ABSTRACT

Title of Thesis:	APPLICATION OF A BAYESIAN NETWORK BASED FAILURE DETECTION AND DIAGNOSIS FRAMEWORK ON MARITIME DIESEL ENGINES
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Diesel engine propulsion has been the largest driver of maritime trade and transportation since its development in the early 20th century and the technology surrounding the operation and maintenance of these systems has grown in complexity leading to rapid advancement in amount

and variety of data being collected. This increase in reliability data provides a fantastic opportunity to improve upon the existing tools troubleshooting and decision support tool used within the maritime engine community to enable a more robust understanding of engine reliability. This work leverages this opportunity and applies it to the Coast Guard and its acquisition of the Fast Response Cutter (FRC) fleet powered by two MTU20V4000M93 engines integrated with top of line monitoring and control equipment.

The purpose of this research is to create procedures for creating a Failure Detection and Diagnosis (FDD) model of a maritime diesel engine that updates existing Probabilistic Risk Analysis (PRA) data with input from the engine monitoring and control system using Bayesian inference. A literature review of existing work within the PRA and Prognostics and Health Management (PHM) fields was conducted with specific focus on the advancement and gaps in the field specific to their use in maritime engine applications. Following this, a hierarchal ruleset was created that outlines procedures for integrating existing PRA data and PHM metrics into a Bayesian Network structure. This methodology was then used to build a Bayesian Network based FDD model of the FRC engine. This model was then validated by Coast Guard Engineers and run through a diagnostic use case scenario demonstrating the model’s suitability in the diagnostic space.

APPLICATION OF A BAYESIAN NETWORK BASED FAILURE DETECTION AND DIAGNOSIS FRAMEWORK ON MARITIME DIESEL ENGINES

by

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Table of Abbreviations

BN	Bayesian Network
CES	Complex Engineering System
CPT	Conditional Probability Tables
DBN	Dynamic Bayesian Networks
FDD	Failure Detection and Diagnosis
FMC	Fully Mission Capable
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Mode Effects & Criticality Analysis
FRC	Fast Response Cutter
FTA	Fault Tree Analysis
MDE	Main Diesel Engine
NMCD	Not Mission Capable Depot
NMCM	Not Mission Capable Maintenance
NMCR	Not Mission Capable Repair
NMCS	Not Mission Capable Supply
OEM	Original Equipment Manufacturer
PHM	Prognostics and Health Management
P&ID	Piping and Instrumentation Drawings
PMC	Partially Mission Capable
POF	Physics-of-failure
PRA	Probabilistic Risk Analysis
BFD	Block Flow Diagram
RUL	Remaining Useful Life
SIPPRA	Systematic Integration of PHM and PRA
SME	Subject Matter Expert
SyRRA	System Risk and Reliability Analysis

1. Introduction

1.1 Motivation

Diesel engine propulsion has been powering maritime trade and transportation since its development in the early 20th century. The first commercial vessel, the Motor Liner Selandia, was commissioned in 1912, and was followed by the first United States diesel-powered military ship, the USS MAUMEE, in 1916 [1], [2]. Now over 100 years later, the U.S. Bureau of Transportation reports that over 62,000 cargos ships visit the U.S annually, accounting for nearly 55% of the value of all U.S. imports [3]. In response to the high demand on the shipping community and increasing awareness of shipping related pollutants, there has been a global call to optimize the shipping economy with a focus on both shipping routes and propulsion efficiencies [4], [5]. With the rapid development of system control and monitoring equipment, more data than ever is being produced, spurring changes to how assets operate and how they are maintained.

On the cusp of technological revolution exists the United States Coast Guard, a department of Homeland Security branch with a maritime fleet of over 150 cutters. From a new acquisition program to replace the Icebreaker POLAR STAR commissioned in the 1970s to the Offshore Patrol Cutter line currently in production, the Coast Guard is rapidly transitioning its aging fleet to a modern more capable fleet [6]. During the 2022 State of the Coast Guard Address, Commandant Admiral Shultz noted that the U.S. Coast Guard is currently amid its largest shipbuilding effort since World War II and has focused acquisition efforts on providing technology that enables and empowers the workforce to work smarter and more efficiently. This mantra extends past the acquisition of existing technology and requires the integration of modern technology into how assets are operated and maintained. While technological improvement come in waves, the evolution of a workforce mindset is a much slower, iterative process that requires buy-in and innovation at every level of an organization. No project better characterizes this evolution of ideologies than the Fast Response Cutter (FRC), a 154' Patrol Boat whose acquisition started in 2012 with 46 of 64 assets delivered [7].

The FRC was created to fill an operational gap between existing Coast Guard Coastal Patrol Boat and Medium Endurance Cutter fleets. The FRC was designed to perform multifunctional missions in support of Coast Guard operations involving drug and migrant interdiction, port and waterways security, fisheries patrols, search and rescue, and national defense [8]. The FRC utilizes two MTU20V4000 M93L series engines in a two-shaft geared drive propulsion system where each shaft line operates independently. Each engine can produce more than 5700 hp and is equipped with advance control and monitoring equipment capable of preserving the engine's long-term health. This system optimizes performance for engine health by altering the engine power output or, in extreme cases, shutting down the engine in response to adverse operating conditions caused by internal component failures or external factors [9]. Engine life preservation features such as these enhance long-term reliability of the engine but are exponentially more complicated than legacy systems. This has created a knowledge gap in the workforce leading to a reliance on commercial assistance for engine repairs and troubleshooting. While the Coast Guard has invested heavily in developing workforce knowledge, alternative options to close this gap must be explored to lower the knowledge ceiling required to service the engines while maintaining high reliability for an always ready fleet [7].

Along with the acquisition of the FRC the Coast Guard acquired reliability engineering analyses including a life cycle maintenance plan for the engine, a Failure Mode Effects &

Criticality Analysis (FMECA), and additional technical publications providing insight into the inner workings of the engine [9]. Data packages such as the above are extremely detailed, and the package for the FRC meet all requirements described in the contract. However, technical data packages such as these are based off initial projections and are unable to be adapted to a changing use case. Improvements to the engine monitoring and tracking system present an opportunity for the Coast Guard to integrate the detailed sensor and alarm information into their existing reliability program. One opportunity is to address how the changes to FRC operational profile affect the reliability of the engines.

The current asset maintenance plan for the FRC diesel engines is primarily based upon the manufacturer recommended life cycle plan [9] created from a combination of in-house factory testing and comparisons to existing/operating engine models. The Coast Guard utilizes maintenance tracking software to make generalized updates to this plan at the fleet level, but the current feedback system relies on field level operators to manually enter a text-based narrative regarding their issue and recommended solution. The Coast Guard has a global presence, and the FRC platform specifically is the organization's most versatile asset with permanent duty stations ranging from Sitka, Alaska to Key West, Florida and even across the Atlantic to Bahrain [7]. Current maintenance and operating practices, with limited exceptions, do not account for the changes to the operating location. In addition to operational location-based issues, the FRC platform is now 10 years into operations, and the mission profile has changed significantly from the use case presented during acquisition. Considering these issues, the Coast Guard requires a mechanism that will allow the FRC maintenance plan to be adjusted for both operational location as well as operational tempo/mission.

This thesis proposes a methodology to integrate existing data and evidence regarding causal effects of operating conditions to create an adaptable FDD model capable of troubleshooting faults within the FRC engine. This model-based approach draws on concepts from both systems and reliability engineering to provide a data driven representation of the engine that can be utilized for failure detection and diagnosis. By utilizing concepts of Bayesian inference, this work creates a framework to show the feasibility of creating a generalized model for a series of similar complex systems that can account for the effects of various operational changes on both the system and individual component reliabilities allowing for informed life cycle actions. The resultant model enables improved life cycle management and maintenance decisions for maritime diesel engines across various operational profiles.

1.2 Objectives and Approach

The purpose of this research is to propose a methodology that utilizes principals of Bayesian inference to integrate existing PRA data with input from the engines PHM system to garner a deeper understanding of maritime diesel engine reliability. Leveraging this improved understanding allows for improvements in the process of diagnosing failures on maritime diesel engines. This process leverages existing PRA practices, identifies collectable data, gaps in current usage, and creates an integrated framework for creation of usable models capable of iterative enhancement. To achieve this there are three main objectives:

- Objective 1: Identify current approach to PRA and PHM for maritime diesel engines and identify knowledge gaps therein.
- Objective 2: Develop a methodology for updating existing PRA data with PHM input into a hierarchal Bayesian Network (BN) model of a maritime diesel engine.

- Objective 3: Demonstrate methodology application through creation and testing of a model.

These three objectives make up the core of this research and are presented visually below in Figure 1.

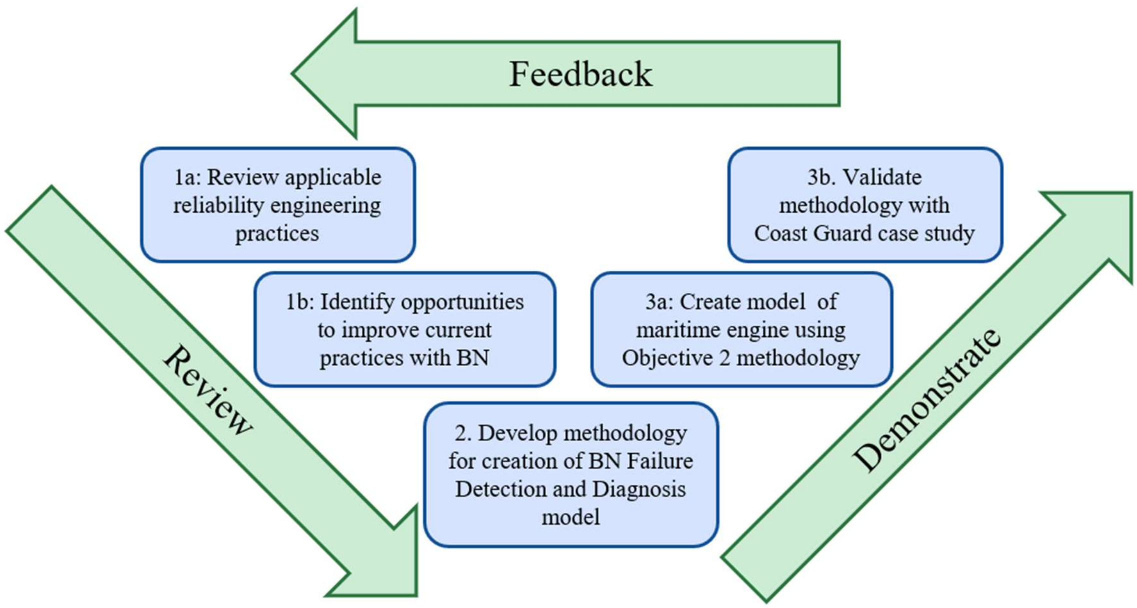

Figure 1: Overview of Thesis Objectives

1.2.1 Objective 1: Identify Current Approach to PRA and PHM for Maritime Diesel Engines and Identify Knowledge Gaps Therein.

Objective 1 consists of Tasks 1a and 1b summarized below:

a. Review current uses of PRA and PHM data in the reliability field broadly and specifically for diesel engines in the maritime community.

b. Identify opportunities to improve existing reliability engineering processes used for maritime diesel engine by integrating multiple data sources through Bayesian inference.

By first assessing the status of the reliability field, it is possible to identify the range in which PRA and PHM data is being used to gain an understanding of the method maturity and reach. This process will enable a comparison of the reliability methods used on maritime diesel engines with more experimental methods being implemented in other engineering disciplines. Additionally, these tasks will work to outline potential areas for improvement in the reliability practices used on maritime diesel engines through integration of data sources using Bayesian inference.

1.2.2 Objective 2: Develop a Methodology for Updating Existing PRA Data with PHM Input into a Hierarchal BN Model of a Maritime Diesel Engine.

Objective 2 focuses on development of a methodology for creating a model that organizes and updates existing PRA with direct input from a systems PHM monitoring component in the context of maritime diesel engines. The proposed methodology offers opportunities to utilize limited existing PRA data with the systems-integrated monitoring capabilities to create a macro model of systems performance that can be used to reason about both system and component level failures. The methodology allows for continued modular updating, representation of complex inter-system relationships, and consideration of external causal factors. The use of Bayesian inference to incorporate both the observation-based data sets and consideration of complex causal relationships makes it possible to gain a more accurate depiction of the systems performance and reliability at a given point in time as well improving the adaptability of maintenance plans to changing operational profiles.

This methodology will focus on developing a model that addresses the gaps identified in Objective 1. It outlines the structural framework necessary for use on maritime diesel engines as well as the potential use in other Complex Engineering Systems (CESs). By replacing traditional

FDD and life cycle tools with models integrating this methodology, stakeholders can make informed life cycle logistics changes as the asset age, operating location, or operational profile changes. Part of this process is the utilization of agile development concepts to hone the model's accuracy by increasing granularity, thus allowing the integration of more specific data, and enabling better predictive and diagnostic capabilities. Early models based on this methodology will focus on producing a working model that provides stakeholders immediate usability, resulting in a less complex model that provides the most insight at a system level but sacrifices lower-level granularity. The operational use case for this model is shown below in Figure 2.

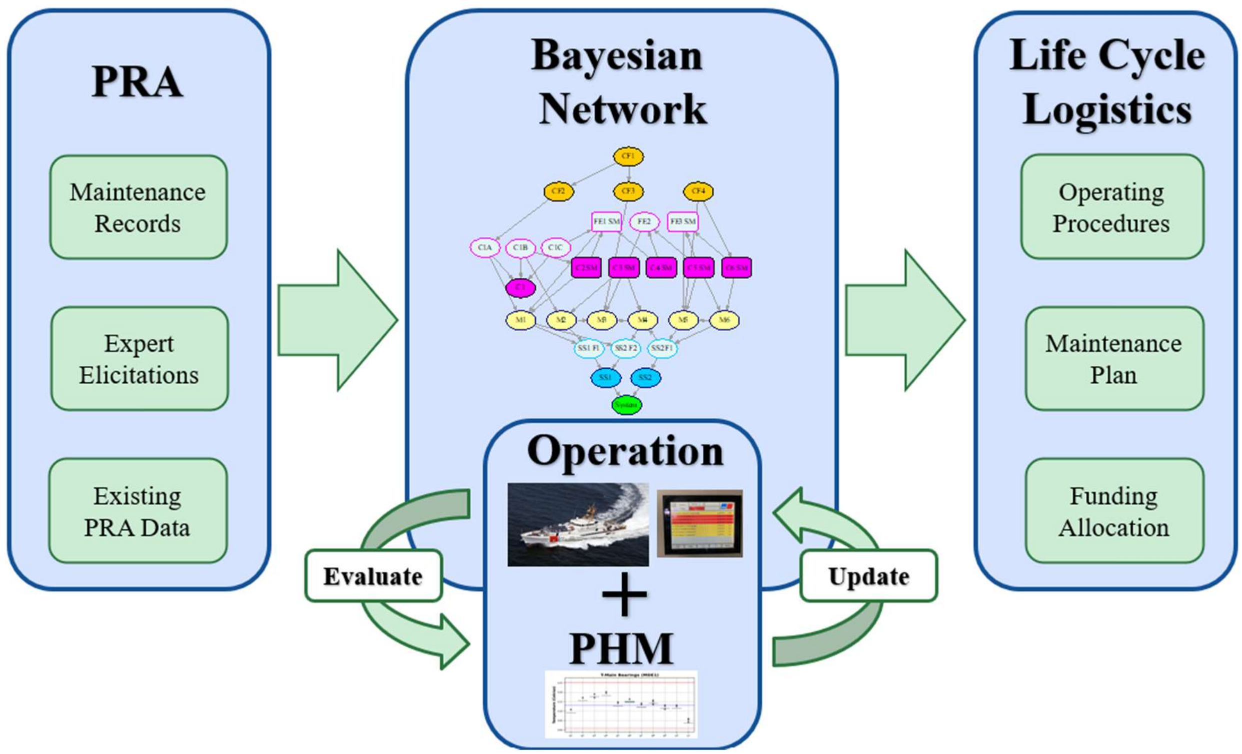

Figure 2:Approach to Development of the BN FDD Model for Maritime Diesel Engines

While the focus of this research is on providing results for immediate application to the maritime diesel engine community, a secondary result is to produce a methodology with applicability across all CESs of interest to the Coast Guard.

1.2.3 Objective 3: Demonstrate Methodology Application Through Creation and Testing of a Model

Objective 3 consists of Tasks 3a and 3b summarized below:

a. Utilizing the methodology proposed in Objective 2, create a BN-based FDD model representing a FRC diesel engine.
b. Demonstrate model capability through execution of a use case scenario on the FRC engine model created in Objective 3a.

Together these tasks show the application of the methodology created in Objective 2 and demonstrated potential use cases for the resultant model.

2. Literature Review

The purpose of this literature review is to provide sufficient background information regarding the methodologies used in this research in addition to outlining ongoing efforts in the PRA and PHM fields with a focus on identifying recent advancements and areas of potential improvement. As the focus of this study is on the methodology application to a maritime diesel engine, focus will be placed on outlining efforts within the maritime engineering community and identifying gaps or deviations from advancements in other disciplines.

2.1 Complex Engineering Systems

As technology and system design increase in capability and complexity, traditional methods of PRA must improve to match the need for a more comprehensive risk analysis process. To create a distinction between simple and complex models, Modarres proposed the use of the term “CES” (Complex Engineering System), which he defines as a system that possesses the characteristics of being evolving, integrated, dynamic, large, and intelligent [10]. As with system complexity, the coinciding models required for CESs should be evolving and integrated in nature allowing for modular changes to the system based on dynamic feedback. While the focus of much CES research [11] focuses on high consequence systems such as nuclear power plants [12], hydrogen facilities [13], and the gas production line, there are opportunities outside of these high consequence disciplines to apply CES reliability concepts [14]. This study is the first conducted with the complex system being a Coast Guard operated FRC.

An ideal designed system is one that will respond and complete the requested mission without issue whenever operation is demanded. Real life constraints make this concept of perfect system performance infeasible, but the necessity of the system being available when needed has led to development of the reliability engineering field tasked with determining what affects this metric and how to optimize it. The term availability be defined as the probability that a given system or asset, when operating under ideal conditions, is available for use when required [15]. With the understanding that any system of simple or complex design will eventually break or require maintenance to continue operations, it is unfeasible to achieve an availability of 1.0. A simplified equation to illustrate the relationship between availability (A), uptime (u) and downtime (d) is shown below in Equation 1 where uptime refers to the time the asset is available to operate, and downtime is all the time the asset is unavailable to operate:

Equation 1: General System Availability

$$A = \frac{u}{u + d}$$

The Coast Guard utilizes an asset-specific form of operational availability to determine the effectiveness of an asset and its support structure. The FRC's health is measured in terms of the percentage of total operational time in which the asset is Fully Mission Capable (FMC), Partially Mission Capable (PMC), Not Mission Capable Depot (NMCD), Not Mission Capable Maintenance (NMCM), Not Mission Capable Supply (NMCS), and Not Mission Capable Repair (NMCR). The terms FMC refer to the total asset up time, terms NMCD and NMCM refer to planned down time, and NMCS and NMCR refer to unplanned downtime [16]. For the purposes of availability calculations, PMC time is considered uptime.

As NMCM or NMCD periods represent planned down time, these metrics are more applicable to the material availability of a system; understanding NMCM and NMCD allows for inference into how the system was designed to operate and the inherent reliability of the system. The NMCS and NMCR metrics provide insight into the effectiveness of the support system and its ability to prevent unplanned downtime.

2.2 Modeling System Reliability and Health

Reliability metrics and consideration provide stakeholders crucial information required to make risk-informed decisions regarding the operation of multiple million-dollar CESs [17]. As technology advances, exponentially more reliability data is being produced to inform increasingly granular failure models, and monitoring and tracking practices are improving. In this context, reliability engineers are challenged to adapt current practices to take advantage of the opportunities to improve how systems are modeled [18]. Areas of improvement are typically focused on two categorical areas: PRA and PHM. Traditionally seen as separate practices with their own research communities, both methodologies share the same end goal of minimizing the occurrence of risk by improving the accuracy of assumptions regarding system health and reliability [11].

2.2.1 Probabilistic Risk Analysis

Probabilistic Risk Assessment (PRA) is the act of estimating the risk of an activity based on the probability of events whose occurrence can lead to adverse consequences [19], [20]. Risk defined simply is the identification of a hazardous scenario, defining the probabilities of that scenario, and determining the consequence of the scenario taking place. By utilizing various physics and/or data-based analyses of system failures to determine the likelihood of each failure mode, it is possible to gain a deeper understanding of how systems fail. PRA therefore allows engineers to predict the occurrence of these failures when the system is operating [15]. The origins of PRA can be traced back to the aerospace field in the 1960s. A series of critical failures during the National Aeronautics and Space Administration Apollo test runs resulted in the creation of quantifiable safety goals and criteria before mission execution [21]. This methodology of acknowledging and quantifying risk was adapted by the U.S. Nuclear

Regulatory Commission in the publication of the Reactor Safety Study WASH-1400 in 1975, referred to by many as the first modern PRA [22]. Since its inception, the practice of utilizing PRA principles has transcended engineering fields to become standard practice in the design and operation all CESs. By providing a structurally sound quantitative method to identify failure scenarios and estimate their probability and consequence, PRA practices work to identify opportunities to mitigate risk in a controllable and quantifiable manner [11].

Along with challenges related to increasing system complexity and multi-state system operation, one of the largest challenges the field faces is how to handle re-assessment and updating of PRA artifacts throughout a system's lifecycle [23]. System degradation and changes to operational use can lead to vast changes in system element wear/operating characteristics and lead to less accurate reliability estimations. Classical PRA methods have historically struggled to adequately model failure dependence on causal factors and the interdependency of sub systems existing within CESs [11]. These and other limitations have led the field to develop newer methodologies utilizing advanced computing software capable of quantifying more complex relationships and a more robust information feedback loop [17]. Newer PRA methods looking to address the limitations of classical PRA can be categorized as hybrid or simulation-based methods.

One form of input PRA data exists as a Failure Modes and Effects Analysis (FMEA) and its expanded form, FMECA. In its base form, a FMEA is a systematic procedure for analyzing a system to identify all the potential failure modes, their causes, how they are detected, and what effects on they have on the systems performance [24]. Widely accepted as the standard for these analysis, MIL-STD 1629 provides guidance on procedures for conducting an FMEA and discusses its use as both a design and decision-making tool [25]. Since its conception, the FMEA process has evolved with private companies altering the process to fit their specific needs, as illustrated by the adaptation of a seven-step process in auto manufacturing to improve how risk is communicated [26]. One of the largest noted issues regarding the FMEA format is the lack of data reusability and applicability, stemming from how the data is collected and organized [27]. Current research in this area has proposed utilizing hybrid PRA models such as model-based methods (e.g., hierarchal trees or BNs) to capture complex causal relationships within a complex system, using structures based on Fault Tree Analysis (FTA) [26], [28], [29]. The use of a BN model allows for a structured knowledge representation in which variables are represented as nodes and whose structure represents dependencies between variables, allowing for complex modeling of dependency across inter-variable dependencies [30]. These and similar methods seek to introduce non-discrete causal factors into reliability calculations, allowing for the consideration of previously unaccounted human, organizational, environmental, or socio-technical factors [31]. Applicability of these hybrid methods has been shown across engineering disciplines with developments stemming from the nuclear, aerospace, and pipeline communities [14], [32], [33]. While these methods show promise in modeling dependency across components, the static structure of a BN struggles to model the dynamic relationships that are perpetuated over time [34].

Simulation-based PRA methods, otherwise known as Dynamic PRA (DPRA), evaluate a model in which states, element, and variable values are changed as functions of time either in a discrete or continuous manner [17]. The methodology allows for the creation of time-dependent probabilities, facilitating a more accurate reflection of the state of the coinciding system in a specific instance. This additional granularity allows for the removal of model assumptions regarding accident/failure progression by enabling safety and reliability evaluations of event sequence/timing [35]. DPRA models, specifically Dynamic Bayesian Networks (DBN), have been a focal point in the development of methods to handle complex time-dependent causal relationships, and models have shown validity for use as both an accident prevention tool and fault diagnosis software [36], [37].

2.2.2 Prognostics and Health Management

The practice of implementing PHM is done to gain insight into the health or Remaining Useful Life (RUL) of components or systems to provide stakeholders a more informed means of developing system life cycle plans. On a more granular level, PHM processes work to improve the ability to detect, diagnosis, and predict potential failures within a system. To accomplish these overarching goals, PHM models rely on the collection and analysis of component, sub system, and system level performance data to make inferences on potential failures or degradation [38]. By identifying likely failure times, stakeholders can alter the maintenance cycles for components and sub systems to improve the RUL of the system and reduce the need for time-based or inspection-based maintenance procedures [39]. PHM methods are categorized by the source data used and can be generally grouped as physics, reliability, data-driven, or probability-based methods [40]. While each methodology has intricacies regarding the accuracy and applicability, the PHM challenges can be generalized to a lack of accurate, applicable data and issues with scalability.

Data related issues in the PHM field can be extrapolated further to issues regarding data collection processes and the Physics-of-Failure (POF) or probability inputs that serve as the basis of PHM models [41]. Data inconsistencies in failure documentation reduces the overall effectiveness of data-based PHM metrics as many failures remain unreported or lack the requisite information to determine causal factors leading to the failure. This data inaccuracy is also seen when looking at POF models that are created under the assumption of a given condition and are often rigid in their adaptability to operational changes [42]. Traditional PHM processes share this challenge with PRA methodologies in that they both struggle to model component failure probabilities/health metrics with regards to equipment operational status and or external causal factors [11]. Cai et al. have conducted research regarding component degradation and its effect on the health of components within the sub system and proposed the use of DBNs to quantify the dependency across systems and sub systems throughout a CES's operation [43]. Along the same line, Liu et al. proposed the use of BNs as a method to organize and interpret large fleet PHM data to gain insight on the effects of operating conditions and other external causal factors on the performance of CESs [44].

Due to the maritime transportation industry's heavy dependence on diesel engine-based propulsion, numerous studies have been made to integrate PHM methods into maintenance practices for use on diesel engines with research focused on component level wear analysis [45]. Soleimani et al. explored the use of DBNs in conjunction with Hidden Markov models to condition sensor input to gain insight into component performance/degradation [30]. Zhang built upon this concept by creating a DBN providing a constant filter data stream that acted as a fault test input into the health of a given sub system [46].

Hybrid methods using tools such as the Hidden Markov models were successful in providing a picture of the general health of the components or sub systems, they analyzed but these methods were not expanded to cover the system as a whole.

2.2.3 Integration of PRA and PHM Data

Systematic Integration of PHM and PRA (SIPPRA) is an methodology presented by Moradi and Groth [11] that outlines a method for combining PRA and PHM data to create informed PRA models for CESs that incorporate PHM concepts to update the accuracy of the model throughout its operation. This field utilizes concept Bayesian inference in the form of either static BNs or DBNs to structure PHM data with supporting PRA networks, allowing for informed failure diagnosis capabilities and reduction of uncertainty in reliability calculations through informed system health parameters. Application of this data fusion on CESs was explored by Moradi and Groth in 2020 [11] with Lewis and Groth summarizing the process in Figure 3 [47].

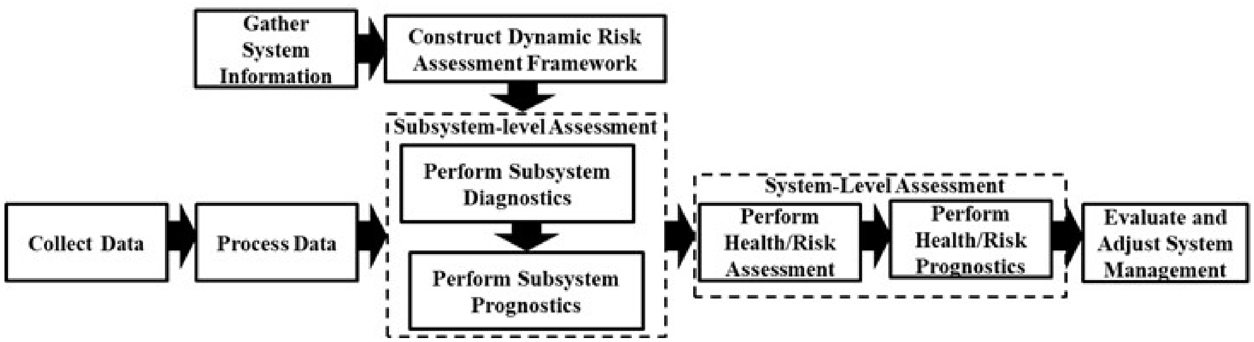

Figure 3:SIPPRA methodological process. Figure from [46].

The main driver behind this branch of research lies in providing the energy production field with a method of improving the accuracy of reliability estimates specific to each system and its given operational conditions. Most studies in this field focused on the application of these principles on CESs within the energy production field, such as nuclear power plants, hydrogen infrastructure, and more traditional energy production methods like combustion engines [48]. One of the most relevant intersections of the PRA and PHM fields comes in the form of linking the end product of FTA or Event Tree Analysis structures to PHM-based health metrics using either static BNs or DBNs to gain insight into condition-based failure probabilities [49].

Wang et al. proposed BN structures for fault detection on mechanical systems and explored the application of the process to a diesel engine injection system [50]. Other studies focused on diesel engines using SIPPRA methodology revolved around fault diagnosis in fluid-based sub systems with lube oil systems being the most prevalent due to the criticality of the sub system within the greater engine hierarchy. For example, Ren et al. explored mapping a diesel engine lube oil system FTA onto a static BN structured to match the branching of a fault tree [51]. Pernestål et al. conducted a similar study but with a focus on the fuel system of a diesel engine [52]. These works were complemented by Liu et al. who combined BN FTAs with oil analysis reports to provide stakeholders insight into the health of engine lube oil systems and other relevant system components [53].

The opportunities for improvements withing the maritime diesel engine community using the SIPPRA ideology, and the existing work done on BN FDDs were found to be:

- Expansion of existing methods that utilize FTA and ETA based BN mapping to a system wide level verse the current use cases that focus on component and or sub system modeling.
- Using BN to represent subsystem and component dependency across the system.
- Introducing causality-based failure definition by creating a structure that defines failure based on the propagation of failure mode effects.
- Integration of sensor-based input into existing BN FDD structures at a system level to optimize use of data streams coming from newer maritime diesel engine systems.

2.3 Chapter Summary

This chapter provided background information on the CESs and difficulties in quantifying risk during their operation. The current state of PRA was discussed, detailing work improvements through utilization of hybrid and simulation methods, while also identifying the need for a means to evaluate the dependency of system and component reliability in a changing operational environment. Advancements in the PHM field, driven by the rapid development and integration of sensor equipment into CESs, have led to advancements in the modeling of component failure mechanisms. These advancements mark significant improvements in the field and spotlight issues regarding the management of an exponentially increasing quantity and variety of data streams. These issues make the scalability of models based on traditional methodologies increasing difficult. The SIPPRA methodology was explored and examples of data fusion in both the energy production and diesel engine specific fields were provided. Finally, gaps withing the maritime diesel engine FDD field were outlined providing a path for future research.

3. Methodology

This chapter focuses on development of a methodology for creating a model that organizes and updates existing PRA with direct input from a systems PHM monitoring component in the context of maritime diesel engines. This will be done in two parts, with the first focusing on data collection and organization and the second focusing on the structure of the BN.

3.1 Develop Background Framework for Data Integration

The purpose of this methodology is to provide a step-by-step process to create an FDD tool for use on maritime diesel engines using BNs. It first provides guidance on organizing existing PRA data and documenting current PHM capabilities of the system before presenting a hierarchical ruleset for data integration in a BN software. This ruleset is a crucial part of the framework as it provides a set of causal rules that guides creation of the structure. This ruleset must:

- Provide guidance on network node structure by mapping system, sub system, component, system measurements, and causal factors onto a BN structure.
- Identify possible parent and child nodes for each node level within the BN structure based on causal flow.
- Identify node states for each node level within the BN structure.
- Identify methods to quantify nodes in each hierarchical level.

The combination of data organizational methods and the BN structural ruleset enable creation of the BN-based FDD.

3.1.1 System Decomposition

The purpose of this step is to create a detailed list of sub systems and components that comprise the system. The first aspect of this process is to identify the elements of the sub system level of the system. Utilizing the principles of functional decomposition [54] when breaking down the system into hierarchical categories is recommended as it allows for the easiest integration of sensor/observational data. In many cases, functional groups serve multiple purposes for the system and should be documented prior to continuing forward in this process to allow for additional granularity when building the accompanying system structure. Depending on the granularity level used when grouping components into sub systems, each sub system may have more than one purpose. For example, when looking at the lube oil system as a sub system of a diesel engine, the sub system's purpose(s) are to a) Lubricate components and b) Provide cooling to components. This example shows that that a failure for the lube oil system would be failure to properly lubricate and/or failure to provide adequate cooling. Said in other words, a lube oil system failure is characterized by the failure to properly lubricate *or* failure to properly cool specified components. An example format for this breakdown is provide below in Table 1.

Sub System	Primary Function	Tertiary Function(s)	
Sub System 1	Function A	Function B	~
Sub System 2	Function C	~	~
Sub System 3	Function E	Function F	Function G
Sub System 4	….		
…..	….		
Sub System X	…		

Table 1: Example System Functional Decomposition

Once the creation of sub systems is complete, a list of components should be created and grouped by most applicable sub system. In many complex systems, components serve or are affected by multiple systems. This dependency should be documented as this will be used later to assist in the creation of the FDD causal connections. An example format for this process is shown below in Table 2.

Component	Primary Sub System	Tertiary Touch Points		
Component 1	Sub System 1	Sub System 2	Sub System 3	~
Component 2	Sub System 1	Sub System 3	~	~
Component 3	Sub System 2	~	~	~
Component 4	Sub System 2	Sub System 1	Sub System 3	Sub System 4
Component 5	Sub System 3	~	~	~
Component 6	Sub System 3	Sub System 1	~	~
Component 7	Sub System 4	Sub System 3	Sub System 1	~
…..	….			
Component X	….			

Table 2: Example Sub system Component Breakdown

3.1.2 Sub System Characteristics

Performance metrics remain an excellent way to measure a system's performance throughout its life or across different operational conditions, but it is critical to document all characteristics of the system rather than just focusing on the readily measurable metrics. The process of describing each sub system performance should be done without regard to feasibility of measurement, as this process aims to create a model that captures the dynamic relationships within a complex system. As a rule, if a measurement could be used as evidence to change the understanding of the system, sub system, or components performance, it should be listed. In systems that transport a medium such as lube oil, this process can be initially viewed as simple but when expanded to include locational measurements, the breadth of data can rapidly expand. An example of this process is shown below in Table 3.

Sub System 1			
Location of Measurement	**Type 1**	**Type 2**	**Type 3**
Location 1	X	X	X
Location 2			X
Location 3	X	X	X
Location 4	X	X	X
Location 5	X		X
Location 6	X	X	X
….		X	X
Location X	X		X

Table 3: Example Sub System Measurement Breakdown

While many of these measurements are not normally available in traditional engine monitoring, they illustrate what is possible in an ideal environment with perfect knowledge. Furthermore, this process provides stakeholders input on potential areas to improve system monitoring.

Once this list is generated, each sub system function/purpose must be defined and linked to system characteristics. While sub system functions may share characteristics, there usually exist distinctions in either the defining characteristics or the reliance on the effectiveness of components. Using the previous example of a diesel engine lube oil system, both functions have a strong dependency on the system's pressure, but the lubrication function has a strong dependence on the quality of the lube oil medium whereas the cooling function has a very weak dependency on quality and could be defined without this characteristic.

An example of the sub system function breakdown is provided below in Table 4.

		Characteristic / Measurement		
Sub System	Function	#1	#2	#3
Sub System 1	Function A	Measurement 1	Measurement 2	~
Sub System 1	Function B	Measurement 2	Measurement 3	~
Sub System 2	Function C	Measurement 4	Measurement 5	Measurement 6
Sub System 2	Function D	Measurement 4	Measurement 6	~
Sub System 3	Function E	Measurement 7	~	~
….				
Sub System X	….	….		

Table 4: Example of Sub System Function Breakdown

As this framework is meant to be usable across system states, measurement ranges that categorize the measurement output as either normal, degraded, or failed must be generated for all possible system states. This aspect of the network can either be integrated using a front-end interface such as GeNIe SMILE [55] or be updated manually by the system user.

3.1.3 Component Failure Modes and Causal Factors

A failure, for the purposes of this research, will be defined as the inability for the system, sub system, or component to fulfill its designed purpose [15]. The component level portion of this framework relies heavily on the availability of component level PRA data existing for the subject system. Current industry standards for this data are provided in a format like that found in a FMECA [25]. If this data is available, it is critical to understand the operational profile in which the FMECA data was generated, as it provides details on how various causal factors play into the base calculations even if they are not specifically called out in the data. This type of analysis is executed with the end goal of outlining the below information for every relevant component within a system:

a) What are the component failure mechanisms?

b) What are the component failure modes?

c) What are the effects of this failure on the component, sub system, and system as a whole?

d) How does this failure mode manifest itself/how is it detected?

e) What is the base probability of this failure mode occurring?

f) What provisions are in place to prevent or detect this failure mode?

g) What is the relative severity of the failure mode?

h) What is the probability of occurrence for the failure mode?

An example of this process is shown below in Figure 4:

ITEM/FUNCTIONAL IDENTIFICATION (NOMENCLATURE)	FUNCTION	FAILURE MODES AND CAUSES	FAILURE EFFECTS			FAILURE DETECTION METHOD	COMPENSATING PROVISIONS	SEVERITY CLASS	FAILURE RATE (λ_p)
			LOCAL EFFECTS	NEXT HIGHER LEVEL	END EFFECTS				
LUBE OIL PUMP	THE OIL PUMP SUCKS OIL FROM THE OIL PAN AND FORCES THE PRESSURIZED OIL TO THE OIL SYSTEM.	OIL PUMP HAS LOW LUBE OIL PRESSURE CAUSED BY LUBE OIL CONTAMINATED OR PRESSURE RELIEF VALVE STUCK OPEN	LUBE OIL BYPASSES THROUGH THE 16 BAR PRESSURE RELIEF VALVE. LOW LUBE OIL PRESSURE	ENGINE SHUTDOWN	MISSION DEGRADATION POSSIBLE	FAULT-MESSAGE	ENGINE IS EQUIPPED WITH A OIL PRESSURE SENSOR	3	1.00E-06
		OIL PUMP - BEARING FAILURE CAUSED BY EXCESSIVE WEAR	LUBE OIL BYPASSES THROUGH THE BEARING BUSHINGS. LOW LUBE OIL PRESSURE	ENGINE SHUTDOWN	MISSION DEGRADATION POSSIBLE	FAULT-MESSAGE	ENGINE IS EQUIPPED WITH A OIL PRESSURE SENSOR	3	1.00E-07
LUBE OIL FILTER	CLEANSES THE ENGINE OIL TO HELP REDUCE WEAR ON THE ENGINE'S INTERNAL COMPONENTS.	OIL FILTER CARTRIDGE HAS CRITICAL EXTERNAL LUBE OIL LEAK CAUSED BY	LEAKAGE, LOSS OF LUBE OIL	LOW LUBE OIL PRESSURE LOW LUBE OIL PRESSURE ENGINE SHUT DOWN	MISSION DEGRADATION POSSIBLE	FAULT MESSAGE EXCESSIVE LUBE OIL CONSUMPTION	ENGINE IS EQUIPPED WITH A LUBE OIL PRESURE SENSOR	3	1.00E-07
		OIL FILTER CARTRIDGE HAS MINOR EXTERNAL LUBE OIL LEAK CAUSED BY	LEAKAGE, LOSS OF LUBE OIL	NONE	NONE	EXCESSIVE LUBE OIL CONSUMPTION	PERFORME PMCS ACCORDING TO TO MAINTENANCE SCHEDULE TOP UP LUBE OIL TO CORRECT LEVEL AND REPAIR EFFECTED ITEM	4	1.00E-07
		OIL FILTER CARTRIDGE HAS INTERNAL LUBE OIL LEAK CAUSED BY	LUBE OIL BYPASSES THE FILTER CARTRIDGE	NONE	NONE	DURING PMCS	NONE	4	1.00E-07

Figure 4: Example FMECA for a Maritime Diesel Engine

It is critical to understand the role each component plays in the overall performance of the sub systems it touches and how each failure mode can affect the associated performance characteristics. This process should be built iteratively as the system design matures, operating experience is gained, and additional knowledge regarding the causal ties are discovered. Methods for categorizing, grouping, and propagating component failure effects will be explored later in the structural portion of methodology.

Often, the most under-extrapolated portion of this data set are the causes and failure effects, as their contributions remain hard to quantify. This aspect of the analysis represents the greatest opportunity for integrating causality in the model and creating a model that can be easily updated to integrate changes in the operational profile and is a key input to the methodology. Causal factors include varied aspects, from how the system was operated in the past to the quality of the manufacturing process. The ability to identify these factors is critical to understanding how the system and individual components operate and degrade. Development of the knowledge of the cause of one component's failure can provide insight into the state of other components within the system. The process of identifying these causal factors for each component failure is currently done in a simplified manner in traditional FMECAs, but FMEA does not rigorously identify the probability of the failure cause happening and how the presence of that condition affects the failure rate for that specific failure mode.

The process of documenting causal factors should strive to identify every possible factor that can influence the occurrence of a certain failure mode. If existing data is being used such as a FMECA, failure mechanisms should serve as a starting point. In addition to operator level input, a feasibility check should be applied to each item based on whether the underlying condition can be quantified and if there were existing data that would allow a prior probability distribution to be generated.

3.2 Creating the BN Structure

With the data generated in the above steps, a model representing the system structure can be made. The core principle behind this model's use is forward and backwards propagation of data using Bayesian inference. The model must be made in a program capable of representing these complex relationships.

This methodology proposes a network consisting of five major levels with intermediate step levels for added granularity. A summary of framework levels is presented below in Figure 5.

Level	Description	Visual Representation	Parent Nodes	Child Nodes	Node States	Quantification Method
5	Causal Factors	Causal Factor 1	5	2a,3,4a,5	Binary or Ternary	Operational Data Expert Elicitation
4a	Failure Modes and Effects	Component 1 Failure Mode 1	2a,3,4a,5	2a,3,4,4a	Binary or Ternary	PRA Driven Expert Elicitation
4	Components	Component 1	4a	2a,3	Binary or Ternary	PRA Driven “OR” gate for 4a
3	Measurements	Sub System 1 Measurement 1	2a,3,4,4a, 5	2a,3,4a	Ternary	Expression Based Expert Elicitation
2a	Sub System Functions	SS1 Function 1	3,4,4a,5	2,3,4,4a	Binary or Ternary	Expression Based
2	Sub Systems	Sub System 1	2a	1	Ternary	Expression Based
1	System	System	2	N/a	Binary	Expression Based Expert Elicitation

Figure 5: Framework Node Hierarchy

When combined in a modeling software for Bayesian inference, the above nodes can be utilized to create model capable of representing causality and propagating evidence throughout the model. This functionality allows the model to be used as a both a diagnostic and predictive tool. BN cannot function if there is a loop connection where a node is both simultaneously informing and being informed by a node. To prevent the creation of loops connections between nodes should always flow in the direction of causality and if there exists an situation where a node may have relationships that create a loop, the most prominent relationship should be modeled while the less likely is removed from the model.

For the purposes of this research the BN software used to create the model was Bayes Fusion’s GeNIe3.0 Academic [55]. An example structure demonstrating the hierarchical structure of the model is shown in Figure 6 with level denoted on the side:

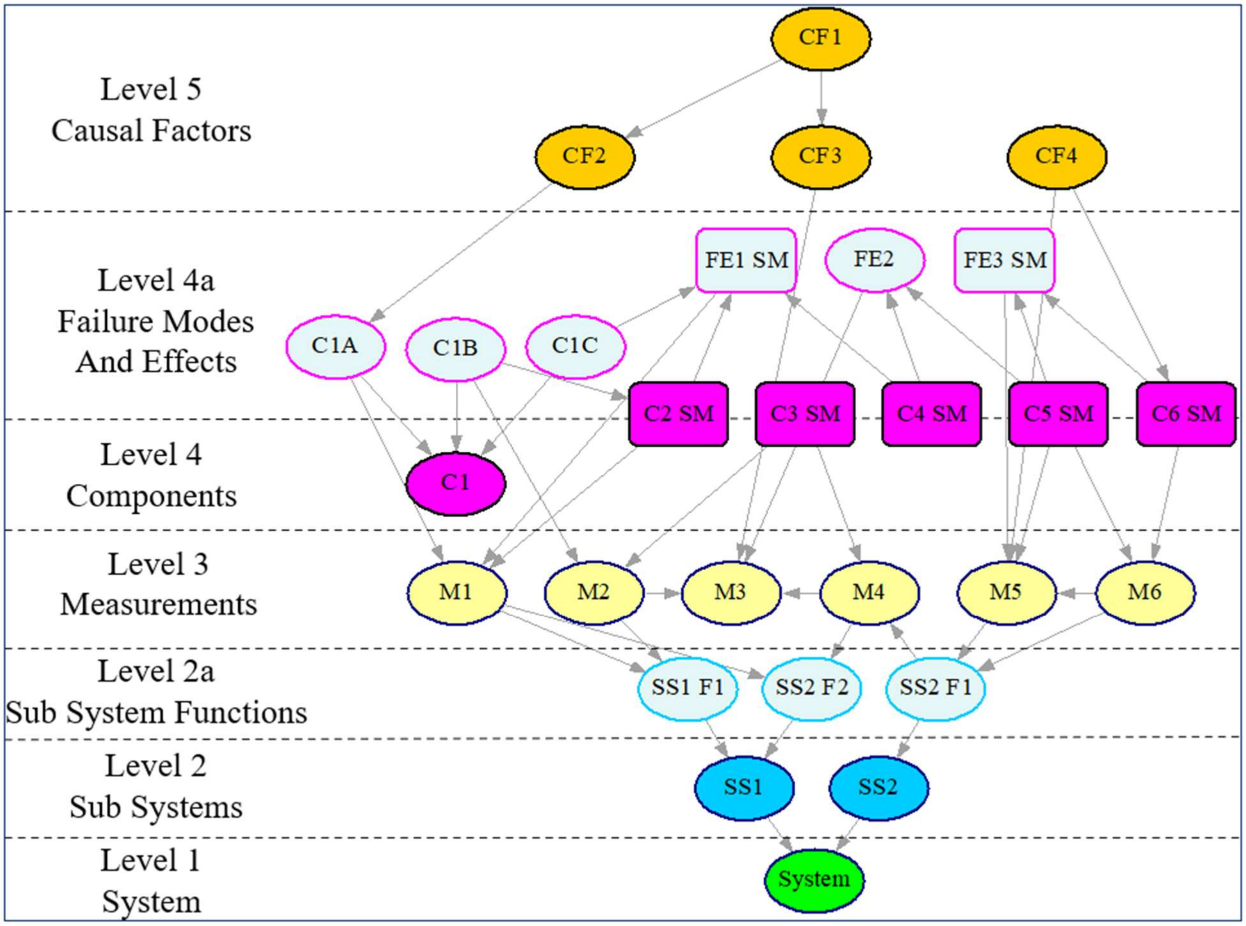

Figure 6: Example BN Structure. Rectangular nodes represent Sub Models which are further decomposed into their own structure.

As outlined in Figure 6, nodes may be represented in either a binary or ternary state configurations based on how the system or component responds while in operation and the granularity level stakeholders are attempting to achieve by creating the model. The recommended configuration for binary nodes is *operation/failed* while the ternary state configuration is *normal/degraded/failed*. As the number of nodal connections increases, the complexity of Conditional Probability Tables (CPTs) will increase exponentially with the addition of nodal states, so it is recommended to minimize the number whenever possible. The representation of both binary(green) and ternary(blue) state nodes is shown below in Figure 7.

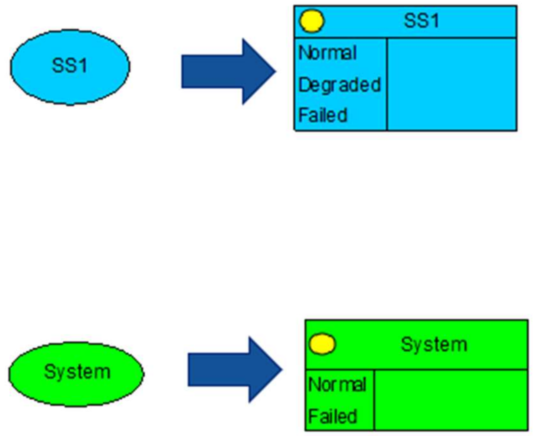

Figure 7: Binary and Ternary Node Representation

3.2.1 Level 1 Node: System

Level 1 of this framework represents the overall failure probability of the system. This framework utilizes a bottom-up construction process focusing on fully defining levels before moving up the framework. This nodal level should be represented as binary with the designation of operational/failed. Level 1 nodes will not have any child nodes. The system's only possible parent nodes are level 2 sub system nodes. The determination of which sub system nodes are added to the model is driven by the results of the system functional decomposition conducted prior to model construction. Level 1 system node construction is shown in Figure 8 demonstrating the relationship between the system nodes and the three constituent sub system nodes as parents.

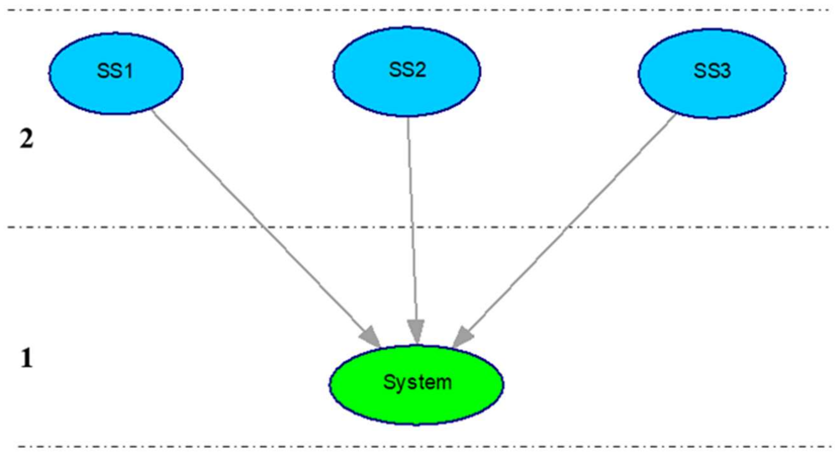

Figure 8: Example Level 1 Node Modeling

Quantification of the system nodes' associated reliability is fully dependent on the status of the sub systems nodes. Methods to quantify the CPT for the system node rely on either expression-based probabilities or input from expert elicitation. As a rule, the failure of a sub system should result in the failure of the system while sub system degradation requires a more detailed approach to determine the effect on the system. In the case where the system node is defined by three sub systems with three states each, the resultant system CPT requires the definition of 27 possible scenarios. Quantification difficulty grows exponentially with the addition of more parent nodes. Expression-based quantification provides a method that reduces the need for either expert elicitation or data informed relationships and simplifies quantification. An example CPT created using GeNIe is provided below in Figure 9 to illustrate the scope of quantification efforts required for a binary system node with three ternary sub system nodes as parents.

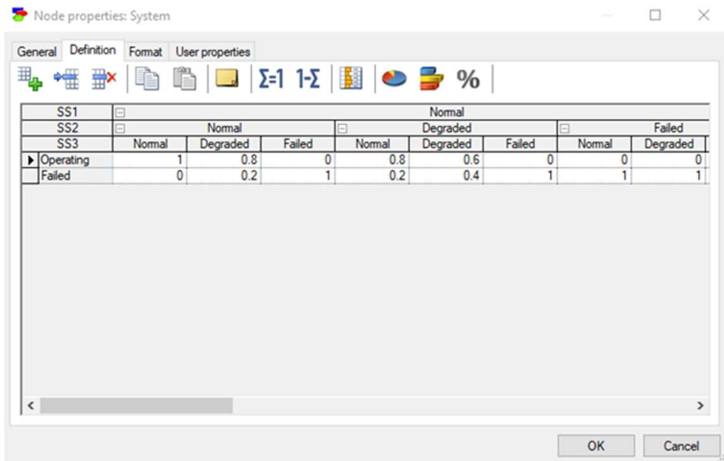

Figure 9: Example CPT for Level 1 Node

3.2.2 Level 2 Nodes: Sub Systems

Level 2 nodes in this framework represent the sub systems defined during the functional decomposition of the system. The sub system nodes act as parents to the system nodes and children of the level 2a sub system functions. Sub system nodes can be represented with either a binary or ternary configuration, but the addition of the intermediate degradation state offers a significant increase in diagnostic capabilities with only a minor addition of quantification complexity as the node relies solely on level 2a functions as parents. Quantification of the CPT for sub system nodes follows like the system level CPT in that failure of a sub system function will result in failure of the sub system function of the sub system while degradation of individual functions requires input either in the form of an expression or expert elicitation. An example of level 2 node construction is provided in Figure 10 showing the construction of Sub System 1 (SS1) and Sub System (SS2) nodes.

3.2.3 Level 2a Nodes: Sub System Functions

Level 2a nodes represent the various function each sub system fills for the system. These functions are derived from the functional decomposition of the system and provide a more granular view of the sub systems purpose within the system. Their presence provides a means to bridge causality across sub systems. Sub system functions are best represented in a ternary configuration but may be simplified to binary if the situation allows it.

Input into the sub system nodes can come from level 3, level 4 and 4a, and level 5 nodes. The primary source of dependency when defining sub system functions should be level 3 measurements as they offer the greatest opportunity for integration of evidence during diagnostic actions. The use of direct causal pathways from level 4/4a nodes to sub systems' functions should be limited to instances where the failure of the component directly affects the sub system function, and its effect cannot be routed through a system characteristic measurement such as mechanical power transmission or functions that have parent and a child system measurement node such as a coolant system function of Cool Lube Oil. Additionally, consideration of level 5 causal factors should again be limited to only those that have a direct impact on the systems functionality. Figure 10 below provides an overview of possible parents of level 2a nodes.

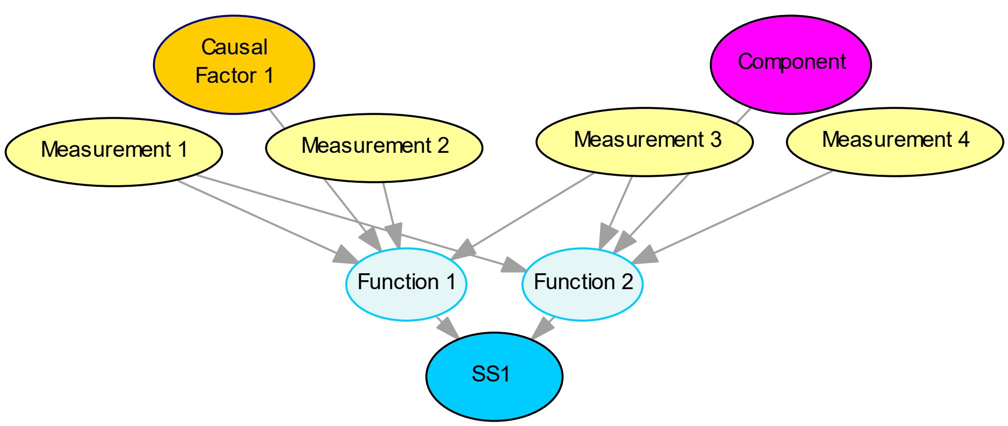

Figure 10: Example of Level 2a Sub system Function Parent-Child Modeling

Sub system function nodes can inform multiple levels of nodes including level 2, 3, and 4/4a. The relationship between level 2 and 2a nodes was considered when outlining sub system quantification and could be categorized as hierarchical but the remaining causal relationships are not tied to this concept and instead focus on flow of causality. Sub systems' functions may act as parents to level 3 nodes, but only for measurements outside of their sub system. This prevents an informing relationship with a level 3 nodes within the same sub system grouping as the sub system's ability to execute a function is defined by the characteristic measurements within the system. As in most complex systems, there exist touch points between the various functional grouping the framework allows, for functions to inform measurements outside the functional grouping, especially in the case where the function has direct impact on the other systems measurement. This relation is the first instance of a parent-child relationship that exists "up" the hierarchical representation of the system, and in doing so introduces sub system dependency into the model. In addition to their influence on measurement nodes, direct causal links up the hierarchal structure between sub system functions and component failure modes may be drawn if there exists a direct causality between the sub system's ability to perform the function and the failure mechanism of the component. As with the relationship to measurements, this relationship should be limited to components receiving input from the sub system and not those enabling the system function. Examples of sub system and component dependency are shown below in Figure 11Figure 11.

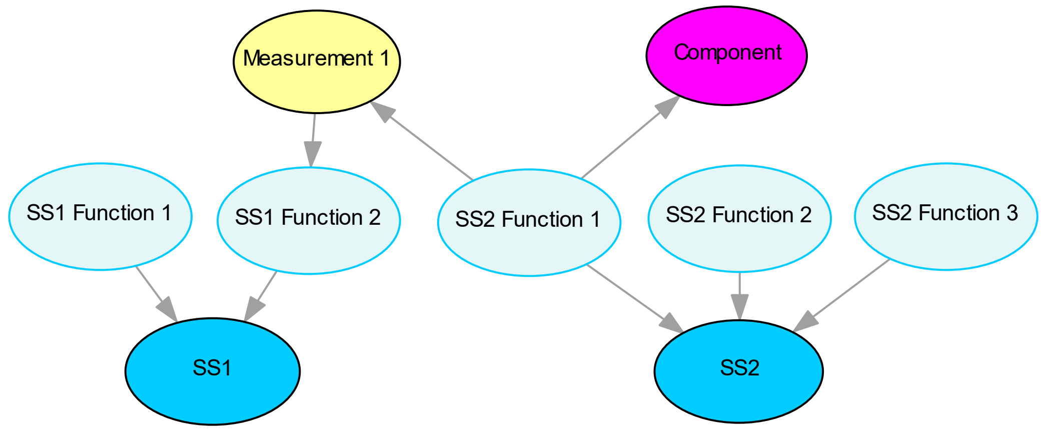

Figure 11: Example of Sub System Dependency Modeling

As there are a variety of inputs into level 2a nodes, quantification efforts can be challenging as the inputs are often not provided in the same form. In the absence of data supporting CPT creation, expert elicitation of probabilities is the preferred method for quantification. Use of an expression-based approach is possible but accounting for data variety require a more complex expression.

3.2.4 Level 3 Nodes: System Measurements

Level 3 nodes represent the characteristic system measurements and act as the main integration point for PHM data while using the model as a diagnostic tool. Measurement nodes should be represented as ternary, as this configuration allows for early identification of issues within the sub system due to the high dependency of sub systems on level 3 nodes. While it is possible to have a system degrade in either up or down, for example, a system would be considered degraded/failed if the pressure was both too high and too low, it is recommended to characterize the measurement with a degradation direction to simplify the resultant CPT.

Level 3 nodes can act as parents only for system functional nodes and measurement nodes within the same system. As discussion in the previous section regarding level 2a nodes, measurements cannot affect other sub systems characteristics directly. Measurement nodes receive definitional input from functional nodes in level 2a, level 3 nodes existing within the same sub system, level 4/4a component failure modes, and level 5 causal factors. A change to a node serving as parents to level 3 should have a direct causal relationship with the measurement and not a secondary effect. Figure 12 below illustrated possible causal pathways influencing the state of level 3 measurements nodes.

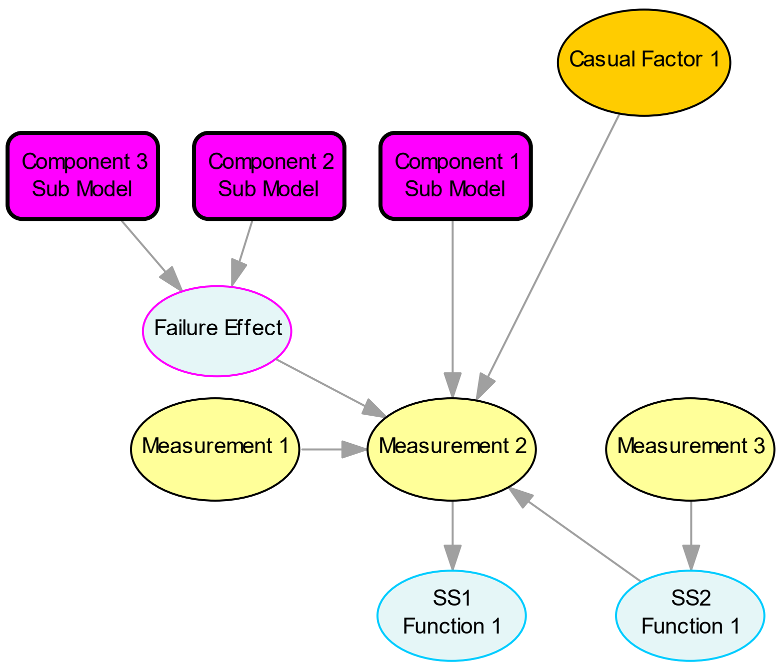

Figure 12: Example Level 3 Measurement Node Construction

Quantification of level 3 nodes is dependent on a wide array of factors thus complicating the process. The preferred method is to use expert elicitation to create initial CPTs based on system level PRA data and operating experience, and then updating these CPTs with operating data once it becomes available.

3.2.5 Level 4 Nodes: Components and Component Failure Modes

Level 4 of this model's framework represents components. In systems that contain multiple instances of the same component(s), models may simplify initial construction by representing the component in question as a single node.

A level 4 node may exist as an independent node with its own reliability considerations or as a product of its failure modes existing in level 4a of the model. If the decision to include granular failure modes is made, the use of sub models in the BN allows for a simplified macro view of the model while allowing for granular construction of component failure modes. Figure 13 below shows the macro view of the component sub model compared to the expanded view contained within the components sub model.

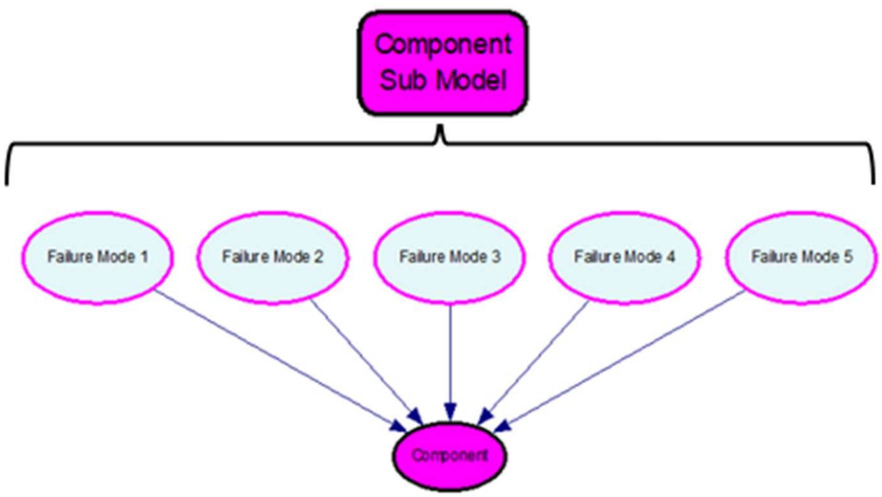

Figure 13: Example Level 4 and 4a Sub Model Representation

Level 4 component nodes can be parent nodes to level 2a, 3, or 4/4a nodes. These pathways are applicable only when the level 4 node is not defined by 4a nodes and exists independently, or when the all the constituent 4a nodes have the same failure effect. CPT quantification of these nodes can be simplified by drawing the causal pathway from the component level. Similarly, to its treatment as a parent, level 4 nodes are defined solely by its 4a failure modes unless it only has a single failure mode that defines the components failure. In this case the node would follow the ruleset for a 4a node where it can receive input from level 2a,4/4a, and 5 nodes. Component nodes should be represented binarily with states *operational* or *failed* unless they are defined by any failure mode in which they may have a ternary configuration to account for levels of failure effects.

As previously discussed, an increase in the number and/or complexity of parent nodes can lead to an exponential increase in the complexity. In the case of component nodes dependent on 4a failure modes, the CPT should reflect a Boolean "OR" gate representing that the realization of any failure mode would mean the failure of the component. This can be coded as an equation or deterministic node in the BN software.

Quantification of level 4 nodes should be driven by PRA data collected in the first portion of this methodology, unless additional factors outside of level 4a failure modes are being considered. If additional factors are being considered, base PRA data should be used as a prior and the CPT should be modified using either additional PRA data or input from expert elicitation to determine the effect of the external factors on the initial prior.

Level 4a component failure mode nodes are treated identical to independent level 4 nodes in that they can be parents to level 2a, 3, and 4/4a nodes and children to level 2a,4/4a, or 5 nodes. Nodal structure for level 4a should be binary unless a specific failure mode has multiple levels such as a leak being classified as minor or critical. Quantification methods for level 4a nodes are identical to those used on level 4 nodes in that they heavily depend on existing PRA data and utilize data-driven or expert elicited input to determine effect or constructing factors.

To reduce CPT complexity in lower levels of the hierarchy, it may be necessary to link the failure effects of multiple components failure modes together in an intermediate level 4a node.

When determining areas where an intermediate node is needed, it is best to determine whether the effect of a failure mode is the same or similar enough to another failure mode existing in the system. These common failure effects can be found across multiple components and instead of having multiple connection between these failure modes and the associated system measurement, an intermediate node is created that combines the total effect and probability of the results from this group of failure modes as illustrated in Figure 14 below.

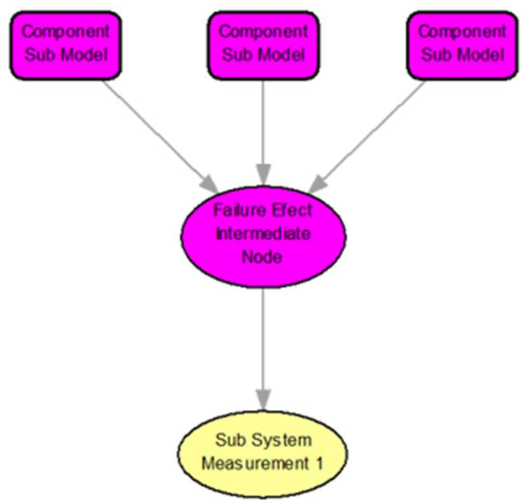

Figure 14: Example Level 4a Intermediate Failure Effect Node Modeling

3.2.6 Level 5: Causal Factors

The final level of the framework is the addition of causal factor considerations into the failure and degradation of system functionality. Level 5 nodes only receive input from other level 5 nodes but can provide input as parent nodes to level 2a, 3,4/4a, and level 5 nodes. This 5th level represents operational conditions or aspects of the system resulting from a certain type of mission set and offers the greatest potential for adding in adaptability to the model.

When creating level 5 nodes from the list of causal factors for component failure modes, the causal factors tree should only be broken out as far as needed to show the full range of external factors the system may experience. Implementing this methodology allows for easy integration of readily available operational data that can be used to create an accurate prior compared to the more specific data required to inform lower-level items. Figure 15 below shows this concept when applied to the operation of a diesel engine. Early models may only choose to utilize information regarding the operating mission or area of responsibility an asset is operating in but in later iterations of the model this causal factor can be expanded upon to a more granular level being used to inform more complex eternal operational characteristics which have been noted as causal factors in the failure probabilities of certain components.

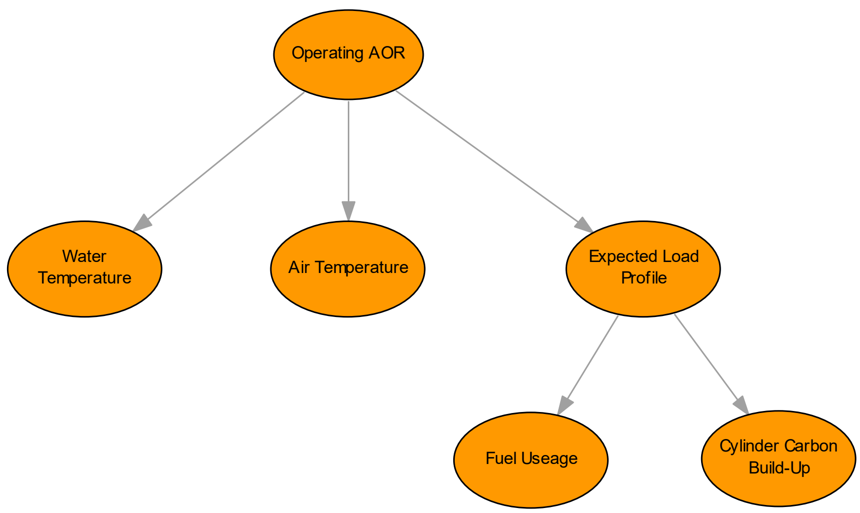

Figure 15: Example Causal Factor Network

3.3 Chapter Summary

This chapter completed Objective 2 by laying out the methodology for creating a BN-based failure detection network that utilizes a combination of PRA data and condition-based PHM sensor input to provide increased troubleshooting capability to stakeholders. The first step to complete this goal was to document procedures for collecting and organizing existing PRA and PHM data sources with example formats provided. Following guidance on data collection, the hierarchal structure of the methodology was laid out detailing node location and causal relationship of nodes across hierarchal level. An example BN structure was provided with this structure to illustrate placement of nodes within the network. Each nodal level was then discussed in detail with guidance on node quantification for state format(s) for each node provided.

4. Results

This chapter demonstrates the validity of the framework outlined in the previous section by first developing a maritime diesel engine model utilizing existing PRA data and fixed PHM structure and then running the model through a diagnostic procedure to show its capability as a FDD tool.

4.1 Developing Coast Guard Specific Model

To show the validity of the above framework, a proof-of-concept model was created for the Coast Guard FRC diesel engine. The resulting model exists to prove the validity of the modeling approach by demonstrating the principles of structure and operations. This model is a first iteration and has reduced system complexity to provide a clearer picture of the model's developmental process and use cases.

In organizations such as the Coast Guard where the number of identical assets numbers over 100, a generalized maintenance plan is created as it is often seen as the most cost-effective approach to designing a best fit plan for each asset. In Figure 16, taken from a 2021 FRC Engine Health Report, it is clear there is a large discrepancy in the distribution of planned operational loading changing the how the engine internally wears and performs [56]. As the Coast Guard maintenance plan relies on the PRA data-based on the expected load profile, this divergence has introduced a large amount of uncertainty regarding component performance and failure probability.

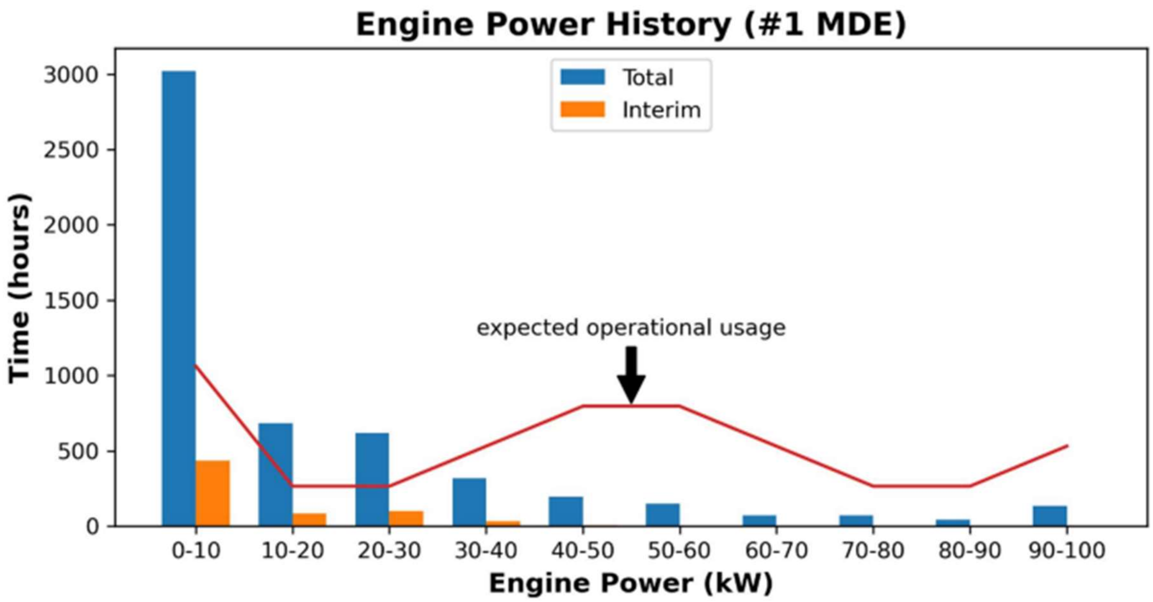

Figure 16: Example of engine power history data collected. From [56] Engine Power(Kw) Provided in Percentage of Rated Power

To close this gap, the Coast Guard has embraced and implemented additional condition-based maintenance concepts aimed at optimizing maintenance actions by utilizing PHM indicators to reduce the need for periodic based maintenance items or inspections. Assets in acquisition are being produced with sensors and indicators integrated into the system design, however, the current Coast Guard infrastructure does not have adequate processes in place to manage the increase in reliability monitoring data. In addition to the benefits conferred from a reduction in maintenance actions, the addition of improved monitoring capabilities will enable the Coast Guard to develop a more targeted approach to asset maintenance.

Input into the proof-of-concept model relies on a unique blend of PRA, PHM, and expert elicited data. Input data for this model was derived from a FMECA conducted by the engine Original Equipment Manufacturer (OEM) prior to commissioning of the first FRC in 2012 [57]. In addition to the failure modes outlined in the FMECA, Coast Guard Subject Matter Experts (SMEs) requested the addition of various consumable/degradation-based failures including various filter failures and cooler effectiveness losses. Probabilities for these added failure modes were created using expert elicitation. Measurement nodes were created using Piping and Instrumentation Drawings (P&ID) drawings with guidance for discretization taken from the FRC Engine Health Report [56], [58]. It was determined that the control and monitoring system for the engine was outside of the scope of this study and that all measurements provided by the system would be treated as perfect evidence.

4.1.1 FRC Engine Sub System Breakdown

To start the system decomposition, a list of sub system groups was created that will be used to group components later in the process. The engine OEM provides a recommend sub system breakdown based on functional grouping [9] which was followed with the exception of breaking down the combustion process and mechanical drive system. To reduce model complexity, these functional groups were combined into one sub system labeled “drive train” which provides the functions of providing torque to the propulsion line and providing exhaust to the exhaust manifold. The grouping and functions of each sub system is shown below in Table 5.

Sub System	Primary Function	Tertiary Function(s)	
Lube Oil System	Lubricate Engine Components	Cool Engine Components	~
Coolant System	Cool Lube Oil	Cool Charge Air	Cool Engine Components
Air System	Provide Charge Air to Combustion Chamber	Exhaust Combustion Gases to Environment	~
Fuel System	Provide Fuel to Injectors	~	~
Raw Water System	Cool Coolant	~	~
Drive Train System	Provide Torque to Propulsion Line	Provide Exhaust Gases to Exhaust System	~

Table 5: FRC Engine Sub System Breakdown

With the sub systems decided upon, the next step is creating Block Flow Diagrams (BFDs) for each medium transfer system. BFDs are built with information from Coast Guard provided P&IDs [58] and validated by Coast Guard SMEs. The participating SMEs consistent of:

- Coast Guard Diesel Engine Equipment Specialist: 48 Years' Experience
- Coast Guard Diesel Engine Equipment Specialist: 35 Years' Experience
- Coast Guard Diesel Engine Data Analyst: 32 Years' Experience
- Coast Guard Diesel Engine Data Analyst: 16 Years' Experience

The BFDs contain additional components not considered in this study to allow for use of the diagrams in future studies, including the addition of various valves and pre-operation features such as the lube oil system pre-lube pump. Figures 17 – 21 show P&IDs for the lube oil system, coolant and raw water system, air system, and fuel system, respectively.

The lube oil system for the FRC's diesel engine is a self-contained system drawing and depositing lube oil from a central sump and utilizing a combination of internal step filters and a centrifugal oil purifying system to remove carbon buildup from the oil. The lube oil system must be manually filled from an external system; for the purposes of this study, the system will be assumed to have had adequate lube oil prior to start. The lube oil is pumped from the sump through the lube oil cooler then fed through the filtration system before being sent throughout the engine to provide lubrication and cooling to a variety of components located central to the engine in the main gallery. The loop is then closed as all lubrication points drain down to the lube oil sump before the process begins again.

The lube oil system has multiple points of interaction with other systems. This introduces performance dependencies across sub systems. Points of interaction include the coolant system via the lube oil cooler, which in addition to being the main source of lube oil cooling also introduces the possibility of coolant contaminating the lube oil. Additional fluid touch points exist with the fuel system at the point of combustion and the exhaust system at the point of combustion as well as in the turbo chargers. The lube oil BFD is shown below in Figure 17.

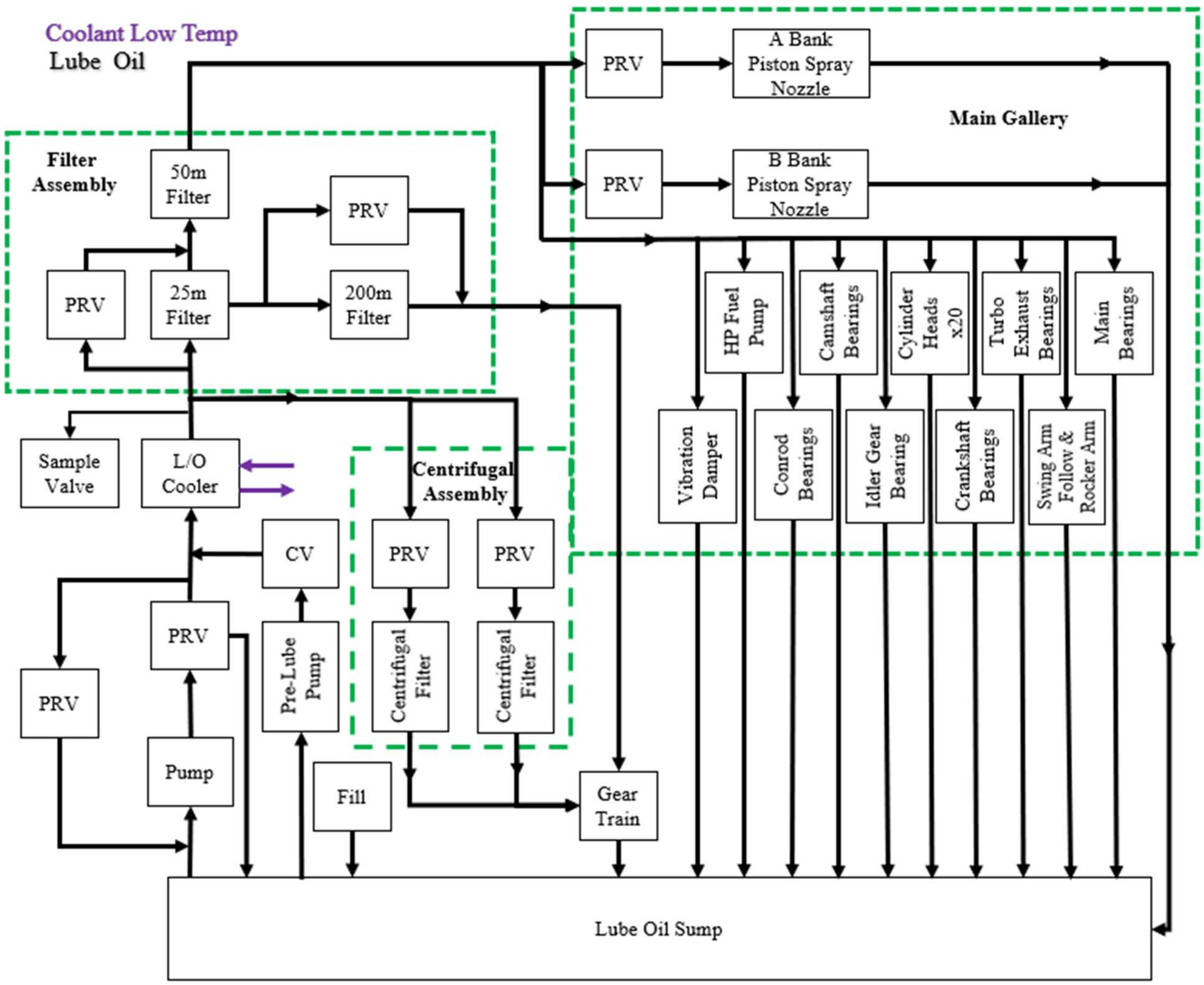

Figure 17: Coast Guard FRC Engine Lube Oil System BFD

Due to the relevantly small size of the raw water system and its limited interaction with the engine, the coolant and raw water system BFDs were combined into one BFD. The coolant system on the FRC's diesel engine is a self-contained, closed loop system requiring external intervention to fill. The coolant system path has two loops: low temperature side and high temperature side. The low temperature side of the system, shown in a light purple color in the BFD, provides cooling to the lube oil cooler, charge air cooler, and turbo intakes. The high temperature loop, shown in dark purple in the BFD, flows to the combustion and exhaust portions of the engines which operate at a higher temperature. The coolant system does not have a sump where coolant accumulates but does include a head tank placed above the engine that maintains positive pressure throughout the system. As the coolant system provides cooling to the lube oil system and both sides of the air system, there is dependency across these sub systems as well as a dependency between the coolant and raw water systems.

The raw water system for the engine pulls sea water from a dedicated sea chest through a strainer before splitting the stream, with part of the flow being routed to the propulsion reduction gear and the other being fed into the coolant cooler before being sent overboard. The other stream of raw water will not be considered in this research as it continues to feed into other systems outside of the engine. As stated above the raw water's only interaction with the engine is via the coolant cooler, making the two systems heavily dependent. The coolant and raw water BFD is shown below in Figure 18.

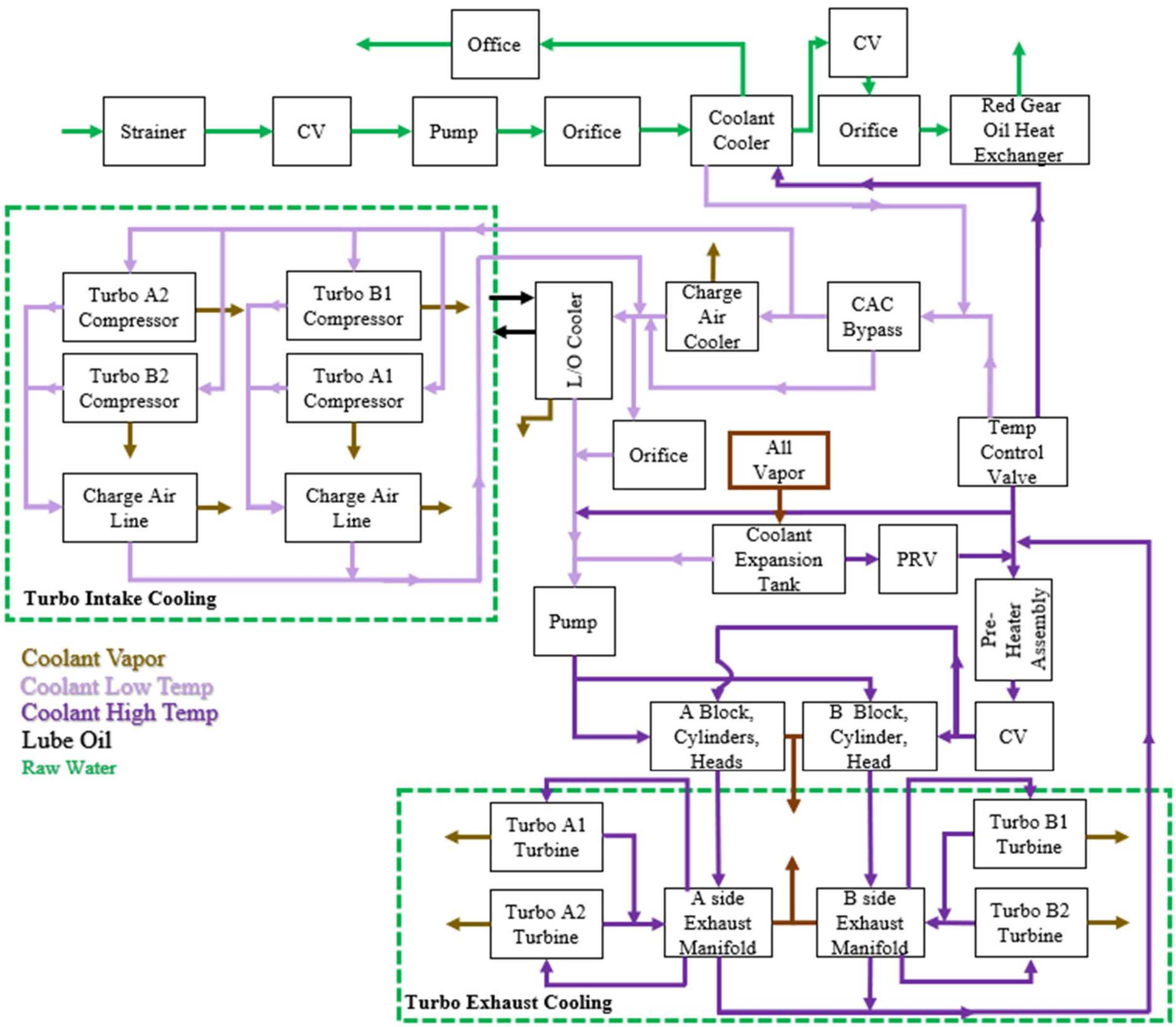

Figure 18: Coolant and Raw Water Systems BFD

The air system for the FRC diesel engine consists of the intake/charge air side and the exhaust side. The air system draws from external to the ship utilizing vacuum created by the intake portion of the turbo(s). The pressurized air, referred to as charge air, is then sent through the charge air cooler before it is distributed via a charge air manifold to the individual combustion chambers, where it is used as a component in the combustion process. Coming out of the combustion chamber, the now exhaust-laden air is fed through the exhaust manifold before being distributed to the exhaust sides of the turbos, while also siphoning fumes from the crankcase via the crankcase breather before it is eventually sent overboard. The turbochargers on this engine are load-activated and the exhaust flap in from the exhaust portions of Turbo A2, B1, and B2 will systematically open as the demand on the engine is increased. The exhaust system has multiple touch points with other systems as outlined in previous sections, but its largest dependence comes from the coolant system's interaction in the charge air cooler. The air system BFD is shown below in Figure 19.

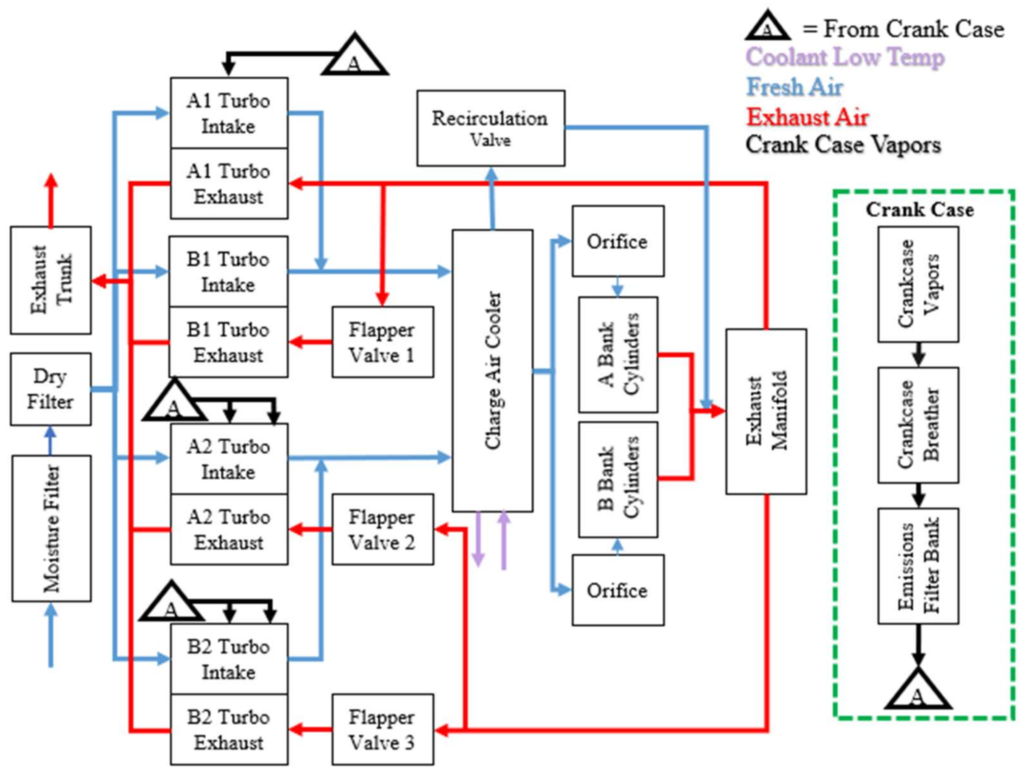

Figure 19: Air System BFD

The fuel system for the FRC diesel engine is responsible for taking fuel from the diesel service tanks, running it through various step filters, and pressurizing it prior to delivering it to the combustion chamber via cylinder fuel injectors. Fuel is drawn directly from the service tank by the fuel delivery pump and then sent at a lower pressure through a series of three filter assemblies to remove sediment and other impurities from the fuel. Following filtration, the fuel is pressurized further in the high-pressure pump before being sent through the high-pressure accumulator and fuel manifold to be distributed to each fuel injector. Fuel not expended in the combustion process is recirculated back to the fuel delivery pump, passing through a fuel cooler before returning to the draw point to run through the system again. The fuel system diagram is provided below in Figure 20.

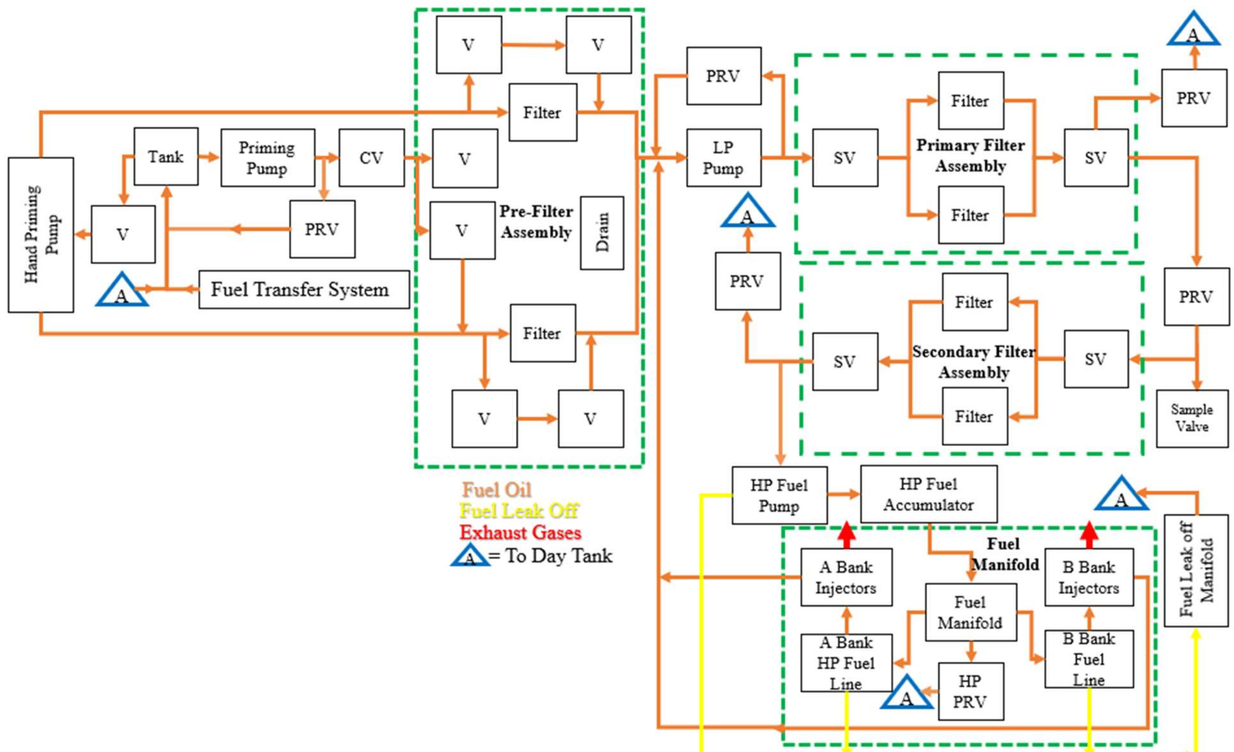

Figure 20: Fuel Oil System BFD

Using the above diagrams as well as input from SMEs, a component list was generated that served as the bounds for the system scope. The list of components was reduced to only include those necessary to the operation of the engine and which had sufficient base FMECA data to create a model structure without additional data collection. This list in shown below in Table 6.

Diesel Engine Component List	
Lube Oil Pump	Fuel Delivery Pump
Lube Oil Centrifugal	High Pressure Fuel Pump
Lube Oil Cooler	High Pressure Fuel Accumulator
Lube Oil Filter	Raw Water Pump
Lube Oil Pan	Crankshaft
Crankcase Breather	Drive Gear
Coolant Pump	Vibration Damper
Coolant Cooler	Crankcase
Intake Air Filter	Camshaft
Exhaust Manifold	Pistons
Air/Exhaust Control Flaps	Valve Drive
Exhaust Flap Actuating Cylinder	Cylinder Head
Charge Air Manifold	Cylinder Liner
Charge Air Cooler	Fuel Injector
Turbos	HP Fuel Line
Fuel Filters	

Table 6: FRC Diesel Engine Major Component List

The Coast Guard FRC's diesel engine consists of a 20-cylinder configuration with four turbos whose operation is dependent on requested load. For the purposes of this study, components with a population greater than one will be treated as a single entity. The model complexity necessary to accurately depict the dependency between cylinders both in pairs and in a whole, and dependency amongst turbos was deemed outside the scope of this research.

Using the list of components, the BFDs, and OEM specifications, components were categorized according to the system they provided the greatest value to. The resultant breakdown is shown in Table 7 with the primary and tertiary function of each sub system grouping.

Component	Primary Sub System	Tertiary Touch Points		
Lube Oil Pump	Lube Oil System	Drive Train		
Lube Oil Centrifugal	Lube Oil System			
Lube Oil Cooler	Lube Oil System	Coolant System		
Lube Oil Filter	Lube Oil System			
Lube Oil Pan	Lube Oil System			
Crankcase Breather	Air System	Lube Oil System		
Coolant Pump	Coolant System	Drive Train		
Coolant Cooler	Coolant System	Raw Water		
Intake Air Filter	Air System			
Exhaust Manifold	Air System	Coolant System		
Air/Exhaust Control Flaps	Air System			
Exhuast Flap Actuating Cylinder	Air System			
Charge Air Manifold	Air System			
Charge Air Cooler	Air System	Coolant System		
Turbos	Air System	Lube Oil System	Coolant System	
Fuel Filters	Fuel System			
Fuel Delivery Pump	Fuel System			
High Pressure Fuel Pump	Fuel System	Drive Train	Lube Oil System	
High Pressure Fuel Accumulator	Fuel System			
Raw Water Pump	Raw Water System	Drive Train		
Crankshaft	Drive Train	Lube Oil System		
Drive Gear	Drive Train	Lube Oil System		
Vibration Dampner	Drive Train	Lube Oil System		
CrankCase	Drive Train	Lube Oil System	Coolant System	Air System
Camshaft	Drive Train	Lube Oil System		
Pistons	Drive Train	Lube Oil System	Air System	
Valve Drive	Drive Train	Lube Oil System	Air System	
Cylinder Head	Drive Train	Coolant System	Lube Oil System	Air System
Cylinder Liner	Drive Train	Coolant System	Lube Oil System	Air System
Fuel Injector	Drive Train	Fuel System		
HP Fuel Line	Drive Train	Fuel System		

Table 7: FRC Diesel Engine Component Sub System Allocation

4.1.2 System Measurements

The next step in the process was to list out areas for potential measurements and compare that to the sensors that the system has available. These values will be entered into the BN as direct evidence allowing for increased diagnostic capability. As system measurements are the primary areas for evidence to be input in the model, this process draws heavily from the PHM processes that the Coast Guard is currently implementing. Current PHM processes on the FRC engine rely heavily on OEM recommendations and the control and monitoring system integrated into the engine. As the Coast Guard's experience in the FRC field has grown, they have developed an internal PHM methodology that relies on trend analysis and expert elicitation to supplement the existing OEM structure.

The MTU20V4000M93 engine senor package is detailed in the Alarm Limit document that provides insight into the OEMs view of alarm importance and how each sensor relates to engine performance [59]. The engine is outfitted with an integrated control system that initiates a warning alarm if a set point is reached, followed by an automatic shutdown of the engine if parameter continues to degrade to another alarm point. For some alarms, an engine slowdown limit can be reached in which the control system will decrease the engine revolutions per minute. For the purposes of this research, slowdown limits on alarms will be viewed the same as shutdown alarms as they both indicate a failure to operate in the given condition.

Alarm set points are typically designated as either a fixed number, or in some cases follow a curve with set points varying throughout the RPM range of the engine [60]. Sensors with limits that included warning and shutdown points were easily transferable to the BN node states, as a shutdown point will translate directly to a failure of any functions that measurement is tied to. There are multiple sensors without slowdown or shutdown limits; an issue in this type of sensor cascades to a critical sensor capable of shutting down the system. Examples of these sensors are lube oil filter pressure differential that would cascade to affect the overall system pressure, or the system raw water pressure that would ultimately affect the temperature of the coolant. In cases where the OEM does not designate a failure state, expert elicitation was used.

The OEM onboard monitoring system does not provide any diagnostic capabilities that would provide insight into the cause(s) of an alarm. Instead, Coast Guard and OEM technicians use a proprietary tool to extract detailed logs of the engine performance including alarm history and sensor outputs over an extended period. These logs are prepared via a Python based filtering program developed by the Coast Guard and then manually reviewed by SMEs to isolate the source of the engine failure or performance degradation using base PRA data regarding component failure modes and effects, as well as experience-based input regarding past failures. The Coast Guard provides feedback on the engine in the form of an "MDE Health Report" which provides guidance on how to approach correcting the issue [56].

Using the list of sensors on the engine as well as input from Coast Guard SMEs regarding what additional input would assist in troubleshooting efforts, the below tables were generated. Table 8-11 below show the potential measurements with the integrated measurement points denoted in yellow.

Lube Oil System			
Location of Measurement	**Pressure**	**Temperature**	**Quality**
Lube Oil Pump Outlet	X		X
Lube Oil Filter Outlet	X		X
Lube Oil Cooler Outlet	X	X	X
Main Gallery Outlet		X	X
At Main Bearing	X	X	X
At Crankshaft Bearings	X	X	X
At Lube Oil Pan		X	X
Centrifugal Outlet	X		X

Table 8: FRC Engine Lube Oil System Measurement Locations

Coolant System			
Location of Measurement	**Pressure**	**Temperature**	**Quality**
Coolant Pump Outlet	X		X
Coolant Cooler Outlet	X	X	X
Lube Oil Cooler Outlet	X	X	X
At Temperature Control Valve		X	X
Exhaust Manifold Outlet	X	X	X
Turbo Outlet	X	X	X
Cylinder Liners Outlet	X	X	X
Cylinder Head Outlet	X	X	X

Table 9: FRC Engine Coolant System Measurement Location

Air System			
Location of Measurement	Pressure	Temperature	Quality
Into Air Filter	X	X	X
Out of Air Filter	X		X
Out of Turbo (Compressor Side)	X	X	X
Out of Charge Air Cooler	X	X	X
Out of Cylinder	X	X	X
Exhaust Comb	X	X	X
Exhaust Manifold		X	X
Out of Turbo (Exhaust side)	X	X	X
At Charge Air Sequence Valve	X	X	X

Table 10: FRC Engine Air System Measurement Location

Fuel System			
Location of Measurement	Pressure	Temperature	Quality
Delivery Pump Outlet	X	X	X
Pre Fuel Filter Outet	X		X
Primary Fuel Filter Outlet	X		X
Secondary Fuel Filter Outlet	X		X
HP Pump Outlet	X		X
High Pressure Accumulator Outlet	X	X	X
HP Line Outlet	X		X

Table 11:FRC Engine Fuel System Measurement Location

Raw Water System			
Location of Measurement	Pressure	Temperature	Quality
Raw Water Pump Outlet	X	X	X
Coolant Cooler Outlet	X	X	X

Table 12:FRC Engine Raw Water System Measurement Location

A common theme across the sub systems was that each sub system was equipped with both pressure and temperature monitoring equipment but did not have a variety of sensor locations within the system. Additionally, none of the systems had internal quality control sensors as the Coast Guard relies on manual extraction and testing of each medium. In addition to the fluid medium-based sensor reading, Coast Guard SMEs requested that the initial model also include consideration of the turbo(s) speed as well as the fuel injection quantity requested by the control unit. In future models, turbo speed will provide a more crucial role in determining the operational status of each of the engine's four turbos, allowing for inference into load issues. Currently, the model will only use this information to inform charge air pressure and exhaust comb temperatures measurement. Similarly, the fuel injection quantity is an excellent indicator of the external load being placed on the engine, but in the current model is limited to allowing inferences to be made regarding the status of the drive train equipment rollers. Future iterations of this model will be able to consider these factors to improve model accuracy and diagnostic capabilities.

4.1.3 PRA and Causal Factors

For this research, the Coast Guard provided an FMECA provided to the organization during acquisition by the OEM. Due to the proprietary information regarding component design, the resultant FMECA will not be displayed in this research but can be requested from the author of this publication.

When considering what causal factors to integrate into this model, the main goal is to find a way to adapt the model to a varying operational profile. While there exist other external factors that may play into the failure probability of the engines, the concept of operational profile combines the largest differences a cutter crew experiences. The operational profile describes where the FRC is operating and its operational use. The first iteration of this model focused on where the FRC was being operated. Much of the engine is self-contained, but it requires input from external sources for both the raw water and the air systems, as these are open to the environment, and both are subject to large temperature and characteristic differences depending on the FRC's operating location. This research focused on the effect of the temperature of each of these mediums as it varied the most across operational locations, while characteristics such as water salinity or air humidity were found to have a smaller effect on performance.

With the above taken into consideration, the two causal factors integrated into the model were Raw Water Temperature and Intake Air Temperature. Obtaining priors accurate to the FRC fleet would require detailed analysis of projected asset location accounting for time of year. As the main use case for this model is diagnostic capability and evidence will always be provided to this node, a generic prior was provided that reflected low probability of being in a high or degraded area. Future iterations of this model can integrate operational tasking information to develop more detailed priors regarding the environmental conditions.

4.1.4 Model Structure

The resultant model static BN was created using Bayes Fusion GeNIe [55]. The model consists of 225 nodes with the level breakdown down presented in Table 13.

Node Level	Nomenclature	Quantity
5	Causal Factors	2
4a	Failure Modes and Effects	144
4	Components	42
3	Measurements	19
2a	Sub System Functions	11
2	Sub Systems	6
1	System	1
	Total	**225**

Table 13: Summary of FRC Engine Model Nodes by Framework Level

Tables showing node nomenclature along with child and parent relationships is provided in Appendix A with the model structure shown below in Figure 21. A larger version of Figure 21 as well as a breakdown of all Sub Models is shown in Appendix B.

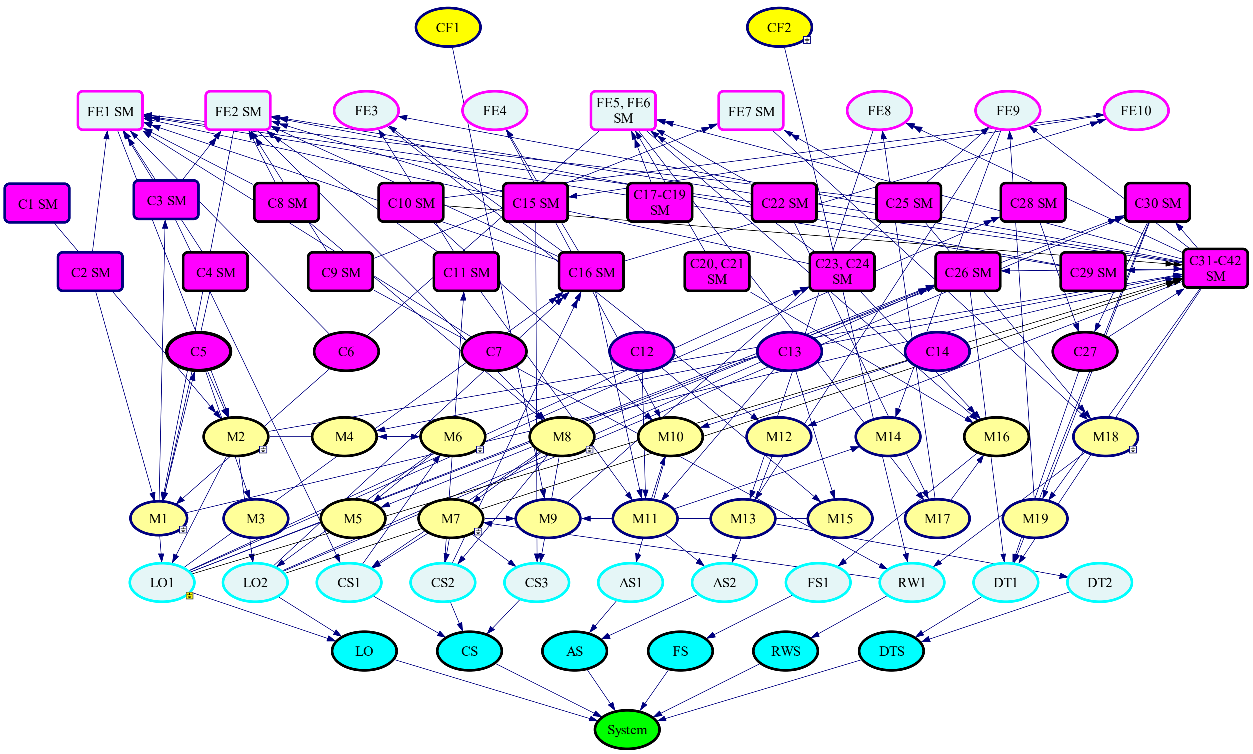

Figure 21: Coast Guard FRC Model

Quantification of the model showed a baseline system failure probability of 1.67E-03 failures per operating hour. The sub system with the highest failure probability was found to be the lube oil system, followed by the coolant and raw water systems. These results along with the remaining level 2 nodes are shown below in Table 14.

Node ID	Nomenclature	Normal	Degraded	Failed
DT	Drive Train System	1.00E+00	1.20E-06	2.93E-05
RW	Raw Water System	9.99E-01	7.80E-04	1.65E-04
FS	Fuel System	1.00E+00	1.16E-06	2.70E-05
AS	Air System	1.00E+00	1.35E-07	2.23E-05
CS	Coolant System	9.97E-01	1.81E-03	7.00E-04
LO	Lube Oil System	9.98E-01	5.37E-04	1.31E-03
System	Engine	9.98E-01	-	1.67E-03

Table 14: FRC Engine Summary of Level 1 and Level 2 Nodes

The main use case of this model in its current iteration is diagnostic reasoning, making the system node number less important than the proportion of this number given to each sub system and component. In future iterations when less assumptions are made, the model can provide greater insight into the likelihood of engine failure.

4.1.5 Model Verification and Discussion of Results

Verification efforts were conducted with Coast Guard SMEs focusing on model utility and the representation of causal dependency amongst sub systems. Coast Guard SMEs had over 30 years of combined experience with the FRC platform and over 100 years of engine maintenance and analytic experience. A consensus was reached that the model provided meaningful utility for diagnostic capabilities on the engine's main fluid systems, and that it successfully provided additional insight into the causes of these sub system faults beyond that currently available onboard the ships. Additionally, Coast Guard SMEs agreed that the model has limited usability for diagnosing drive train and air system issues, as the current model oversimplifies these components, severely limiting the model's ability to account for degradation within these sub systems. The model does provide indications of issues within the system, but the model depth in this area must be improved before it could be an diagnostics tool for these issues. As previously mentioned, the addition of these components is critical for the next model's iteration but will require extensive work to quantify the effects of component dependency.

4.2 Use Case: Diagnostic Capability for Elevated Lube Oil Temperature

To demonstrate the model's usability as a diagnostic tool, the model was run through a troubleshooting scenario initiated by the operator of the FRC engine receiving an alarm indicating an elevated lube oil temperature. In this scenario, the engine has been running a constant load and there are no contributing external factors. This model can accept all sensor-based evidence at one time, but as this model is improving upon traditional methodologies, a step-based evidence approach will be used to show the effect of each evidence node first. After each layer of evidence, the resultant causes and ramification of the evidence will be explored and documented. While every node in the model is affected by the application of evidence to nodes withing the model, the below tables only show the effect on the most relevant nodes to the troubleshooting process as displaying the effect across all 225 nodes isn't needed to show the failure diagnostic capabilities.

Introduction of the initial evidence was completed by setting node M6 representing "Lube Oil Temperature out of Cooler" to the degraded intermediate step representing an elevated temperature. The result of this change on node M6's direct parents is outlined in Figure 22 below:

				Prior			Evidence	Posterior		
Node ID	**Level**	**Node Nomenclature**	**Parents**	**Normal**	**Degraded**	**Failed**		**Normal**	**Degraded**	**Failed**
M6	3	Lube Oil Temperature out of Cooler	CS1, M2	9.97E-01	1.74E-03	9.56E-04	**Lube Oil Temperature "Elevated"**	0.00E+00	**1.00E+00**	0.00E+00
Direct Parents										
M2	3	Lube Oil Pressure out of Pump	C1A, C1B, C5, FE1	1.00E+00	3.36E-05	9.72E-06		9.96E-01	3.88E-03	5.60E-09
CS1	2a	Cool Lube Oil	C3E, M7, M8	9.97E-01	2.31E-03	4.81E-04		3.85E-03	9.96E-01	8.85E-11

Figure 22:FRC Engine Model Propagation of Initial Evidence of Elevated Lube Oil Temperature

Analysis of these results show high dependency on the “Cool Lube Oil” (CS1) node and the “Lube Oil Pressure” (M2). As CS1 is not a measurable metric, it must be quantified by analyzing the parents while M2 can be informed by using the ship’s monitoring system.

In this scenario, the sensor representing the M2 node came back with a reading of *normal*. This evidence was then entered into the model, informing the remainder of the target nodes as shown below in Figure 23.

				Prior			Evidence	Posterior		
Node ID	**Level**	**Node Nomenclature**	**Parents**	**Normal**	**Degraded**	**Failed**		**Normal**	**Degraded**	**Failed**
M6	3	Lube Oil Temperature out of Cooler	CS1, M2	0.00E+00	**1.00E+00**	0.00E+00	**Lube Oil Pressure "Normal"**	0.00E+00	**1.00E+00**	0.00E+00
M2	3	Lube Oil Pressure out of Pump	C1A, C1B, C5, FE1	9.96E-01	3.88E-03	5.60E-09		**1.00E+00**	0.00E+00	0.00E+00
Direct Parents										
CS1	2a	Cool Lube Oil	C3E, M7, M8	3.85E-03	9.96E-01	8.85E-11		0.00E+00	1.00E+00	0.00E+00
C3E	4a	Lube Oil Cooler Efectivness	M1	1.21E-01	8.47E-01	3.24E-02		1.18E-01	8.50E-01	3.25E-02
M7	3	Coolant Temperature out of Cooler	M8, RW1	8.82E-01	9.22E-02	2.54E-02		8.82E-01	9.25E-02	2.55E-02
M8	3	Coolant Pressure out of Pump	C8C, FE2	1.00E+00	3.57E-04	4.69E-06		1.00E+00	3.59E-04	4.67E-06

Figure 23: FRC Engine Model Propagation of Lube Oil Pressure Evidence

The results from the expansion of CS1 and the evidence M2 above indicate that the initial evidence is a direct result of the degradation of the CS1 which is influence by “Lube Oil Cooler Effectiveness” (C3E), Coolant Temperature (M7), and Coolant Pressure (M8). With this level of information, the most probable cause of the initial issue is the degradation of C3E. As C3E is not a measurable function, it must be broken into its constituent parts for further analysis, while M7 and M8 can be informed using the ships monitoring system.

In this scenario the sensor representing M7 provides a reading of elevated temperature while the M8 Sensor provides a reading within the normal range. M7 is informed by RW1 and M8, but as M8 was found to be within normal operating range, it will be excluded from further analysis. RW1 was broken into its parent nodes as it cannot be informed with direct evidence.

Using the additional information regarding the M7 and M8 sensors, the model was updated providing the results shown below in Figure 24.

				Prior			Evidence	Posterior		
Node ID	**Level**	**Node Nomenclature**	**Parents**	**Normal**	**Degraded**	**Failed**		**Normal**	**Degraded**	**Failed**
M6	3	Lube Oil Temperature out of Cooler	CS1, M2	0.00E+00	**1.00E+00**	0.00E+00		0.00E+00	**1.00E+00**	0.00E+00
M2	3	Lube Oil Pressure out of Pump	C1A, C1B, C5, FE1	**1.00E+00**	0.00E+00	0.00E+00		**1.00E+00**	0.00E+00	0.00E+00
M7	3	Coolant Temperature out of Cooler	M8, RW1	8.82E-01	9.25E-02	2.55E-02	**Coolant Temperature "Elevated"**	0.00E+00	**1.00E+00**	0.00E+00
M8	3	Coolant Pressure out of Pump	C8C, FE2	1.00E+00	3.59E-04	4.67E-06		**1.00E+00**	0.00E+00	0.00E+00
Direct Parents										
CS1	2a	Cool Lube Oil	C3E, M7, M8	0.00E+00	1.00E+00	2.78E-07		0.00E+00	1.00E+00	0.00E+00
C3E	4a	Lube Oil Cooler Efectivness	M1	1.18E-01	8.50E-01	3.25E-02		9.93E-01	7.06E-03	1.22E-04
RW1	2a	Cool Coolant	C9E, CF2, M18	8.82E-01	1.01E-01	1.70E-02		0.00E+00	1.00E+00	0.00E+00
Second Level Parents										
M1	3	Lube Oil Quality	C2A, C4FM2	1.00E+00	3.50E-05	4.99E-05	**Coolant Pressure "Normal"**	1.00E+00	2.80E-06	2.63E-06
C9E	4a	Coolant Cooler Effectiveness	N/A	8.86E-01	1.02E-01	1.15E-02		4.16E-02	9.14E-01	4.44E-02
CF2	5	Raw Water Temperature	N/A	9.95E-01	3.77E-03	1.37E-03		9.58E-01	2.94E-02	1.28E-02
M18	3	Raw Water Pressure out of Pump	C25A, C25B, FE7	1.00E+00	1.77E-05	2.10E-04		1.00E+00	1.63E-04	2.41E-04

Figure 24: FRC Engine Model Propagation of Coolant Temperature and Pressure Evidence

The addition of the evidence regarding M7 and M8 reduced the likelihood of C3E being the primary cause of the initial issue but did not remove it. This probability can be further informed by getting evidence on the “Lube Oil Quality” (M1) node, which in this system requires a manual test. In addition to the inference on the state of C3E, the evidence showed a high dependency on “Coolant Cooler Effectiveness” (C9E), “Raw Water Temperature” (CF2), and “Raw Water Pressure” (M18). Information of C9E cannot be found without depot-level maintenance on the engine, but nodes CF2 and M18 are monitored via the engine monitoring system.

In this scenario, both sensors for M7 and M8 came back reading in the normal range and the manual lube oil test came back with a reading of normal as well. This evidence was then entered into the model providing the results shown in Figure 25.

				Prior			Evidence	Posterior		
Node ID	Level	Node Nomenclature	Parents	Normal	Degraded	Failed		Normal	Degraded	Failed
M6	3	Lube Oil Temperature out of Cooler	CS1, M2	0.00E+00	**1.00E+00**	0.00E+00	**Raw Water Temperature "Normal"**	0.00E+00	1.00E+00	0.00E+00
M2	3	Lube Oil Pressure out of Pump	C1A, C1B, C5, FE1	**1.00E+00**	0.00E+00	0.00E+00		**1.00E+00**	0.00E+00	0.00E+00
M7	3	Coolant Temperature out of Cooler	M8, RW1	0.00E+00	**1.00E+00**	0.00E+00		0.00E+00	**1.00E+00**	0.00E+00
M8	3	Coolant Pressure out of Pump	C8C, FE2	**1.00E+00**	0.00E+00	0.00E+00		**1.00E+00**	0.00E+00	0.00E+00
CF2	5	Raw Water Temperature	N/A	9.95E-01	3.77E-03	1.37E-03	**Raw Water Pressure "Normal"**	**1.00E+00**	0.00E+00	0.00E+00
M18	3	Raw Water Pressure out of Pump	C25A, C25B, FE7	1.00E+00	1.77E-05	2.10E-04		**1.00E+00**	0.00E+00	0.00E+00
M1	3	Lube Oil Quality	C2A, C4FM2	1.00E+00	2.80E-06	2.63E-06		**1.00E+00**	0.00E+00	0.00E+00
		Direct Parents								
CS1	2a	Cool Lube Oil	C3E, M7, M8	0.00E+00	1.00E+00	2.78E-07	**Lube Oil Quality "Normal"**	0.00E+00	1.00E+00	0.00E+00
C3E	4a	Lube Oil Cooler Efectivness	M1	9.93E-01	7.06E-03	1.22E-04		**9.93E-01**	**7.06E-03**	**1.22E-04**
RW1	2a	Cool Coolant	C9E, CF2, M18	8.82E-01	1.01E-01	1.70E-02		0.00E+00	1.00E+00	0.00E+00
C9E	4a	Coolant Cooler Effectiveness	N/A	4.16E-02	9.14E-01	4.44E-02		**0.00E+00**	**9.54E-01**	**4.64E-02**

Figure 25: FRC Engine Model Propagation of Lube Oil Quality, Raw Water Pressure, and Raw Water Temperature Evidence

The results shown above outline potential causes of the initial issue being the Coolant Cooler Effectiveness(C9E) or Lube Oil Cooler Effectiveness(C3E). The model shows that either or both nodes, being degraded, failed or a combination of both, are the source of the elevated lube oil temperature. As both nodes cannot be informed any further without depot-level maintenance, the most time and cost-efficient maintenance methodology would be to first replace/repair the Coolant Cooler as the model states it is either degraded or completely failed, while the Lube Oil Cooler has a high probability of not being the issue. The posterior model showing the propagation of the evidence chain following discovery of the initial issue and investigation efforts is show below in Figure 26.

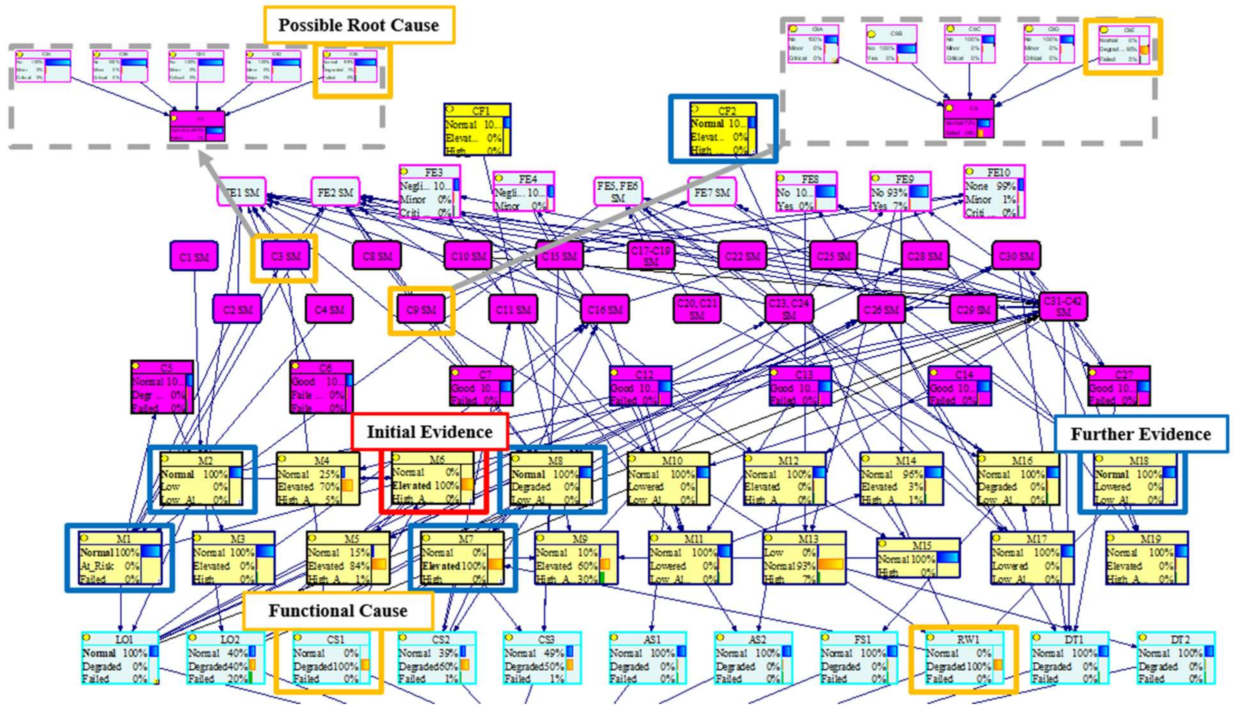

Figure 26: FRC Engine BN FDD Final Posterior Model

4.3 Chapter Summary

The purpose of this chapter was to validate the methodology proposed in Objective 2 by first creating and then testing a BN created using the framework outlined in the previous chapter. Using the existing PRA data, the Coast Guard had for the FRC diesel engines data was first organized and then mapped onto a BN using Bayes Fusion GeNIe. This model's failure diagnostic capability was then evaluated using a test case where the operator receives an alarm notifying them of an elevated lube oil temperature. Results for the case study were presented stepwise to show comparison to traditional troubleshooting methods with evidence applied as its need is discovered. The resultant posterior model was then presented, and the results discussed.

5. Conclusions

5.1 Technical Contributions

This research provided the following technical contributions:

1. A structured analysis of gaps in the reliability field as applied to maritime diesel engines.
2. A methodology outlining an iterative approach to updating existing PRA data with PHM input using a BN to support maritime diesel engine fault diagnosis.
   - Created a hierarchal organization of a maritime diesel engine integrating functional decomposition with sub system health metrics.
   - Outlined procedure for manipulation of existing FMECA data for a maritime diesel engine into a BN-based FDD structure.
   - Defined causal relationships amongst hierarchical levels allowing for representation of causal dependency across sub systems.
   - Identified avenues for integration of operational environment and concepts into existing structure allowing for increased model accuracy across varying operational profiles.
3. A model that demonstrates applicability through the creation and testing of a model based on the engine for a Coast Guard FRC.
4. A validated model that demonstrates usability through execution of diagnostic use case scenario.

In the modern era of military operations, asset capabilities are stretched and altered on nearly a yearly basis, presenting decision makers the unique problem of either having to create a generalized maintenance plan that tends to decrease asset availability or to develop an adaptable condition-based maintenance plan that accommodates a more fluid operational profile. By applying the framework developed herein to a project such as the Coast Guard's FRC diesel engine, stakeholders will receive a model that can be utilized immediately to detect system abnormalities that integrates the PHM capabilities built into the system as well as the base PRA knowledge received during acquisition and collected over the first 10 years of the platforms operation. Integration of this framework into daily maintenance and troubleshooting allows for improved data usage as well as provides stakeholders with key information regarding effects of changing operations and mission profile on life cycle logistics consideration.

5.2 Recommendations and Future Work

Current research within the maritime engine reliability field has been focused on gaining insight into individual component and sub system health. The methodology developed in this research presents a structured format for integrating the work currently being conducted into a single model that provides a holistic view of the engine's health. While the model created in Chapter 4 primarily focused on utilizing FMECA mapping and quantification of failure effects, the causal reasoning and nodal structure presented in Figure 5 serves as a foundation for future integration of other PRA methodologies.

The model created and tested in Chapter 4 makes simplifications to the overall structure of the engine that lowered diagnostic capabilities of the model and decreased the usability of the model as a predictive tool. Expanding the model to incorporate a greater range of components within the engine will also facilitate a more detailed view of the system but will result in a much larger and potentially more complicated model. Additional research must be conducted to apply this framework to model the drive train and air sub systems of the engines. These two sub systems were the principal areas of simplification in the engine as multiple iterations of similar components were combined under a single node. The expansion of these sub systems to accurately represent the operations of 20 cylinders within the engine and four turbochargers will require further research into the common cause failures as well dependency across the multiple iterations of components. As the engine can operate in a degraded state where one or more of the cylinders or turbos is partially failed, quantification of these relationships and their effect on the systems overall performance will require a more complex representation of these sub systems within the model.

Another aspect not explored in this research was the concept of component age and wear on the probabilities of each failure mode. The failure probabilities used to populate component CPTs reflect a good-as-new system absent of any wear. As with most complex systems, components within the FRC's diesel engine wear at different rates and depend on the status of the engine within its maintenance cycle. A more accurate model would allow for user input of component or system age that will modify the CPTs within the model. There are various methods for integrating this functionality into the model, including introducing a Python wrapper as a user interface to modify the CPTs based on operator input. Additional research into the feasibility of each method is needed before this step can be added to the methodology. Like the addition of age, the effect and impact of the human element of the system was not analyzed but could be added to improve the coverage of the model. By including human factors into the model, it allows for inclusion of maintenance induced error or operator error that may have influenced select failure modes

One of the key characteristics of this model is it assess the status of the system or a component at a specific point in time. This is because the methodology relies on a static BN structure which is unable to analyze the effects of individual failures on the system throughout time. While this characteristic of the methodology limits its use in predictive failure analysis and severely impacts its ability to project failures, the resultant model successfully acts as a failure diagnostic tool. Translating this methodology and associated hierarchal and causal categorization into a simulation-based environment such as a DBN may provide a solution to this gap in model reach, but additional research should be conducted on a simpler system before scaling the model up to the complexity represented in this research. In addition to these benefits, DBN based models may offer the opportunity to shift node structure away from the binary and ternary discrete ranges used in this methodology to a wider range of values that provides a more granular approach to performance degradation.

Further research is also needed to document and utilize effective language when describing failure mechanisms and failure effects at the component and system level. The variability in detail in which a failure mechanism or failure effect is currently documented can drastically increase the difficulty in modeling complex causal pathways. Current industry practices outline the need to document failure effects across various levels of system function hierarchy but have few requirements regarding documentation of causal factors influencing the probability of the failure mechanism. Improving this aspect of how risk is communicated, along with standardizing language used in documenting both failure effects and mechanisms, would improve the ability to model connections between one component's failure effect and another's failure mechanism.

5.3 Anticipated Impact

This research provides a basis for the Coast Guard to begin improving their existing reliability practices for the FRC and potentially other assets within their fleet by embracing concepts of SIPPRA. The methodology presented in Chapter 3 provides guidance on how to use reliability engineering practices to develop the FRC diesel engine model. In Chapter 4, the methodology was implemented to create a full-scale diesel engine model, thereby demonstrating suitability for purpose. Furthermore, it also serves as a guide for creating similar models for their other platforms that utilize diesel engines. By embracing use of this methodology, the Coast Guard will be able to improve their utilization of the data provided by their engine monitoring systems to achieve a more accurate understanding of the engine's reliability. This increase in knowledge will directly enable more informed decision support at both the strategic and deck plate levels, leading to improvement in both the engine and overall cutters availability.

At a broader level, this research also demonstrates the validity of the SIPPRA methodology on a complex system in a previously untested application, maritime diesel engines. The methodology developed in Chapter 3 of this work was designed to support modeling of a maritime diesel engine, but the hierarchical rule set is easily transferable to any complex system as it relies on concepts of functional decomposition and creating connection based on causal flow. The diesel engine case study in Chapter 4 illustrates a method of updating knowledge of the systems reliability using PHM input from the system monitoring and control system for real engineering problems. Adapting this methodology for use on other complex systems creates the possibility of achieving equivalent results that provide more accurate, data-driven insights into system reliability.

Appendix A: List of Nodes

Node ID	Level	Node Nomenclature	Parents	Children	States
System	1	Engine	LO, CS ,AS, FS, RW, DT	N/A	2
LO	2	Lube Oil System	LO1, LO2	System	3
LO1	*2a*	*Lubricate Engine Components*	*M1, M2*	*LO, C16A, C16B, C16C, C16D, C23C, C23D, C23E, C23G, C23H, C26A, C26B, C28A, C28B, C30A, C30B, C30C, C42A, C42B, C42D*	*3*
LO2	*2a*	*Cool Engine Components*	*M2, M6*	*LO, C16A, C16B, C16C, C16D, C26A, C26B, C30C, C41A, C42A, C42C*	*3*
CS	2	Coolant System	CS1, CS2, CS3	System	3
CS1	*2a*	*Cool Lube Oil*	*C3E, M7, M8*	*CS, M6*	*3*
CS2	*2a*	*Cool Engine Components*	*M7, M8*	*CS, C11C, C16E, C16F*	*3*
CS3	*2a*	*Cool Charge Air*	*C15, M7, M8*	*CS*	*3*
AS	2	Air System	AS1,AS2	System	3
AS1	*2a*	*Provide Charge Air*	*M10*	*AS*	*3*
AS2	*2a*	*Exhaust Combustion Gases*	*M12, M11*	*AS*	*3*
FS	2	Fuel System	FS1	System	3
FS1	*2a*	*Provide Fuel to Injectors*	*M16*	*FS*	*3*
RW	2	Raw Water System	RW1	System	3
RW1	*2a*	*Cool Coolant*	*C9E, CF2, M18*	*M7, RW*	*3*
DT	2	Drive Train System	DT1, DT2	System	3
DT1	*2a*	*Translate Torque to Propulsion Line*	*C26,C27,C30, C31 IN1*	*DT*	*3*
DT2	*2a*	*Provide Cumbsition Gases*	*M13*	*DT*	*3*

Table 15:List of Level 1, 2, and 2a

Node ID	Level	Node Nomenclature	Parents	Children	States
M1	3	Lube Oil Quality	C2A, C4FM2	C33B, C37A, C37B, C3E, C5, LO1	3
M2	3	Lube Oil Pressure out of Pump	C1A, C1B, C5, FE1	C37A, LO1, LO2, M6	3
M3	3	Lube Oil Filter Differential Pressure	C5	N/A	3
M4	3	Lube Oil Splash Temperature	C41A, M6	N/A	3
M5	3	Main Bearing Temperature	C26A, M6	N/A	3
M6	3	Lube Oil Temperature out of Cooler	CS1, M2	LO2, M4, M5	3
M7	3	Coolant Temperature out of Cooler	M8, RW1	CS1, CS2, CS3, M9	3
M8	3	Coolant Pressure out of Pump	C8C, FE2	CS1, CS2, CS3, M7	3
M9	3	Charge Air Temperature	CF1, M15, M7	FE9	3
M10	3	Charge Air Pressure	C10A, C14, FE4, M11	AS1	3
M11	3	Turbo Speed	C11C, C12, C13, C16 IN1	M10, M14, AS2	3
M12	3	Crankcase Pressure	C41A, FE3	AS2	3
M13	3	Cylinder Exhaust Temperature	FE8, FE9	DTS	3
M14	3	Exhaust Comb Temperature	FE9, M11	N/A	3
M15	3	Air Temperature at Charge Air Sequence Valve	C12, C13	M9	2
M16	3	Fuel Pressure out of HP Pump	C23 IN1, FE5, M17, C21B, C24 IN1	FS1	3
M17	3	Fuel Pressure out of LP Pump	C22B, FE6	FE8, M16	3
M18	3	Raw Water Pressure out of Pump	C25A, C25B, FE7	RW1	3
M19	3	Inj v. DBR	C30A, C33A	FE9	3

Table 16: List of Level 3 Nodes

Node ID	Level	Node Nomenclature	Parents	Children	States
C1	4	Lube Oil Pump	C1A, C1B	*N/A*	2
C1A	*4a*	*Lube Oil Pump Failure to Operate*	*N/A*	*C1, M2*	*2*
C1B	*4a*	*Pressure Control Valve Stuck Open*	*N/A*	*C1, M2*	*2*
C2	4	Lube Oil Centrifugal	C2A, C2B	N/A	2
C2A	*4a*	*Lube Oil Centrifugal Failure to Operate*	*N/A*	*C2, M1*	*2*
C2B	*4a*	*Lube Oil Centrifugal External Lube Oil Leak*	*N/A*	*C2, FE1-A2*	*3*
C3	4	Lube Oil Cooler	C3A-E	N/A	2
C3A	*4a*	*Lube Oil Cooler Internal Lube Oil Leak*	*N/A*	*C3, FE1-B*	*3*
C3B	*4a*	*Lube Oil Cooler External Lube Oil Leak*	*N/A*	*C3, FE1-A2*	*3*
C3C	*4a*	*Lube Oil Cooler External Coolant Leak*	*N/A*	*C3, FE2-A4*	*3*
C3D	*4a*	*Lube Oil Cooler Internal Coolant Leak*	*N/A*	*C3, FE2-C1*	*3*
C3E	*4a*	*Lube Oil Cooler Effectiveness*	*M1*	*C3,CS1*	*3*
C4	4	Lube Oil Filter Assembly	C4A, C4B	N/A	2
C4A	*4a*	*Lube Oil Filter Assembly External Leak*	*N/A*	*C4, FE1-A2*	*3*
C4B	*4a*	*Lube Oil Filter Assembly Internal leaky*	*N/A*	*C4, M1*	*2*
C5	4	Lube Oil Filter	M1	M2, M3	3
C6	4	Lube Oil Pan	*N/A*	FE1-A2	3
C7	4	Crankcase Breather	*N/A*	FE-A1a	2
C8	4	Coolant Pump	C8A-C	N/A	2
C8A	*4a*	*Coolant Pump Oil Seal Failure*	*N/A*	*C8, FE1-A3*	*2*
C8B	*4a*	*Coolant Pump External Coolant Leak*	*N/A*	*C8, FE2-A4*	*3*
C8C	*4a*	*Coolant Pump Failure to Operate*	*N/A*	*C8, M8*	*3*
C9	4	Coolant Cooler	C9A-E	N/A	2
C9A	*4a*	*Coolant Cooler Internal Coolant Leak*	*N/A*	*C9, FE2-B*	*3*
C9B	*4a*	*Coolant Cooler Internal Raw Water Leak*	*N/A*	*C9, FE7-B*	*2*
C9C	*4a*	*Coolant Cooler External Coolant Leak*	*N/A*	*C9, FE2-A4*	*3*
C9D	*4a*	*Coolant Cooler External Raw Water Leak*	*N/A*	*C9, FE7-A*	*3*
C9E	*4a*	*Coolant Cooler Effectiveness*	*N/A*	*C9, RW1*	*3*
C10	4	Intake Air Filter	C10A, C10B	N/A	2
C10A	*4a*	*Intake Air Filter Clogged*	*N/A*	*C10, M10*	*2*
C10B	*4a*	*Air Filter Material Degraded*	*N/A*	*C10, C39A, C42B, FE10*	*3*
C11	4	Exhaust Manifold	C11A-C	N/A	2
C11A	*4a*	*Exhaust Manifold External Coolant Leak*	*N/A*	*C11, FE2-A3*	*3*
C11B	*4a*	*Exhaust manifold Internal Coolant Leak*	*N/A*	*C11, FE2-D*	*3*
C11C	*4a*	*Exhaust Manifold Exhaust Gas Leak*	*CS2*	*C11, FE3, M11*	*2*
C12	4	Exhaust Control Flaps	*N/A*	M11, M15	2
C13	4	Exhaust Flap Actuating Cylinder	*N/A*	M11, M15	2
C14	4	Charge Air Manifold	*N/A*	M10	2

Table 17: List of Component Level 4 and 4a Nodes 1 of 5

Node ID	Level	Node Nomenclature	Parents	Children	States
C15	4	Charge Air Cooler	C15A-D	N/A	2
C15A	*4a*	*Charge Air Cooler Internal Coolant Leak*	*N/A*	*C15, FE2-D*	*3*
C15B	*4a*	*Charge Air Cooler External Coolant Leak*	*N/A*	*C15, FE2-A3*	*3*
C15C	*4a*	*Charge Air Cooler Air Leak*	*N/A*	*C15, FE2-A3*	*2*
C15D	*4a*	*Charge Air Cooler Effectivness*	*FE10*	*C15, CS3*	*3*
C16	4	Turbochargers	C16 IN1, C16 IN2, C16 IN3, C16 IN4	*N/A*	2
C16A	*4a*	*Turbine Wheel Severed*	*LO1, LO2*	*C16 IN1*	*2*
C16B	*4a*	*Turbine Wheel Seized*	*LO1, LO2*	*C16 IN1*	*2*
C16C	*4a*	*Turbine Wheel Blade Severed*	*LO1, LO2*	*C16 IN1*	*2*
C16D	*4a*	*Turbine Bearing Failure*	*LO1, LO2*	*C16 IN1*	*2*
C16E	*4a*	*Turbo Housing Exhaust Leak*	*CS2*	*C16 IN2, FE3*	*2*
C16F	*4a*	*Turbo Housing Air Leak*	*CS2*	*C16 IN2, FE4*	*2*
C16G	*4a*	*Turbo External Lube Oil Leak*	*N/A*	*C16 IN3, FE1-A3*	*2*
C16H	*4a*	*Turbo Combustion Side Internal Lube Oil leak*	*N/A*	*C16 IN3, FE1-C, FE10*	*2*
C16I	*4a*	*Turbo Exhaust Side Internal Lube Oil Leak*	*N/A*	*C16 IN3, FE1-C*	*2*
C16J	*4a*	*Turbo External Coolant leak*	*N/A*	*C16 IN3, FE2-A3*	*3*
C16K	*4a*	*Turbo Combustion Side Lubing Piston Lube Oil Seal Fail*	*N/A*	*C16 IN4, FE1-C, FE10*	*2*
C16L	*4a*	*Turbo Exhaust Side Lubing Piston Lube Oil Seal Fail*	*N/A*	*C16 IN4, FE1-C*	*2*
C16 IN1	*4a*	*Intermediate Node:Turbo Catastrophic Failure*	*C16A-D*	*C16, M11*	*2*
C16 IN2	*4a*	*Intermediate Node: Turbo Exhaust/Air Failure*	*C16E-F*	*C16*	*2*
C16 IN3	*4a*	*Intermediate Node: Turbo Oil/Coolant Failure*	*C16H-J*	*C16*	*2*
C16 IN4	*4a*	*Intermediate Node: Turbo Piston Failures*	*C16K-L*	*C16*	*2*
C17	4	Pre Fuel Filter	C17A	*N/A*	2
C17A	4a	Pre Filter Fuel Leak	*N/A*	FE6	3
C18	4	Primary Fuel Filter	C18A	*N/A*	2
C18A	4a	Primary Filter Fuel Leak	*N/A*	FE6	3
C19	4	Secondary Fuel Filter	C19A	*N/A*	2
C19A	4a	Secondary Pre Filter Fuel Leak	*N/A*	FE6	3
C20	4	High Pressure Fuel Accumulator Assembly	C20A, C21	N/A	2
C20A	*4a*	*High Pressure Accumulator External Fuel Leak*	*N/A*	*C20, FE5-A*	*3*
C21	4	HPA Limitator Valve	C21A, C21B	C20	2
C21A	*4a*	*HPA Pressure Limit Valve Stuck Open*	*N/A*	*C21*	*2*
C21B	*4a*	*HPA Pressure Limitor Valve Stuck Closed*	*N/A*	*C21, M16*	*2*
C22	4	Fuel Delivery Pump	C22A, C22B	*N/A*	2
C22A	*4a*	*Fuel Delivery Pump External Fuel Leak*	*N/A*	*C22, FE6*	*3*
C22B	*4a*	*Fuel Delivery Pump Fail to Operate*	*N/A*	*C22, M17*	*2*

Table 18: List of Component Level 4 and 4a Nodes 2 of 5

Node ID	Level	Node Nomenclature	Parents	Children	States
C23	4	High Pressure Fuel Pump	C23 IN1, C23A, C23B, C23F, C24	N/A	2
C23A	*4a*	*HP Fuel Pump External Fuel Leak*	*N/A*	*C23, FE5-A*	*3*
C23B	*4a*	*HP Fuel Pump Internal Fuel Leak*	*N/A*	*C23, FE5-B*	*3*
C23C	*4a*	*HP Fuel Pump Con Shaft Failure*	*LO1*	*C23 IN1*	*2*
C23D	*4a*	*HP Fuel Pump Camshaft Failure*	*LO1*	*C23 IN1*	*2*
C23E	*4a*	*HP Fuel Pump Bearing Failure*	*LO1*	*C23 IN1*	*2*
C23F	*4a*	*HP Fuel Pump Lube Oil External Leak*	*N/A*	*C23, FE1-A3*	*2*
C23G	*4a*	*HP Fuel Pump Roller Tapper Failure*	*LO1*	*C23 IN1*	*2*
C23H	*4a*	*HP Fuel Pump Cylinder Failure*	*LO1*	*C23 IN1*	*2*
C23 IN1	*4a*	*HP Cat Failure*	*C23C, C23D, C23E, C23G, C23H*	*M16*	*2*
C24	4	High Pressure Pump Suction Valve	C24 IN1, C24D	N/A	2
C24A	*4a*	*Suction Valve Jam/Failure*	*N/A*	*C24 IN1*	*2*
C24B	*4a*	*Magnetic Coil Failure*	*N/A*	*C24 IN1*	*2*
C24C	*4a*	*Suction Valve Not Tight*	*N/A*	*C24 IN1*	*2*
C24D	*4a*	*Suction Valve Stuck Closed*	*C24 IN1*	*C24*	*2*
C24 IN1	*4a*	*Suction Valve Stuck Open*	*C24A-C*	*C24, M16*	*2*
C25	4	Raw Water Pump	C25A-D	N/A	2
C25A	*4a*	*Raw Water Pump Bearing Failure*	*N/A*	*C25, FE7-A, M18*	2
C25B	*4a*	*Raw Water Pump Efficenciey Loss*	*N/A*	*C25, M18*	2
C25C	*4a*	*Raw Water Pump Lube Oil Leak*	*N/A*	*C25, FE1-A3*	2
C25D	*4a*	*Raw Water Pump External Raw Water Leak*	*N/A*	*C25, FE7-A*	3
C26	4	CrankShaft	C26A,C26B	DT1	2
C26A	*4a*	*CrankShaft Journal Bearing Failure*	*C26B, LO1, LO2*	*C26, M5*	2
C26B	*4a*	*Crankshaft Severed*	*LO1, LO2*	*C26, C26A, C37*	2
C27	4	Drive Gear	C28A, C30B	C37, DT1	2
C28	4	Vibration Dampner	C28A, C28B	N/A	2
C28A	*4a*	*Vibration Dampner Fracture/Shatter*	*C28B*	*C27, C28*	2
C28B	*4a*	*Vibration Dampner Sleeve Broken*	*N/A*	*C28A*	2
C29	4	Crankcase	C29A-F	*N/A*	2
C29A	*4a*	*Crankcase Lube Oil Gasket/Sealing Failure*	*N/A*	*C29, FE-A1a*	2
C29B	*4a*	*Crankcase External Lube Oil Leak caused by Crack*	*N/A*	*C29, FEA1a*	2
C29C	*4a*	*Crankcase Internal Coolant Oil Leak casued by Crack*	*N/A*	*C29, FE2-C2*	3
C29D	*4a*	*Crankcase Internal Lube Oil Leak Casue by Crack*	*N/A*	*C29, FE1-C1*	2
C29E	*4a*	*Crankcase Coolant Gasket/Sealing Failure*	*N/A*	*C29, FE2-A2*	2
C29F	*4a*	*Crankcase External Coolant Leak caused by Crack*	*N/A*	*C29, FE2-A2*	3

Table 19: List of Component Level 4 and 4a Nodes 3 of 5

Node ID	Level	Node Nomenclature	Parents	Children	States
C30	4	Camshaft	C30A-C	DT1	2
C30A	*4a*	*Camshaft Countor Chipped*	*C36A, LO1*	*C30, M19*	*2*
C30B	*4a*	*CamShaft Severed*	*LO1*	*C27, C30*	*2*
C30C	*4a*	*Camshaft Bearing Failure*	*LO1, LO2*	*C30*	*2*
C31	4	Power Pack Assembly	C32, C35, C37, C38, C39, C40, C41	N/A	2
C31 IN1	4a	Power Pack Cat Failures	C33B, C34, C36, C37, C41	DT1	
C32	4	Valve Drive Assmebly	C32A, C33, C34	C31, FE8	2
C32A	*4a*	*Valve Drive Lube Oil Leak*	*N/A*	*C32, FE-A1b*	*2*
C33	4	Valve Drive Swing Arm	C33A, C33B	C32	2
C33A	*4a*	*Valve Driver Swing Bearing Roller Surface Chip*	*N/A*	*C33, M19*	*2*
C33B	*4a*	*Valve Drive Swing Follwer Bearing Failure*	*M1*	*C33, C31 IN1*	*2*
C34	4	Valve Rocker Arm	C34A, C34B	C31 IN1, C32	2
C34A	*4a*	*Valve Drive Rocker Arm Severed*	*N/A*	*C34*	*2*
C34B	*4a*	*Valve Drive Rocker Arm Exessive Wear*	*N/A*	*C34*	*2*
C35	4	Cylinder Head	C35A-D, C36	C31	2
C35A	*4a*	*Head Internal Coolant Leak*	*N/A*	*C35, C41A, FE2-C3*	*3*
C35B	*4a*	*Head External Coolant leak*	*N/A*	*C35, FE2-A1*	*3*
C35C	*4a*	*Head External Lube Oil Leak*	*N/A*	*C35, FE-A1b*	*3*
C35D	*4a*	*Head Exhaust Leak*	*N/A*	*C35, FE3*	*2*
C36	4	Head Valve	C36A-C	C31 IN1, C35, FE8	2
C36A	*4a*	*Head Valve Spring Fracture*	*N/A*	*C30A, C36*	*2*
C36B	*4a*	*Head Valve Exessive Wear*	*N/A*	*C36, C41*	*2*
C36C	*4a*	*Head Valve Severed*	*N/A*	*C36, C41*	*2*
C37	4	Conrod	C26B, C27, C37A-C	C31, C31 IN1, FE8	2
C37A	*4a*	*Conrod Upper Bearing Failure*	*M1, M2*	*C37, C41*	*2*
C37B	*4a*	*Conrod Lower Bearing Failure*	*M1*	*C26, C37*	*2*
C37C	*4a*	*Conrod Severed*	*N/A*	*C29, C37*	*2*
C38	4	Injector	C38A-D	C31	2
C38A	*4a*	*Injector Not Injecting*	*N/A*	*C38, C38B, FE8*	*2*
C38B	*4a*	*Injector Continous Injection*	*C38A*	*C38, FE9*	*2*
C38C	*4a*	*Injector External Fuel Leak*	*N/A*	*C38, FE5-A*	*3*
C38D	*4a*	*Injector Out of Calibration*	*N/A*	*C38, FE8*	*2*

Table 20: List of Component Level 4 and 4a Nodes 4 of 5

Node ID	Level	Node Nomenclature	Parents	Children	States
C39	4	Cylinder Liner	C39A, C39B, C41	C31	2
C39A	*4a*	*Cylinder Liner Honing Damaged*	*C10B*	*C39, C42C*	*2*
C39B	*4a*	*Cylinder Liner Crack*	*N/A*	*C39, FE2-C3*	*2*
C40	4	HP Fuel Line	*N/A*	C31, FE5-A	3
C41	4	Piston Assmembly	C36B, C36C, C37A, C41A	C31, C31 IN1, C39, FE8	2
C41A	*4a*	*Piston Overheat*	*C35A, C42, LO1, LO2*	*C41, M12, M4*	*2*
C42	4	Piston Ring	C42A-D	C41A	2
C42A	*4a*	*Piston Ring Cracked*	*LO1, LO2*	*C42*	*2*
C42B	*4a*	*Piston Ring Jam*	*LO1, C39B*	*C42*	*2*
C42C	*4a*	*Piston Ring Overheat*	*LO2*	*C42*	*2*
C42D	*4a*	*Piston Ring Wear*	*LO1*	*C42*	*2*

Table 21: List of Component Level 4 and 4a Nodes 5 of 5

Node ID	Level	Node Nomenclature	Parents	Children	States
FE1	4a	Lube Oil Leaving System	FE1-A, FE1-B, FE1-C	M2	3
FE1-A	4a	Lube Oil to External	FE1-A1, FE1-A2, FE1-A3	FE1	3
FE1-A1	4a	Lube Oil from Drive Train to External	FE1-A1a, FE1-A1b	FE1-A	3
FE-A1a	4a	Lube Oil From Crankcase to External	C29A, C29B, C7	FE1-A1	3
FE-A1b	4a	Lube Oil From Power Pac to External	C32A, C35C	FE1-A1	3
FE1-A2	4a	Lube Oil from Lube Oil System to External	C2B, C3B, C4A, C6	FE1-A	3
FE1-A3	4a	Lube Oil From Auxilliary Engine Systems to External	C16G, C23F, C25C, C8A	FE1-A	3
FE1-B	4a	Lube Oil to Coolant	C3A	FE1	3
FE1-C	4a	Lube Oil to Exhaust	C16H, C16I, C16K, C16L, FE1-C1	FE1	3
FE1-C1	4a	Lube Oil from Crankcase to Exhaust	C29D	FE1-C	3

Table 22: List of Level 4a Intermediate Failure Effect Nodes 1 of 2

Node ID	Level	Node Nomenclature	Parents	Children	States
FE2	4a	Coolant Leaving System	FE2-A,FE2-B,FE2-C,FE2-D	M8	3
FE2-A	4a	Coolant to External	FE2-A1, FE2-A2, FE2-A3, FE2-A4	FE2	3
FE2-A1	4a	Coolant From Power Pac to External	C35B	FE2-A	3
FE2-A2	4a	Coolant from Crankcase to External	C29E, C29F	FE2-A	3
FE2-A3	4a	Coolant from Auxilliary Engine Systems to External	C11A, C15B, C15C, C16J	FE2-A	3
FE2-A4	4a	Coolant from Coolant System to External	C3C, C8B, C9C	FE2-A	3
FE2-B	4a	Coolant to Raw Water	C9A	FE2	3
FE2-C	4a	Coolant to Lube Oil	FE2-C1, FE2-C2, FE2-C3	FE2, M1	3
FE2-C1	4a	Coolant from Coolant System to Lube Oil	C3D	FE2-C	3
FE2-C2	4a	Coolant from Crankcase to Lube Oil	C29C	FE2-C	3
FE2-C3	4a	Coolant From Power Pac 1 to Lube Oil	C35A, C39B	FE2-C	3
FE2-D	4a	Coolant to Exhaust	C11B, C15A	FE2	3
FE3	4a	Exhaust to Engine Room	C11C, C16E, C35D	M12	3
FE4	4a	Intake Air to Engine Room	C16F	M10	2
FE5	4a	HP Fuel Leaving System	FE5-A, FE5-B	M16	3
FE5-A	4a	HP Fuel to External	C20A, C23A, C38C, C40	FE5	3
FE5-B	4a	HP Fuel to Lube Oil	C23B	FE5, M1	3
FE6	4a	LP Fuel Loss to External	C17A, C18A, C19A, C22A	M17	3
FE7	4a	Raw Water Leaving System	FE7-A,FE7-B	M18	3
FE7-A	4a	Raw Water to External	C25A, C25D, C9D	FE7	3
FE7-B	4a	Raw Water to Coolant	C9B	FE7	2
FE8	4a	Lowering Exhaust Temperature	C32 C36, C37, C38A, C38D, C41, M17	M13	2
FE9	4a	Raising Exhaust Temperature	C38B, M19, M9	M13, M14	2
FE10	4a	Contamination to Charge Air Cooler	C10B, C16H, C16K	C15D	3

Table 23:List of Level 4a Intermediate Failure Effect Nodes 1 of 2

Node ID	Level	Node Nomenclature	Parents	Children	States
CF1	5	Intake Air temperature	N/A	M9	3
CF2	5	Raw Water Temperature	N/A	RW1	3

Table 24: List of Level 5 Nodes

Appendix B: FRC Engine Bayesian Network

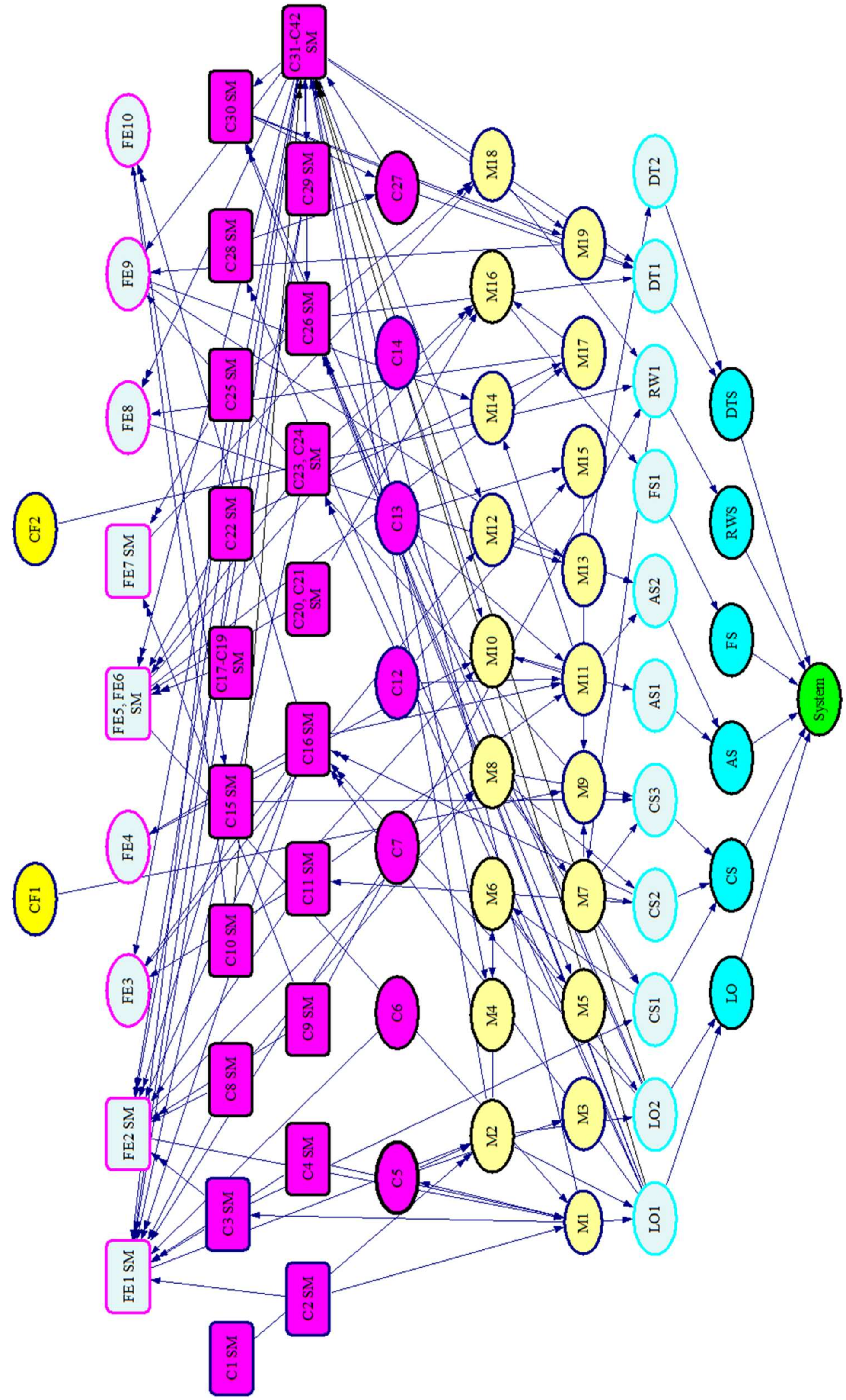

Figure 27: Expanded FRC Engine Bayesian Network

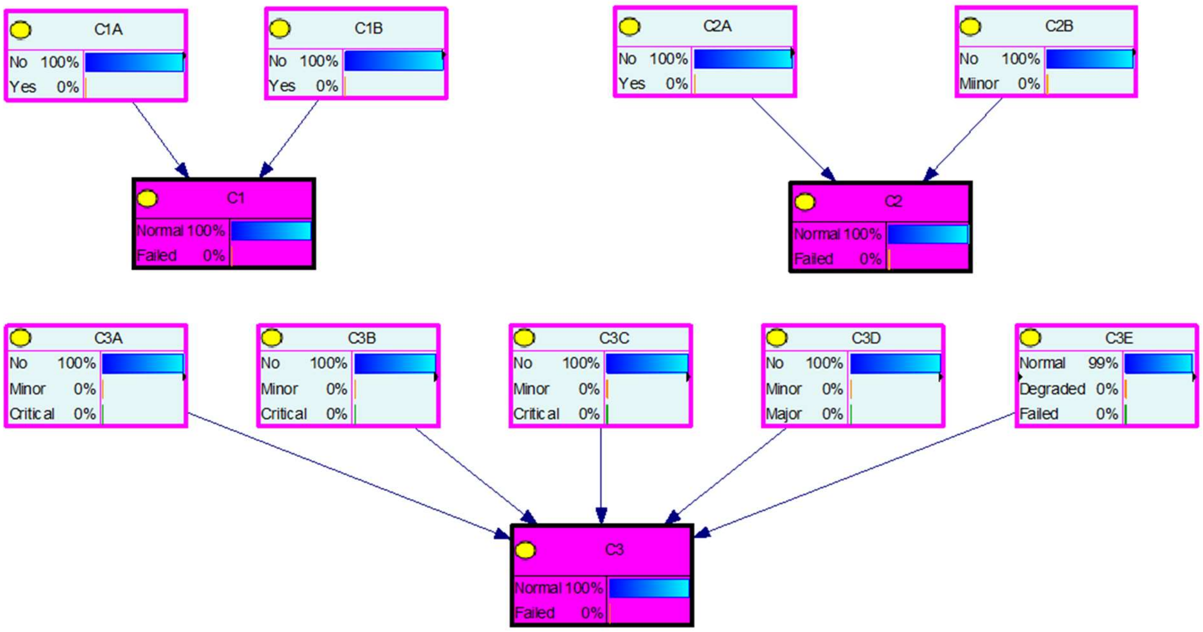

Figure 28: Component 1, 2, and 3 Sub Models

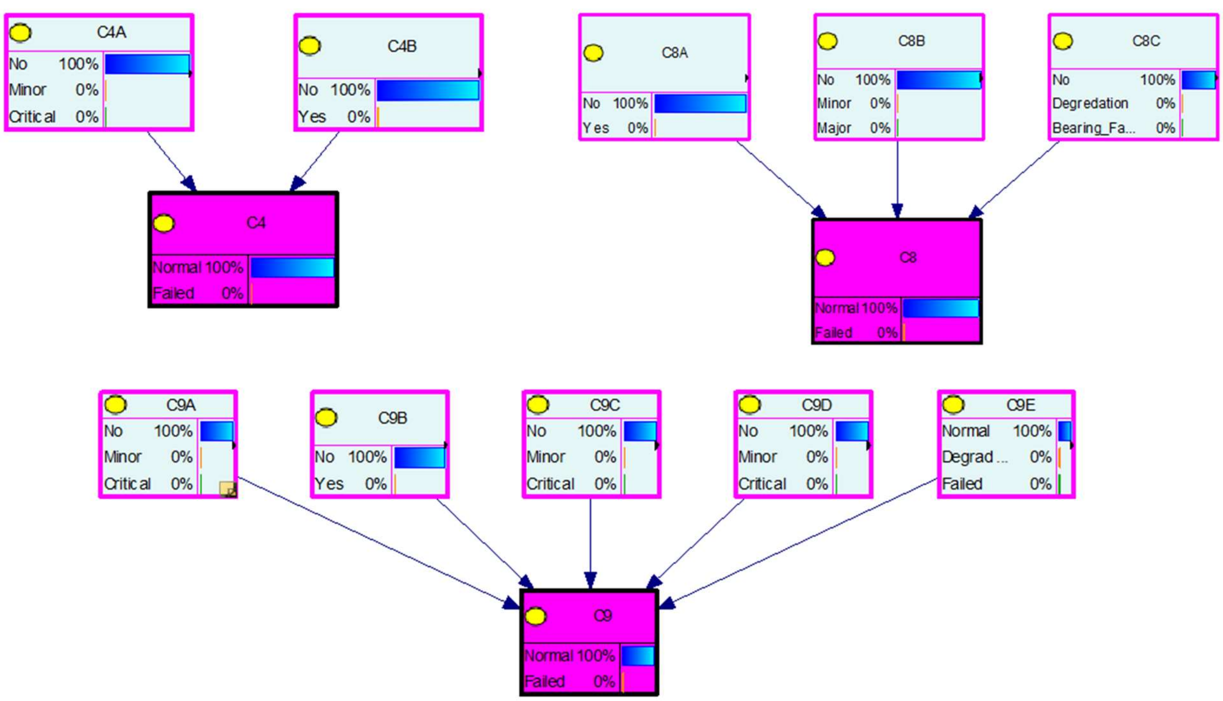

Figure 29: Component 4, 8, and 9 Sub Models

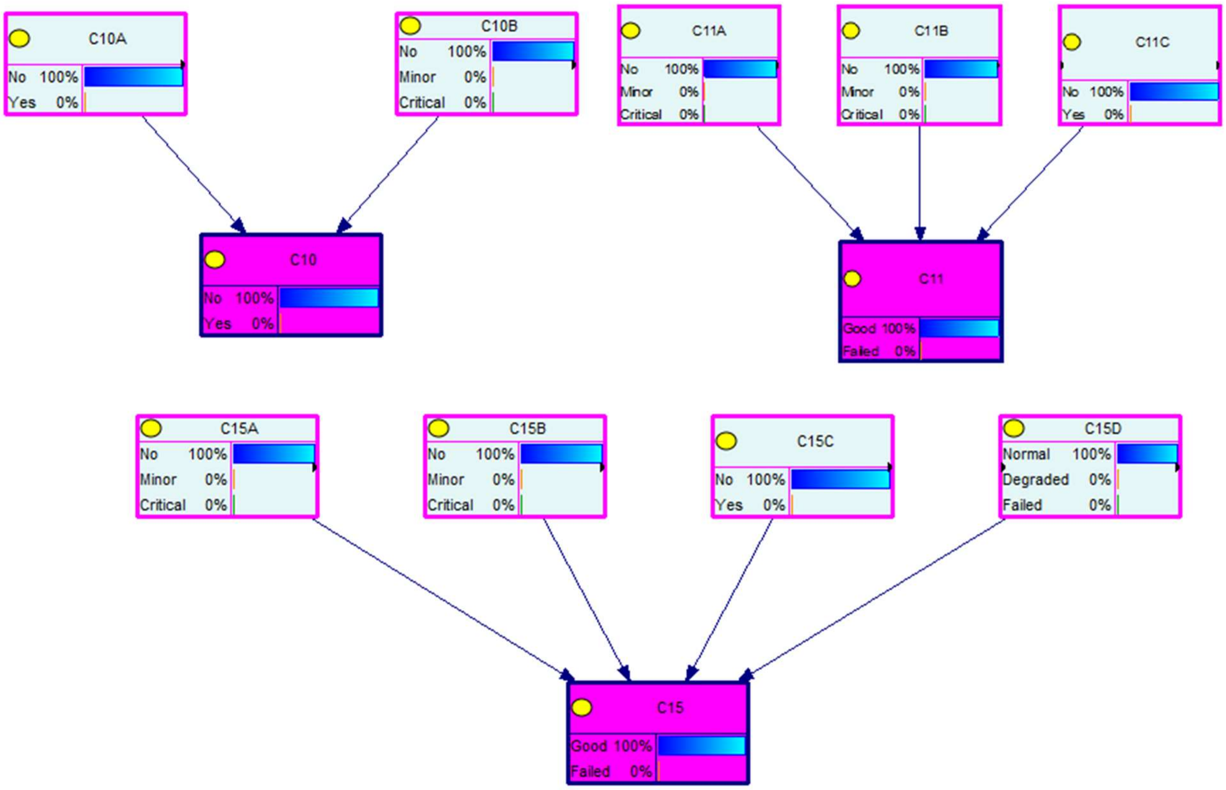

Figure 30:Component 10, 11, and 15 Sub Models

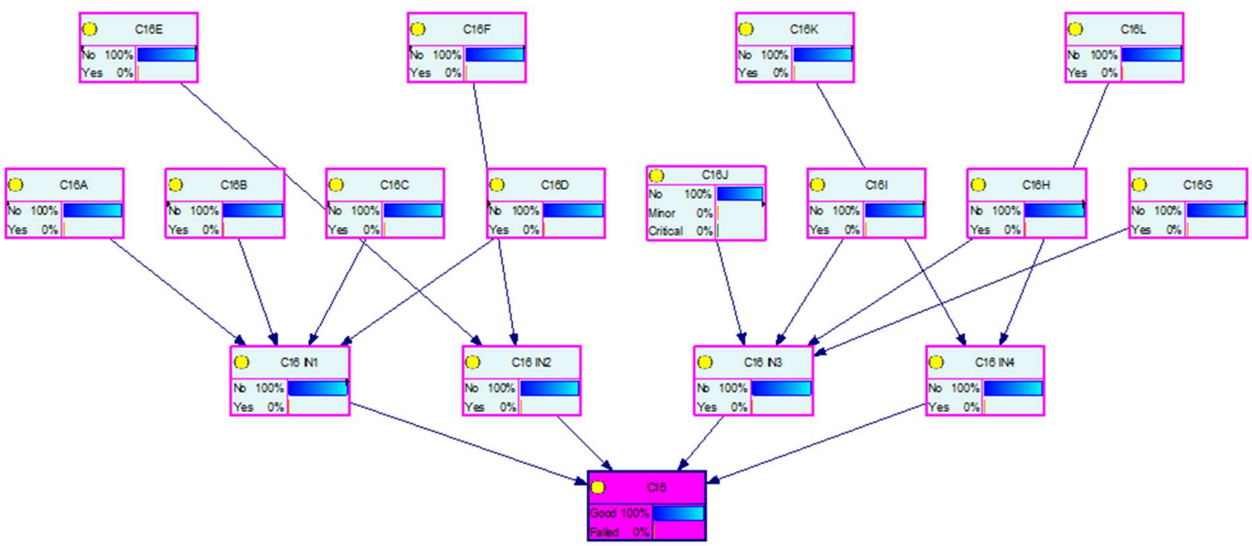

Figure 31:Component 16 Sub Model

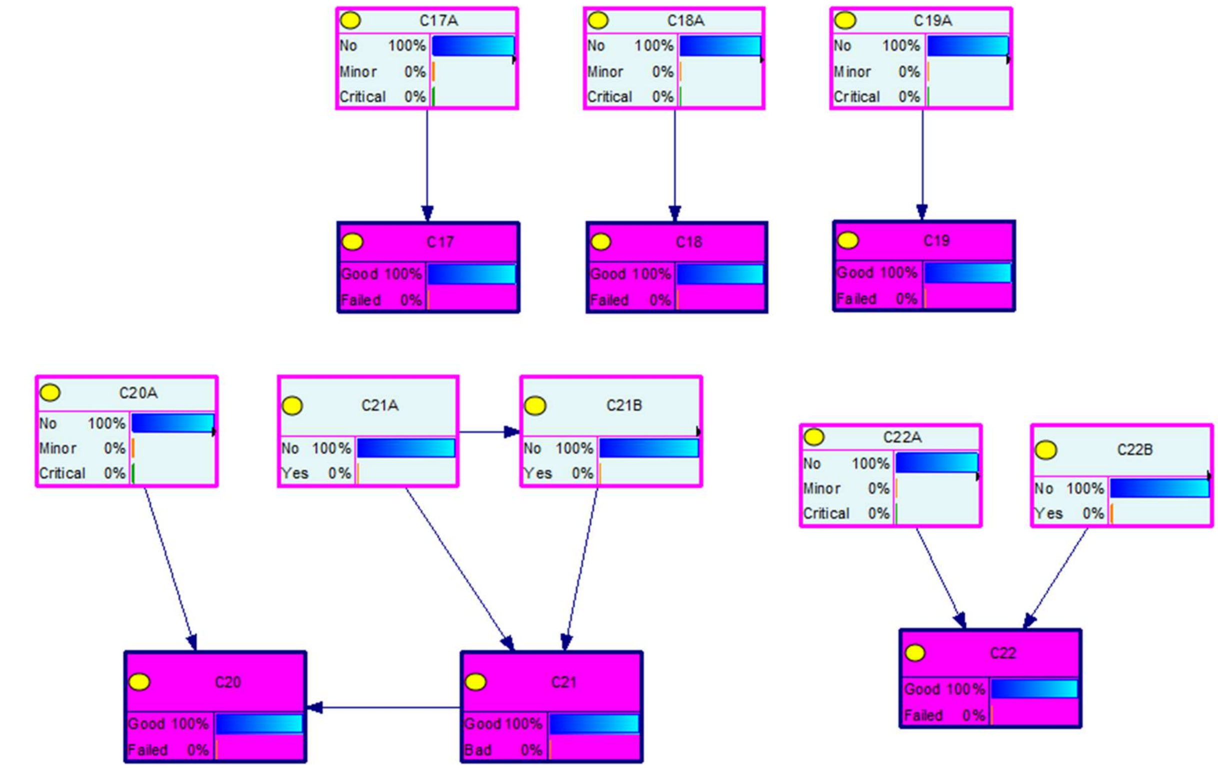

Figure 32: Components 17-22 Sub Models

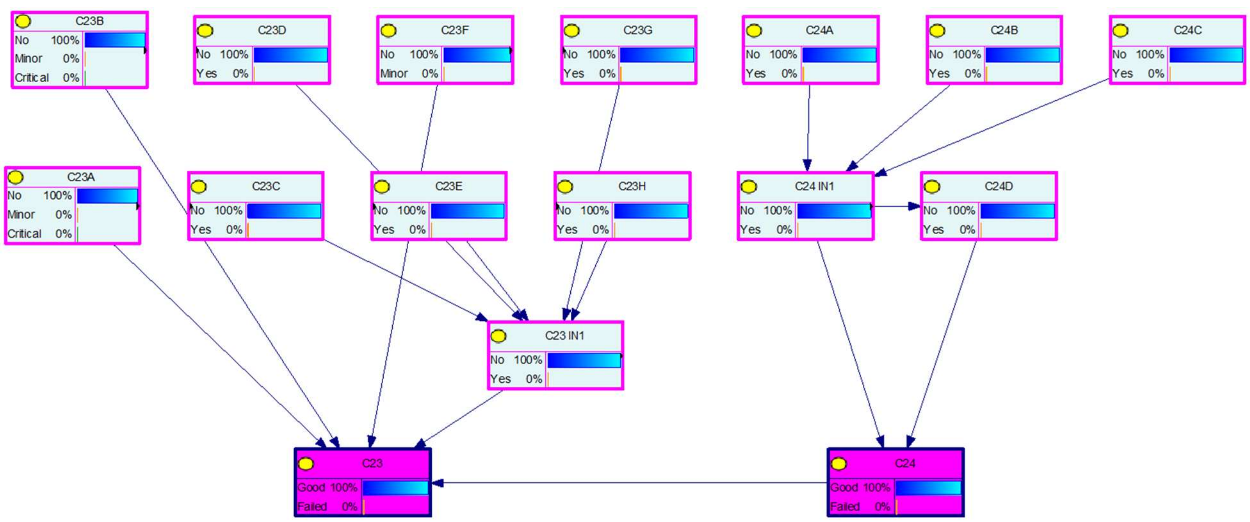

Figure 33: Component 23 and 24 Sub Models

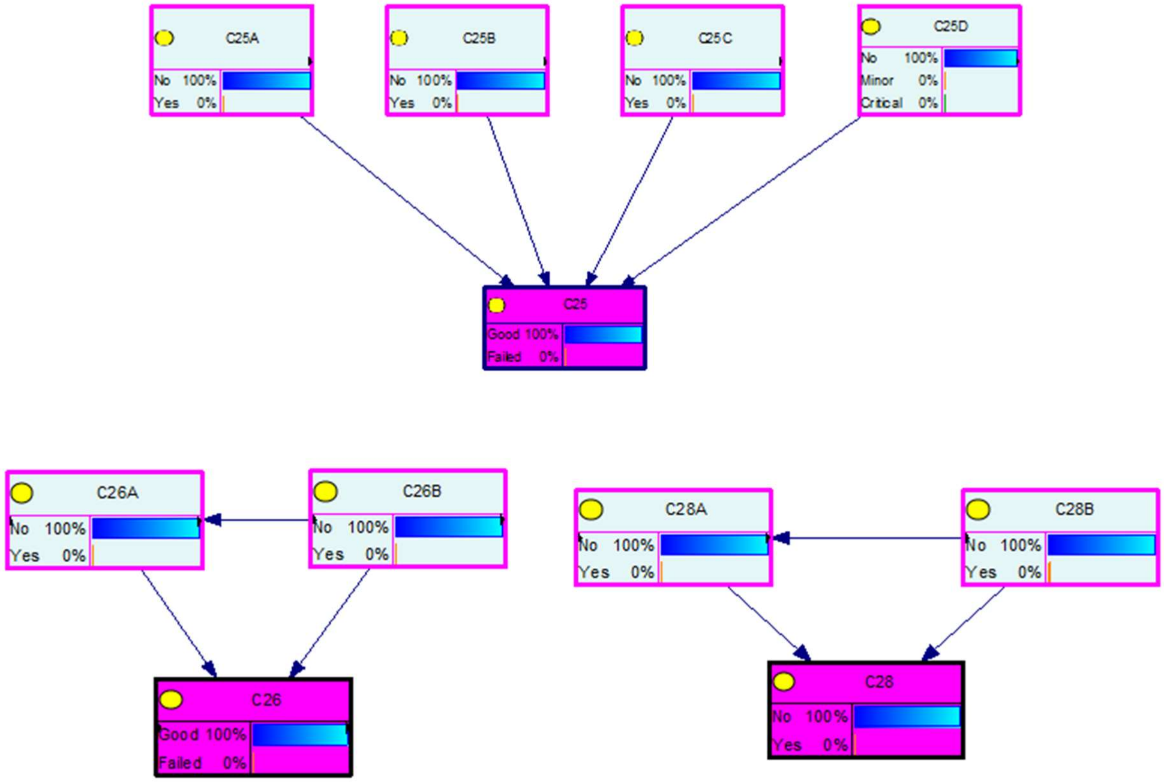

Figure 34: Components 25, 26, and 28 Sub Models

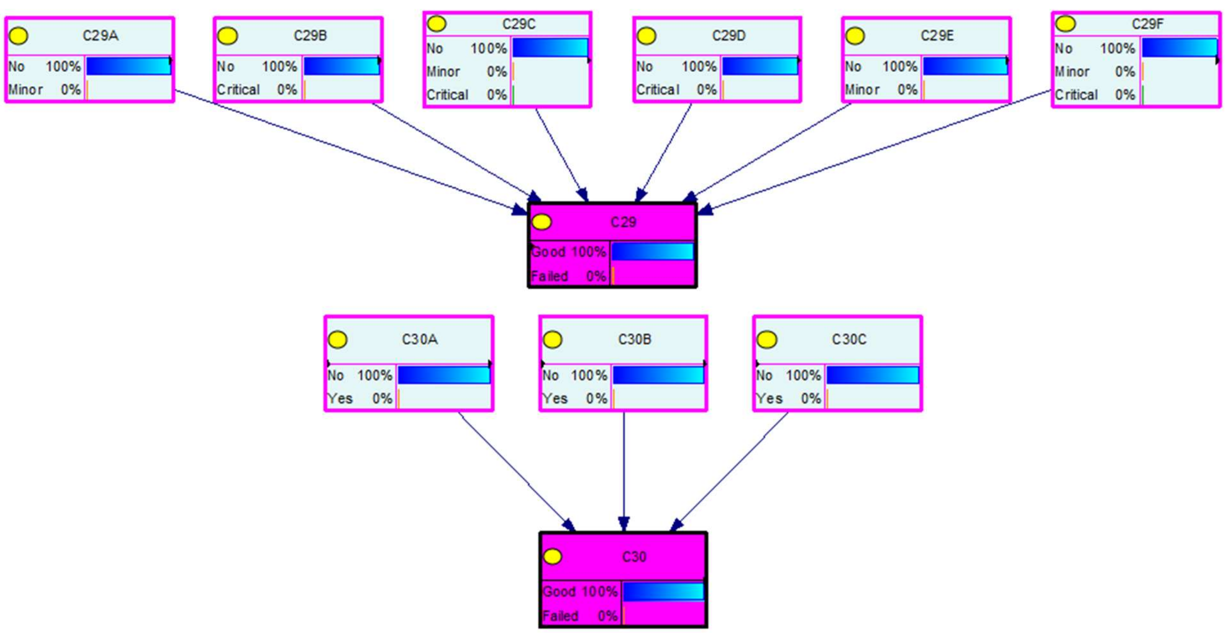

Figure 35:Component 29 and 30 Sub Models

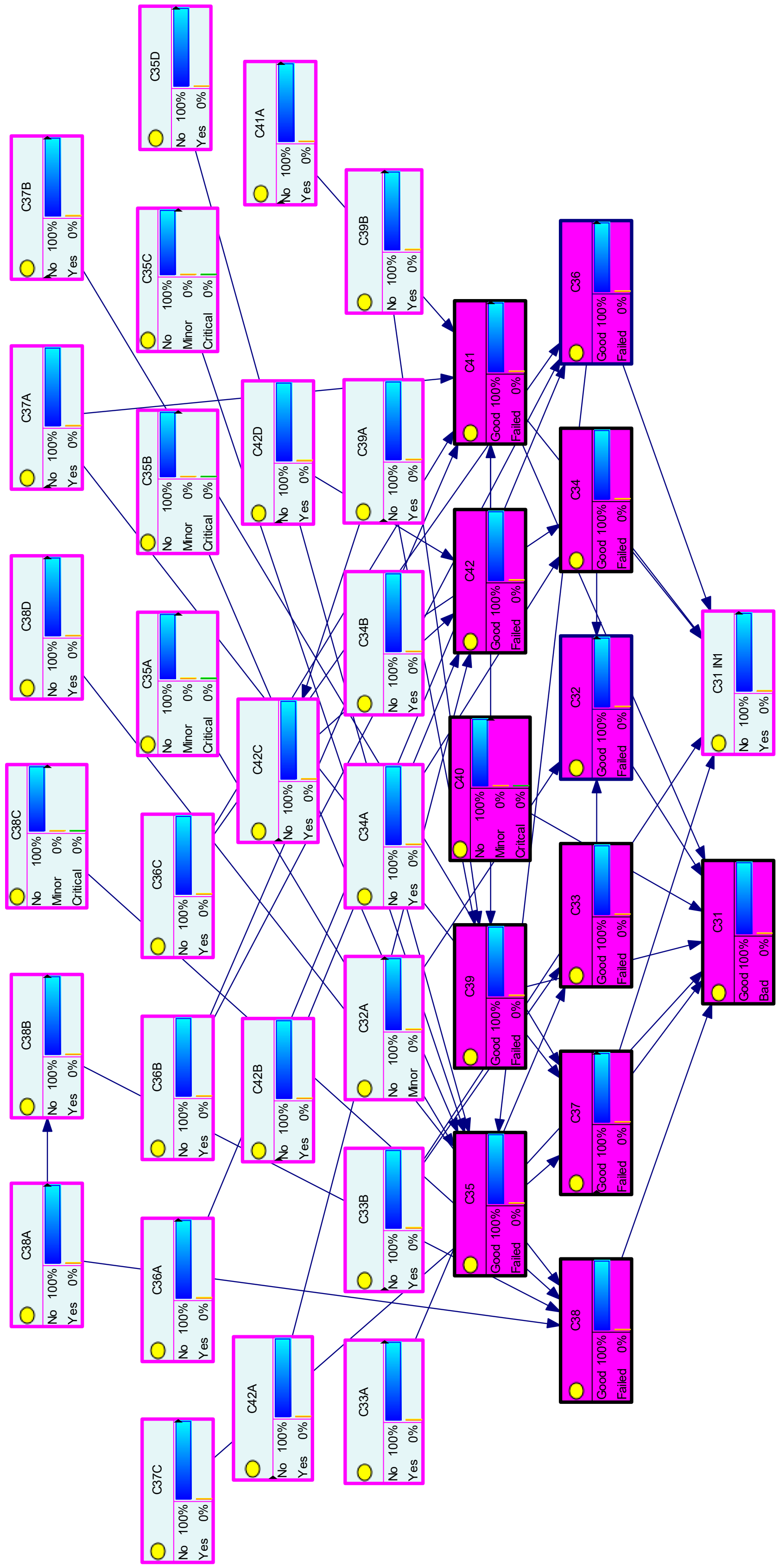

Figure 36: Component 31-42 Sub Models

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