ABSTRACT

Title of dissertation: A BAYESIAN APPROACH TO SENSOR PLACEMENT AND SYSTEM HEALTH MONITORING

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System health monitoring and sensor placement are areas of great technical and scientific interest. Prognostics and health management of a complex system require multiple sensors to extract required information from the sensed environment, because no single sensor can obtain all the required information reliably at all times. The increasing costs of aging systems and infrastructures have become a major concern, and system health monitoring techniques can ensure increased safety and reliability of these systems. Similar concerns also exist for newly designed systems.

The main objectives of this research were: (1) to find an effective way for optimal functional sensor placement under uncertainty, and (2) to develop a system health monitoring approach with both prognostic and diagnostic capabilities with limited and uncertain information sensing and monitoring points. This dissertation provides a functional/information –based sensor placement methodology for monitoring the health (state of reliability) of a system and utilizes it in a new system health monitoring approach.

The developed sensor placement method is based on Bayesian techniques and is capable of functional sensor placement under uncertainty. It takes into account the uncertainty inherent in characteristics of sensors as well. It uses Bayesian networks for modeling and reasoning the uncertainties as well as for updating the state of knowledge for unknowns of interest and utilizes information metrics for sensor placement based on the amount of information each possible sensor placement scenario provides.

A new system health monitoring methodology is also developed which is: (1) capable of assessing current state of a system's health and can predict the remaining life of the system (prognosis), and (2) through appropriate data processing and interpretation can point to elements of the system that have or are likely to cause system failure or degradation (diagnosis). It can also be set up as a dynamic monitoring system such that through consecutive time steps, the system sensors perform observations and send data to the Bayesian network for continuous health assessment.

The proposed methodology is designed to answer important questions such as how to infer the health of a system based on limited number of monitoring points at certain subsystems (upward propagation); how to infer the health of a subsystem based on knowledge of the health of the main system (downward propagation); and how to infer the health of a subsystem based on knowledge of the health of other subsystems (distributed propagation).

A BAYESIAN APPROACH TO SENSOR PLACEMENT AND SYSTEM HEALTH MONITORING

by

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Dedication

In memory of my father, Hossein Pourali

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It is with great sincerity that I thank my mentor and advisor, Professor Ali Mosleh, for his constant support throughout my graduate studies at the University of Maryland. I thank him for his encouragement, constructive criticism, and belief in my abilities. I thank him especially for his patience during the countless hours we spent working together. I also wish to thank the members of my committee, Professor M. Modarres, Professor S. Azarm, Professor A. Christou, and Professor Y. Zhang , for their constructive advices.

And finally, I would like to sincerely thank my family, without their endearing support, I might not have conquered this.

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List of Abbreviations

AGP	Art Gallery Problem
BBN	Bayesian Belief Network
BN	Bayesian Network
BSP	Bayesian Sensor Placement
CBM	Condition-Based Maintenance
CPT	Conditional Probability Tables
DBN	Dynamic Bayesian Network
DAG	Acyclic Directed Graph
DGA	Dissolved Gas Analysis
DP	Degree of Polymerization
EKF	Extended Kalman Filter
EPA	Environmental Protection Agency (United States)
GUI	Graphical User Interface
HCL	Hybrid Causal Logic
IMS	Inductive Monitoring System
IPL	Inverse Power Law
LSE	Least Square Error
$MCMC$	Markov chain Monte Carlo
PDF	Probability Distribution Function
PHM	Prognostics and Health Management
PoF	Physics of Failure
PPM	Parts per million
PRA	Probabilistic Risk Assessment
RCM	Reliability Centered Maintenance
RS	Relative Saturation
SIV	Sensor Information Vector
$SPOT$	Sensor Placement Optimization Toolkit
SV	State Vector
UOI	Unknowns of Interest
ε	Evidence set
σ^2	The variance of a distribution
μ	The mean value of a distribution

Chapter 1

Introduction

1.1 Research Motivations

System health monitoring and optimum sensor placement are areas of increasing technical interest. Rising costs of aging systems and infrastructures have become a major concern, and system health monitoring techniques are viewed as a way of reducing costs while increasing safety and reliability of these systems.

One way to minimize both maintenance and repair costs as well as the probability of failures, is through continuous health assessment of systems and prediction of future failures based on current health and maintenance history. Therefore, one of the goals of implementing system health monitoring is to alleviate the growing concerns over the maintenance of legacy equipment by replacing scheduled maintenance with as-needed maintenance and saving the cost of unnecessary maintenance and preventing unscheduled maintenance activities. In other words, system health monitoring allows condition-based maintenance (CBM) inspection instead of schedule-driven inspections. Similarly, when new systems are designed and developed, appropriate system health monitoring can be embedded in design which is expected to reduce the life-cycle operating cost.

Another method of utilizing reliability estimates of a system is to formulate a cost-effective maintenance plan, often called reliability centered maintenance

(RCM). The goal of RCM methodologies is to find logical ways to identify what equipment is required to be maintained on a preventive maintenance basis rather than let it run to failure.

Reviewing current system health monitoring techniques and various sensor placement optimization methods including Dhillon et al [1], Hart et al [2] and Vickers et al [3], it is apparent that almost all of these methods have attempted to optimize the physical location (geometry) of sensors. In addition, it is a common practice to assume that all data sets inferred by sensors are non-overlapping. Data sets are considered overlapping when: (1) the sets are drawn from observations that occur at the same time, and (2) the sets are dependent on the same system or process. Hamada et al [4] presented a Bayesian approach to combine data sets and other statistics of events at all levels in a fault tree, and they assumed that data sets were non-overlapping. Jackson and Mosleh [5], [6], [7] presented Bayesian methods to analyze overlapping data sets, however, deriving the presented likelihood functions might appear to be difficult. And finally, in most cases, the uncertainties associated with sensors are ignored. Further details on current state of the art on sensor placement and system health monitoring techniques are presented in Chapter 2.

The main motivation for this research was to develop an effective approach for sensor placement based on sensors' functional locations in a logic diagram to monitor systems' health more efficiently and also address the weaknesses in current methodologies.

This research developed new algorithms for sensor placement under uncertainty and utilized them in a new system health monitoring approach. The overall methodology is designed to answer important questions such as how to infer the health of a system based on limited number of monitoring points at certain subsystems (upward propagation); how to infer the health of a subsystem based on knowledge of the health of the main system (downward propagation); and how to infer the health of a subsystem based on knowledge of the health of other subsystems (distributed propagation).

Specifically, the main objectives of this research were to (1) find an effective way for optimal functional sensor placement under uncertainty, and (2) develop a system health monitoring approach with both prognostic and diagnostic capabilities with limited, uncertain, and overlapping information sensing and monitoring points.

A system's reliability information can be obtained through the placement of sensors in various places of the system. However, in many applications, due to physical, technological or resource limitations, one may not be able to place sensors where they are needed the most. We developed a Bayesian framework to optimize the sensor placement in a system based on functional locations, and to gather maximum reliability data about the system. *Information metric* is defined as a scale to measure the amount of information each sensor placement scenario provides, and its domain is a set of real numbers that can be interpreted directly as expected gains on the chosen scale such as amount of information, entropy, etc. Bayesian belief networks are utilized to combine the information obtained from evidence, with our prior knowledge of the unknowns of interest being the failure probabilities of lower level components, subsystems and system. This presents the heart of a novel methodology for optimum sensor placement and health monitoring techniques in a complex system.

1.2 Overview of the Approach and Contributions

One of the strongest motivations for this research was to find a general methodology for sensor placement based on logical or functional placement of sensors. The Bayesian methodology developed for placing the sensors throughout a system is aimed at finding the optimum sensor placement scenario for extracting the most amount of reliability information from the measured data. The approach takes into account all uncertainties within the probabilistic framework and combines the different sources of information using the rules of probability.

The Bayesian sensor placement (BSP) algorithms utilize Bayesian networks for modeling, updating and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest (UOI) as they are defined by (1) failure probabilities of lower level components, subsystems or system, (2) value of parameters, and (3) the probability of physical parameters taking specific values. "Information metrics" are used to assess the amount of information each sensor placement scenario provides and the results are used to identify the optimized sensor placement scenario based on the amount of information each possible sensor placement scenario provides.

The process starts with identifying the system functional failure modes and failure mechanisms and relevant stress models. A logic diagram (e.g. fault tree) is chosen to represent the logical relationships among the components and subsystems within a complex system. A Bayesian network of the system is then constructed, and through engineering considerations, several potential sensor placement scenarios are identified. Lastly, the value of "information metrics" are used to compare the amount of information among sensor placement scenarios.

Contributions of the research include:

- A new functional point sensor placement method based on Bayesian techniques is developed which is capable of functional sensor placement under uncertainty.
  - Bayesian networks are utilized for modeling, updating and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest as they are defined by: failure probabilities of lower level components, subsystems or system; value of parameters; and the probability of physical parameters taking specific values.
  - "Information metric" is used to optimize sensor placement based on the amount of information each possible sensor placement scenario provides.
  - The placement process is based on functional locations od sensors on a logic diagram.
  - The uncertainty inherent in the characteristics of sensors is taken into account.
  - To model the case study and other presented examples, several algorithms in MATLAB and other software programs are developed.

- A new system health monitoring methodology is developed.
  - The methodology is capable of assessing current state of a system's health and can predict the remaining life of the system (prognosis), and through appropriate data processing and interpretation can point to elements of the system that have or are likely to cause system failure or degradation (diagnosis).
  - It can be set up as a dynamic monitoring system such that through consecutive time steps, the system sensors perform observations and send data to the Bayesian network for continuous health assessment. This makes the Bayesian network a dynamic Bayesian network.

1.3 Dissertation Overview

Chapter 2 presents a summary of current state of the art on subjects related to sensor placement and system health monitoring. It starts with a summary of literature on Bayesian sensor placement optimization followed by literature summaries on other sensor placement optimization techniques, such as multi-objective optimization, genetic algorithm, statistical methods and neural networks. The chapter continues with literature review on system health monitoring under two major categories: (1) Bayesian methods and system health monitoring, and (2) PHM and other techniques for system health monitoring. It follows with an overview of other relevant literature such as multi-sensor data fusion and a discussion on overlapping and non-overlapping data sets. At the end of Chapter 2, a summary of shortcomings and concerns in regard to current state of the art in sensor placement and system health monitoring are presented.

Chapter 3 provides an overview of key building blocks and the proposed methodologies for Bayesian sensor placement and system health monitoring. The chapter starts with presenting Bayesian belief networks and dynamic Bayesian networks, followed by discussions on "information metrics" and "entropy". The second half of Chapter 3 is dedicated to overview of Bayesian sensor placement and the proposed health monitoring system methodologies. It starts with a description of Bayesian sensor placement algorithms, followed by an overview of the "inference engine". It then presents two new definitions: "components state vectors" and "sensor information vectors (SIV)" and is continued by a description of sensor placement algorithms. The chapter ends with an overview of the proposed health monitoring system.

Chapter 4 presents the building blocks of the inference model construction for the proposed Bayesian sensor placement algorithms. The chapter starts with an overview of a power transformer chosen as a case study system. Then its functional failure modes, failure mechanisms, and physics of failures are reviewed, followed by a summary of various stress and life models. Then a sub-set of the power transformer (partial system) is considered as the case study system. The rest of the chapter deals with the details of building the Bayesian inference model, selecting potential sensor types and locations, and building the components state vectors and sensor information vectors.

Chapter 5 presents the proposed Bayesian framework algorithm for sensor placement using the case study system presented in Chapter 4. The details of the developed algorithms show how to measure the amount of information for various sensor placement arrangements for the case study. The prior knowledge of the system is used to simulate numerous evidence sets which in turn provide several posterior information sets in the form of "Sensor Information Vectors". Information metric functions are employed to compare the amount of information for various sensor configurations and optimized sensor placement scenario is presented. In addition, solution for cases with no historical data is discussed as well. The Chapter ends with scalability analysis for the proposed Bayesian sensor placement algorithms.

Chapter 6 presents another example to show the details of the proposed Bayesian sensor placement methodology in a more complex system with a larger Bayesian network model as well as larger historical data sets and more potential sensor places. In this example, the BSP is utilized to find the best locations of sensors for a power transformer taking into account all of its subsystems.

Chapter 7 presents the proposed Bayesian system health monitoring methodology in conjunction with the proposed Bayesian sensor placement techniques discussed in previous chapters. Chapter 7 starts with an introduction on system health monitoring and then followed by an overview of current system health monitoring philosophies and techniques. Then it is followed by details of the proposed Bayesian system health monitoring methodology. The chapter ends with presentation of an application of Bayesian system health monitoring in an example and presents various scenarios as part of this example.

Chapter 8 presents a summary of the research methodology and its contributions. Also provided are suggestions for future work.

Chapter 2

Current State of the Art

2.1 Introduction

Current sensor placement optimization methodologies are focused on optimizing the physical location (geometry) of sensors. Most of current health monitoring systems operate in "upward propagation" of data and their goal is to infer information at system level based on data gathered at component or subsystem levels. In addition, it is almost a common practice to assume that all data sets inferred by multiple sensors in one system are independent. Likewise, in most cases, the uncertainties associated with sensors are assumed insignificant and ignored.

This chapter, reviews current state of the art in sensor placement optimization methods, system health monitoring techniques, and a few other topics related to sensor placement and health monitoring. We summarized all of the reviewed literature on Bayesian sensor placement optimization in Section 2.2 and on system health monitoring in Section 2.3 to present the range of current methodologies in sensor placement optimization and health monitoring systems.

2.2 Current State of the Art in Sensor Placement Optimization (SPO)

The most widely used techniques for sensor placement optimization are based on finding the best possible physical location of sensors, given the constraints. Through the years, numerous methodologies have been proposed to achieve this goal. These techniques include various Bayesian approaches as presented in [8], [9], [10], [11] and [12]. Other approaches include multi-objective optimization [2], [13], [14], [15], genetic algorithm [16], statistical methods [1], [3], [17] and neural networks [18]. And Guratzsch [11], [12] utilized finite element analysis to find approximate placement of sensors under uncertainty. Section 2.2.1 presents the current state of the art in Bayesian sensor placement optimization methods and Section 2.2.2 presents the state of the art in other sensor placement optimization methods. Section 2.3 presents the current state of the art in system health monitoring approaches.

2.2.1 Bayesian Sensor Placement Optimization Methods

Applications of Bayesian methodologies for sensor placement optimization are mostly focused on updating the state of knowledge regarding the operating environment using sensory data [9]. In other applications, Bayesian techniques are used to develop a smarter sensing strategy utilizing decision theoretic approaches [19]. In the latter application, prior knowledge and evidence sets form one or more sensed points are used to maximize an information metric function, with the goal of improving the sensory strategies for the next sensing location. Most of the current literature on Bayesian sensor placement optimization revolves around utilizing Bayesian decision theory to formalize an optimization problem [9], [11], [12]. The following sections present samples of the current literature on Bayesian sensor placement optimization and current approaches of these methodologies which are mainly used for optimizing the "physical" location of sensors within a system.

2.2.1.1 Durant-Whyte Bayesian Approach

Durant-Whyte [20] presented an application of Bayesian methods for sensor placement optimization. Specifically, he used a statistical decision theoretic approach (Bayesian Decision Theory) to develop a sensing strategy and to determine the optimal sensing locations for performing recognition and localization operations.

2.2.1.2 Kristensen Bayesian Approach

Kristensen [10] presented another Bayesian approach for sensor planning to be utilized in a robot. The method uses Bayesian decision analysis to decide what sensing actions need to be taken in a dynamic situation (i.e. a robot operation). The author's approach to sensor planning is mainly on how to use the sensors given that the decisions have already been made on what types of sensors to use and where to place them. The main reason claimed for using a Bayesian approach in aforementioned research was its framework, which allows for reasoning about uncertainties as well as for modularity and scalability.

The heart of this approach is the utilization of Bayesian decision analysis to

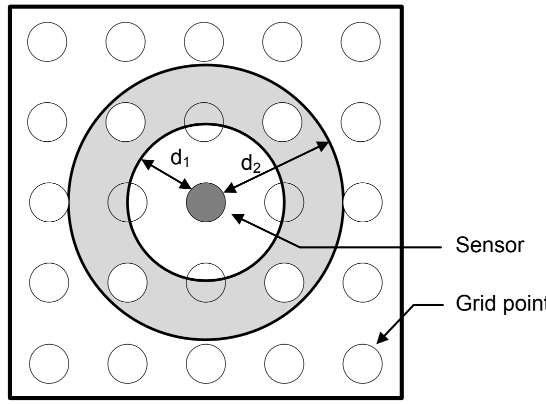


Figure 2.1: Dhillon's sensor detection model

evaluate different sensing actions against each other according to their given tasks and state of their environment. Then, based on assigned utility functions, cost or benefit of different actions are evaluated and the most beneficial "sensing task" is selected.

The problem is formulated through decision tree for various decision problems for each sensor. The tree starts with a root decision as to what module this sensor should be assigned and is followed by various chance nodes and decision nodes. Typically the result of analyzing through decision tree is finding the "best" path through different nodes. The same procedure needs to be repeated for all sensors implemented in the system (i.e. robot).

2.2.2 Other Sensor Placement Optimization Methods

Dhillon et al [1] presented an optimization framework for sensor resource management with the goal of covering a specific two-dimensional field. In this methodology, the first assumption is that the sensor field is made up of grid points. The granularity of the grid (distance between consecutive grid points) is determined by the accuracy with which the sensor placement is desired. The second assumption is that the probability of detection of a target by a sensor varies exponentially with the distance between target and the sensor. This model is illustrated in Figure 2.1.

A target at distance d from a sensor is detected by that sensor with probability of $e^{-\alpha d}$ where α can be correlated with the quality of sensor. The detectability of the sensor will decrease as the distance between the target and sensor increase.

There is a very close resemblance between this approach and the famous art gallery problem (AGP) which was addressed by the art gallery theorem. The AGP can be stated as determining the minimum number of guards required to cover the interior of an art gallery (the interior of the art gallery is represented by a polygon) with one main difference that, in contrast to the guards in AGP, sensor detection outcomes are probabilistic.

Hart et al [2], through a joint program between Sandia Lab and the US Environmental Protection Agency (EPA), developed a sensor placement optimization toolkit (SPOT) for contamination detection in drinking water. The main idea of SPOT is to place n sensors on a set of L vertices, with the objective of minimizing the expected impact of a set $\mathcal{A}$ of contamination events. The optimization of mean impact is formulated as

$$
\begin{aligned}
\min \sum_{a \in \mathcal{A}} \alpha_a & \sum_{i \in \mathcal{L}_a} d_{ai} x_{ai} && && (2.1)\\
\text{s.t.} \sum_{i \in \mathcal{L}_a} x_{ai} &= 1 && \forall a \in \mathcal{A} \\
x_{ai} &\le s_i && \forall a \in \mathcal{A},\ i \in \mathcal{L}_a \\
\sum_{i \in L} s_i &\le n \\
s_i &\in \{0, 1\} && \forall i \in L \\
0 \le x_{ai} &\le 1 && \forall a \in \mathcal{A}
\end{aligned}
$$

where a is a contamination event with likelihood of α_a such that $\sum_{a \in A} \alpha_a = 1$; s_i is the binary decision variable for each potential sensor location $i \in L$ which is equal to 1 if a sensor placed in location i and 0 if not; $\mathcal{L}_a$ is a subset of locations that could be contaminated by event a; d_{ai} is the pre-computed contamination impact of event a; x_{ai} indicates whether the event has been detected or not; and $d_{ai}x_{ai}$ is the impact of event a for all locations.

Vickers et al [3] used environmental information, derived from a computational river current model, to optimize sensor placement, increasing detection rates and decreasing the number of required sensors. In a case study, they focused on a small segment of the Hudson River adjacent to New York City and used a variety of available environmental data, such as current speed at different points of the river, etc. A diver's interaction with the environment was modeled to describe the likelihood of a diver choosing or managing to swim in water of various current speeds.

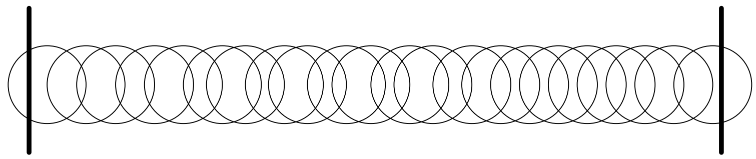


Figure 2.2: Equally distributed arrangement of 35 sensors across 1340 meter wide of river. Vertical lines represent shore lines. Circles represent maximum detection range of sensors [3].

Figure 2.2 shows a cross section of the river with 35 sensors across 1340 meter wide of river. The conditional probability that the i^{th} sensor from this array will detect the diver, given that he crosses the line at a particular point, x, will be $P(D^i \,|\, x)$.

Assuming independence among the sensors' operations, the total probability of a diver, crossing at point x, being detected by the sensor array is given by

$$P(D^T \,|\, x) = 1 - P(\bar{D}^T \,|\, x) = 1 - \prod_i \big(1 - P(D^i \,|\, x)\big). \tag{2.2}$$

Stolkin et al (and others) calculated the terms $P(D^i \,|\, x)$ as

$$P(D^i \mid x) = \begin{cases} 0.95\Big(1 - \frac{|x - x_i|}{50}\Big) & \text{if } 0 \le |x - x_i| < 50 \\ \\ 0 & \text{all other } |x - x_i| \end{cases} \tag{2.3}$$

where x_i denotes the position of the sensor.

Figure 2.2 shows 35 sensors equally distribute across the Hudson river. It also shows how much overlap the sensors create, which in turns, provide relatively high probability of detection. Ignoring the environmental effects and assuming (er-

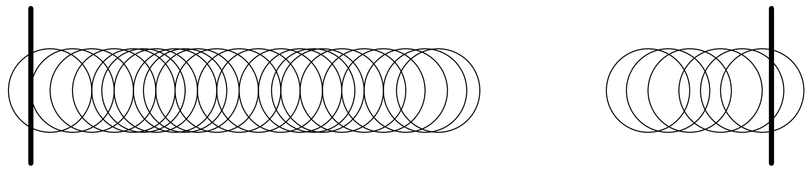


Figure 2.3: Optimal arrangement of 35 sensors to maximize total probability of detection, given prior knowledge of the environment derived from computational current model [3].

roneously) that the diver is equally likely to attempt an attack in any part of the river, leads to the conclusion that probability of detection at any point of the river will be equally distributed.

To optimize the placements of sensors with respect to the additional environmental information, standard non-linear optimization techniques were used to optimize all sensor positions using total probability of a diver will be detected should he attempt to cross the sensor array line, which can be calculated by

$$P(D^T) = \int_{\text{x on east bank}}^{\text{x on west bank}} P(D^T \mid x)\, p(x)\, dx. \tag{2.4}$$

Figure 2.3 shows the layout of sensors when optimized with respect to the prior environmental information.

2.3 Current State of the Art in System Health Monitoring

The current literature refers to a variety of health monitoring systems with almost similar goals: better prognosis and better diagnosis. Among them are: structural health monitoring (SHM), system health management, health management

(HM) model, prognostics and health management (PHM), software health management (SWHM) system, system reliability monitoring, etc. Many of these health monitoring systems utilize Bayesian inference techniques for learning complex systems and for updating the state of knowledge for unknowns of interest. In addition, in recent years, due to significant progress in artificial intelligence, researchers have started realizing the vast potentials of Bayesian belief networks for utilizing in various monitoring systems.

This section presents a summary of current state of the art in system health monitoring. Given that this field is relatively new, therefore there is no formal classification of topics. We divided the literature to two large categories on this subject: (1) health monitoring systems using Bayesian methodologies , and (2) Health monitoring systems utilizing various PHM and other techniques.

2.3.1 Bayesian Methods and System Health Monitoring

Dawsey et al [21] presented a real-time water distribution monitoring system utilizing "dynamic Bayesian networks (DBN)," which will be discussed further in Chapter 3. New observations are combined with past system behavior through the application of DBN. Bayesian networks were used to model discrete and continues variables, and also to represent causal relationships. The variables such as hydraulic head at monitoring points, a pump operational status, presence of biological contaminants at a node and concentration of certain chemicals at monitoring points are considered as variables or inputs to the Bayesian network. Assuming a pre-defined time step, the DBN is intstantiated by the variables from monitored points. Then the current state of nodes that are not monitored, are inferred from current observation data sets and knowledge of previous states. This is a classic use of dynamic Bayesian networks.

Maglogiannis et al [22] utilized Bayesian networks for modeling and risk analysis for patients with chronic diseases to better mange chronic care, to control health delivery costs, and increase the quality of health delivery systems.

Morales et al [23] used Bayesian networks combined with Markov chain Monte Carlo and Bayesian Score methodologies for system health monitoring of fuel cells.

Wang et al [24] utilized Bayesian networks for autonomous diagnosis of web services such as document delivery through the internet, etc. In this approach, the web alerts (i.e. a service being unavailable) were used as a diagnosis, and several observable variables were used as evidences to model through a Bayesian network as a tool for "reasoning."

2.3.2 PHM and other Techniques for System Health Monitoring

Iverson [25] at NASA Ames Research Center utilized data mining methodologies as system and software health monitoring tools for NASA's spaceships. Obviously, mission critical systems such as spaceships are equipped with abundant number of monitoring systems for subsystems and components. Iverson employed existing data mining techniques for anomaly detection to utilize the wealth of knowledge available from other monitoring systems for more sophisticated health monitoring systems.

More specifically, two data driven software tools were utilized: Orca, and the Inductive Monitoring System (IMS). Orca looks for unusual data points or outliers by calculating the distance of data points from neighboring points. IMS uses clustering techniques to analyze archived spacecraft data to recognize nominal interactions among selected parameters and stores it in its knowledge base. During the operation of spaceships, these parameters are compared with the knowledge base to produce a measure of how well the monitoring data match the nominal state of operation.

Martin et al [18] used artificial neural networks for structural health monitoring. The presented approach uses an array of piezoelectric sensors to emulate receptor connectivity of the biological nervous system, along with neural networks for structural health monitoring.

In 2010, GE Aviation Systems announced their Integrated Vehicle Health Management (IVHM) solution [26] and claimed that "it would work as a virtual proactive maintenance, determining the status of the aircraft and its subsystems". The onboard portion of the management unit is capable of communication with ground services for storage and further analysis. According to GE, this web-based health monitoring system is intended to monitor the entire aircraft and has the potential to reduce both unscheduled and scheduled maintenance, reduce return to service time, and reduce overall operations and maintenance costs.

Roemer et al [27] and Sheldon et al [28] used prognostics and health management methodologies as a health monitoring tool for gas turbine engine bearings. They used a component-level prognostic approach and utilized available sensor information from vibration transducers, along with material-level component fatigue models to calculate remaining useful life for the engine's critical components such as bearings.

Byington et al [29] used on-line fuel oil quality monitoring as a way of assessing the health of diesel engines. Their rationale was that maintaining healthy fluid systems is critical to keeping machinery in a high readiness state. In other words, they used the fuel oil quality as the "canary in the mine" for the health of engine operation.

The Center for Advanced Life Cycle Engineering (CALCE) of the University of Maryland is extensively involved with prognostics and health management (PHM) research. Cheng et al [30] presented a sensor selection strategy specifically for prognostics and health monitoring. They provided a sensor selection procedure with three major components. First, they provided a detailed list of consideration such as: parameters to be monitored, requirements for physical characteristics of PHM sensor system, requirements for the functional attributes of PHM sensor system, cost, reliability, and availability. The second step, involves with searching the available sensors and the third step deals with tradeoffs.

Kumar et al [31] presented "symbolic time series analysis technique for health monitoring of electronic products. They divided their analysis in four steps. In the first step, data sets are collected from a healthy system and time series are calculated. The second step involves with reduction of noise and conversion of the time series to symbolic time series. In the third step, Markov state model from symbolic time series are constructed. And the last step is involved with the identification of prognostics measures to detect anomaly during system diagnosis and prognosis.

Vichare et al [32] utilized CALCE Life Consumption Monitoring (LCM) methodology as a health monitoring technique for analyzing product take-back decisions. The core of CALCE LCM methodology includes six main steps: (1) conduct failure modes, mechanisms and effect analysis, (2) conduct a virtual reliability assessment to assess the failure mechanisms with the earliest time-to-failure, (3) monitor appropriate product environmental and operational parameters, (4) conduct data simplification to make sensor data suitable for stress and damage models, (5) perform stress and damage accumulation analysis, and (6) estimate remaining life of the product.

He et al [33] proposed the use of Dempster–Shafer theory (DST) and the Bayesian Monte Carlo (BMC) method for prognostics of lithium-ion batteries. First, they developed an empirical model of physical degradation behavior of lithium-ion batteries. Then, to properly estimate the models parameters, available battery data sets along with Dempster–Shafer theory (DST) were used to initialize these parameters. Then actual battery monitoring data and BMC were used to update the model parameters and predict the remaining useful life of the batteries. The authors state that as the system continued monitoring the batteries and more battery data became available, the accuracy of the model in estimating remaining useful life was improved.

Kumar et al [34] presented a methodology for selecting precursor parameters for health monitoring. They start with failure modes, mechanisms, and effects analysis (FMMEA) and life cycle profile analysis of the product to be monitored and risk priority numbers (RPN) of each failure mechanism is calculated. The performance parameters that can be associated with the failure mechanisms with higher RPN are selected for health monitoring of the product.

2.4 Overview of Other Relevant Literature

In this section, we review two other important topics related to Bayesian sensor placement optimization and system health monitoring. Section 2.4.1 presents an overview of multi-sensor data fusion techniques and Section 2.4.2 reviews the concept of overlapping data sets.

2.4.1 Multi-Sensor Data Fusion

One of the basic methods of reducing uncertainty, is performing multiple observations from a single source. This could translate to aggregating the data in a rational way. Another method of reducing uncertainty is obtaining more complete knowledge of the state of nature by using multiple sources of data and utilizing data fusion methods. When using data from diverse sources, two major concerns arise. The first is the relevance of each data point with regard to the state of nature. Second, how reliable each data point is [9].

Let's assume $\mathcal{N}$ is the set of all available information sources (sensors)

$$\mathcal{N} = \{i\}, \quad for: i = 1, 2, 3, \ldots, N. \tag{2.5}$$

The most simplest and rational way of sensors' data fusion could be obtaining a weighted average of sensors' direct measurements, $x_j^{'}$, of the state of x which can be presented as

$$\hat{x} = \sum_j w_j x_j^{'} \tag{2.6}$$

where $\sum_j w_j = 1$.

Obviously, this rather simplistic method comes with its own shortcomings. First, it does not take into account the uncertainties inherent in the nature of sensors. The other problem is that some sensor measurements, z may not be necessarily correlated with the state of x. One way to overcome these difficulties, could be fusion of data in probabilistic sense. This will build a probabilistic description of the sensing and the inference process.

Let's define the set of all observations made by the set of sensors $\mathcal{N}$ up to the time step k as

$$\{Z^k\} = \cup_i Z_i^k, \qquad \forall i \in \mathcal{N}, \tag{2.7}$$

where

$$Z_i^k = \{z_i(1), z_i(2), z_i(3), ..., z_i(k)\},$$

and Z_i^k is information source $i's$ set of observations up to the time step k. Then compute the posterior distribution $p(x \mid \{Z^k\})$, given the information contributed by each source [9], [35].

2.4.2 Overlapping and Non-Overlapping Data Sets

It is customary to use only lower level information and statistics in analysis of fault trees. Typically, the quantitative analysis of fault trees include three main steps: (1) determining the basic event probabilities, (2) identifying the cut sets and calculating the minimal cut set probabilities, and (3) determining the system (the top event) relevant statistics. This can also be labeled as "upward propagation" of data when analyzing the fault trees.

Given that in real systems operation, testing might generate data sets at various levels in a system which are not necessarily all "basic event" data sets. Consequently, it is important to have a process to include data sets at all levels of a fault tree when analyzing it.

Hamada et al [4] presented a fully Bayesian approach to combine data sets and other statistics of events at all levels in a fault tree. Therefore, in quantitative analysis of a fault tree, the propagation of data is not limited to only from basic events to top event. Hamada assumed that data sets are non-overlapping and presented a Bayesian approach which can simultaneously combine basic events and "independent" higher-level data sets in a fault tree analysis.

Overlapping data sets analysis has been discussed in various literature. Graves [36] proposed methodology to incorporate overlapping data sets for binary state on-demand system. It considers each demand in isolation and cannot incorporate data from multiple demands on the system.

Jackson and Mosleh [5], [6], [7] presented Bayesian methods to analyze overlapping data sets and defined the overlapping data sets are those that: (1) the sets are drawn from observations that occur at the same time (simultaneity); and (2) the sets are dependent on the same system or process (correspondence). He used the methodology to find function-point optimum sensor placement. A related example of overlapping data is collecting data sets from multiple sensors in a system. Jackson and Mosleh developed a methodology that allows overlapping data that is based on multiple demands of a binary state on-demand system to be analyzed. He developed a three-step process to compute the overlapping data likelihood function that observes the permutations of all possible instances of (i.e.) component failures.

The relevance of discussion about overlapping and non-overlapping data sets in this dissertation is that one of the main goals of this research is to optimize sensor placement based on sensors' functional locations in a logic diagram (e.g. fault tree). That means the sensors may be placed at different levels of a logic diagram and the input data may come from different levels of fault tree. Therefore, considering current methods, it is important to know the type of data sets (for example) whether overlapping or non-overlapping to properly treat the data and include in analysis.

In addition, it is important to have the capability of analyzing a logic diagram both "upward" and "downward" accurately. Because most of reliability analyses are involved with assessing the status of system and inferring the health of subsystems or components. This is a common example of downward propagation of information. In other analyses we may need to estimate the reliability of a system based on the knowledge of components or subsystems. This represents an example of upward propagation of data. In all of these cases, considering available methodologies including Hamada's and Jackson's, it is important for the analyst to know whether the data sets are overlapping or not. We will discuss how our presented methodologies will simplify the analyses related to overlapping and non-overlapping data sets as well as upward and downward propagation.

2.5 Summary

In this chapter, summaries of current state of the art on subjects related to sensor placement optimization and system health monitoring were presented. Chapter started with a summary of current sensor placement optimization methods and followed by the state of the art in system health monitoring. Multi-sensor data fusion concept was briefly touched and the chapter ended with a discussion on treatment of overlapping and non overlapping data sets.

Reviewing various sensor placement optimization methods and health monitoring systems, the following shortcomings were recognized:

1. Sensor placement optimization

    a. Most of the current methods assume that the data sets are non-overlapping [4], which is a significant assumption.

    b. Majority of sensor placement optimization methods have attempted to optimize the physical location (geometry) of sensors [1], [3], and none of the reviewed studies referred to "logical" or "functional" placement of sensors.

    c. Almost all methods concentrate on upward propagation. In other words, their goal is to optimize inferring information at system level based on data gathered at component or subsystem levels. Except for the work by Jackson and Mosleh [5], [6], [7], none of the reviewed literature had suggested methodologies for both upward and downward propagation that can be used for prognosis and diagnosis.

d. Some of the presented sensor placement methodologies utilize qualitative techniques such as failure mode, mechanisms, and effects analysis (FMMEA) [30], [34] which are considered subjective screening tools. Cheng et al [30] started with FMMEA to identify the parameter that need to be monitored for PHM implementation.

e. In many cases, to simplify the analysis, the uncertainties associated with sensors have been ignored [1].

f. Many of the sensor placement optimization methods suffer from computational complexity, which were acknowledged by the method developers [1].

2. Sensor placement optimization

   a. Many health monitoring systems are focused only on certain contributors to system failures (i.e. vibration) and disregarded others [37].

   b. Some of the health monitoring systems are faced with the challenges of properly modeling the systems due to to many reasons including lack of data to verify model's parameters.

c. Other health monitoring systems have difficulty with real time reasoning mainly due to resource constraints including limited memory and processor speed.

This research developed a new approach in sensor placement based on sensors' functional locations in a logic diagram, and utilized core aspects of the methodology in a new system health monitoring and also addressed shortcomings mentioned in 1.a, 1.b, 1.c, 1.e, 2.a and 2.c. The new Bayesian sensor placement method is based on Bayesian techniques and is capable of functional sensor placement under uncertainty using reliability of components and subsystems as metrics of interest. It also takes into account the uncertainty inherent in the characteristics of sensors. It uses Bayesian networks for modeling and reasoning the uncertainties as well as for updating the state of knowledge for metrics of interest. It utilizes information metrics for sensor placement based on the amount of information each possible sensor placement scenario provides on reliability metrics. And finally, it significantly decreases the computational complexities of current methodologies. For example Jackson and Mosleh [5], [6], [7] sensor placement methodology requires calculation of complex likelihood functions, while in our proposed method, Bayesian network are significantly reducing these difficulties.

A new system health monitoring methodology is also developed which is capable of assessing current state of a system's health and can predict the remaining life of the system (prognosis), and through appropriate data processing and interpretation can point to elements of the system that have or are likely to cause system failure or degradation (diagnosis). Also it can be set up as a dynamic monitoring system such that through consecutive time steps, the system sensors perform observations and send data to the Bayesian network for continuous health assessment. This makes the Bayesian network, a dynamic Bayesian network.

Similar to any other new methodology, our approach presents areas for improvement too. One area is the use of Bayesian network and its exponential complexity with the increased size of the network. This is also true for almost any algorithm that uses Bayesian network. Another area is our reliance on historical data that may not always be available which is true for other methodologies too. Chapter 5 discusses these issues and presents potential solutions and in Chapter 8 we present suggestions for future research on these and other related topics.

Chapter 3

Overview of the Proposed Methodology

3.1 Introduction

One of the strongest motivations for this research was to find a general methodology for optimum sensor placement based on logical or functional placement. The Bayesian methodology developed for optimally locating the sensors throughout a system is aimed at finding the optimum sensor placement scenario for extracting the most amount of reliability information from the measured data. The approach takes into account all uncertainties within the probabilistic framework and combines the different sources of information using the rules of probability.

The developed Bayesian sensor placement (BSP) algorithm utilizes Bayesian networks for modeling, updating and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest. Information metrics are used to assess the potential information gain for each sensor placement scenario and the results are used to select the sensor placement scenario with the highest amount of reliability information.

This chapter provides all necessary background information on key building blocks of the proposed sensor placement methodology and health monitoring system.

3.2 Overview of Key Building Blocks

This section presents three key building blocks of the proposed methodology. They include Bayesian belief networks, dynamic Bayesian networks, and "information metric".

Bayesian belief networks are utilized for modeling, updating and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest (UOI) as they are defined by: failure probabilities of lower level components, subsystems or system; value of parameters; and the probability of physical parameters taking specific values.

Dynamic Bayesian networks are used as the backbone of an online monitoring system such that through consecutive time steps, the system sensors perform observations and send data to a Bayesian network for continuous health assessment.

"Information metrics" are used to assess the amount of "reliability information" each sensor placement scenario provides and the value of information metrics are used to select the sensor placement scenario that provides the highest amount of information.

3.2.1 Bayesian Belief Networks (BBN)

A Bayesian belief network or Bayesian network, also known as a Bayesian net, is a graphical modeling tool for specifying probability distributions that utilizes directed graphs together with associated set of probability tables. These graphical structures are used to represent knowledge about a system. In particular, each node in the graph represents a random variable, while the edges between the nodes represent probabilistic dependencies among the corresponding random variables. These conditional dependencies in the graph are often estimated by using known statistical and computational methods [38], [39], [40].

A BBN is a compact representation of the joint probability distribution of the system variables. Formally, it is known as an acyclic directed graph (DAG) with nodes connected by arcs. The nodes are random variables whose values represent the observed or unobserved system variables. The arcs represent the causal relationship between variables. They are quantified by the conditional probabilities that a child node would reach to a certain value, given values of all its parent nodes [41].

BBN can also be used to represent the generic knowledge of a domain expert, and to function as a computational architecture for storing factual knowledge and manipulating the flow of knowledge in the network structure. The graph structure in the network significantly reduces the storage required for the joint probability distribution, and the computational burden associated with the inference process [41].

Causal Networks and d-Separation. A causal network consists of a set of variables and a set of directed links (also known as arcs) between variables [38]. Specifically, the structure is called a *directed graph*. In a causal network, a variable represents a set of possible affairs.

Figure 3.1 shows a simple causal network with only serial connections. It is obvious that a has an influence on b, and b in turn has influence on c. Therefore,

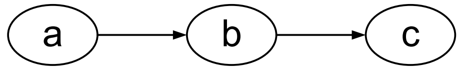


Figure 3.1: A serial connection in causal network

evidence about a will influence b and in turn c. Similarly, evidence on c will influence the certainty of a and b.

On the other hand, when the state of b is known, then the channel between a and c is blocked and they become independent. In this case, we say that a and c are *d-separated* given b. Additionally, when the state of a variable is known, such as variable b in this example, we say that the variable is *instantiated* [38].

BBN Structure. In a BBN, each node represents a variable and relationships are indicated with arcs. The nodes must be defined in such a way that each node is a distinctly defined entity, even if it is causally influenced by other elements. For example in Figure 3.1 we can define three separate nodes and we can logically connect them to create a simple BBN with three nodes. The first step in development of the causal model is to identify the variables to be included as nodes in the model. This is not a trivial task since the variables in the model must be distinctly defined. The second step is to identify the relationships (arcs) between the variables. The arcs are used to represent a causal relationship between two variables, with the arrowhead indicating the direction of the influence. In Figure 3.1 node a is a root node as it has no arcs pointing into it. Node c is an end node as it has no arcs pointing out of it. Node b has one parent node a and one child node c [42].

BBN Quantification. After all relationships among BBN nodes are defined, a marginal or conditional probability table is assigned to each node. These probability tables contain all known information concerning the state of the system based on both expert opinion and available data. In a BBN, each node is assigned a probability distribution based on the possible states of its parent nodes. Once each probability distribution is set, the initial model is complete. As new information becomes available, the probabilities of all nodes in the model can be automatically updated based on the evidence [42].

Each node in a discrete BBN has a finite number of possible states. Many BBNs use binary nodes, where 0 and 1 represent the positive and negative states of the node. The sum of the marginal probabilities of all states within the same node must equal 1. Each possible state of a root node is quantified with the marginal probabilities of the states. For example in Figure 3.1, node a would be the only node quantified with marginal probabilities. Assuming that a has two possible states of $P(a) = p$ and $P(\overline{a}) = 1 - p = q$ [42].

Nodes with one or more parents are quantified with conditional probability tables (CPT). The size of the conditional probability table depends on the number of parents. The conditional probability table will contain values for every possible combination of states of the node and its parents. For a binary node with n parents, the conditional probability table will contain $(2^{(n+1)}/2)$ columns. Each column in the conditional probability table must add up to 1. Table 3.1 shows a simple conditional probability table for nodes a and b of Figure 3.1.

Table 3.1: Conditional probability table for node b with a single parent a

		Parent	
		$P(a)$	$P(\overline{a})$
Child	$P(b)$	$P(b\|a)$	$P(b\|\overline{a})$
	$P(\bar{b})$	$P(\bar{b}\|a)$	$P(\bar{b}\|\overline{a})$

Hard Evidence (Instantiation). Hard evidence (instantiation) for a node X is evidence that the state of X has definitely a particular value. For example, suppose X represents the result of a particular college basketball game match (win, lose, draw). Then an example of hard evidence would be the knowledge that the match is definitely won. In this case we also say X is instantiated as the value "win".

Soft Evidence. Soft evidence for a node X is any evidence that enables us to update the prior probability values for the states of X. In other words, the evidence is not conclusive. For example, we may get an unreliable report that event X happened which in turn may increase our belief in event X, but not to the point that we would consider it certain. One of the key concerns related to soft evidence is how to specify its strength [40].

Discretization of Bayesian Networks. When the node variables in a BBN take continues values, the network is considered continues BBN. Generally, analyzing continues BBN is a difficult task. For example, conditional distributions can only be linear functions of the parent nodes. The computational burden increases exponentially with the number of possible states at each node. The amount of memory for storing tables of conditional probabilities also increases dramatically. It is therefore, imperative that when the continuous BBN is discretized, the number of states at each node is kept at a minimum. To maximize the usefulness of discrete states, a maximum entropy criterion is adopted in the determination of the optimal partition of the range of each continuous variable [41].

For continuous BBNs with arbitrary nonlinear conditional probability distributions, the BBNs must first be approximated by a discrete BBN. A discrete BBN is one in which each node can only take on finite number of values (states). The discretization process amounts to partitioning the continuous probability distribution function into intervals [41].

Let's assume that the continuous range of the variable associated with a node has been partitioned into n segments, $a_1, a_2, \ldots, a_n$. Let the prior probability of the occurrence of the i^{th} segment a_i be p_i. We can view the discretized node as an information source with entropy given by:

$$H(S) = -\sum_{i=1}^{n} p_i \, \log(p_i) \tag{3.1}$$

and we wish to adjust the partition so that $H(S)$ is maximized [41]. It is easy to see that the optimal solution is given by p_i such that each interval is as likely to happen as the other, or

$$p_1 = p_2 = \ldots = p_i = \frac{1}{n}. \tag{3.2}$$

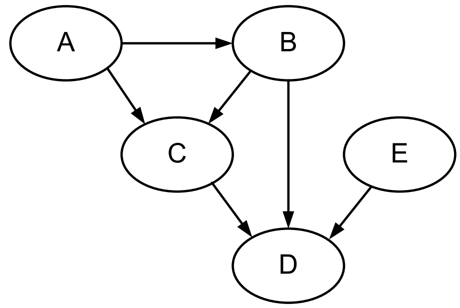


Figure 3.2: A Bayesian network to illustrate discretization algorithm

To formulate an algorithm for discretization, suppose we have a Bayesian network as illustrated in Figure 3.2. Node C has two parents A and B. D has three parents C, B and E; and C and D have a common parent B.

If we specify that we want to get the prior probability table for Node D, the algorithm will check if the parent nodes of node D have been segmented and the joint probabilities of B, C, and E are available [41]. Following is summary of the major steps of the algorithm.

Segmentation: This procedure segments the probability distribution of a variable into a desired number of intervals. The segmenting points along the value range and centroids of each interval are calculated and recorded in a structure representing this node. Least Square Error (LSE) approximation is employed to evaluate integration.

Joint Probability: In a set of parent nodes, either all the nodes have one or more common ancestors, or some of them have. This set can be divided into several subsets of nodes with common ancestors or no ancestors. Zhong et al [41] used "unit" to represent these subsets. If there is only one unit and there is one parent node in it, the joint probability actually is the prior probability of the only parent. Otherwise, the joint probability can only be acquired either by looking for the joint probability entity with this set of parent nodes or marginalizing a joint probability entity with a set of nodes which include all the parents' nodes. If there are multiple units and they are independent to each other, the joint probability could be calculated separately, then combined together by simple multiplication. This process resembles to acquiring joint probability of independent variables.

Conditional Probability: The procedure for calculating conditional probability is the main procedure in this algorithm. Main recursion occurs here. When the desired node in a Bayesian network is assigned to this procedure, it checks if its parent(s) has been segmented. If not, the procedure will call itself to process those parents. This is the main recursion in this algorithm. A Bayesian network is an acyclic directed graph. There is no loop in the graph. Therefore, by such recurrence, the ancestor nodes could be eventually reached and the recursion is terminated. All the nodes in the Bayesian network are processed one by one in a fashion of bottom-up then top-down. With the information of segmentation, centroids and joint probability of parent nodes, the centroids of one node could be evaluated by applying the deterministic relationship equation of that node and its parents and the continuous probability distribution of the node could be calculated. Then, the discrete conditional probability of this node conditional on its parents can be derived by integrating over each interval of this node along the continuous probability distribution of every set of combination of intervals of all its parents [41].

Marginalization: In this final step of the process, marginalization theory is applied to remove unnecessary variable in the joint probability. For example, if the joint probability of P(A,B,C) and prior probability of A are known, then we can obtain

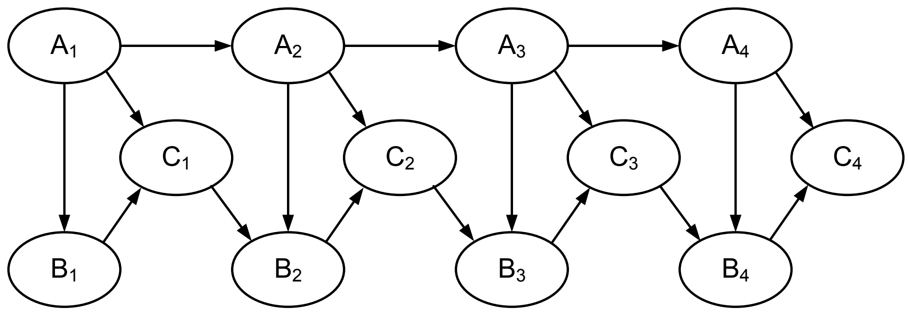


Figure 3.3: A four-time-slice Bayesian net

P(B,C) by marginalizing P(A,B,C) over A. Zhong et al [41] presented a detailed flow chart of the process and the results of their experiment.

3.2.2 Dynamic Bayesian Network Model

Dynamic Bayesian network (DBN) is a series of Bayesian belief networks which is expanded over the time. Each discrete time stamp for a unit of time is known as *time slice*. Different time slices are linked by arcs that are responsible for capturing the evolution of the probabilities of variables with time. The arcs between the time slices are similar to the arcs inside the BN, therefore the DBN itself is a BN. Consequently, the same BN rules apply to DBN and same properties and inference engines can be used.

Figure 3.3 shows an example of a model that repeats four times and Figure 3.4 shows a time slice for this model. These are simple examples in which the time slices are identical and the *temporal links* are the same for different time slices. In a case that in addition to the states, the conditional probabilities are also identical, then we call the model a *dynamic Bayesian network model* [40], [43].

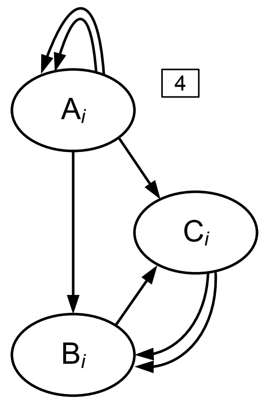


Figure 3.4: One time slice of a four-time-slice Bayesian net

There are many inference engines for different types of DBNs; some perform exact inference, while others approximate the results. Approximate inference is used where exact inference method cannot be developed or exact inference is not efficient. The exact inference allows estimating the final probability distribution of the non-observed variables given the evidence in any order. This property of the exact algorithms lets the fusion system developed over an exact inference algorithm estimate the state of non-observed variables given out-of-sequence measurements and so update the state of variables as soon as any piece of information becomes available [43].

3.2.3 Information Metric

Information metric is defined as a scale to measure the amount of reliability information. Its domain is a set of real numbers on the chosen scale such as value of information, entropy, etc.

As decision makers, we are interested in making the best possible decisions given the model in hand. The information metrics are represented by functions that are chosen by decision makers and each information metric associates a value with each configuration of its domain variables. The goal of this analysis is to identify the decision option (or the value of information metric) that produces the highest value of reliability information. In other words, the information metric translates the amount of reliability information to a numerical value.

Examples of information metric for an unknown of interest θ include:

$$U_I(\theta) = \sum_j \ln[\pi(\theta_j)]\,\pi(\theta_j), \text{ and} \tag{3.3}$$

$$U_I(\theta) = \sum_j \frac{1}{\sigma^2_{\theta_j}}. \tag{3.4}$$

The information metric function presented in Equation 3.3 describes the amount of information similar to entropy also known as Shannon information [44]. Entropy is one of the fundamental measures of probability distribution. Entropy is the uncertainty associated with a probability distribution which gives a measure of the descriptive complexity of a probability distribution function (PDF). The relevance of this choice for information metric function is that in decision making process, the main reason for acquiring additional information is to decrease uncertainty about a hypothesis.

Selecting information metric function is assumed to be at the discretion of the decision maker, considering the problem domain. In decision making process, the main reason for acquiring additional reliability information is to decrease uncertainty about a hypothesis. Equation 3.4 measures the (inverse of) spread of information.

Jackson [7] used one version of this equation. In this research, Equation 3.4 is considered as the framework for information metric function of choice. Given that the information metric function is based on uncertainty about the unknowns of interest, we select an information metric function that takes into account all unknowns of interest relevant parameters which in this case is the probability of failure the lower level components. It is important to mention that even though Equation 3.4 was used in this research, it should not be interpreted as the best function for information metric for other sensor placement problems. For example if the system being analyzed has extremely reliable elements, perhaps σ in Equation 3.4 can be exchanged with σ/μ.

3.3 Overview of Methodology

The Bayesian sensor placement (BSP) algorithms utilize Bayesian networks for modeling, updating and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest (UOI) as they are defined by: failure probabilities of lower level components, subsystems or system; value of parameters; and the probability of physical parameters taking specific values. "Information metrics" are used to assess the amount of information each sensor placement scenario provides and the results are used to select sensor placement scenario that provides the highest amount of information.

The process starts with identifying the system functional failure modes and failure mechanisms and relevant stress models. A logic diagram (e.g. fault tree) is chosen to represent the logical relationships among the components and subsystems within a complex system. A Bayesian network of the system is then constructed, and through engineering considerations, several potential sensor placement scenarios are identified. Lastly, the value of "information metrics" are used to compare the amount of information among sensor placement scenarios.

The proposed system health monitoring algorithm, utilizes the results of Bayesian sensor placement for both prognosis and diagnosis of systems. This process starts by sensors detecting the physical phenomena and translates to component states. Based on each variable instantiation, the Bayesian network provides the probability of failure for any point (node) of interest on system's Bayesian network. This process can be repeated through consecutive time steps for a continuous health assessment.

3.3.1 Description of BSP Algorithms

As mentioned earlier, after identifying the system functional failure modes and failure mechanisms and relevant stress models, we build a fault tree (or other preferred logic diagram) of the system. The next step is building the Bayesian network of the system, however, one might suggest that the Bayesian network could be constructed directly without building a fault tree. The reasons behind building a fault tree before constructing the Bayesian network for this application are:

- The fault trees are the best graphical representations of a system to show how the failures occur. On the other hand, even though Bayesian networks provide representations similar to the system operation, some of the abstract failures such as human errors [45] may be overlooked.

- Fault trees are built based on engineering considerations and principles used by engineers. Therefore, as a risk and reliability engineer, fault trees would be the first choice for identifying failure events [1].

Assuming the fault tree of the system is built, the next step is the construction of the system's Bayesian network. The Bayesian sensor placement (BSP) algorithms utilize Bayesian networks for modeling, updating and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest (UOI). This involves three major steps [40]. First the set of relevant variables and their possible values need to be identified. Second, the graphical network is drawn and the variables are connected through acyclic directed graph (DAG). This step is also known as defining the network's edges. The last step in constructing the Bayesian network is defining the conditional probability tables (CPT). The objectivity of this step might vary for different problems, however, for some networks, the CPTs can be determined directly from the system and for others, CPTs might be based on subjective beliefs [40]. In some other cases, CPTs may be estimated from historical data.

To illustrate how Bayesian networks are utilized in BSP algorithms, we present the concept through a simple Bayesian network as shown in Figure 3.5. This figure shows the inference engine building blocks of a simple three-node Bayesian network in which p_i^t is the "true" value of element i probability of failure and p_i^a is its "as-

[1]In Chapter 8 we explain how the fault tree and Bayesian network could be combined.

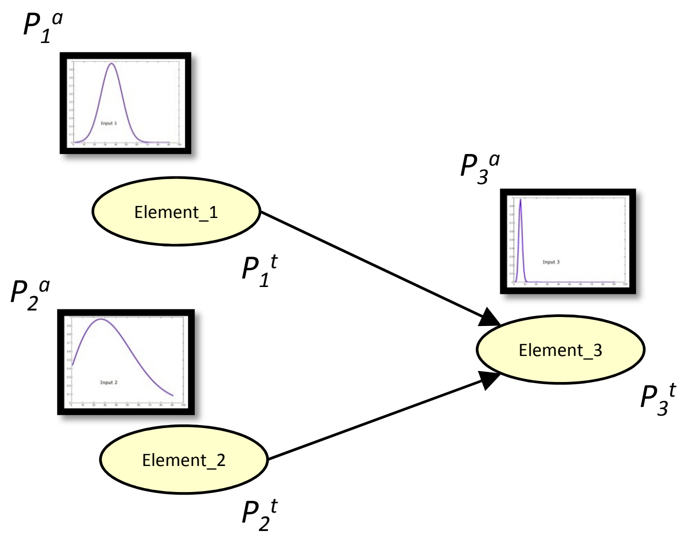


Figure 3.5: Inference engine building blocks

sessed" value. Each "element" in Figure 3.5 can represent a component, subsystem or system. We define "true" value as the distribution of p_i as we know it (assuming prior knowledge), and "assessed" value is the distribution of p_i through the sensory mechanisms we utilize. Obviously, the difference between the "true" value and "assessed" value of the same element will be in various uncertainties including uncertainties associated with the value of parameters, accuracy of sensors, state of components (which they have their own distributions), and the uncertainties on physical parameters. In addition, we define $p_i s$ (probability of failure of element i) as the "unknowns of interest" (UOI) which will be discussed in details in Section 4.5.1.

Assuming that we are interested in assessing the health of this three-node system, the goal is to place sensor(s) to maximize the amount of information obtained from the system as assess values. To perform this "placement" process, we consider several potential sensor placement scenarios, calculate the value of "information metric" function for each scenario to identify the sensor placement scenario that provides the highest amount of reliability information. The next section, defines how the Bayesian network performs the inference and defines the "inputs" and outputs of the system Bayesian network.

3.3.1.1 Overview of Inference Engine

One of the primary objectives of the Bayesian inference application is combining the knowledge about a parameter with new observations to update the belief about the value of the parameter. This can be interpreted in various ways, among them is revising the level of uncertainties of a model's parameters. In Bayesian analysis, parameters follow a probability distribution and the knowledge about this distribution is typically summarized in *prior* distribution of unknowns of interest (UOI). Often a prior reflects a hypothesis about the nature of parameters or modeling assumptions. In other situations, the existing knowledge may be difficult to summarize as an informative prior.

The developed inference engine has three major blocks as shown in Figure 3.6. The first one is the input block, which deals with prior information and how it is processed before entering the Bayesian network model. First, all prior information related to environmental physical data such as temperature, relative humidity, pressure, etc. for the lower level components are gathered. Then, considering the functional failure modes, failure mechanisms, and physics of failure of the lower level components and subsystems, the physical phenomena are translated to states (i.e.

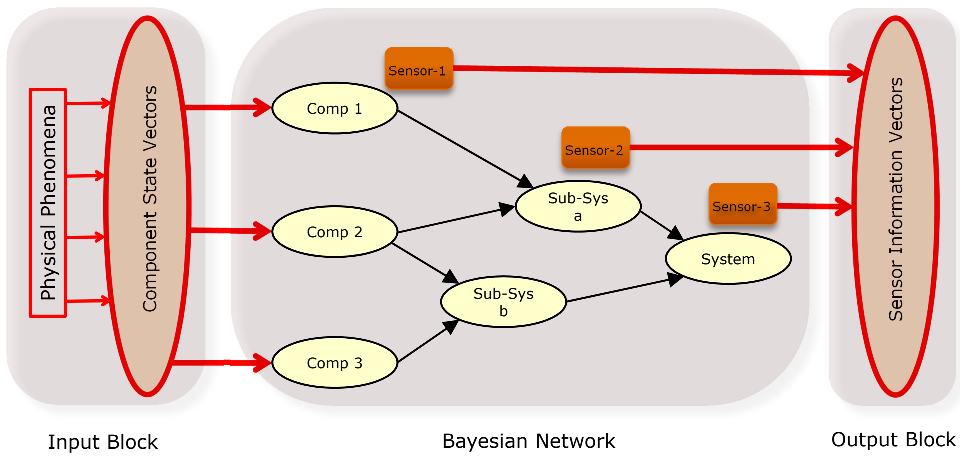
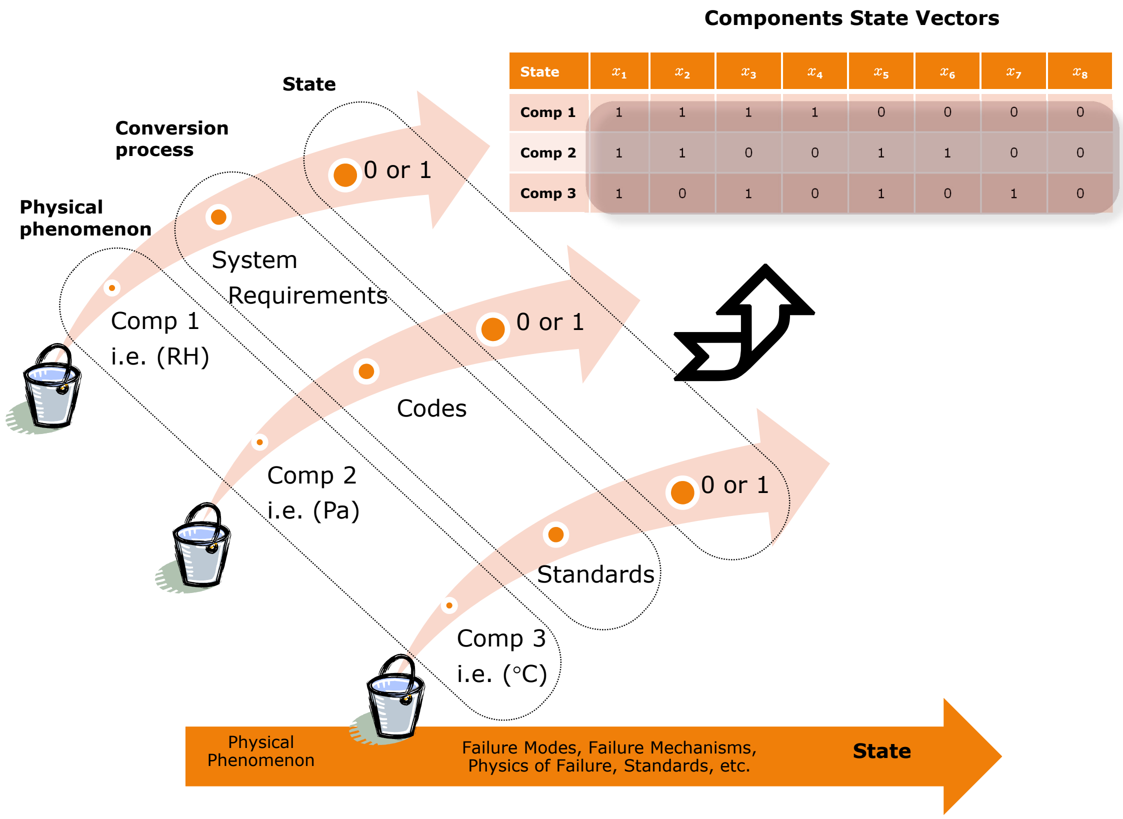


Figure 3.6: Inference engine block diagram

$1'$s and $0'$s).

Figure 3.7 presents the input block of Figure 3.6 in more details. The output of this block is the *components state vectors* which will be defined in more details in the following sections.

The Bayesian network of the system, makes up the next block which is the heart of the inference engine of Figure 3.6. The Bayesian network contains the information on relations among the elements, functional relations between systems and their elements (components, subsystems, etc.), and their probabilities. The inputs of the Bayesian network are components state vectors which will be discussed in Section 3.3.1.2 and the outputs are Sensor Information Vectors (SIV) which will be discussed in Section 3.3.1.3 and shown as the last block in inference engine block diagram of Figure 3.6.



State	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Comp 1	1	1	1	1	0	0	0	0
Comp 2	1	1	0	0	1	1	0	0
Comp 3	1	0	1	0	1	0	1	0

Figure 3.7: Inference engine input block

3.3.1.2 Components State Vectors

All possible combinations of inputs' states are defined as *components state vectors* and presented as

$$\widetilde{x} = \{x_1, x_2, \ldots, x_j, \ldots, x_n\}, \tag{3.5}$$

where n is the number of all possible arrangements of combinations and x_j is the vector of j^{th} arrangement.

A k-state system with L lower level components, generates k^L vectors in components state vector. In other words components state vectors are defined for multi-state status. For simplicity, binary states are shown as example in Figure 3.7. Another example of a multi-state system could be a case when the states are defined as "working", "degraded", and "not working". In that case, the components state vectors will grow larger, i.e. 3^3 instead of 2^3 for the three-input case of Figure 3.6 and Figure 3.7. As for the inference by the Bayesian network, the Bayesian network will be instantiated at various probability of failures (related to each state) for each input node instead of being instantiated at only "0" or "1" at each node for the "working" or "not working" state.

3.3.1.3 Sensor Information Vectors (SIV)

Sensor information vectors (SIV) are defined as the set of states detected by sensors and presented as

$$SIV \ : \quad \widetilde{x}^s = \{x_1^s, x_2^s, \ldots, x_i^s, \ldots, x_m^s\}, \tag{3.6}$$

where x_i^s is the vector representing the i^{th} set of sensors' states, out of m combinations of states detected by the set of sensors. For the network shown in Figure 3.6 with three potential sensors detecting binary states, the SIV may have up to eight elements. However, it is important to mention that depending on the possible range of physical phenomena (inputs to Bayesian network), some output combinations (SIV elements) may not occur and that is why we state that SIV may have "up to" 2^m elements assuming m potential sensor places and binary states.

Given that the Bayesian network's "outputs" are recorded only where the sensors were placed, the SIV represents the outputs of the Bayesian network to components state vectors only at those nodes that we placed the sensors.

In addition, it is important to note that the Bayesian network updates the state of knowledge after receiving new information and these updates are available throughout the Bayesian network, even though we are only monitoring the nodes where sensors are placed. This shows one of the most important strengths of Bayesian network which we will utilize in a new system health monitoring described in details in Chapter 7.

3.3.1.4 Placement Process

Ideally, a system's reliability information can be obtained through the placement of sensors in various places of the system. However, in many applications, due to physical, technological or resource limitations, one may not be able to place sensors where they are needed the most. Therefore, as decision makers, we have to decide where would be the most optimum places to install the sensors to obtain the maximum amount of reliability information, given the constraints. We start this phase of the BSP, by selecting multiple sensor placement arrangements and we called them "sensor placement scenarios". Our goal is to identify which sensor placement scenario would provide the maximum amount of reliability information when comparing the selected scenarios.

This process starts with identifying the lower level components and defining the components state vectors as described in Section 3.3.1.2. In the next step, we define the sensor information vectors (Section 3.3.1.3) for each sensor placement scenario and utilizing Monte Carlo simulations method as will be discussed in details in Chapter 5, numerous evidence sets will be generated and used to calculate the value of the information metric function (Section 3.2.3) associated with each sensor placement scenario. The sensor placement scenario with the highest value of information metric represents the "optimum" sensor placement scenario.

The next section presents how this optimum sensor placement methodology can be used to build an efficient health monitoring system.

3.3.2 Description of the Proposed Health Monitoring System

System health monitoring can ease the maintenance difficulties by replacing a regular / scheduled maintenance with a planned maintenance and provide relief in schedule and cost saving by eliminating unnecessary maintenance and shut downs. Similar concerns exist for newly designed systems as well. System health monitoring assesses the state of a system's health and through appropriate data processing and interpretation, can predict the remaining life of the system.

The framework for the proposed Bayesian system health monitoring concept is shown in Figure 3.8. For this single sensor system, the sensor detects the physical phenomena and through an algorithm which takes into account the failure modes, failure mechanisms, physics of failure and various standards and codes, and translates the physical phenomena to component states as shown in Figure 3.7. The states are then fed to the Bayesian network of the system to be monitored. The

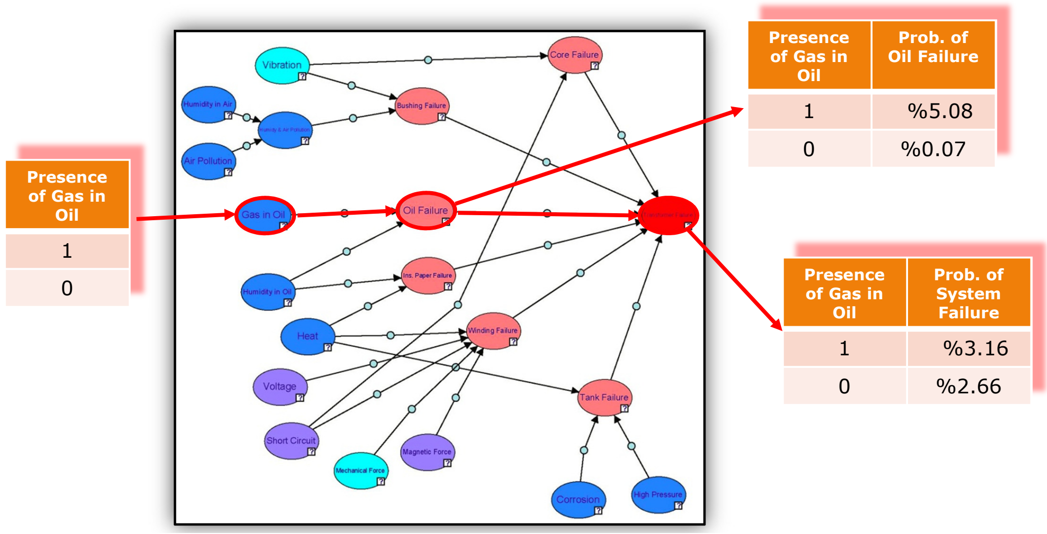


Figure 3.8: Schematic diagram of the proposed system health monitoring concept

Bayesian network provides the probability of failure for subsystem of interest as well as probability of failure at system level based on that specific instantiation (also called a truth assignment, a variable assignment, or a variable instantiation). This provides a snapshot of system health (or the complement of the probability of failure) based on one observation.

This process can be expanded to multiple sensors for more precise estimates. The process can also be set up as a dynamic monitoring system such that through consecutive time steps, the system sensors perform observations and send data to the Bayesian network for continuous health assessment. This makes the Bayesian network, a dynamic Bayesian network. We will discuss this methodology and its development details in Chapter 7.

3.4 Summary

This chapter provided the key building blocks of the proposed Bayesian sensor placement (BSP) methodology. It started with the description of Bayesian belief networks, dynamic Bayesian networks, and few definitions such as "information metric" and "value of reliability information". Then it followed by an overview of the proposed methodology including a description of Bayesian sensor placement, the proposed inference engine, and additional definitions such as "state vectors" and "sensor information vector". The chapter ended with an overview of the proposed system health monitoring.

Chapter 4 will discuss the inference model constructions in details and a case study will be presented as a running example as the methodology is developed. Chapter 5 will continue on the same case study and provides the details of the proposed sensor placement methodology.

Chapter 4

Inference Model Construction

4.1 Introduction

This chapter presents the details of inference model construction that will be used for sensor placement process. The steps of model construction are presented using a simple case study of a power transformer. This chapter starts with background information on major components of a power transformer, continues with the description of their functional failure modes and failure mechanisms. It also presents a brief summary of Physics of Failure (PoF) concept; then presents associated stress models and life, related to this case study. This chapter also presents the Bayesian network of the case study system, unknowns of interest (being failure probabilities of lower level components, subsystems or system), inputs, outputs, potential sensor locations and sensor types.

4.2 Example System Overview

Transformers make the electric power systems operate more efficiently. They step the voltage up so that more power can be transmitted efficiently at longer distance. Power transformers operate at both transmission and distribution levels. They step the voltage down for use in commercial and industrial facilities as well as

Figure 4.1: A typical power transformer

residences to a level at which the equipment and appliances operate.

Power transformers operate in series with generation, transmission and distribution equipment and consequently, in most cases, are considered a single point of failure. Therefore, their reliability and availability have major effect in overall power system operation. In this case study, we introduce an all-inclusive system health monitoring concept for power transformers and present our Bayesian sensor placement methodology.

The following sections start with background information on functional failure modes and failure mechanisms on major components of a power transformer. Then follows with a brief summary of Physics of Failure (PoF) concept. Then associated stress models and life related to this case study are presented. This section also presents the Bayesian network of the case study system, its specific inputs, outputs, potential sensor locations and sensor types.

4.2.1 Functional Failure Modes

Figure 4.2 shows the fault tree for a typical power transformer and Figure 4.3 present its equivalent Bayesian network. The failure modes for each major sub-component within a power transformer are presented as follows [46].

Tank. The transformer tank is primarily a container of the oil. In addition, it provides physical protection for the active parts of the transformer. It also serves as a support structure for auxiliaries and control equipment. The transformer tank is made of sheet metal and is subject to both environmental effect as well as internal stress. Tank's failure can be described as any condition that it either cannot hold the oil (leak) or degraded structurally.

Corrosive atmosphere, high humidity and sun can accelerate tanks aging. Internal fault (arc) and lightning, vaporize the oil and increase the tank pressure which may cause the tank to rupture.

Core. The core's primary function is to carry the magnetic flux; and its failure mode is reducing transformer's efficiency. Manufacturing flaws, mechanical damage due to fault or during shipping, and core steel displacement are among the major causes of core malfunctions.

Winding. Transformer windings carry the current and typically are wound around cylinder shape cores. Winding wire materials are typically copper or aluminum

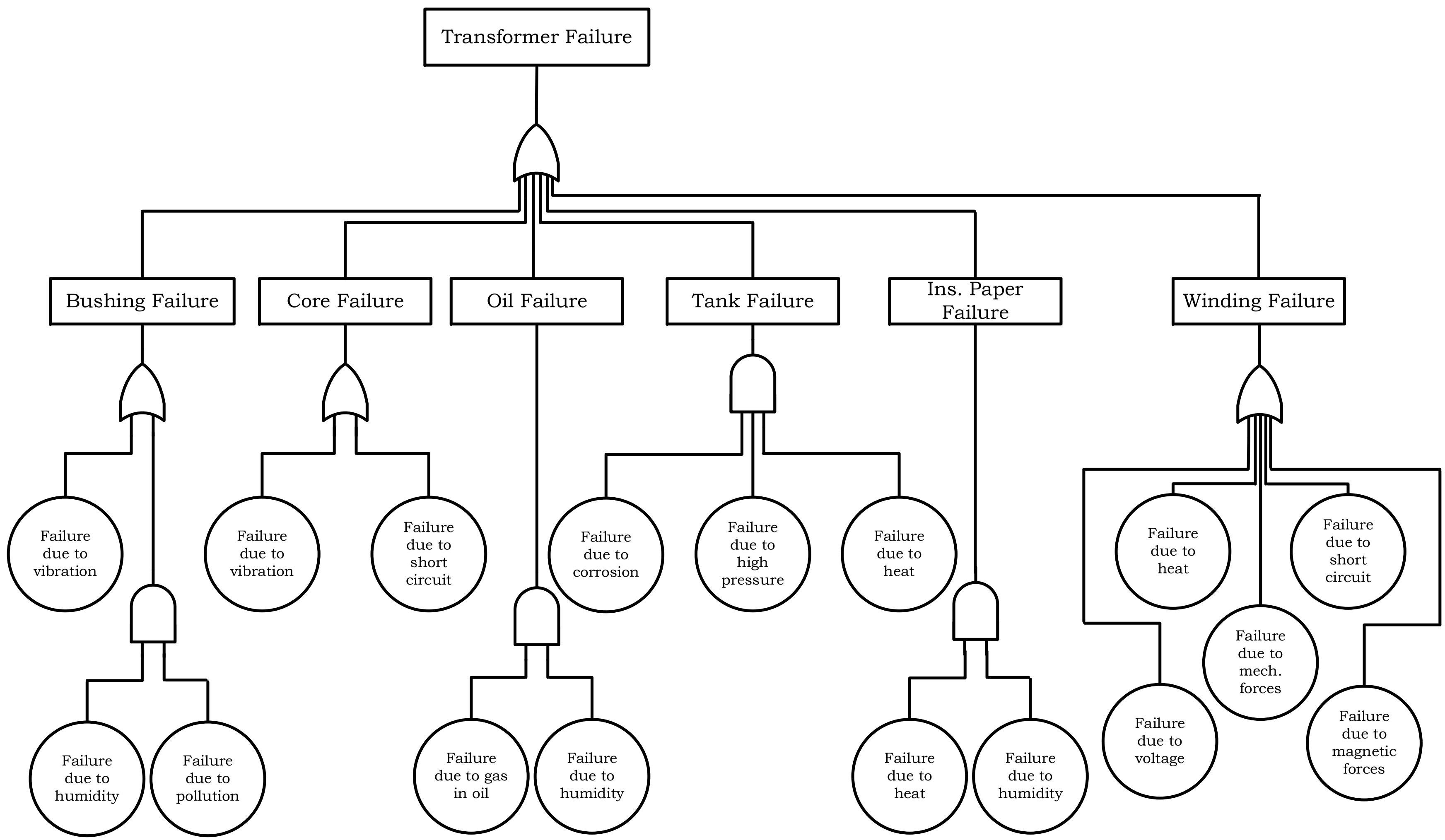


Figure 4.2: Typical power transformer fault tree

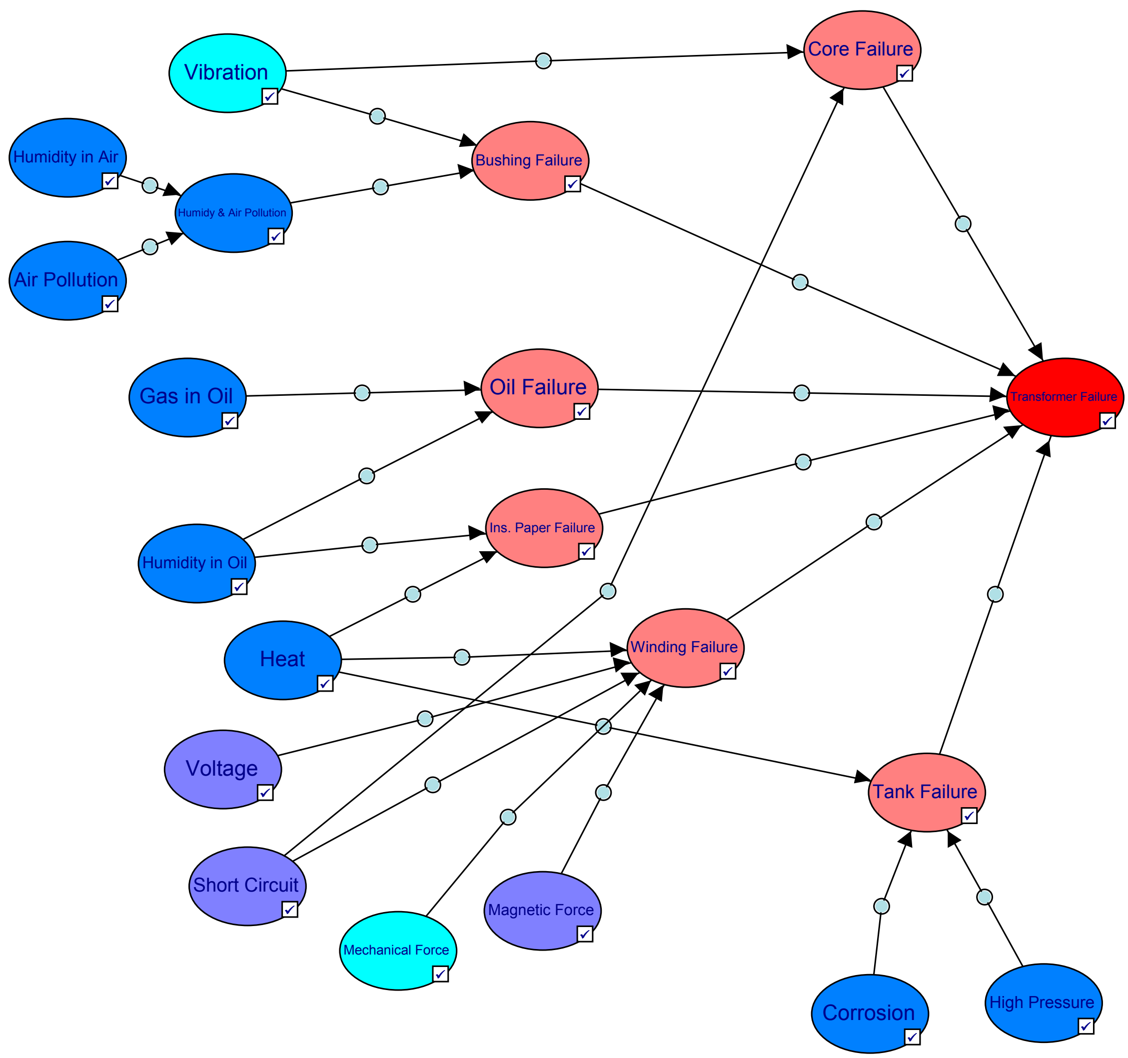


Figure 4.3: Power transformer Bayesian belief network

and are usually insulated from each other through layers of oil impregnated insulation papers. Windings have to withstand dielectric stress, thermal stress as well as mechanical forces of magnetic fields. Short circuits and lightning may impose significant forces on transformer windings.

Insulation Paper. The insulation paper in transformers is made of cellulose and its main function is providing dielectric and mechanical isolation to the windings.

Cellulose is made of long chains of glucose rings. When cellulose degrades, these chains get shorter. The condition of these papers is measured in degree of polymerization (DP) which is the average number of rings in a chain. A new paper has DP value of around 1,400. A DP value of 200 or less indicates poor mechanical strength and may not withstand short circuit and similar mechanical forces. Heat, moisture and various gases (in oil) are among the major causes of insulation paper degradation and eventually failure [47], [48].

There are several ways to mitigate insulation paper degradation. One is removing the oil, filtering it and placing it back to the tank. The filter can remove significant amount of gas (i.e. oxygen) and water. The other solution is completely replacing the oil.

Oil. The transformer oil is a highly refined product from mineral and crude oil and consists of hydrocarbon composition of which the most common are paraffin, naphthene and other mineral oils. The oil serves as both a cooling medium as well as insulation. The major causes of oil degradation are oxygen, humidity and solid objects.

As part of transformers insulation system, the oil keeps the insulation paper saturated with oil and also provides insulation between parts of components within the tank. Degradation in oil quality will increase the chance of internal short circuit. To keep the oil quality at an acceptable level, the oil needs to be regularly tested. When test results show degradation, either the oil needs to be removed and filtered or completely replaced.

Fans. Most power transformers are equipped with fans. Their function is to keep the transformer at proper temperature. They are usually packaged in groups and most of the transformers are equipped with redundant fans which make them non-critical components of the transformers.

Bushings. The function of bushings is to prevent flash over between transformer winding end and wires that connect the transformer to the network. Bushings are mainly made of insulated materials such as ceramic, and are typically filled with oil.

The main failure mode of bushings is short circuiting. This could happen through the degradation of bushing material, dust and humidity on the outside of bushing, or physical damage either through natural disaster or during shipping.

4.2.2 Failure Mechanisms

Transformers are subject to thermal, mechanical, chemical and electrical stresses. The following sections describe more details on adverse effect of each stress on transformer sub-components and suggest potential monitoring points for each component.

Thermal Stress. In a power transformer, tank, windings, core, oil, control panels and bushings are subject to thermal stress. Temperature's adverse effects on transformers include high steady state temperature, temperature range, temperature cycles, spatial temperature gradients, temperature ramp rates and heat dissipation.

Potential monitoring points include ambient temperature, tank temperature, oil temperature and windings temperature.

Mechanical Stress. Mechanical stress caused by pressure magnitude, pressure gradient, vibration, shock load, acoustic level, strain and stress may have fatal effects on transformers. High pressure within the tank can cause the tank to rupture. Vibration can damage core structure, bushings and electronic and control equipment. Shocks during transportation can cause structural and physical damage. High noise level can interfere with control and communication systems. In addition, stress and strain can damage the tank too.

Potential monitoring points include tank pressure, tank vibration, noise level within a few inches from tank, strain sensor on the outside of the tank, shear stress sensor on the outside of the tank, and shock recorders on transformer crate during the transportation.

Chemical Stress. Chemical stress such as chemical aggressive versus inert environment, humidity level, contamination, ozone, pollution and fuel spills can contribute to transformers failures. High humidity and pollutant can accelerate tank corrosion which in turn cause oil leak and short circuit. Pollutant and humidity can also cause flash over on bushings. And fuel spills can cause fire.

Potential monitoring points include ambient humidity and leak sensor.

Electrical Stress. Electrical stress such as current, voltage and power can con-

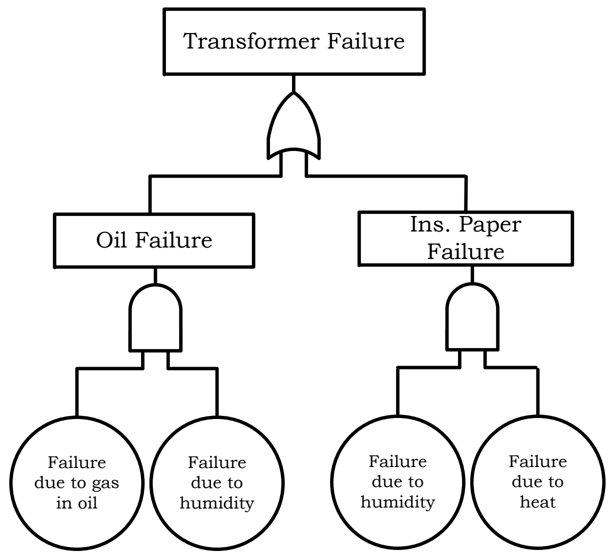


Figure 4.4: Partial fault tree of power transformer

tribute to transformers failure. Lightning on transmission lines can instantly move to transformer windings and put a very high voltage stress, beyond the transformer insulation level, and cause short circuit. A major short circuit inside or outside the transformer can cause significant amount of current passing through the windings.

Potential monitoring points include voltage, current, power, transient voltage, and transient current.

4.3 Case Study - Partial Transformer System

In order to simplify the presentation of the developed methodology, a simplified (partial) version of the power transformer is considered for our case study. Figure 4.4 presents a partial fault tree of the power transformer discussed earlier. Figure 4.5 shows the same fault tree with potential sensor locations and Figure 4.6 shows the equivalent Bayesian network of the partial fault tree of power transformer. This

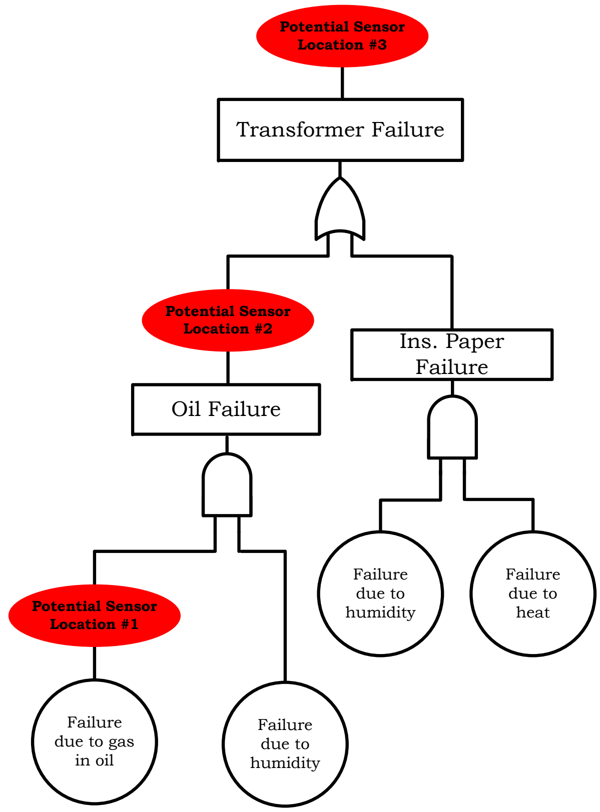


Figure 4.5: Potential sensor locations on transformer partial fault tree

partial fault tree and its equivalent Bayesian network are considered here to support the steps of methodology. The following sections of this chapter provide these steps. Chapter 5 presents the details of all the steps of sensor placement process for this simple example.

4.4 Bayesian Network Model

The lower level components states are considered as inputs to the Bayesian network. For this case study, the state of "Gas in Oil", "Humidity (moisture) in Oil" and "Heat (transformer temperature)" represent the three inputs in the Bayesian network model. Figure 4.7 presents how the inputs are fed into the Bayesian net-

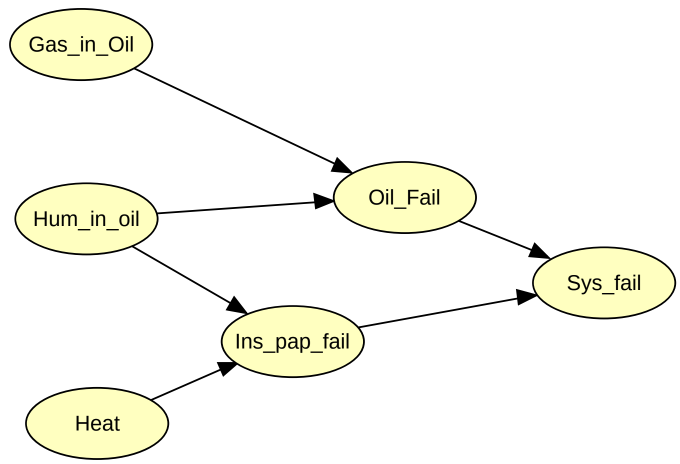


Figure 4.6: Bayesian network of power transformer partial fault tree

work. For this case study, the three inputs are as follows.

Input-1: Gas in Oil. The insulation paper in transformers is made of cellulose and its main function is providing dielectric and mechanical isolation to the windings. According to standard ASTM D-2945, maximum total gas content of transformer oil shall not be more than 1.0%.

Input-2: Moisture in Oil. Moisture in oil significantly degrade the insulation characteristics of oil. Many references including NETA (www.netaworld.org) provide a generally accepted maximum moisture content of **35 ppm** for mineral oil. Moisture content of oil is controlled by relative humidity and typically when monitored (or tested) the relative humidity is measured. Water in Oil Solubility as a function of temperature can be expressed as

$$\log S_o = -1567/T + 7.0895 \tag{4.1}$$

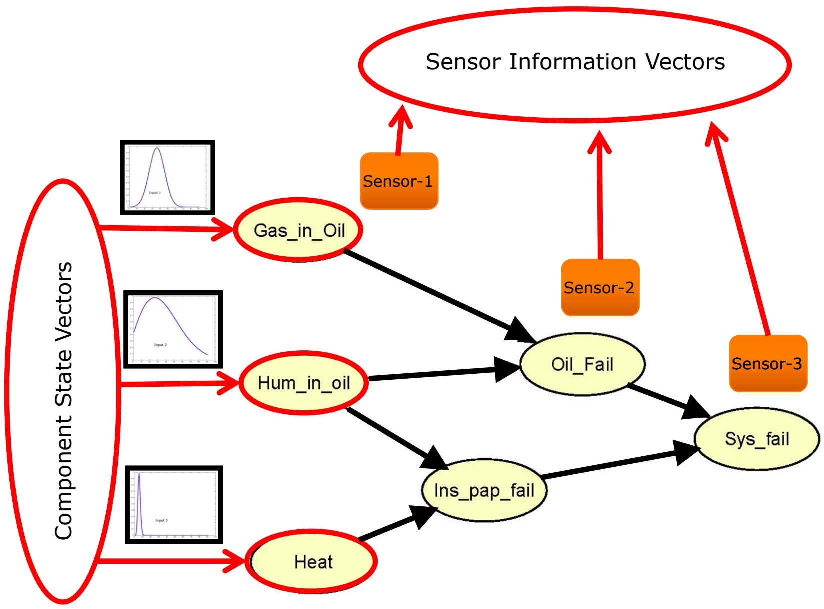


Figure 4.7: Bayesian network inputs and outputs

where S_o is the solubility of water in mineral oil.

Relative Saturation (RS) is the actual amount of water measured in oil in relation to solubility at certain temperature.

$$RS(\%) = W_c/S_o \tag{4.2}$$

where W_c is the water content (moisture) in oil (ppm) for various temperatures.

Input-3: Heat. IEEE Std. C57.91-1995, the Guide for Loading Mineral-Oil-Immersed Transformers, provides calculation methodology to measure oil and winding temperatures. An industry accepted methodology for calculating transformers top-oil temperature rise is given by

$$TO_2 = TO_1(i_2/i_1)^{1.8} \tag{4.3}$$

where TO_2 is the ultimate top-oil rise, TO_1 is the initial or known top-oil rise, and i_2/i_1 is the per-unit current loading.

For this case study, we assume that oil temperature has been directly measured through oil immersed temperature sensors.

Inputs vs. Sensor Readings Inputs in our model represent the set of historical data that is assumed will be available from the system site. While the sensor readings are referred to those data sets that will be generated through the detection of physical phenomena by proposed sensors.

Considering Sensor Uncertainty For simple cases of sensors with known percentage of error, the amount of inaccuracy is included in the Bayesian network model by adding an extra node for each sensor.

4.4.1 Physics of Failure (PoF) Analysis

Physics of failure analysis is an approach to design, reliability assessment, testing, screening and stress margins assessment. It uses knowledge of root-cause failure processes to prevent product failures through robust design and manufacturing practices which involves identification of potential failure mechanisms, failure sites, and failure modes; the appropriate failure models and their input parameters. The objective of any physics of failure analysis is to determine or predict when a specific end-of-life failure mechanism will occur for an individual component in a specific application.

There are several areas of concern in conventional approaches (i.e. constant failure rate) towards reliability analysis which physics of failure approach is attempting to address [49]. Among them are:

Zero Failure Criteria. Zero failure criteria is a case in which a reliability test ends in zero units having failed. Traditional reliability calculations suggest that the estimated failure rate is also zero, assuming an exponential distribution. Obviously, this is not a realistic estimate of a failure rate, as it does not take into account the number of units.

Single Failure Mechanisms vs. Competing Failure Mechanisms. Single failure mechanisms vs. competing failure mechanisms refers to application of accelerated life testing in cases with multiple failure mechanisms and compares them with single failure mechanism. It also offers details on how to deal with multiple failure mechanisms and provides detailed calculations.

4.4.2 Stress Models and Life

Arrhenius Relationship. The Arrhenius life-stress model is a widely used model describing the effect of heat on accelerating chemical reactions and it is probably the most common life-stress relationship utilized in accelerated life testing. It is derived from the Arrhenius reaction rate equation proposed by the Swedish physical chemist Svandte Arrhenius in 1887 [50] and is given by

$$L(V) = Ae^{B/T} \tag{4.4}$$

where L is life, A and B are constants that depend on the aging rate and end-of-life definition and T is the absolute temperature in Kelvins (°C+273).

Eyring Relationship. The Eyring relationship is another model used when thermal stress (temperature) is the acceleration variable. However, the Eyring relationship sometimes is used for stress variables other than temperature, such as humidity [50].

Inverse Power Law (IPL) Relationship. The inverse power law (IPL) model is commonly used for non-thermal stresses such as voltage and is given by

$$L(V) = \frac{1}{KV^n} \tag{4.5}$$

where L represents a quantifiable life measure, such as mean life, characteristic life, median life, etc., V represents the stress level, K is one of the model parameters to be determined, (K > 0), and n is another model parameter to be determined.

Temperature – Humidity Relationship.

The temperature – humidity (T-H) relationship is used for predicting the life at use conditions when both temperature and humidity are considered as stress factors.

Temperature – Non-Thermal Relationship. When temperature and a second non-thermal stress (such as voltage) are the stress factors, then the Arrhenius and the inverse power law relationships can be combined to yield the temperature – non-thermal (T-NT) relationship and is given by

$$L(V,U) = \frac{C}{U^n e^{\frac{-B}{V}}} \tag{4.6}$$

where U is the non-thermal stress (such as voltage, etc.), V is the temperature (in absolute units), and B, C, and n are the parameters to be determined.

General Log-Linear Relationship. When in a system, multiple stress factors exist, a general multivariable relationship such as general log-linear relationship can describe the life characteristic as a function of a vector with n stresses, or $\overline{X} = (X_1, X_2, ..., X_n)$. Mathematically the relationship is given by

$$L(\overline{X}) = \exp\left(\alpha_0 + \sum_{j=1}^{n} \alpha_j X_j\right) \tag{4.7}$$

where $\alpha_j s$ are model parameters and X is a vector of n stresses.

4.5 Model Inputs and Outputs

In this section, we present details of model inputs and outputs and how they interact with unknowns of interest.

4.5.1 Unknowns of Interest (UOI)

Failure probabilities of lower level components, subsystems or system; value of parameters; and the probability of physical parameters taking specific values are defined as unknowns of interest (UOI) for this case study. For example, in the Bayesian network of power transformer partial fault tree as shown in Figure 4.6, probabilities of gas in oil, humidity in oil, heat, oil failure, insulation paper failure and system failure are considered unknowns of interest. For this case study, it is assumed that we are interested in assessing the health of a system and have already determined that three lower level components failure probabilities (gas in oil, humidity in oil and heat) have major role in overall system health. However, due to practical and resource limitations in physical placement and number of sensors, it might be beneficial to assess the system health through limited number of sensors in locations other than where health assessment is desired. This, presents the heart of the Bayesian sensor placement (BSP) methodology which will be described in detail in Chapter 5.

4.5.2 Components State Vectors

As stated earlier, all possible combinations of inputs' states are defined as *components state vectors*, $\widetilde{x} = \{x_1, x_2, \ldots, x_j, \ldots, x_n\}$. For this case study with binary states and three lower level components (inputs to the Bayesian network), the components state vectors $\widetilde{x}$ will contain $2^3 = 8$ elements.

The Bayesian network inputs (components state vectors) need to be in the form of finite set of states (i.e. 1's and 0's) or as probabilities of success or failure, while in real systems, the available inputs are physical phenomena such as temperature, pressure, relative humidity, etc. Therefore, through an appropriate process, the physical phenomena need to be converted to components states. Figure 3.7 presented a general scheme for a typical process. Figure 4.8 presents the details of the process for this case study.

The algorithms for the conversions utilize all the known physics of failure related to each phenomenon, taking into account uncertainties, related standards, functional failure modes and failure mechanisms to convert the sensory data for each physical phenomenon to a component state.

The three buckets represent three data sets of physical phenomena to be considered as inputs to the case study system Bayesian network, which could be obtained either from historical data or through testing. For example, historical oil temperature data set may contain various temperature readings in degrees Celsius. To assign a "state" to each data point, the failure modes, failure mechanisms, physics of failure and various standards and codes related to transformer oil need to

State	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Gas in Oil	1	1	1	1	0	0	0	0
Hum in Oil	1	1	0	0	1	1	0	0
Heat	1	0	1	0	1	0	1	0

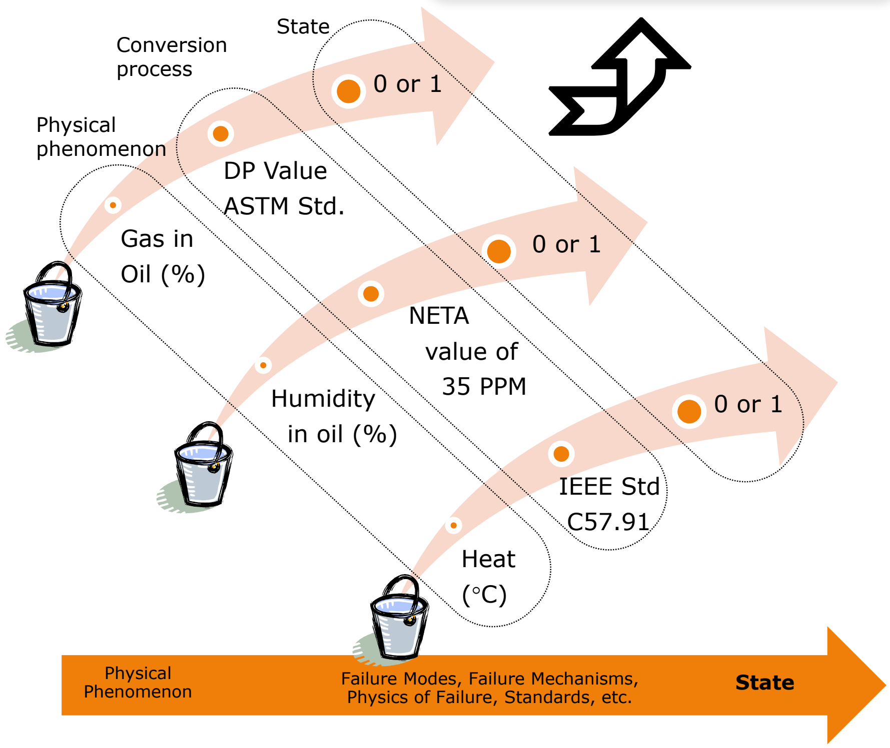


Figure 4.8: Conceptual diagram for conversion of physical phenomena to components states

be examined and translated in computer codes (conversion process in Figure 4.9) to convert the temperature readings to components states. Similarly, other conversion algorithms have been written to translate the percentage of gas in oil and humidity in oil data sets to components states. As a result, this process generates the components state vectors as presented in Figure 4.9.

This process assumes sampling each element of each state vector at a time. It is also possible to consider sampling joint distribution of all elements (e.g. three) of state vector at a time. In that case there will be one bucket filled with historical

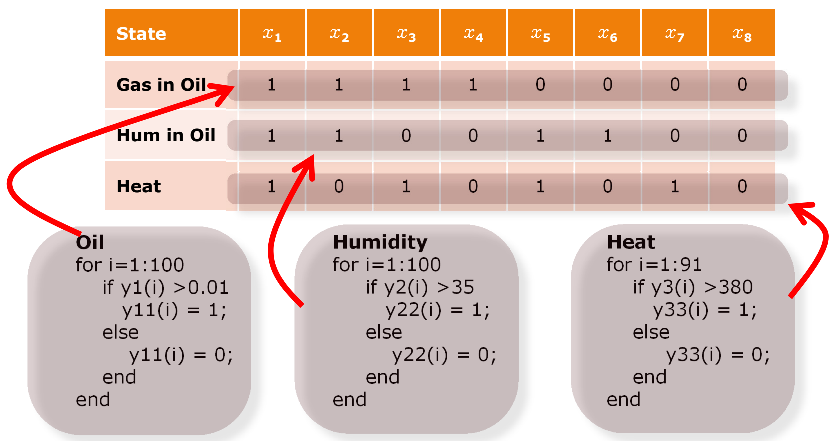


Figure 4.9: Algorithm snapshot for conversion of physical phenomena to components states

data sets with each set comprised of a pack of three points: a percentage of gas in oil reading, an oil humidity percentage reading and a transformer temperature reading.

4.5.3 Sensor Selection

Referring to Figure 4.7, three types of sensors for three locations (based on the functional location on the logic diagram) have been proposed as follows:

Sensor-1. A HYDRAN-M2 sensor as shown in Figure 4.10 , monitors built up gas in power transformer's oil and for this case study, is considered as a candidate for sensor -1 location. The HYDRAN-M2 sensor measures the level of combustible gases in power transformer dielectric oil, which is important to be evaluated for potential dangerous conditions, bubbling temperature and aging. M2 is sensitive to four gases that are primary indicators of initial faults in oil-filled power transform-

Figure 4.10: HYDRAN-M2 gas monitor (courtesy of General Electric Company)

ers: hydrogen, carbon monoxide, ethylene and acetylene.

Sensor-2. Kelman TRANSFIX (Dissolved Gas Analysis) and moisture sensor for power transformers as shown in Figure 4.11 is considered for sensor-2 location. It has configurable sampling rates from daily to hourly, uses photo-acoustic spectroscopy for better detection results, and is equipped with full embedded processor which is capable of storing over two years of data at its default sampling rate of one sample taken every four hours.

Sensor-3. A typical voltmeter as shown in Figure 4.12, is considered for sensor-3 location. It is located on the secondary of the power transformer (through potential transformers) to monitor whether the transformer is operational or not.

4.6 Summary

In this chapter we presented the key building blocks of the inference model construction for the proposed Bayesian sensor placement algorithms. The chapter started with an overview of power transformers chosen as a case study system.

Figure 4.11: Kelman TRANSFIX online DGA and moisture sensor (courtesy of General Electric Company)

Figure 4.12: A typical analog voltmeter (courtesy of SiGMA ELECTRiK Company)

Next, its functional failure modes, failure mechanisms, and physics of failures were reviewed, followed by a summary of various stresses and stress and life models. A sub-set of a typical power transformer (partial system) was considered as the case study system. The rest of the chapter dealt with the details of building the Bayesian inference model, selecting potential sensor types and locations, and building the components state vectors and sensor information vectors. The next chapter describes how these model elements are used to find the

sensor placement scenario that would provide the most of amount of reliability information about the system.

Chapter 5

Bayesian Sensor Placement

5.1 Introduction

We define Bayesian sensor placement (BSP) as a set of sensor placement scenarios and an information metric to measure the expected amount of reliability information that each possible sensor placement scenario provides. This presents the heart of a novel methodology for optimum sensor placement in a complex system. Information metric is defined as a scale to measure the amount of information each sensor placement scenario provides, and its domain is a set of real numbers that can be interpreted directly as expected gains on the chosen scale such as amount of information, entropy, etc. Potential applications of Bayesian sensor placement solutions include health monitoring of a simple power system, an aircraft, or a complex system.

This chapter presents the details of the proposed Bayesian sensor placement process. The Bayesian sensor placement problem is defined by: (1) a set of candidate sensor placement scenarios; (2) a measure of assessing the expected values associated with each sensor placement scenario, called "information metric"; and (3) a comparison of the information metric values to determine which placement scenario yields the highest expected information metric value. The sensor placement process is presented for the case study of Chapter 4.

5.2 Bayesian Sensor Placement Flow Chart

Figure 5.1 illustrates the flow chart of the proposed Bayesian sensor placement process. To further explain the details of this sensor placement methodology, we utilize a simplified form of the transformer example presented in the case study of Chapter 4. Throughout this chapter, all the steps of the sensor placement process are explained and in parallel, the transformer case study will be used as a running example.

5.3 The Case Study Bayesian Sensor Placement Algorithm

It is assumed that we are interested in the failure status of three lower level components, however, due to physical, technological or resource limitations, it is not possible to place sensors at all three lower level components positions. Alternatively, there are other potential places that sensors can be installed, and in specific, the goal is to find the sensor placement scenario that would provide the most amount of information about the health of the system. As discussed in Section 4.5.1, we defined failure probabilities of lower level components, subsystems or system, value of parameters, and the probability of physical parameters taking specific values as unknowns of interest (UOI) in the proposed Bayesian sensor placement algorithms.

Considering the fault tree of Figure 4.5 and Bayesian network of Figure 4.6, the goal is to find the sensor placement scenario providing the highest amount of reliability information given that only two sensors can be utilized.

Step 1. Identify system functional failure modes.

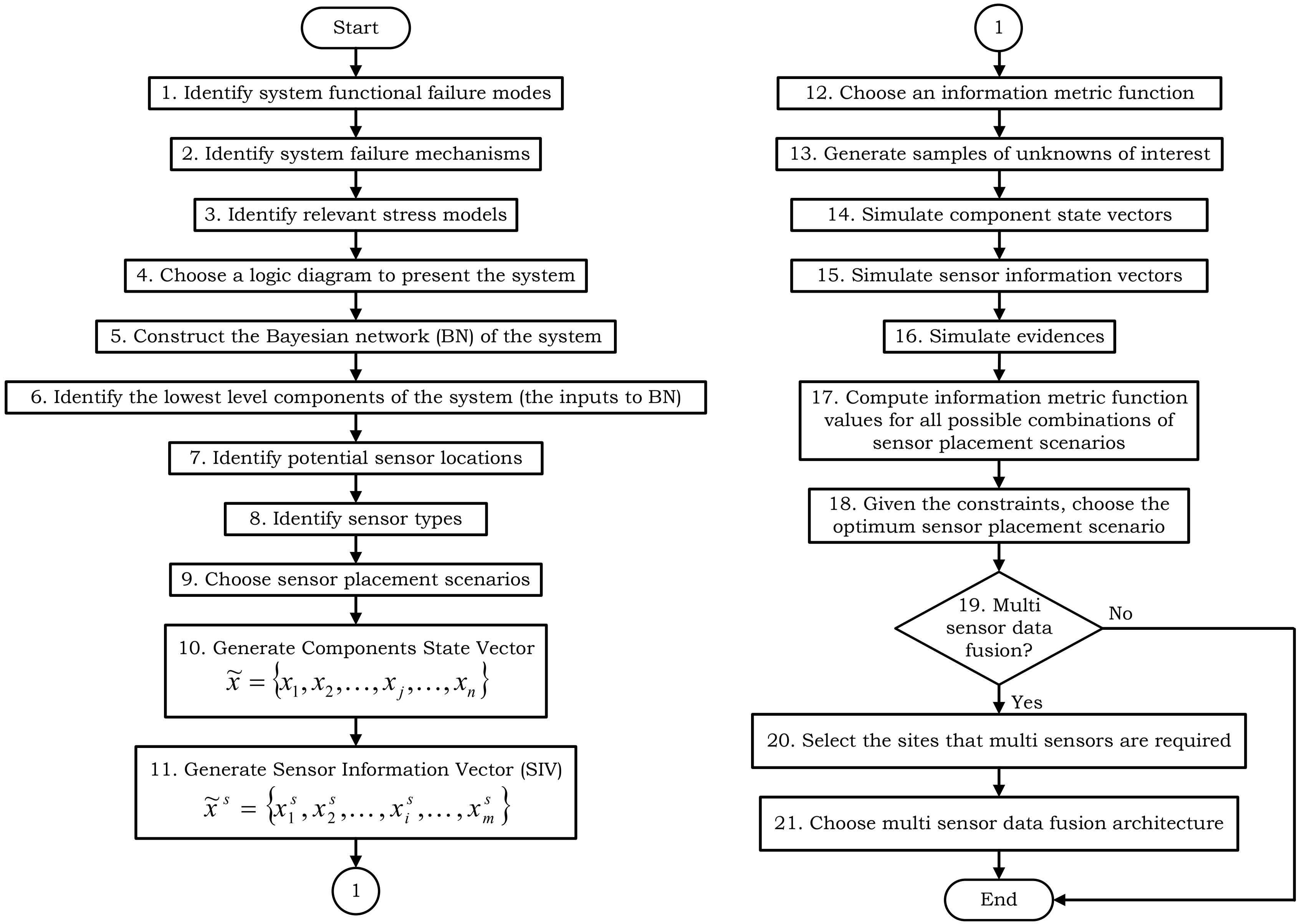


Figure 5.1: Bayesian sensor placement flow chart

The overall transformer major functional failure modes include tank, core, winding, insulation paper, oil, fans, bushings, heat exchangers, tap changers and auxiliary equipment, however, the simplified version of the transformer fault tree in this case study includes limited number of transformer parts. For this example, the system functional failure modes include failures of bushings, oil, insulation paper, windings and tank.

Step 2. Identify system failure mechanisms.

The system failure mechanisms include thermal stress, mechanical stress, chemical stress and electrical stress.

Step 3. Identify relevant stress models.

Arrhenius life-stress model, Eyring relationship, inverse power law, temperature – non-thermal relationship and general log-linear relationship are among the models being considered for this example.

Note on Step 1 through 3. The main purpose of identifying system failure modes, functional failure mechanisms, physics of failure and stress models is to be able to translate the physical phenomena obtained from historical data, testing, sampling and direct sensor readings, to "states". As described in Section 3.3.1.1 and presented in Figure 3.7, the Bayesian network inputs need to be in the form of finite set of states (i.e. 1's and 0's) or as probabilities of success or failure, while in real systems, the available inputs are physical phenomena such as temperature, pressure, relative humidity, etc.

Step 4. Choose a logic diagram to present the system.

A fault tree is the chosen logic diagram and it is presented in Figure 4.5. As discussed earlier, the hallmark of the proposed Bayesian sensor placement is its capability in finding sensor locations on system's logic diagram (i.e. its fault tree) that would provide the highest amount of reliability information.

Step 5. Construct the Bayesian network (BN) of the system.

The system Bayesian network is presented in Figure 4.6. In this process, system Bayesian network is utilized for modeling and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest.

There are various approaches in building Bayesian networks. The most frequently used methods in building Bayesian networks are: (1) based on expert knowledge, (2) based on system design, and (3) by learning from historical data. For the proposed Bayesian sensor placement algorithm, we utilize a combination of these methodologies. In specific, we followed three basic steps to fully specify the system's Bayesian network:

First, we identified the variables with the most impact on system health. Typically, these variables are the nodes associated with the lower level components which their failure would propagate through the subsystems and eventually to the system level (top event). We labeled these variables as the lower level components. In separate efforts, we tried to collect historical data related to any / all of the lower level components and the goal was to use those historical data sets to train the Bayesian network.

Second, we identified the network's structure through defining the edges between the nodes. The system logic diagram (fault tree in this case study) was used to identify the correlations among network nodes.

Third, we combined our knowledge of network variables, network structure and engineering experience to define the relationships among the nodes and edges,in the form of conditional probability tables (CPT).

Step 6. Identify the lower level components of the system (the inputs to BN).

The data sets with values of lower level components' states are considered as inputs to the Bayesian network. For this case study, the states of "Gas in Oil", "Humidity (moisture) in Oil" and "Heat (transformer temperature)" represent the three inputs in Bayesian network.

Step 7. Identify potential sensor locations.

Three potential sensor sites as shown in Figure 5.2 are considered. They can monitor system state (top level), transformer oil state, and potential gas in transformer oil.

Given that technically, sensors could be installed almost at any Bayesian network node, however, due to physical, technological and financial restrictions, this may not be possible. Therefore, as decision makers, we have to decide upon the sensor placement scenarios to obtain the maximum amount of reliability information, given the constraints.

Step 8. Identify sensor types.

A HYDRAN-M2 sensor as shown in Figure 4.10 , monitors built up gas in transformers oil and is considered as a candidate for sensor -1 location. A Kelman TRANSFIX online DGA (Dissolved Gas Analysis) and moisture sensor for transformers as shown in Figure 4.11 is considered for sensor-2 location. A typical voltmeter as shown in Figure 4.12, is considered for sensor-3 location.

Also as part of this step, sensor uncertainty is incorporated to the model.

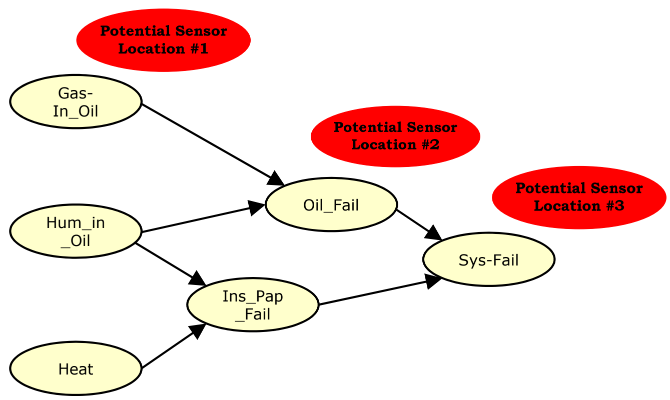


Figure 5.2: Potential sensor location for the case study

Given that uncertainty is an inherent characteristic of sensors, therefore, what sensors report may have some deviations from the actual physical phenomenon they are monitoring. To capture this inconsistency, we modeled the uncertainties probabilistically and updated the Bayesian network with these probabilities at sensor locations. For this example, probabilistic uncertainty values associated with each sensor was added to the example Bayesian network.

Step 9. Choose sensor placement scenarios.

Given the number of sensor types, the number of potential sensor locations and the constraints for each sensor type, several combinations of sensor scenarios can be generated. In general, assuming k_1 is the potential number of sensor locations for each sensor, k_2 is the number of sensors are allowed for each sensor type, and j is the number of sensor types, then the total number of scenarios can be calculated by

$$\sum_j \frac{k_{1j}!}{k_{2j}!\,(k_{1j} - k_{2j})!} \tag{5.1}$$

When there is no specific constraints for each type of sensor, with three potential sensor locations and a constraint to utilize only two sensors (of any type), the number of possible combinations for exactly two sensors will be

$$\binom{k_1}{k_2} = \frac{k_1!}{k_2!\,(k_1 - k_2)!} = \frac{3!}{2! \times 1!} = 3 \tag{5.2}$$

where k_1 is potential number of sensor locations and k_2 represents the number of sensors are allowed. We also added one additional scenario with three sensors just to examine how a case with one additional sensor would stack up against the reset of two-sensor scenarios. Therefore, the sensor placement scenarios are:

- Scenario 1: Utilize sensor 1, 2 and 3 (a test scenario)
- Scenario 2: Utilize sensor 1 and 3
- Scenario 3: Utilize sensor 2 and 3
- Scenario 4: Utilize sensor 1 and 2

and the sensor placement process goal is to evaluate which scenario provides the highest amount of information assuming the system constraint is to use only two sensors. In addition, it was assumed that even the sensor's types are different, however, the cost of sensors are the same and all sensors provide equal amount of information.

Defining sensor scenarios is meant to structure a sensor placement process. Additionally, we bring the "human factor" (in a positive way) into the decision making process. Otherwise, we could use a computer generated set of various combinations of sensors, which for a large Bayesian network can be enormous. Instead,

Table 5.1: The case study components state vectors

State Vector	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Gas in Oil	1	1	1	1	0	0	0	0
Humidity	1	1	0	0	1	1	0	0
Heat	1	0	1	0	1	0	1	0

as engineering experts (in this case study), we specifically chose certain combinations of sensor placements (scenarios) that make engineering sense.

Step 10. Generate Component State Vectors.

All possible combinations of input states are defined as *components state vectors* and presented as

$$\widetilde{x} = \{x_1, x_2, \ldots, x_j, \ldots, x_n\} \tag{5.3}$$

for a system with n lower level components where x_j is the j^{th} set of input vector. A k-state system with n lower level components generates k^n vectors in component state vector. For this example with three inputs, the components state vector includes $2^3 = 8$ vectors as shown in Table 5.1.

In Section 4.5.2, we discussed that in real world, the historical data sets are measurements of physical phenomena such as degrees Celsius for temperature measurement, etc., while the Bayesian network can be instantiated by states or probabilities (success or failure). The process for this conversion was summarized in Figure 4.8. We later called this process the "conversion process" for translating physical phenomena to components states. In Step 10 of sensor placement process, the Bayesian network is instantiated by all possible combinations of these components states to generate all possible sensor information vectors which will be discussed next.

Step 11. Generate Sensor Information Vectors (SIV).

Sensor information vectors (SIV) is defined as the set of states detected by sensors and presented as

$$SIV \ : \quad \widetilde{x}^s = \{x_1^s, x_2^s, \ldots, x_i^s, \ldots, x_m^s\} \tag{5.4}$$

where x_i^s is the vector representing the i^{th} set of sensors states out of m combinations of states detected by the set of sensors.

As described earlier, the case study inference engine has three major blocks as shown in Figure 3.6. The input block represents the component state vectors, the output block represents the sensor information vectors (SIV) and the middle block is the Bayesian network. For sensor placement scenario 1 of this example with three sensors detecting binary states, the SIV may have up to eight elements. The reason behind the potential lesser number of SIV elements than mathematical combinations of sensor points is that in reality, some combinations are almost impossible. The proof comes at the end of process of generating SIV and realizing that the probability of occurring certain SIV elements is zero. Table 5.4 shows the exact number of vectors for this case study.

Figure 5.3 presents the detailed step by step of the process for inferring sensor information vectors for scenario 1 of the case study.

Step 12. Choose an information metric.

Information metric is defined as a scale to measure the amount of reliability infor-

Table 5.2: The case study sensor information vectors for scenario 1

Sensor Information Vector	x_1^s	x_2^s	x_3^s	x_4^s	x_5^s
Sensor 1	1	1	1	0	0
Sensor 2	1	0	0	1	1
Sensor 3	1	1	0	1	0

mation. Its domain is a set of real numbers on the chosen scale such as value of information, entropy, etc.

As discussed in Chapter 3, example information metrics for an unknown of interest θ include:

$$U_I(\theta) = \sum_j \ln[\pi(\theta_j)]\,\pi(\theta_j), \text{ and} \tag{5.5}$$

$$U_I(\theta) = \sum_j \frac{1}{\sigma^2_{\theta_j}}. \tag{5.6}$$

For this case study, Equation 5.6 is considered as the framework for information metric function of choice. Given that the information metric function is based on uncertainty about the unknowns of interest, we select an information metric function that takes into account all unknowns of interest relevant parameters which in this case is the probability of failure the lower level components.

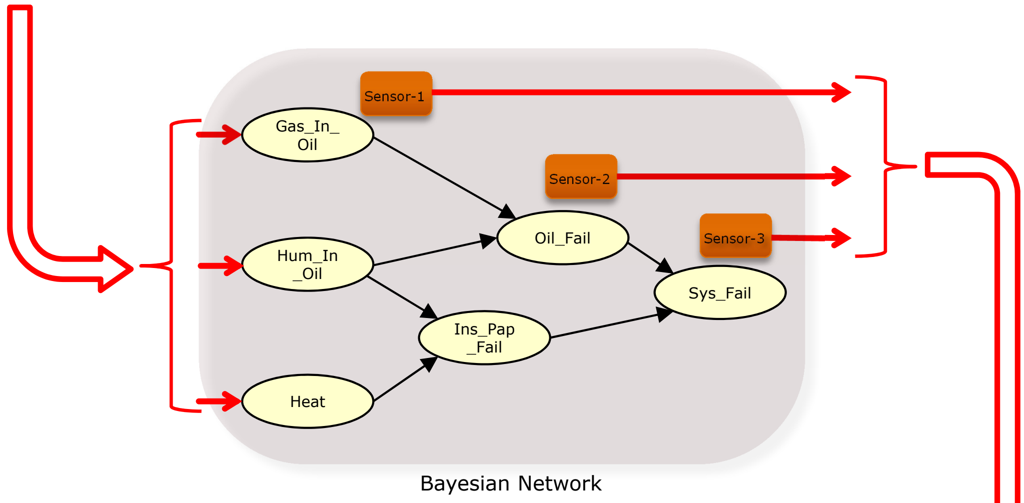
Step 13. Generate samples of unknowns of interest.

Monte Carlo simulation is used to randomly draw joint samples of states of the lower level components.

Step 14. Simulate component state vectors.

Component State Vectors

State	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Oil	1	1	1	1	0	0	0	0
Hum	1	1	0	0	1	1	0	0
Heat	1	0	1	0	1	0	1	0



Possible Sensor Information Vectors (SIV)

State	SIV1	SIV2	SIV3	SIV4	SIV5	SIV6	SIV7	SIV8
S1	1	1	1	1	0	0	0	0
S2	1	1	0	0	1	1	0	0
S3	1	0	1	0	1	0	1	0

Figure 5.3: Sensor information vectors (SIV) inference details

Each randomly drawn set of unknown of interest defines the lower level components states. Monte Carlo and Bootstrap simulation methods were utilized to draw joint samples of three historical information (as shown schematically in three buckets in Figure 4.8). Figure 5.4 shows the process of simulating components state vectors . Assuming uniform distribution, first we randomly draw one data point from each bucket of Figure 4.8, run them through the "conversion process" presented in Figure 4.8 and generate one data set (called state vector) which represents a set of lower

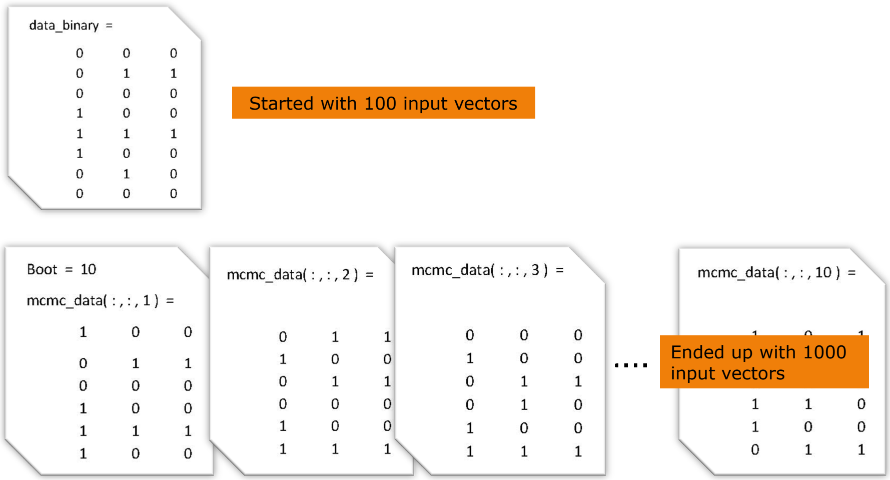


Figure 5.4: Monte Carlo simulation to simulate components state vectors

level components states. We repeat this process a large number of times to create a large set of components state vectors. Given that we started with three individual data sets (three buckets) and considering binary states, there are $2^3 = 8$ possible distinct state vectors that can be generated. In other words, the components state vectors will have eight elements. Then by counting the numbers of each element and dividing by the total components state vectors, the probability of occurrence of each vector element is calculated and shown in Table 5.3.

These state vectors will be used as inputs to the Bayesian network. The next step is to run all of these inputs through the Bayesian network and record the network's outputs, which we called them *Sensor Information Vectors*, and will be discussed in the following section.

Step 15. Simulate sensor information vectors.

Each vector generated on the output of the state vector simulation process is fed to the system's Bayesian network which in turn, would generate corresponding output

Table 5.3: The case study state vectors and their probabilities

State Vector	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Gas in Oil	1	1	1	1	0	0	0	0
Humidity	1	1	0	0	1	1	0	0
Heat	1	0	1	0	1	0	1	0
Probability	0.002	0.014	0.024	0.096	0.023	0.100	0.109	0.629

Table 5.4: The case study SIV and associated probabilities for scenario 1

Sensor Information Vector	x_1^s	x_2^s	x_3^s	x_4^s	x_5^s
Sensor 1	1	1	1	0	0
Sensor 2	1	0	0	1	0
Sensor 3	1	1	0	1	0
Probability	0.01648	0.0241	0.0967	0.1230	0.7395

states. Each set of output states at suggested location of sensors on a logic diagram, generates a set of vectors which as described earlier, are called sensor information vectors (x_i^s). The same process is repeated for all state vectors to generate system sensor information vectors ($\widetilde{x}^s$) for each sensor placement scenario. Tables 5.4 and 5.5 present the sensor information vectors for Scenario 1 and 2 for the case study. Similar process was repeated for sensor placement scenarios 3 and 4 to generate their sensor information vectors.

Step 16. Simulate evidence.

Starting with the sensor information vectors of Table 5.4 and utilizing Monte Carlo simulation 100,000 times and assuming 4 demands each time, a large set of evidence

Table 5.5: The case study SIV and associated probabilities for scenario 2

Sensor Information Vector	x_1^s	x_2^s	x_3^s	x_4^s
Sensor 1	1	1	0	0
Sensor 3	1	0	1	0
Probability	0.04175	0.09340	0.14395	0.72087

sets were generated. Figure 5.5 presents an overview of the process for generating these evidence sets.

Step 17. Compute information metric function values for selected evidence sets. Figure 5.6 presents the roadmap for calculating information metric function values for each evidence set.

The process starts with component state vectors that are fed to the Bayesian network. The Bayesian network outputs generate the sensor information vectors. Running the SIV through the process of generating evidence sets as shown in Figure 5.5, generates a large number of evidence sets. Starting with the first evidence set, here are the steps to calculate the information metric function value for the first evidence set of the first sensor placement scenario:

a. Instantiate the Bayesian network at sensor nodes with the values of the first element of evidence set (0 0 0 as shown in Figure 5.6) and record the values of unknowns of interest which are the failure probabilities at the lower level components in system's Bayesian network. These values were calculated as $p_1 = 0$, $p_2 = 0.0362$, and $p_3 = 0.0247$, where p_1 is the probability of presence of gas in oil, p_2 is the probability of presence of humidity in oil, and p_3 is the probability of transformer

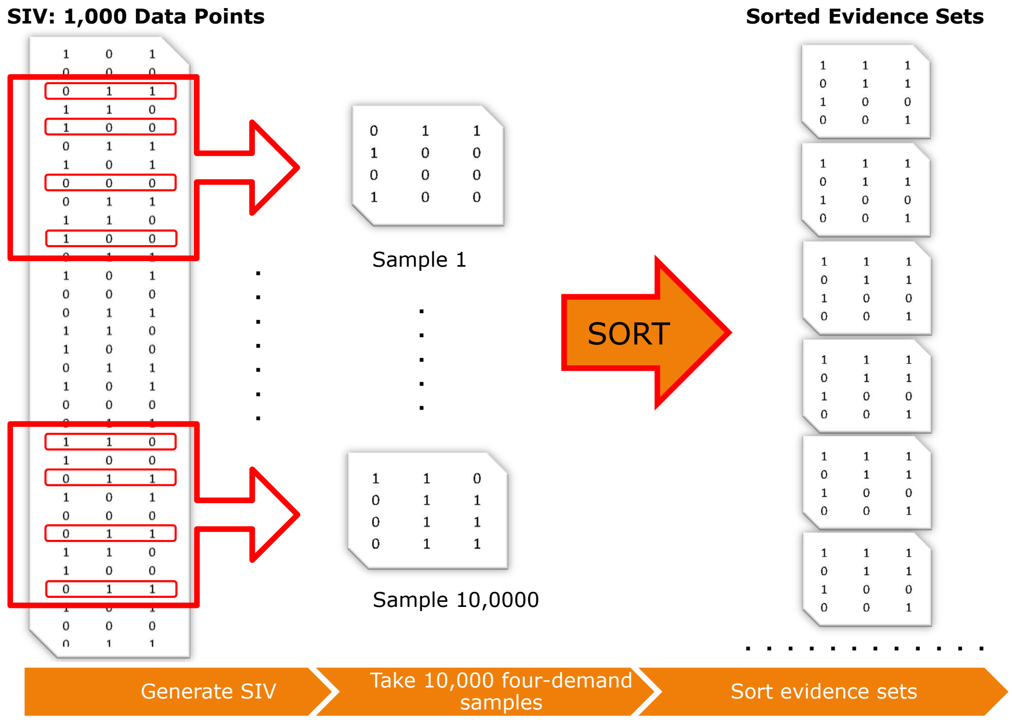


Figure 5.5: Procedure for generating evidence sets

overheating, all for the the first line of evidence set #1 of scenario 1 of sensor placement scenarios.

b. Repeat step **a.** for the other three elements of evidence set #1.

c. Calculate $\sigma^2_{p_1}$ for four p_1 values calculated in previous steps.

d. Repeat step **c** for p_2 and p_3.

e. Calculate $1/\sigma^2_{p_1}$, $1/\sigma^2_{p_2}$, and $1/\sigma^2_{p_3}$ and add them up. This value (13333560.62) will be recorded as the information metric function value associated with the first evidence set of sensor placement scenario 1. Record this value under "Information Metric (U_i)" in the table shown in top part of Figure 5.6. Also see Figure 5.7 for the details of this analysis.

f. Calculate the probability of occurrence of evidence set #1 by counting the number

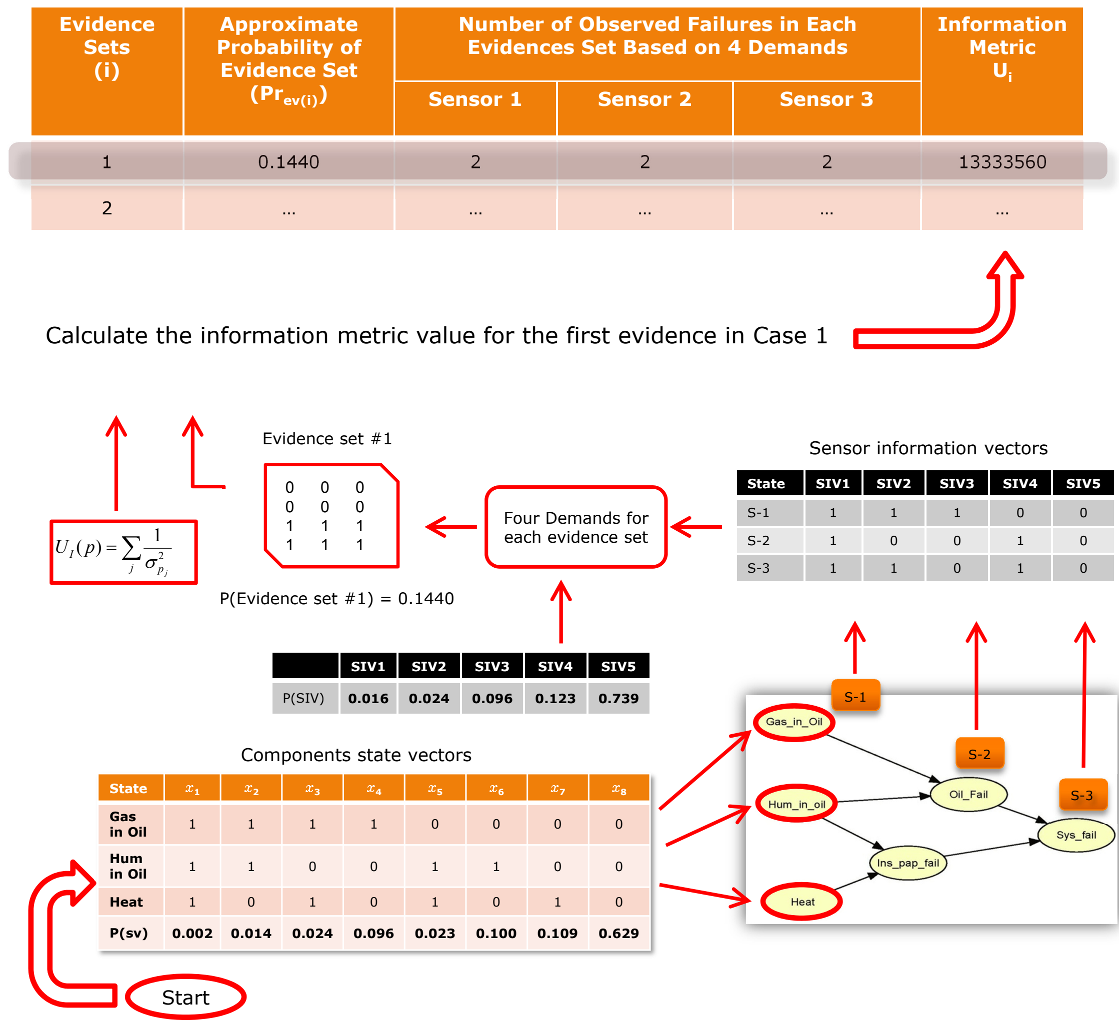


Figure 5.6: Roadmap for calculating information metric function values for each evidence set

of times it appeared in the pool of evidence sets and dividing by the total number of evidence sets. Record this number under "Approximate Probability of Evidence Set ($Pr_{ev(i)}$)" column for evidence set #1 in the table shown in top part of Figure 5.6.

A similar process is repeated for the rest of evidence sets and the information metric function values associated with individual evidence sets for scenario 1 are presented in Table 5.6.

The expected information metric function value for scenario 1 can be calculated

	P1	P2	P3
SIV5	0	0.0362	0.0247
SIV5	0	0.0362	0.0247
SIV1	1	0.1582	0.0252
SIV1	1	0.1582	0.0252
VAR	0.3	0.004465	7.5E-08
1/VAR	3.333333	223.9541	13333333

$$\boxed{U_I(p) = \sum_j \frac{1}{\sigma^2_{p_j}} = 3.333 + 223.954 + 13333333 = 13333560}$$

Figure 5.7: Detailed analysis of U_i

by

$$\overline{U}_{I(1)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.1440 \times 1333 \times 10^4 + 0.1296 \times 9.7 \times 10^4 + \cdots = 882 \times 10^4. \quad (5.7)$$

Table 5.7 presents the information metric function values associated with individual evidence sets for scenario 2 and the expected information metric value of

Table 5.6: Most probable evidence sets - case study scenario 1

Evid. Sets (i)	**Apprx. Prob. of Evid. Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evidences Set Based on 4 Demands**			**Info. Metric U_I**
		Sensor 1	**Sensor 2**	**Sensor 3**	
1	0.1440	2	2	2	1333 $\times 10^4$
2	0.1296	2	1	2	9.7 $\times 10^4$
3	0.1264	2	2	1	1492 $\times 10^4$
4	0.1243	1	2	2	1333 $\times 10^4$
...	...	...	...	...	...

scenario 2 can be calculated by

$$\overline{U}_{I(2)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.14204 \times 8.5946 \times 10^4 + 0.09348 \times 11.4587 \times 10^4 + \cdots = 5.37 \times 10^4. \tag{5.8}$$

Table 5.8 presents the information metric function values associated with individual evidence sets for scenario 3 and the expected information metric value of scenario 3 can be calculated by

$$\overline{U}_{I(3)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.14348 \times 1200 \times 10^4 + 0.09608 \times 1200 \times 10^4 + \cdots = 539.7 \times 10^4. \tag{5.9}$$

Finally, Table 5.9 presents the information metric function values associated with individual evidence sets for scenario 3 and the expected information metric

Table 5.7: Most probable evidence sets - case study scenario 2

Evid. Sets (i)	**Apprx. Prob. of Evid. Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evidences Set Based on 4 Demands**			**Info. Metric U_I**
		Sensor 1	**Sensor 2**	**Sensor 3**	
1	0.14204	2	-	2	8.5 $\times 10^4$
2	0.09348	2	-	1	11.4$\times 10^4$
3	0.09344	3	-	2	8.5 $\times 10^4$
4	0.09152	1	-	2	7.0 $\times 10^4$
...	...	...	-	...	...

Table 5.8: Most probable evidence sets - case study scenario 3

Evid. Sets (i)	**Apprx. Prob. of Evid. Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evidences Set Based on 4 Demands**			**Info. Metric U_I**
		Sensor 1	**Sensor 2**	**Sensor 3**	
1	0.14348	-	2	2	1200$\times 10^4$
2	0.09608	-	3	2	1200$\times 10^4$
3	0.0918	-	1	2	7.6$\times 10^4$
4	0.09156	-	2	1	1600$\times 10^4$
...	...	-	...	...	...

Table 5.9: Most probable evidence sets - case study scenario 4

Evid. Sets (i)	**Apprx. Prob. of Evid. Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evidences Set Based on 4 Demands**			**Info. Metric U_I**
		Sensor 1	**Sensor 2**	**Sensor 3**	
1	0.1443	2	2	-	208
2	0.0970	2	3	-	7636
3	0.0951	2	1	-	277
4	0.0934	3	2	-	209
...	...	...	...	-	...

function value of scenario 3 can be calculated by

$$\overline{U}_{I(4)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.1443 \times 208 + 0.0970 \times 7636 + \cdots = 0.08 \times 10^4. \qquad (5.10)$$

Step 18. Given the constraints, choose the optimum sensor placement scenario.

The results are summarized in Table 5.10. Reviewing the information metric values associated with each sensor placement scenario, we see that the first scenario with three sensors being utilized would provide the highest amount of information, which is also a rational conclusion. Now, should we have a constraint to choose only two places for sensors, this table can be used as a selection tool to compare scenarios 2 through 4 and conclude that scenario 4 with sensors placed in location 1 and 2 would provide the highest amount of information; therefore, it would be considered the optimum sensor placement scenario.

Step 19. Is multi-sensor data fusion required?

Table 5.10: The case study Bayesian sensor placement

Scenario	**Sensors Utilization**	**Expected Info. Metric**
1	Sensors 1, 2 and 3	882×10^4
2	Sensors 1 and 3	5.37×10^4
3	Sensors 2 and 3	$\mathbf{539 \times 10^4}$
4	Sensors 1 and 2	0.08×10^4

Multi-sensor data fusion is assumed not to be required.

This will conclude the sensor placement process by selecting scenario 4 with sensors placed in location 1 and 2.

5.4 Case with No Historical Data

In case when historical data is not available, an alternate method is required to build the components state vectors. From analytical stand point, this condition would leave the Bayesian network of the algorithm without an informative prior. For these cases, we use noninformative distributions for lower level components state distributions.

There are a number of methodologies for developing noninformative prior distributions, and the most common one is called "Jeffreys' rule". Other techniques include "histogram method" and "prior estimates of moments" [19].

For Bayesian sensor placement algorithms with no prior data, we introduce a new methodology and call it "maximum range prior". This is essentially a flat prior which contains the entire possible range of each lower level component state and incorporate them as inputs to the algorithm of Bayesian network. To generate the component state vectors when no historical data is available, the following steps should be taken:

- Select the potential lower level components that their historical data is not available.

- Identify the possible range of the input.

- Through the previously presented conversion process (Figure 4.8), translate physical phenomena to "states".

- Continue the placement process as presented in the flow chart of Figure 5.1

Figure 5.8 summarizes the above steps in a simple graphical representation for the transformer oil temperature of the case study example presented earlier. It shows the possible range of temperature variations and how it is divided to three areas: functional (acceptable), degraded (marginally accepted), and failed. These three states were translated to states 1, 1 and 0 respectively.

In a separate analysis for the transformer system case study example that was presented in this chapter, we assumed that no historical data was available for any of the three lower level components and re-ran the entire Bayesian sensor placement algorithm using the "maximum range prior" method to generate component state vectors. The results confirmed that even without historical data, the sensor placement algorithm selected the same sensor placement scenario and validated the methodology.

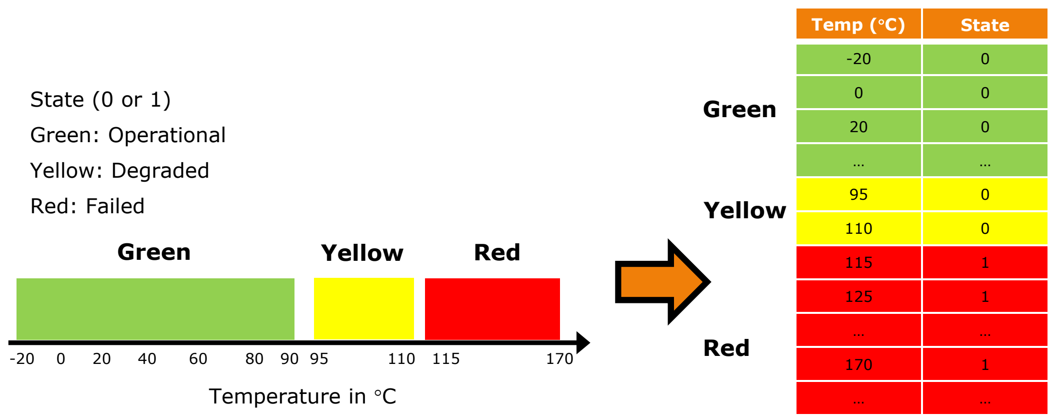


Figure 5.8: Component states for case with no historical data

5.5 Scalability Analysis

The scalability of a protocol or process is defined as its ability to support the increase of system limiting parameters without degrading performance. An important aspect of Bayesian sensor placement performance analysis is the study of how the algorithm performance varies with parameters such as fault tree and Bayesian network size, potential number of sensor locations, types and complexity of sensors, and types and advancement of utilized processors. The objective of this section is to qualitatively evaluate the scalability of Bayesian sensor placement algorithms.

To analyze the scalability of the protocol, we start with partitioning the algorithm to major subsystems based on algorithm components inputs and outputs. Figure 5.9 presents the major subsystems of the Bayesian sensor placement algorithm. The main analytical subsystems of the algorithm include generating the state vectors, Bayesian network, generating sensor information vectors, generating the evidences and calculating the information metrics. Except the Bayesian network, the

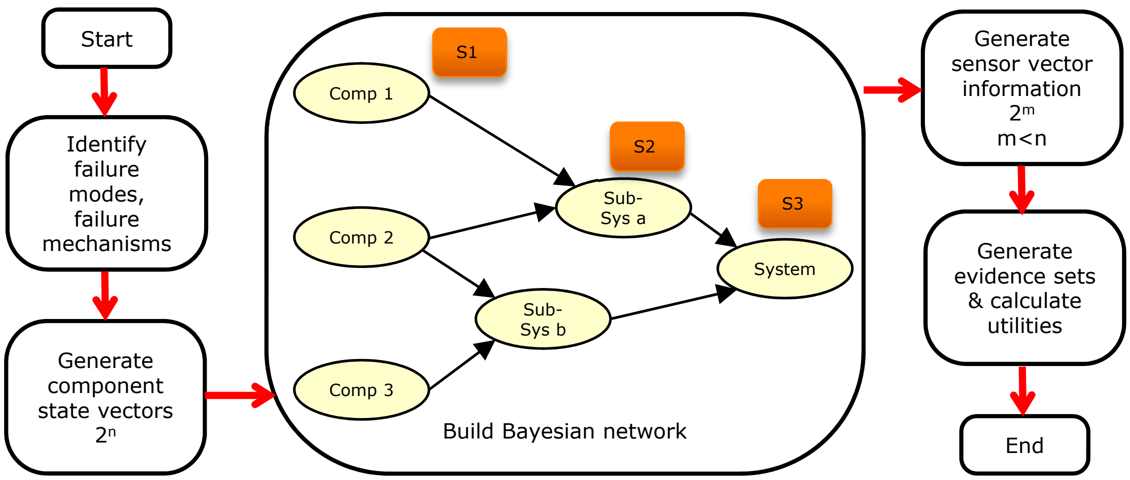


Figure 5.9: BSP subsystems for scalability analysis

size of the system will not have any major impact on the rest of algorithm. The Bayesian network will be the only subsystem of the algorithm being heavily impacted by the size of system.

As for Bayesian networks, there are two main classes of inference algorithms, exact algorithms and approximate algorithms. Exact algorithms are meant to provide correct answers and typically are more demanding computationally, while, approximate algorithms are utilized where simplicity of computational methods is more important than exact answers [40]. We discuss these two categories of Bayesian inference in Section 5.5.1 and Section 5.5.2.

5.5.1 Bayesian Network Exact Inference

The two main classes of Bayesian network exact inference algorithms are based on the concept of elimination and conditioning.

Variable elimination is a process by which we successively remove variables from a Bayesian network while maintaining its ability to answer queries of interest. The complexity associated with this procedure is exponential relative to the number of variables in the Bayesian network.

Conditioning algorithms are stemmed from human reasoning practices which are used in mathematical proofs as well. Based on this methodology, one can solve a larger problem by breaking it down to smaller cases, given certain assumptions, then solve the smaller cases under the given assumptions and then combine the results to obtain a solution to the main problem. There are various methodologies under "conditioning" process which almost all of them present exponential complexity relative to the size of Bayesian networks.

5.5.2 Bayesian Network Approximate Inference

The approximate inference of Bayesian networks are grouped in two categories. One is based on reducing the inference problem to constrained sensor placement problem and leading it to belief propagation algorithms. The other is related to algorithms that are based on stochastic sampling. Both methods' complexities are significantly less than exponential; however, the trade-off is lower accuracy of the Bayesian inference. Given that for Bayesian sensor placement algorithm, the amount of information is the basis for sensor placement algorithm, we concluded that approximate Bayesian inference will not be appropriate tool for Bayesian inference.

5.5.3 The Proposed Approach

As discussed, Bayesian network is the most critical part of the proposed Bayesian sensor placement in regard to scalability. From one stand point, we are concerned with the number Bayesian network nodes because of the processors' time required to analyze the network. Another related concern is that with a larger Bayesian network comes a higher number of potential sensor locations and in turn a larger combinatorial selection of sensor placement scenarios. Considering these facts about the Bayesian network and their effect on the BSP algorithm being affected by the system size, we propose the following mitigation methods:

- Utilize "approximate inference" for the Bayesian network instead of "exact inference" when speed of the process is more important than the precision of the Bayesian network inference.

- Consider Modular approach by breaking up the system to smaller functions and build the Bayesian model of those modules. This approach will significantly decrease the size of each Bayesian network.

- Keep the Bayesian network size to under 500 nodes. Experience shows that given current commercially available microprocessors' speed and also available Bayesian network analysis software programs, the Bayesian networks up to 500 nodes can be reasonably processed.

5.6 Summary

In this chapter we presented a Bayesian framework for sensor placement for a partial system of a power transformer. An algorithm was developed to measure the amount of information for various sensor placement arrangements for a case study. The prior knowledge of system was used to simulate numerous evidence sets which in turn provided several posterior information sets in the form of Sensor Information Vectors. Then information metric function was employed to compare the amount of information for various sensor configurations and the sensor placement scenario that would provide the highest amount of reliability information was identified. In addition, solution for cases with no historical data was discussed. The Chapter ended with a discussion on scalability analysis for the proposed Bayesian sensor placement algorithm.

Chapter 6

Application of Bayesian Sensor Placement

6.1 Overview

In Chapter 5 we presented the details of Bayesian sensor placement methodology in details through a rather simple case study. In this chapter, we present another example of a more complex system with a larger Bayesian network model as well as larger historical data sets and more potential sensor places.

6.2 Power Transformer BSP

Considering the fault tree of Figure 6.1 and Bayesian network of Figure 6.2, we are looking for the sensor placement scenario that would provide the highest amount of reliability information, given that only four potential sensor places exist as shown in Figure 6.4 and only three sensors can be used. We assumed that even the sensor's type are different, however, the cost of sensors are the same and all sensors provide equal amount of information.

Referring to Bayesian sensor placement flow chart as presented in Chapter 5, the following steps are taken.

Step 1. Identify system functional failure modes.

The system functional failure modes include failure of bushings, oil, insulation paper,

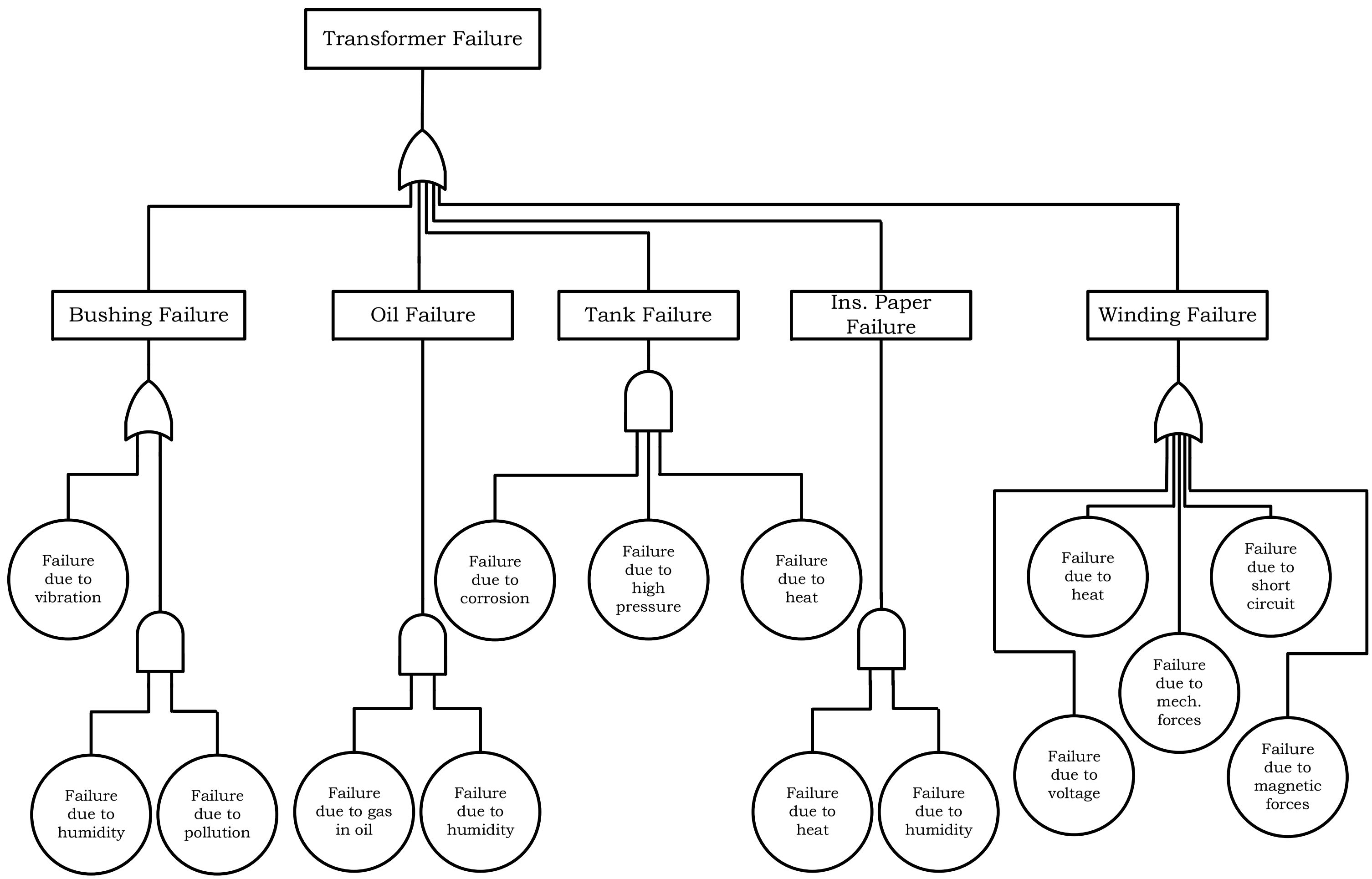


Figure 6.1: Power transformer fault tree

windings and tank.

Step 2. Identify system failure mechanisms.

The system failure mechanisms include thermal stress, mechanical stress, chemical stress and electrical stress.

Step 3. Identify relevant stress models.

Arrhenius life-stress model, Eyring relationship, inverse power law, temperature – non-thermal relationship and general log-linear relationship are among the models being considered for this example.

Step 4. Choose a logic diagram to present the system.

A fault tree is the chosen logic diagram and it is presented in Figure 6.1.

Step 5. Construct the Bayesian network (BN) of the system.

The system Bayesian network is shown in Figure 6.2.

Step 6. Identify the lower level components of the system (the inputs to BN).

For this example, five inputs (lower level components states) are considered to be "vibration", "gas in oil", "moisture in oil", "heat" (transformer temperature) and "tank pressure". The mechanisms related to gas in oil, moisture in oil and heat have already been discussed in Chapter 3. Here we present how vibration and tank pressure would affect the life of a power transformer.

Youn [37] proposed a health grade for power transformers based on monitoring transformer vibration. The idea is that through various transducers, one measure the frequencies of transformer vibration at different points such as tank, core, etc. and records these frequencies for certain period of time and creates a data base. In addition, the following two metrics were introduced:

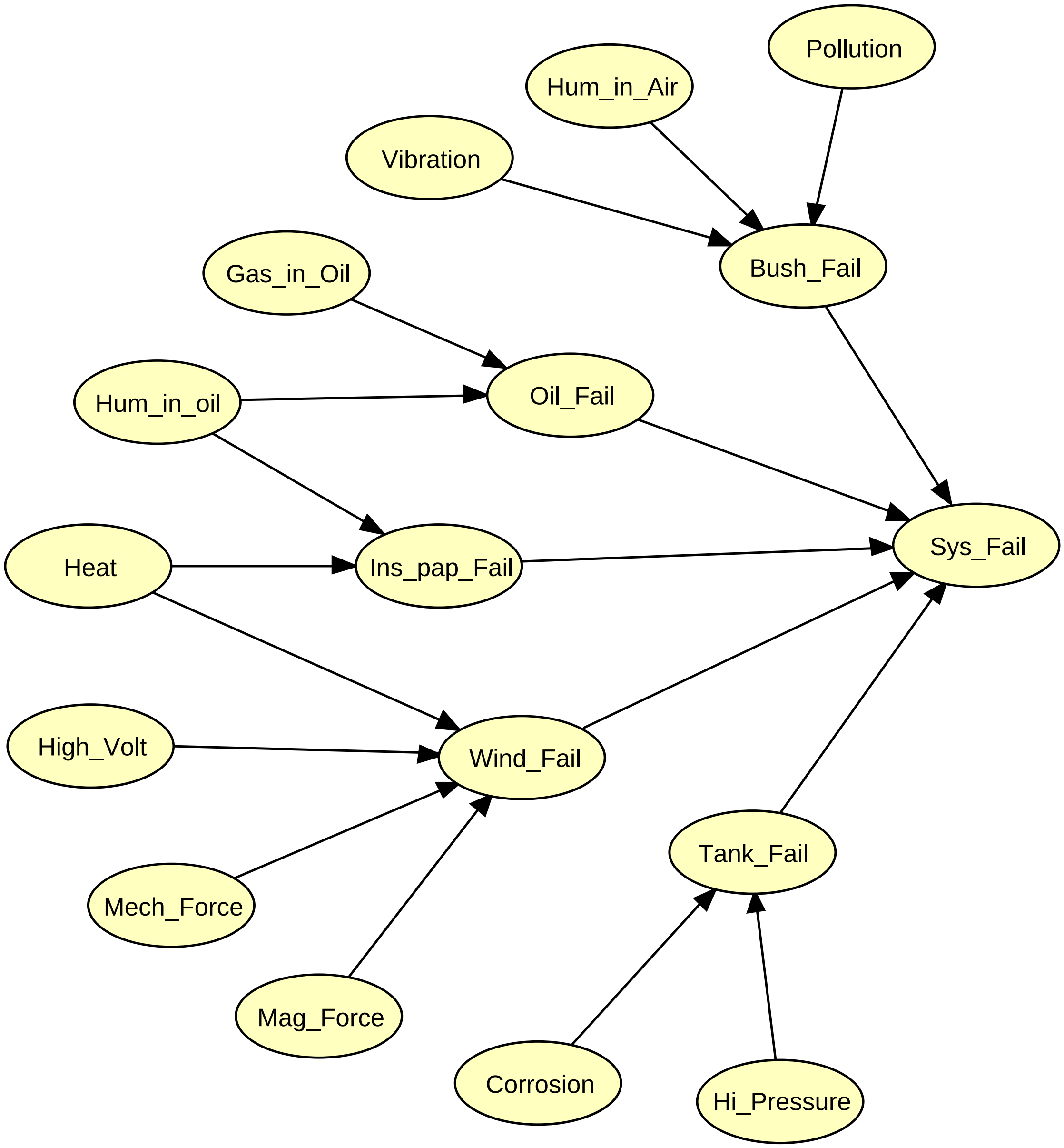


Figure 6.2: Power transformer Bayesian network

RMS. Root mean square, also known as the quadratic mean or a statistical measure of the magnitude of a varying quantity (the frequency of vibration in this application) and is calculated by

$$RMS = \sqrt{\sum_f \mu_f^2} \tag{6.1}$$

where μ_f is the mean at a frequency f.

RSS. RSS is the measure of differences between the mean value μ_f at a frequency and individual values observed by different sensors at the frequency. RSS is calculated by

$$RSS = \sqrt{\sum_f \sigma_f^2} \tag{6.2}$$

where σ_f is the standard deviation at frequency f.

Then, based on these two values, which are used as health condition metrics, a "health grade map" is introduced as shown in Figure 6.3. It presents five grades of health with "A" being the healthiest and "F" being a failing grade. For this example, we used this health grade to distinguish the state of "vibration" input in state vectors.

The transformer tank pressure is another input for the Bayesian network. In most cases, the tank failures are the result of tank rupture due to electrical shorts or other similar events [51]. Therefore, the tank pressure is one of the key indicators and considered as one of the input points to the model. IEEE standard C57.12.10 requires a pressure relief device to be mounted on the tank cover and set to be

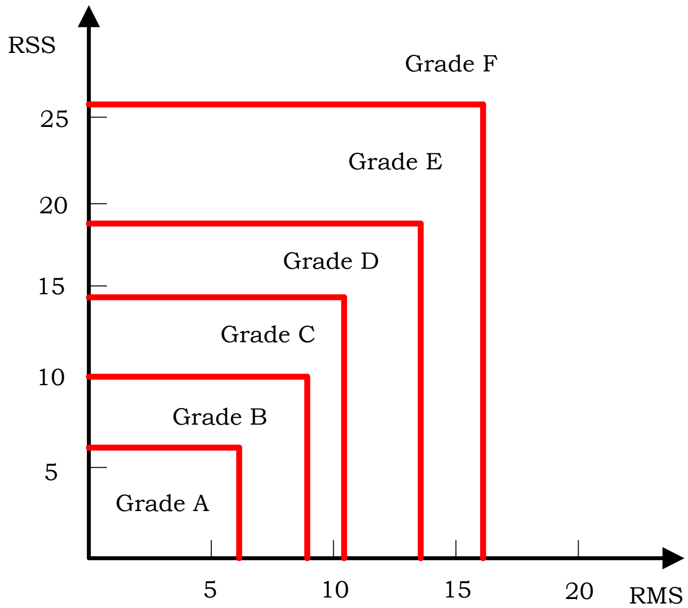


Figure 6.3: A transformer health grade map

activated at 5 to 10 psig. Tank pressure withstand rating can be calculated using

$$P_s = F\left[100\sqrt{\frac{1}{4} + \frac{kE}{100C}} - 50\right] \tag{6.3}$$

where P_s is calculated tank pressure withstand, F is time and location (dynamic) amplification factor, E is fault energy level to withstand, k is arc energy conversion factor and C is tank expansion coefficient.

Step 7. Identify potential sensor locations.

Four potential sensor sites as shown in Figure 6.4 are considered. They can monitor system state (top level), bushing, transformer oil, and tank states.

Step 8. Identify sensor types.

Referring to Figure 6.4, four types of sensors for four locations (based on the functional location on the logic diagram) have been proposed as follows:

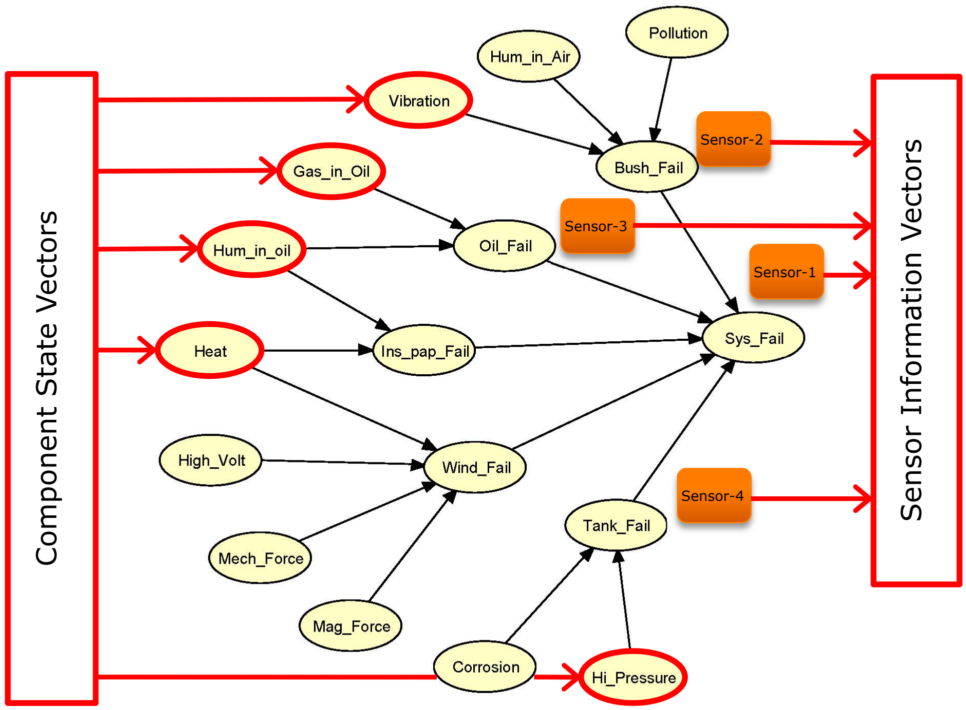


Figure 6.4: Power transformer potential inputs and possible sensor locations

Sensor-1: A typical voltmeter as shown in Figure 4.12, is considered for sensor-1 location. It is located on the secondary of the power transformer (through potential transformers) to monitor whether the transformer is operational or not.

Sensor-2: GridSense bushing monitor as shown in Figure 6.5 is proposed to monitor the transformer bushings.

Sensor-3: Kelman TRANSFIX online DGA (Dissolved Gas Analysis) and moisture sensor for power transformers as shown in Figure 4.11 is considered for sensor-3 location.

Sensor-4: There is a wide range of methods to monitor the tank integrity of power transformers. These include methodologies based on physics of failure of tank materials at one end of the complexity spectrum all the way to a simple leak detector,

Figure 6.5: GridSense bushing monitor (courtesy of GridSense Inc.)

Figure 6.6: QUALITROL 039 Remote electronic oil level indicators (courtesy of Qualitrol Company)

at the other end of the complexity spectrum. The sensor that is suggested here is a QUALITROL 039 remote electronic oil level indicator that monitor the oil level within the tank. The idea is that while the tank's integrity remains intact, the oil level should stay within an acceptable range. Any deviation from that can be interpreted as anoil tank leak, potentially due to damage or degradation of the tank. Figure 6.6 shows a sample of this type oil level monitor.

Also, as part of this step, sensor uncertainties are incorporated to the model.

Step 9. Choose sensor placement scenarios.

Considering four potential sensor locations and a constraint to put only three sensors, the number of possible combinations for exactly three sensors will be:

$$\binom{k_1}{k_2} = \frac{k_1!}{k_2!\,(k_1 - k_2)!} = \frac{4!}{3! \times 1!} = 4 \tag{6.4}$$

where k_1 is potential number of sensor locations and k_2 represents the number of sensors are allowed. As stated earlier, it was assumed that even the sensor types are different; however, the cost of sensors are the same and all sensors provide an equal amount of information.

We also added one additional scenario with two sensors just to examine how a case with two sensors would be compared with the reset of three-sensor scenarios. Therefore, the sensor placement scenarios are:

- Scenario 1: Utilize sensor 1, 2 and 3
- Scenario 2: Utilize sensor 1, 3 and 4
- Scenario 3: Utilize sensor 1, 2 and 4
- Scenario 4: Utilize sensor 2, 3 and 4
- Scenario 5: Utilize sensor 1 and 2 (a test scenario)

and the sensor placement process goal is to evaluate which scenario provides the highest amount of information should the system constraint is to use only three sensors.

Table 6.1: Power transformer state vectors and their probabilities

State Vector	x_1	$\cdots$	x_j	$\cdots$	x_{31}	x_{32}
Vibration	1	$\cdots$	$\cdots$	$\cdots$	0	0
Gas	1	$\cdots$	$\cdots$	$\cdots$	0	0
Humidity	1	$\cdots$	$\cdots$	$\cdots$	0	0
Heat	1	$\cdots$	$\cdots$	$\cdots$	0	0
Pressure	1	$\cdots$	$\cdots$	$\cdots$	1	0
Probability	0	$\cdots$	$\cdots$	$\cdots$	0.0701	0.4909

Table 6.2: Power transformer SIV and their probabilities for scenario 1

SIV	x_1^s	x_2^s	x_3^s	x_4^s
Sensor 1	1	1	0	0
Sensor 2	0	0	0	0
Sensor 3	1	0	1	0
Probability	0.0170	0.1075	0.1165	0.7588

Step 10. Generate Components State Vectors.

For this example with five inputs, the components state vector includes thirty two vectors as shown in Table 6.1.

Step 11. Generate Sensor Information Vectors (SIV).

For sensor placement scenario 1 of this example with three sensors detecting binary states, the SIV may have up to eight elements. Table 6.2 shows the exact number of vectors.

Step 12. Choose an information metric function.

For this example we chose

$$U_I(\theta) = \sum_j \frac{1}{\sigma^2_{\theta_j}}$$

as the information metric function where θ is the unknown of interest. We defined lower level components probability of failures as the unknowns of interest.

Step 13. Generate samples of unknowns of interest.

Monte Carlo simulation is used to randomly draw joint samples of states of the lower level components.

Step 14. Simulate component state vectors.

Each randomly drawn set of unknown of interest defines the lower level components state. Therefore, Monte Carlo simulations was used to randomly draw components state vectors and computed their probabilities. Table 6.1 presents the results.

Step 15. Simulate sensor information vectors.

Each vector generated on the output of the state vector simulation process is fed to the system Bayesian network which would generate corresponding output states. Each set of output states at the suggested location of sensors on logic diagram generate a vector as described earlier is called a sensor information vector (x_i^s). The same process is repeated for all state vectors to generate system sensor information vector $(\widetilde{x}^s)$. Table 6.2 presents the vectors and their probabilities

Step 16. Simulate evidences.

Starting with the sensor information vectors of Table 6.2, utilizing Monte Carlo simulation 100,000 times, and assuming 4 demands each time, a large number of evidence sets were generated.

Table 6.3: Power transformer most probable evidence sets - scenario 1

Evid. Sets (i)	**Apprx. Prob. of Evid. Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evidences Set Based on 4 Demands**					**Info. Metric U_I**
		S1	**S2**	**S3**	**S4**	**S5**	
1	0.1929	0	0	0	-	-	9016
2	0.0931	1	0	0	-	-	8175
3	0.0923	1	0	0	-	-	8175
4	0.0916	0	0	1	-	-	26.61
...	...	...	...	...	-	-	...

Table 6.4: Power transformer most probable evidence sets - scenario 2

Evid. Sets (i)	**Apprx. Prob. of Evid. Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evidences Set Based on 4 Demands**					**Info. Metric U_I**
		S1	**S2**	**S3**	**S4**	**S5**	
1	0.1788	0	-	0	0	-	9150
2	0.0932	0	-	1	0	-	26.60
3	0.0912	1	-	0	1	-	4015
4	0.0896	1	-	0	1	-	4015
...	...	...	-	...	...	-	...

Step 17. Compute information metric function values for selected evidence sets. The information metric function values associated with individual evidence sets for Scenario 1 are presented in Table 6.3. The expected value of information metric of Scenario 1 can be calculated by

$$\overline{U}_{I(1)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.1929 \times 9016 + 0.0931 \times 8175 + \cdots = 4005. \qquad (6.5)$$

Table 6.4 presents the information metric function values associated with individual evidence sets for Scenario 2 and the expected information metric of Scenario 2 can be calculated by

$$\overline{U}_{I(2)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.1788 \times 9150 + 0.0932 \times 26.60 + \cdots = 2715. \qquad (6.6)$$

Similarly, Table 6.5 presents the information metric function values associated with individual evidence sets for Scenario 3 and the expected value of information metric of Scenario 3 can be calculated by

$$\overline{U}_{I(3)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.2172 \times 4550 + 0.1230 \times 5085 + \cdots = 3368. \qquad (6.7)$$

Table 6.6 presents the information metric function values associated with individual evidence sets for Scenario 4 and the expected value of information metric of Scenario 4 can be calculated by

$$\overline{U}_{I(4)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.2022 \times 9055 + 0.1166 \times 4006 + \cdots = 4512. \qquad (6.8)$$

Table 6.5: Power transformer most probable evidence sets - scenario 3

Evid. Sets (i)	**Apprx. Prob. of Evid. Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evidences Set Based on 4 Demands**					**Info. Metric U_I**
		S1	**S2**	**S3**	**S4**	**S5**	
1	0.2172	4	0	-	0	-	4550
2	0.1230	3	0	-	0	-	5085
3	0.1188	4	0	-	1	-	3079
4	0.1180	3	0	-	0	-	3853
...	...	...	...	-	...	-	...

Finally, Table 6.7 presents the information metric function values associated with individual evidence sets for Scenario 5. We included this scenario to just prove that lower number of sensors would lead to lower amount of information. The expected value of information metric of Scenario 5 can be calculated by

$$\overline{U}_{I(5)} = \sum_i U_i \cdot Pr_{ev(i)} = 0.0400 \times 8276 + 0.0131 \times 6698 + \cdots = 621. \tag{6.9}$$

Table 6.8 summarizes the information metric values of all five scenarios.

Step 18. Given the constraints, choose the optimum sensor placement scenario.

Reviewing the expected value of information metrics for four scenarios (1 through 4) shows that Scenario 4 utilizing sensors 2, 3 and 4 would provide the highest amount of information about the system and this scenario is selected as the optimum placement scenario assuming that only three sensors should be used.

Step 19. Is multi-sensor data fusion required?

Table 6.6: Power transformer most probable evidence sets - scenario 4

Evid. Sets (i)	**Apprx. Prob. of Evid. Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evidences Set Based on 4 Demands**					**Info. Metric U_I**
		S1	**S2**	**S3**	**S4**	**S5**	
1	0.2022	-	0	0	0	-	9055
2	0.1166	-	0	0	0	-	4006
3	0.1164	-	0	0	1	-	4006
4	0.1134	-	0	0	1	-	8896
...	...	-	...	...	...	-	...

Table 6.7: Power transformer most probable evidence sets - scenario 5

Evid. Sets (i)	**Apprx. Prob. of Evidence Set ($Pr_{ev(i)}$)**	**Number of Observed Failures in Each Evid. Set Based on 4 Demands**					**Info. Metric U_I**
		S1	**S2**	**S3**	**S4**	**S5**	
1	0.0400	0	0	-	-	-	8276
2	0.0131	1	0	-	-	-	6698
3	0.0131	1	0	-	-	-	6698
4	0.0131	1	0	-	-	-	6698
...	...	...	...	-	-	-	...

Table 6.8: Power transformer Bayesian sensor placement

Scenario	**Sensors Utilization**	**Expected Info. Metric**
1	Sensors 1, 2 and 3	4005
2	Sensors 1, 3 and 4	2715
3	Sensors 1, 2 and 4	3368
4	Sensors 2, 3 and 4	**4512**
5	Sensors 1 and 2	621

Multi-sensor data fusion assumed not to be required.

6.3 Summary

In this chapter, another example was presented to show the details of the proposed Bayesian sensor placement methodology in a more complex system with a larger Bayesian network model as well as larger historical data sets and more potential sensor places. In this example, the BSP was utilized to find the best locations of sensors for a power transformer taking into account all of its subsystems.

Chapter 7

Bayesian System Health Monitoring

7.1 Introduction

System health monitoring is defined as a set of activities implemented on a system to assure its operable condition. Monitoring activities are often limited to the observation of current state of operations. In other cases, systems are monitored solely for the prediction of future operation status and predictive diagnosis of future failure states.

System health monitoring and sensor placement are areas of great technical and scientific interest. Prognostics and health management of a complex system require multiple sensors to extract required information from the sensed environment, because no single sensor can obtain all the required information reliably at all times. The increasing costs of aging systems and infrastructures have become a major concern and system health monitoring techniques can ensure increased safety and reliability of these systems. Similar concerns exist for newly designed systems as well. System reliability monitoring assesses the state of systems health and, through appropriate data processing and interpretation, can predict the remaining life of the system.

One way to minimize both maintenance and repair costs as well as the probability of failure is through continuous health assessment of the system and prediction of future failures based on current health and maintenance history. Therefore, one of the goals of implementing system health monitoring is to alleviate the growing concern over the maintenance of legacy equipment by replacing scheduled maintenance with as-needed maintenance and saving the cost of unnecessary maintenance, as well as preventing unscheduled maintenance activities. In other words, system health monitoring allows condition-based maintenance (CBM) inspection instead of schedule-driven inspections. Similarly, when new systems are developed and designed, appropriate power system health monitoring can be embedded in a design which is expected to reduce the life-cycle operating cost.

Another method of utilizing reliability estimates of a system is to formulate a cost-effective maintenance plan, which is often called reliability centered maintenance (RCM). The goal of RCM methodologies is to find logical ways to identify what equipment is required to be maintained on a preventive maintenance basis rather than let it run to failure.

This chapter presents Bayesian system health monitoring techniques, combined with previously discussed Bayesian sensor placement methodology for monitoring systems' health.

7.2 System Health Monitoring Philosophies and Techniques

System health monitoring techniques are focused on improving the reliability of systems and predicting the systems' health to minimize unscheduled downtime. Maintenance philosophies, in a very broad term, can be divided into "reactive" and "proactive". In the reactive category, the system is repaired after being broken; therefore, almost all of the maintenance activities, result in unplanned downtime. The proactive approach, responds primarily to equipment assessment and predictive procedures. The proactive maintenance practices can be further divided to "preventive maintenance" and "predictive maintenance".

In preventive maintenance strategy, all systems, subsystems and equipment go through scheduled preventive maintenance with the goal of reducing the chance of failures and or degradation. Intervals are selected such that to balance the cost of regular maintenance and cost of system failure due to unscheduled downtime. Often, these types of maintenance start after the system has reached a certain age.

The predictive maintenance philosophy is based on adaptively determined maintenance schedules. In order to properly perform predictive maintenance, it is extremely important to accurately predict the health of a system and its components.

Predictive maintenance techniques can be organized in three main categories: reliability-based maintenance, model-based techniques, and statistical methodologies [52]. This might be a rather subjective categorization and perhaps one may put the reliability-based and statistical methodologies in the same category. We attempt to describe these techniques further in the following sections.

Reliability-based maintenance. Various techniques are utilized to estimate the time to failure distribution of systems. Even though these methodologies are being used for a long time, however, many of them suffer from low precision. Their main downside is that often in one system, different failure mechanisms exist and they interact with each other, mostly in unknown manner.

Model-based techniques. In this approach, an ideal mathematical model of the system is constructed and the outputs of the model are continuously compared with signals received through the sensors from the actual system. The goal is to identify faults or potential failures through these comparisons. The main shortcomings of this methodology include: model errors may be significant, sensors' uncertainties are mostly ignored, and almost always it is assumed that the collected data from the actual system is non-overlapping which is a significant assumption.

Statistical-based methods. Statistical-based maintenance techniques are primarily use Bayesian statistics for modeling and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest. Often, these statistical models are incorporated with prognostics and health management (PHM) techniques as well.

7.3 The Proposed Bayesian System Health Monitoring Methodology

System health monitoring techniques can ensure increased safety and reliability of systems. System health monitoring can also ease the maintenance difficulties by replacing the regular / scheduled maintenance with planned maintenance and provide relief in schedule and cost saving by eliminating unnecessary maintenance and shut downs. Similar concerns exist for newly designed systems as well. System health monitoring assesses the state of systems' health and, through appropriate data processing and interpretation, can predict the remaining life of the system.

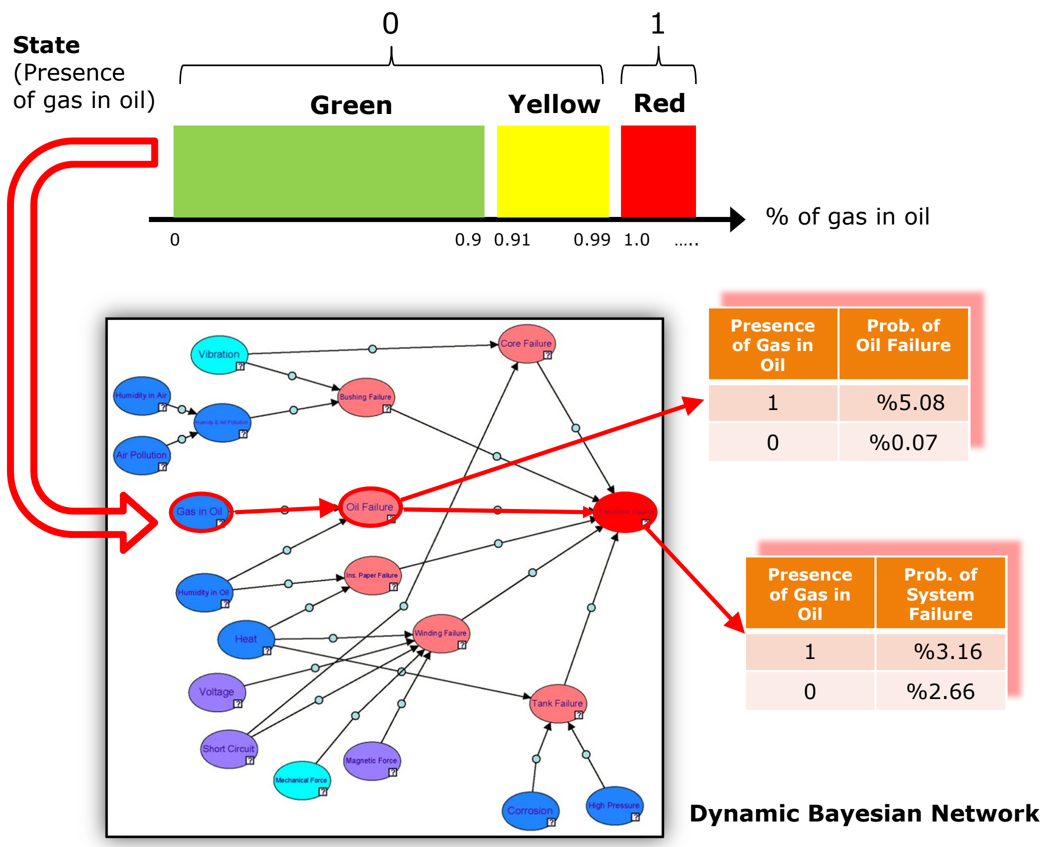


Figure 7.1: Process algorithm for calculating probability of failure

The framework for the proposed Bayesian system health monitoring concept is shown in Figure 7.1. For this single sensor system, the sensor detects the physical phenomenon and through an algorithm which takes into account the failure modes, failure mechanisms, physics of failure and various standards and codes, and translates the physical phenomenon to component states. This is shown in the top part of Figure 7.1. The states are then fed to the Bayesian network of the system to be monitored. The Bayesian network provides the probability of failure for subsystem of interest as well as probability of failure at system level based on that specific instantiation (also called a truth assignment, a variable assignment, or a variable instantiation). This provides a snapshot of system health (or the complement of the probability of failure) based on one observation.

This process can be expanded to multiple sensors for more precise estimates. The process can also be set up as a dynamic monitoring system such that through consecutive time steps the system sensors perform observations and send data to the Bayesian network for continuous health assessment. This makes the Bayesian network a dynamic Bayesian network.

Another important fact about the proposed Bayesian system health monitoring, in conjunction with Bayesian sensor placement, is that every instantiation of Bayesian network would update the entire Bayesian network which in turn would provide updated information at every node of the Bayesian network.

Assuming that Bayesian sensor placement or other sensor placement methodologies have already been utilized to identify the optimum location of sensors throughout the system to be monitored, the following steps can be followed to design a Bayesian system health monitoring scheme.

Step 1. Identify system functional failure modes, failure mechanisms and related physics of failure.

Step 2. Construct the Bayesian network (BN) of the system.

Step 3. Identify the lower level components of the system (the inputs to BN).

Step 4. Generate Components State Vectors.

Step 5. Generate Sensor Information Vectors (SIV) when binary outputs are desired and perform Bayesian sensor placement. Alternatively, other sensor placement methods can be utilized as well.

Step 6. Place sensors at the "input" nodes of the Bayesian network as defined in BSP algorithms. See Figure 7.2.

Step 7. Optimum sensor placement nodes that resulted from BSP, are the nodes that the Bayesian network values are to be utilized in system health monitoring.

Step 8. Transform the Bayesian network to "dynamic" Bayesian network by setting a time period between instantiations of Bayesian network by components state vectors and recording the SIV (or BBN values at designated nodes).

Step 8. Archive and plot dynamic Bayesian network outputs for further analysis depending on specific application.

The following section provides an example of the proposed dynamic Bayesian system health monitoring for health assessment of a power transformer.

7.4 Application of Bayesian System Health Monitoring

Considering the previous example as shown in Figure 7.1 and assuming one year between the readings and monitoring the system over ten years, we recorded sensor data points to monitor "vibration", "gas in oil", "humidity in oil", "tank pressure" and "transformer temperature". The results are recorded in the table presented at the bottom of Figure 7.3. This table summarizes the probability of failure at four sensor locations. Figure 7.2 presents the power transformer Bayesian

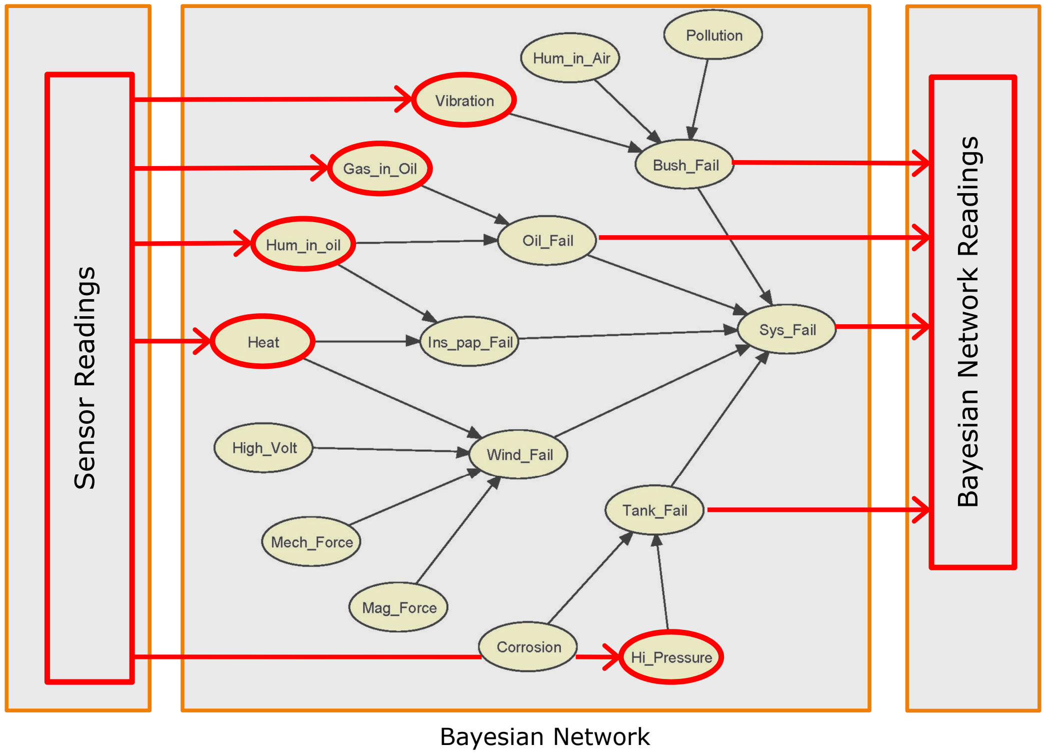
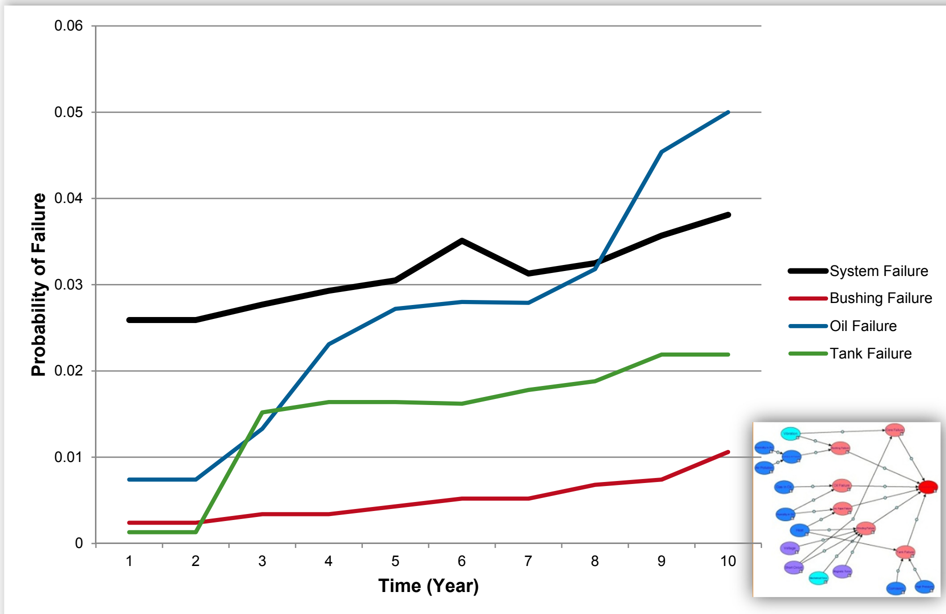


Figure 7.2: Bayesian network of the power transformer and sensor locations

network. Going back to Figure 7.3, the top part of this figure shows the trend of probability of failure at four locations: at system level, bushing, oil and tank. In other words, these probability of failures are the Bayesian network inference based on earlier knowledge of the system and each set of sensor readings every year.

In very broad terms, Figure 7.3 shows monitoring of a power transformer for ten years (reading once a year) with the goal of anomaly identification. The graphs also show how the health of the system and subsystems degrade through the years. For example, in this graph it is apparent that power transformers, comparing to many other electrical equipment, degrades rather slowly.

One important observation in Figure 7.3 is the trend of system health through the set period of time that these graphs provide. This means we are more focused



Time (Year)	1	2	3	4	5	6	7	8	9	10
	Probability of Presence (%)									
Vibration	9.12	9.12	19.41	19.41	28.65	37.58	37.58	54.63	60.09	93.05
Gas in Oil	9.17	9.17	16.81	28.78	28.78	33.56	25.19	40.24	66.89	90.99
Hum in Oil	11.76	11.76	21.05	36.36	44.44	44.44	47.6	49.38	66.67	66.67
Tank Pressure	12.28	12.28	23.54	30.55	30.55	29.1	38.11	43.49	60.62	60.62
Heat	10.44	10.44	20.41	20.41	33.99	36.3	36.3	38.48	56.18	96.25

Figure 7.3: System health monitoring for power transformer at subsystems and system level

on the overall health of the system or any of its subsystems over a period of time rather than just snapshots of health at certain points of time.

Another note regarding Figure 7.3 is the consideration of uncertainties associated with the value of parameters, accuracy of sensors, state of components (which they have their own distributions), and the uncertainties on physical parameters. When all of these uncertainties exist, the real system health assessment would be more accurately presented when shown within their uncertainty upper and lower bands. Figure 7.4 shows similar assessment as shown in Figure 7.3, however, we

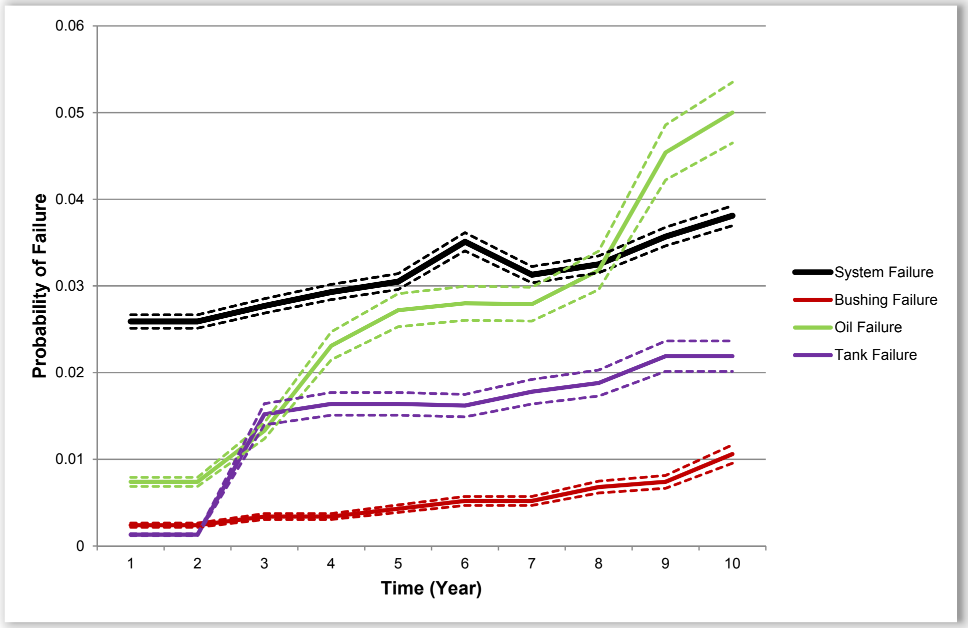
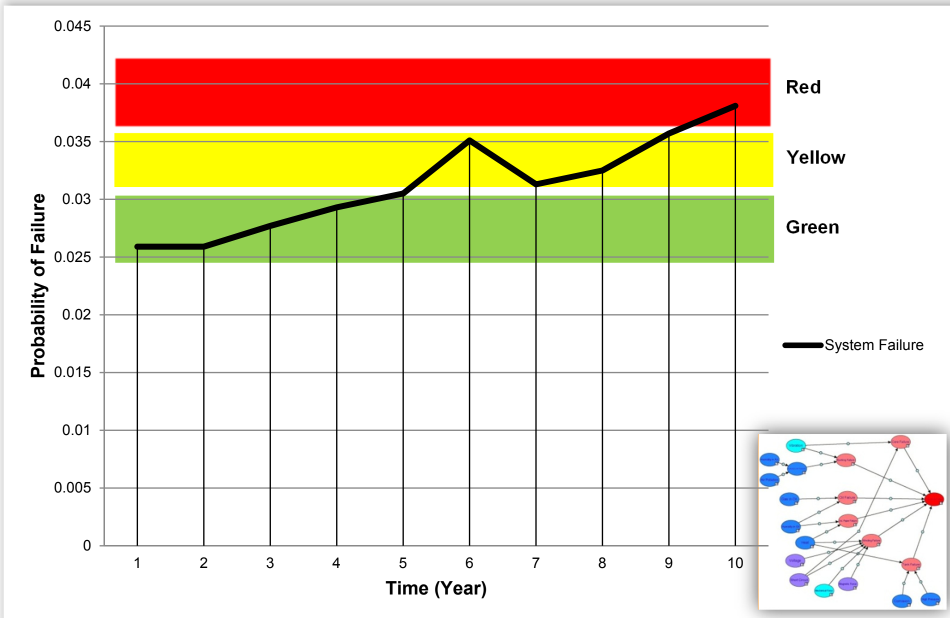


Figure 7.4: System health monitoring for power transformer with uncertainty upper and lower bands

included the abovementioned uncertainties and schematically plotted ±3% total uncertainty for system failure, ±2.5% total uncertainty for bushing failure, ±5.5% total uncertainty for oil failure, and ±4% total uncertainty for tank failure.

Figure 7.5 shows the previous power transformer system probability of failure graph with three color-coded regions – green, yellow and red – to present the health status of the transformer at system level. In the green region, the probability of failure of the system is within an acceptable margin of risk. The yellow region represents a relatively mild risk operation region that requires actions to be taken in the near future. The red region represents a very high-risk area in which immediate action must be taken.

Figure 7.6 shows a schematic diagram of the control panel of a Bayesian system health monitoring for a power transformer with health monitoring at system level



Time (Year)	1	2	3	4	5	6	7	8	9	10
	Probability of Presence (%)									
Vibration	9.12	9.12	19.41	19.41	28.65	37.58	37.58	54.63	60.09	93.05
Gas in Oil	9.17	9.17	16.81	28.78	28.78	33.56	25.19	40.24	66.89	90.99
Hum in Oil	11.76	11.76	21.05	36.36	44.44	44.44	47.6	49.38	66.67	66.67
Tank Pressure	12.28	12.28	23.54	30.55	30.55	29.1	38.11	43.49	60.62	60.62
Heat	10.44	10.44	20.41	20.41	33.99	36.3	36.3	38.48	56.18	96.25

Figure 7.5: System health monitoring for power transformer

and six subsystems. System health monitoring approach as presented in Figure 7.6 can also be used as a methodology to identify precursors to failure at each subsystem as well as at system level. Similar techniques can be utilized for re-evaluating the results of accelerated life tests for determining the reaming life of a product or system.

The presented Bayesian system health monitoring methodology may also be used for the following applications where due to physical, technological or resource limitations, one may not be able to place a sensor where it is needed the most:

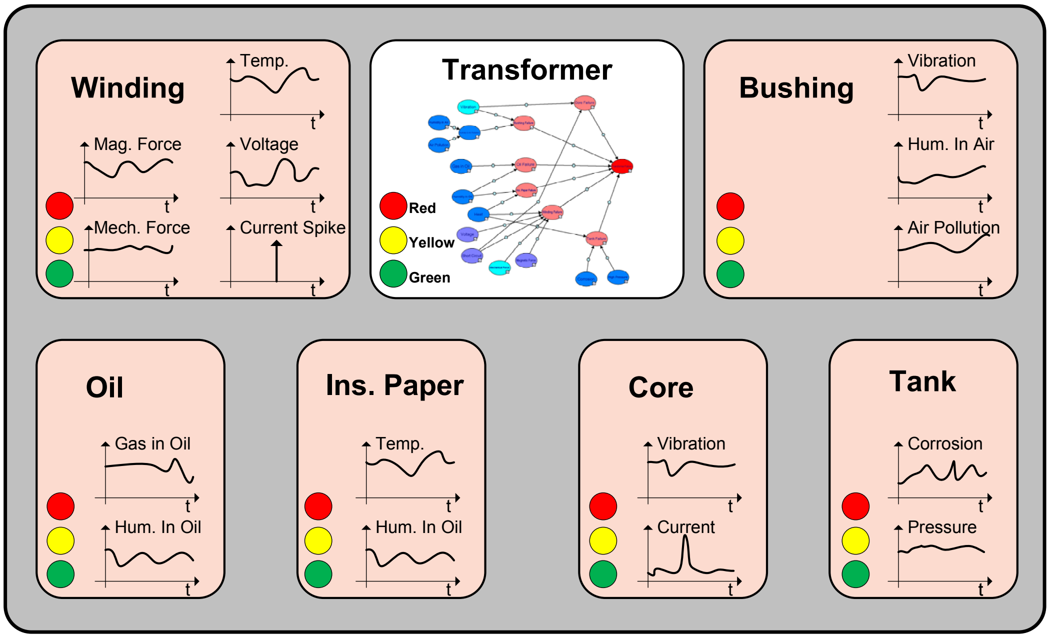


Figure 7.6: Schematic diagram of a power transformer system health monitoring panel

- To infer the health of a system (e.g. top level in a fault tree) based on limited number of sensor information points at certain subsystems (upward propagation),
- To infer the health of a subsystem based on knowledge of the health of main system (downward propagation),
- To infer the health of a subsystem based on knowledge of the health of other subsystems (distributed propagation).

The previous example shows the significance of the proposed Bayesian sensor placement in health monitoring where degradation in complex systems is difficult to detect. A large system may encounter multiple faults within its subsystems throughout its lifetime, however none may lead to a failure or loss of operation. Therefore, it is important to have a mechanism to monitor the progression of degradation for mission critical operations.

It is also important to note that as described in Section 5.5, Bayesian networks provide inference with some degree of approximation depending on what type approximation are considered. Therefore, we have to be mindful of the degree to which we are confident in the conclusions made by a Bayesian network. Therefore, when an extreme level of precision is necessary, we may require to perform sensitivity analysis where we are interested in the sensitivity of probabilistic queries with respect to changes in the network parameters of a Bayesian network.

7.5 Summary

In this chapter we presented a Bayesian system health monitoring methodology in conjunction with the proposed Bayesian sensor placement discussed in previous chapters. The chapter started with an introduction on system health monitoring and then followed by an overview of current system health monitoring philosophies and techniques. This is followed by details of the proposed Bayesian system health monitoring methodology. The chapter ended with a presentation of an application of Bayesian system health monitoring in an example and presented various scenarios as part of this example.

Chapter 8

Summary, Conclusions and Future Work

8.1 Summary and Conclusions

This research developed a new algorithm for Bayesian sensor placement under uncertainty and utilized it in a new system health monitoring methodology. The methodology is designed to answer important questions such as how to infer the health of a system based on a limited number of monitoring points at certain subsystems (upward propagation); how to infer the health of a subsystem based on knowledge of the health of the main system (downward propagation); and how to infer the health of a subsystem based on knowledge of the health of other subsystems (distributed propagation).

Specifically, the main objectives of this research were to (1) find an effective way for functional sensor placement under uncertainty, and (2) develop a system health monitoring approach with both prognostic and diagnostic capabilities with limited, uncertain, and overlapping information sensing and monitoring points.

Uncertainties considered in the analyses include:

- Sensor uncertainty
- Uncertainty on parameters of physics of failure models
- Uncertainty on relations between components and system (or the conditional

probability tables (CPT) in Bayesian network of the system)

- Uncertainty on unknowns of interest.

The proposed Bayesian sensor placement methodology significantly reduces the computation complexities through Bayesian network modeling, mainly by eliminating the need for calculating complicated likelihood functions. The sensor placement methodology was tested on a simple case study followed by a more detailed example.

Contributions of the research include:

- A new functional point sensor placement method based on Bayesian techniques is developed which is capable of functional sensor placement under uncertainty.
  - Bayesian networks are utilized for modeling, updating and reasoning the causal relationships and uncertainties as well as for updating the state of knowledge for unknowns of interest as they are defined by: failure probabilities of lower level components, subsystems or system; value of parameters; and the probability of physical parameters taking specific values.
  - "Information metric" is used for sensor placement based on the amount of information each possible sensor placement scenario provides.
  - The sensor placement process is based on sensors functional locations on a logic diagram.
  - Taken into account the uncertainty inherent in the characteristics of sensors.

  - To model the case study and other presented examples, several algorithms in MATLAB and other software programs are developed.

- A new system health monitoring methodology is developed.
  - The system is capable of assessing current state of a system's health and can predict the remaining life of the system (prognosis), and through appropriate data processing and interpretation can point to elements of the system that have or are likely to cause system failure or degradation (diagnosis).
  - The system can be set up as a dynamic monitoring system such that through consecutive time steps, the system sensors perform observations and send data to the Bayesian network for continuous health assessment. This makes the Bayesian network a dynamic Bayesian network.

8.2 Future Work

Similar to any other new methodology, our approach presents multiple areas for improvement too. One area is the use of Bayesian network and its exponential complexity with the increased size of the network. This is also true for almost any algorithm that uses Bayesian network. Another area is dependency to historical data or evidence data that may not be available for every system. Again, this is perhaps true for any analysis that would require historical data. Lastly, our reliance on physics of failure of components may pose challenges as these physics of failure data are not always available which is also true for other methodologies too. Chapter

5 discussed these issues and presented potential solutions. In this section we present suggestions for future research on these and other related topics.

Future research work can focus on creating a graphical user interface (GUI) for all of the algorithms and software programs that were written for this project. A roadmap for developing that GUI could be the Bayesian sensor placement flow chart in Figure 5.1. To make it practical for a wide range of applications, it may include categories of sensors such as physical, electromagnetic, etc. and for each category it may include an exhaustive list of various sensors available in the market with their specifications, a picture, etc. as shown in Table 8.1. The GUI may also include detailed lists of known failure modes, failure mechanisms, physics of failure models and stress life models. The GUI may also include integration of the analytical engine with the Bayesian network engine and offer a user interface with the Bayesian network for data input and assessment.

Future implementations of the methodology should investigate efficient analytical modeling techniques associated with incorporating sensor uncertainties. We incorporated sensor uncertainty into the model Bayesian network by updating the Bayesian network with related probabilities associated with sensors uncertainties. This is based on the assumption that "uncertainty" data will be available in the form that can be incorporated into the Bayesian network. Obviously, this assumption cannot be generalized. The specific goal for this investigation could be the development of sensor uncertainty analysis procedure to be added to the Bayesian sensor placement methodology.

Utilization of extended Kalman filter (EKF) [53] as a virtual sensor for non-

Table 8.1: Sample sensor data sheet

Product Name:	**ACR SmartButton Temperature Data Logger**
Manufacturer:	ACR Systems Inc.
Temperature Sensor:	-40°C to +85°C range
Measurement Accuracy:	±1°C from -30°C to +45°C
Power Rating:	3.0 volt Lithium, approximate 10 year battery life
Size:	17.35mm diameter × 5.89mm height
Weight:	4 grams
Interface with host:	Serial port or USB
Interface type:	RS232 serial ACR SmartButton interface or USB/ACR SmartButton
Mounting details:	Magnetic backing or plastic plate mount
Number of sensor's channels:	1
Channel configuration:	One internal channel for ambient temperature
Type of sensors that can be connected:	Temperature sensor
Ability to connect to external sensors:	No
On board memory size:	2kB
Illustration	

measurable states and unknown parameters, can be another topic for further investigation [54]. This virtual sensor can be added to the sensor information vector (SIV) and eventually become part of the sensor placement scenarios. This could possibly enhance the Bayesian sensor placement even more without the added cost of real sensors.

Future research topics also need to include the investigation of methods to account for sensitivity at various points of the sensor placement.

Development of analytical models for scalability analysis of Bayesian sensor placement algorithms could be another topic for future research.

Also, future related research work needs to investigate potential applications of influence diagrams in sensor placement. Influence diagrams have great potential for this application and given that there are several commercially available software that can process influence diagrams, it makes it a great candidate to be considered as another tool for sensor placement [55], [56], [57].

Finally, another potential future work could be on researching the possibility of combining the Bayesian network sensor placement methods developed in this research with Jackson and Mosleh [5], [6], [7] likelihood algorithms in a Hybrid Causal Logic (HCL) model. HCL is capable of merging a deterministic model, such as a fault tree, with non-deterministic factors, such as uncertain soft data collected by sensors under one framework. Jackson's likelihood algorithms were developed for binary data sets and binary propagation of data through the system being analyzed. Bayesian sensor placement can deal with soft data such as sensors measurements and sensors uncertainties, and also can easily propagate this information throughout the system's Bayesian network. Probabilistic Risk Assessment (PRA) methods utilize deterministic relationships among the basic events and combine them to generate various risk scenarios. Among these deterministic approaches are fault trees, event trees, and event sequence diagrams. Given that for many instances, probabilistic risk assessment is not a purely deterministic domain, it is prudent to consider non-deterministic factors such as uncertain soft data collected by sensors, in overall risk assessment methodologies. As described earlier, Bayesian belief networks have the capability to probabilistically model these soft data. The combination of these two methods make up the *Hybrid Causal Logic* methodology (HCL) [58].

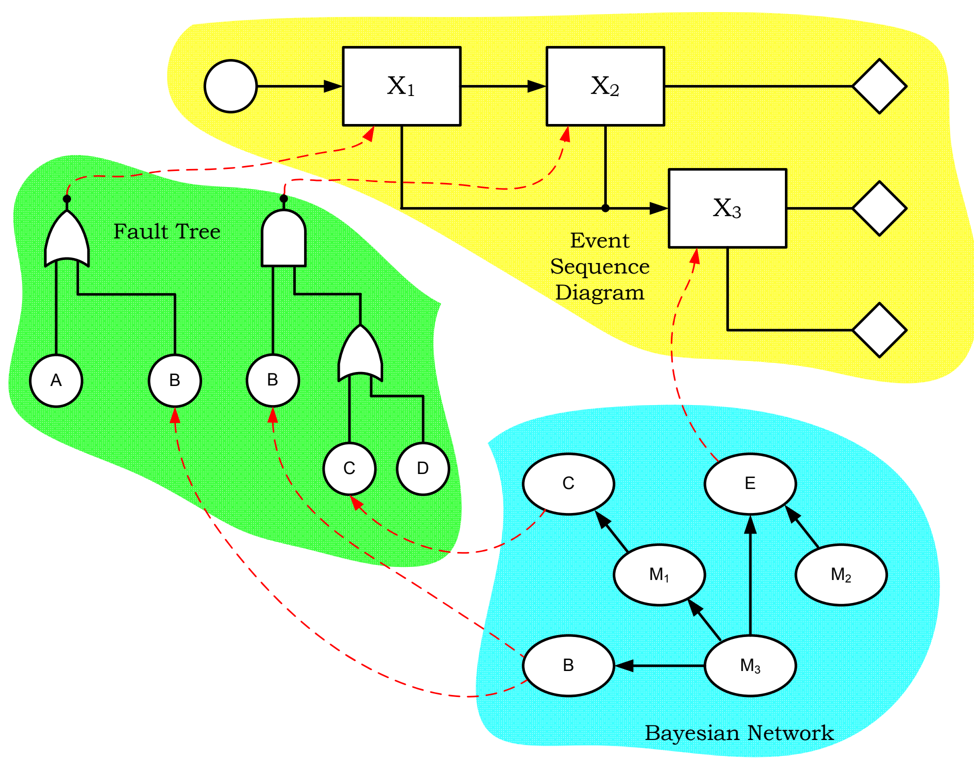


Figure 8.1: Illustration of a three-layer hybrid causal logic

Trilith (also known as IRIS) software is capable of generating a decision support system that implements the Hybrid Causal Logic methodology, combining the

Boolean logic-based PRA methods such as fault trees and event trees with BBN. The Hybrid Causal Logic core extends conventional risk analysis techniques to include the ability to deal with uncertain or unavailable data.

Groth et al [58] presented a detailed analysis of the functionality of the HCL computational engine. The framework includes a multi-level modeling approach that allows different PRA techniques to be applied to different parts of a system. Risk scenarios are modeled in the top layer using Event Sequence Diagrams. In the second layer, fault trees are used to model the factors contributing to the properties and behaviors of the physical system (e.g., hardware, software, environmental factors). Bayesian belief networks comprise the third layer, which extends the causal chain of events to potential soft data such as uncertainties in sensor detection [58].

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