggests necessary actions to be taken. It does not itself take decisions. It extracts and presents the information needed to enable a manager to take those decisions.

4.1 Model Formation

The generic mechanism of failure consists of abnormal operating conditions and some measurable, early symptoms. Sensors register these early symptoms. If not identified and corrected, the abnormal conditions can lead to failures. A causal representation of the above factors gives the following chain of events and transitions, which is of interest for PdM under uncertainty and for the purpose of decision support for corrective actions, as shown in Fig. 3(i). The BN model for PdM reflects the causal chain of dependency relations as shown in Fig. 3(ii).



(i) (ii)

Figure 3: (i) Mechanism of Failure (ii) Corresponding BN using GeNIe

The dependency relations are among the three symbolic layers of random variables in the problem domain where {Abnormal Conditions} varies from 1 to m, {Early Symptoms} from 1 to n and {Probable Failures} from 1 to p.

The set of {Abnormal Conditions} can be assessed by the set of {Early Symptoms}, which precede the set of {Probable Failures}. The set of {Early Symptoms} can be observed and measured by sensors. The three sets of variables {Abnormal Conditions}, {Early Symptoms} and {Probable Failures} can be viewed as three conceptual BN layers (i.e. Abnormal Conditions → Early Symptoms → Probable Failures), as shown in Fig. 3.

5. CASE STUDY

In a routine Condition Monitoring check up, it was found that there was high vibration and noise in Primary Air (PA) Fan-2A of Steam and Power Plant, NALCO Alumina Refinery, Damanjodi. Performing FFT analysis, it was found that the dominant frequencies of vibration were 1xRPM and 2xRPM, which indicated imbalance of impeller and structural weakness respectively. If the equipment were not spared for repair due to production pressure, it would lead to failure of bearings and/or foundation. A manager wants to decide whether or not to take remedial actions. To construct a model for this, similar nodes are added to the BN shown in Fig-3(ii) using the software GeNIe 2.0. In order to have analysis for decisions, a decision node is added to the BN. After addition of the decision node, the BN becomes an ID. As each decision involves cost, a utility node representing cost of repair, which includes costs of spares, labour and production loss, is added to the decision node. To perform sensitivity analysis, an additional indexing variable is added. It indexes various values for parameters in question and the software computes the impact of these values on the results. Suppose that we are uncertain as to the actual probability of the impeller imbalance. Believing that the nominal value of 0.65 is approximately right, we feel that it can be as low as 0.45 and as high as 0.85. To express this we will add a Decision node called Sensitivity with three states: Low, Nominal, and High.

As this 'Sensitivity' is regarding the probability of 'Impeller Imbalance' and 'Structural Weakness', we need to define the relationships among these nodes. We may add an arc from 'Sensitivity, node to 'Maintenance Decision' node in order to introduce an explicit temporal order between the decisions. This arc will be dotted to indicate that it signifies temporal order between nodes. The model is shown in Figure 4.

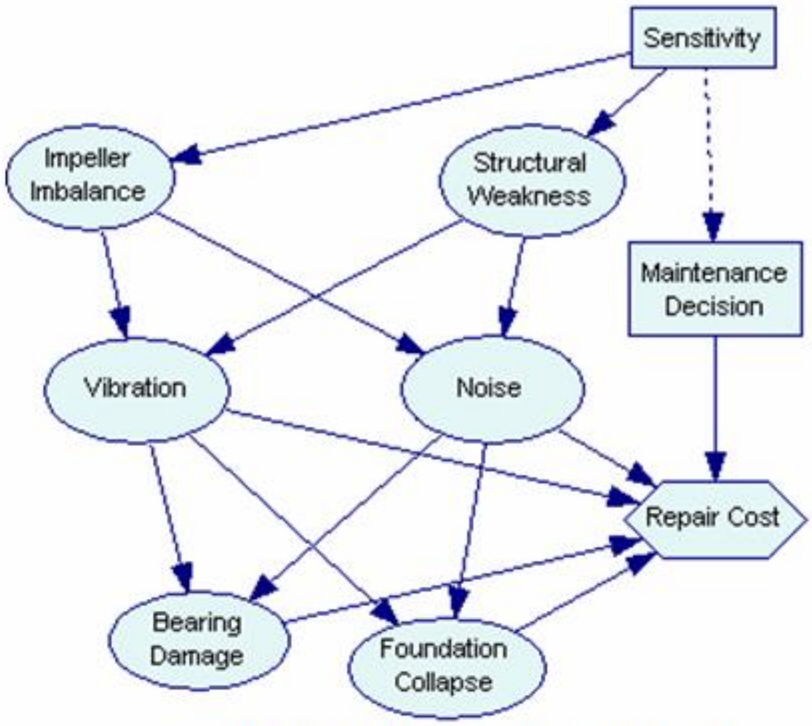


Figure 4: ID for Primary Air Fan-2A

Figure-4 shows the complete qualitative representation of the ID. To get the quantitative representation as well, we need to construct the conditional probability table (CPT) for each chance node and the utility table for the utility node. A decision node does not have any table. The CPTs and Utility Tables are given in the Appendix-I.

The main decision strategy is acting to maximize the company benefit. The inference results provide decision support on: "Which corrective action to take: Repair or DonotRepair." The above outlines a scenario of decision support on the urgency of corrective actions. It is modeled as an ID, as shown in Figure 4.

GeNIe has two algorithms that can be used here. They are 'Policy Evaluation' and 'Find Best Policy'. If the focus of reasoning is finding the best decision option rather than computing the expected values (or expected utilities) of a set of decision options, the algorithm for finding the best policy is used. The 'Policy Evaluation' algorithm solves the whole model, exploring all the possible combinations of decision nodes and observations. For all those combinations, it also calculates the posterior probabilities of all those nodes in the network that are impacted by them. All this information may not be necessary for some systems, notably those in which it is enough to identify the best decision option for the next decision step. This is precisely what the ‘Find Best Policy’ option algorithm is about. The algorithm calculates this best choice much faster than when evaluating all policies. The algorithm only calculates the best choice for the first undecided decision node. Once the network is updated, the best choice for the first undecided decision node will be the one containing a "1" in the node value. The rest of the choices will contain 0. The algorithm is applicable only to those ID whose first undecided decision node has no undecided/unobserved parents.

In the above model, setting the evidences for ‘Vibration’ and ‘Noise’ nodes as ‘High’ and applying ‘Policy Evaluation’ algorithm, it was found that the cost of ‘Repair’ is less than the cost of ‘DonotRepair’ which means that the observed early symptoms such as high vibration and noise, if not corrected, will lead to failure of bearing and/or foundation and the value of production loss will be higher than the cost of repair. So the manager decided to update the maintenance schedules to rectify the impeller imbalance and structural weakness problems taking shutdown of the above Primary Air fan. The posterior distribution of all the nodes of the above model is given in Appendix-II

This procedure is not only fan specific, but it can be used in general for deciding on the urgency of maintenance actions for any equipment. The difference would be in the specific ‘abnormal conditions, early symptoms and probable failures’ and on their corresponding cost and utility functions on the basis of whichthe decision is taken.

6. Conclusions

BN and ID are the most suitable tools to develop a DSS for PdM to handle single fault generating multiple symptoms and different faults showing similar symptoms, which may lead to single or multiple failures.

A well-designed DSS is a beneficial system and can assist in decision-making at a number of levels. When combined with data acquisition and analysis systems, it becomes a powerful tool for protecting equipment and optimizing their performance. It enables the plant manager to take up the maintenance activities when it is really required. It helps reduce financial overheads and downtimes by eliminating unnecessary service works and thereby increases the overall profitability of the orgainastion.

APPENDIX-I

CONDITIONAL PROBABILITY TABLES:

Table 1: Impeller Imbalance

Sensitivity		Low	Nominal	High
Impeller Imbalance	Yes	0.45	0.65	0.85
	No	0.55	0.35	0.15

Table 2: Structural Weakness

Sensitivity		Low	Nominal	High
Structural Weakness	Yes	0.32	0.55	0.75
	No	0.68	0.45	0.25

Table 3: Vibration

Impeller Imbalance		Yes		No	
Structural Weakness		Yes	No	Yes	No
Vibration	Low	0.12	0.14	0.17	0.61
	Medium	0.23	0.28	0.32	0.27
	High	0.65	0.58	0.51	0.12

Table 4: Noise

Impeller Imbalance		Yes		No	
Structural Weakness		Yes	No	Yes	No
Noise	Low	0.11	0.19	0.16	0.68
	Medium	0.23	0.32	0.33	0.25
	High	0.66	0.49	0.51	0.07

Table 5: Bearing Damage

Vibration		Low			Medium			High		
Noise		Low	Medium	High	Low	Medium	High	Low	Medium	High
Bearing Damage	Yes	0.16	0.23	0.29	0.25	0.32	0.37	0.55	0.65	0.73
	No	0.84	0.77	0.71	0.75	0.68	0.63	0.45	0.35	0.27

Table 6: Foundation Collapse

Vibration		Low			Medium			High		
Noise		Low	Medium	High	Low	Medium	High	Low	Medium	High
Foundation Collapse	Yes	0.07	0.12	0.21	0.25	0.28	0.34	0.52	0.64	0.77
	No	0.93	0.88	0.79	0.75	0.72	0.66	0.48	0.36	0.23

Table 7: Repair Cost

Maintenance Decision	Vibration	Noise	Bearing Damage	Foundation Collapse	Repair cost in Rs lakh
	Low	Low	Yes	Yes	43
				No	37
			No	Yes	25
				No	0
		Medium	Yes	Yes	45
				No	38
			No	Yes	29
				No	5
		High	Yes	Yes	48
				No	41
			No	Yes	32

				No	7
Repair	Medium	Low	Yes	Yes	52
				No	43
			No	Yes	34
				No	10
		Medium	Yes	Yes	57
				No	50
			No	Yes	46
				No	12
		High	Yes	Yes	61
				No	52
			No	Yes	50
				No	16
	High	Low	Yes	Yes	64
				No	55
			No	Yes	52
				No	17
		Medium	Yes	Yes	67
				No	57
			No	Yes	55
				No	19
		High	Yes	Yes	72
				No	59
			No	Yes	57
				No	23
Do not Repair	Low	Low	Yes	Yes	77
				No	61
			No	Yes	59
				No	27
		Medium	Yes	Yes	81
				No	65
			No	Yes	63
				No	34
		High	Yes	Yes	83
				No	66
			No	Yes	65
				No	37
	Medium	Low	Yes	Yes	87
				No	67
			No	Yes	63
				No	39
		Medium	Yes	Yes	91
				No	68
			No	Yes	65
				No	41
		High	Yes	Yes	93
				No	72
			No	Yes	66
				No	43
		Low	Yes	Yes	95
				No	75
			No	Yes	67
				No	45

	High	Medium	Yes	Yes	97
				No	78
			No	Yes	69
				No	47
		High	Yes	Yes	100
				No	81
			No	Yes	70
				No	50

APPENDIX-II

Posterior Probabilities (PP):

Table 8: PP of Impeller Imbalance

Impeller Imbalance	Yes	0.847012
	No	0.152988

Table 9: PP of Structural Weakness

Structural Weakness	Yes	0.722892
	No	0.277108

Table 10: Evidence of Vibration

Vibration	Low	0
	Medium	0
	High	1

Table 11: Evidence of Noise

Noise	Low	0
	Medium	0
	High	1

Table 12: PP of Bearing Damage

Bearing Damage	Yes	0.73
	No	0.27

Table 13: PP of Foundation Collapse

Foundation Collapse	Yes	0.77
	No	0.23

Table 14: Expected Repair Cost

Repair Cost (in Rs)	Repair	6365590
	DonotRepair	8746790

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