Condition Monitoring of a Centrifugal Pump using Bayesian Networks

by

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To improve the viability of nuclear power plants, there is a need to reduce their operational costs. Operational costs account for a significant portion of a nuclear plant's yearly budget. This is due to their reactive and uninformed maintenance approach. In order to reduce these costs, proactive condition monitoring methods are required that can estimate the state of a machine in real-time and aid operators in optimizing maintenance schedules. In this research, we use Bayesian networks to develop a condition monitoring platform that can diagnose pump faults, infer their root cause, and estimate it's remaining-useful-life. This solution provides an informed probabilistic viewpoint of the pumping system for the purpose of preventative maintenance.

In this thesis, we analyze a centrifugal pump to estimate its current state. We combine domain expertise with physical laws to create a cause-and-effect relationship between the pump components to estimate the root cause of two major pump faults. We incorporate survival analysis with Bayesian statistics to forecast the health of the pump conditional to its current state. We complete our condition monitoring analysis by successfully implementing the final Bayesian network in case studies for three modes of pump operation.

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1.0 Condition Monitoring And Asset Management

The purpose of this project is to develop a condition monitoring system that can be integrated into a larger asset management framework for nuclear plants.

Nuclear power plants have scheduled maintenance outages at regular intervals [1]. When a machine starts developing faults and stops operation, it requires repair or replacement. If the timeline of machine repair does not fall within the scheduled outages, the nuclear plant needs to have an unplanned outage to inspect the machine. Unplanned outages cause nuclear plants to lose millions of dollars every day. Even during planned outages, the maintenance process can be conservative and time-consuming, which can potentially increase operational costs [2]. In order to reduce these costs, a proactive asset management approach is needed that improves operations and maintenance (O&M) using advancements in data analytics.

Asset management is the systematic organisation of a plant machinery's life cycle in order to satisfy its business and financial objectives. Asset management uses information gathered from condition monitoring, supply chain reliability, and financial parameters to provide the optimal decision that results in the highest value gained. This value metric is usually predefined by the decision makers and varies between industries. Asset management allows us to optimize maintenance resources and reduce operating costs.

To initiate the process of asset management, we develop a condition monitoring framework for the purpose of preventative maintenance. Condition monitoring is the process of estimating the health of a machine based on available parameter data, such as sensors readings. Analyzing different parameters provides a range of information about developing faults and inefficiencies in the machinery. Condition monitoring is composed of three parts: monitoring, diagnosis, and forecasting. Monitoring observes a component, device, or process and alerts when a failure occurs. Diagnosis determines the root cause of failure which can be addressed by performing informed maintenance. Forecasting provides an estimate of the remaining-useful-life (RUL) of a machine and its components. These processes can be used to make risk-based decisions about inventory, maintenance and inspection outages, and ordering components.

There is a critical need to create condition monitoring models that not only diagnose the occurrence of faults, but also determine the root cause of failure. Furthermore, there is also a need to forecast component health for the foreseeable future. The forecasting estimates also need to be flexible, since different faults degrade the machine at different rates. Methods need to be developed that use information from sensors to predict if, how, and when a machine will fail. Understanding why a component fails rather than just knowing the probability of failure is also important for asset management, as it allows the proper decisions to be made for mitigating future failures.

This evolution of condition monitoring will allow maintenance to be scheduled in advance rather than having unplanned replacement outages during the plant's operation. These maintenance schedules can then be aligned with the predetermined outages that are performed on nuclear power plants, thus increasing plant efficiency.

This thesis provides and in-depth analysis on a centrifugal pump installed in a nuclear power plant. Pumps are one of the most commonly used machinery in power plants. Their simple function of transferring energy to liquid can be adapted for various applications. This research adopts preexisting pump condition monitoring methods and improves those techniques to create a comprehensive condition monitoring platform.

The primary concept used in this research is Bayesian networks. Bayesian networks are probabilistic models that represent a set of variables and their conditional dependencies. Bayesian networks can be used to analyze the health of a machine from a probabilistic perspective. Determining the probability of failure rather than a deterministic conclusion allows the addition of risk and estimation in predictions. Asset management methods can then be used to weigh the estimated machine health against the risk of machine failure and select an optimal inspection and maintenance plan.

1.1 Objectives

This project successfully creates a comprehensive and robust condition monitoring tool to improve the estimation of a machine's health. The following objectives are addressed and accomplished:

- *Relate disparate systems in a common framework for better forecasting and diagnosis:* A machine consists of various components operating together. It is also part of a bigger system in a plant. Therefore, it is vital to account for data from the unique interactions that a machine has with its surroundings and its individual components. These subsystems operate on different physical laws and engineering principles, as well as different units of measurement. Combining different types of information provides a comprehensive view of the entire system and improves the condition monitoring process.
- *Infer the condition of hidden states using data:* Faults occur in pumps as hidden states. Hidden states are processes that are impossible to observe directly for diagnosis. We must infer the occurrence of faults indirectly based on causal relations and sensor readings. If we have measurements from sensors, we can infer the state of the machine using Bayesian networks.
- *Provide the root cause of machine failure in order to improve decision making in a plant:* For the purpose of asset management, it is vital to know the root cause of failure so the correct decisions and actions can be taken to mitigate those risks and prevent future breakdowns. If a fault has multiple causes, the decision maker can determine mitigation strategies and choose the optimal solution. A condition monitoring model is created using conditional probabilities which connects each diagnosed fault to its probable root cause.
- *Predict the condition of components using sensor data and historical trends:* Machine sensor data is processed through predictive models, which in turn provide a probabilistic analysis of machine health. Using forecasting techniques, the health of components is estimated at a future time interval. Developing a forecasting tool informs the plant operator about any potential fault developing in the machinery. This information allows outages to be scheduled instead of dealing with unplanned outages.

1.2 State Of The Art

Fault diagnosis for centrifugal pumps is most commonly performed with vibration analysis [3, 4, 5, 6, 7, 8, 9] . Vibration analysis is the process of monitoring vibration signals within a machine to detect abnormal operating levels or patterns to evaluate its condition. A vibration signature consists of the amplitude and frequency of the signal. These signatures are unique for each pump fault detected, which in turn provide information about the health of the machine. Vibration is at its lowest when the pump is running at its best efficiency point (BEP), and excessive vibration is a common indicator of a developing fault inside a pump.

In the frequency domain, many pump faults are seen as large amplitudes at multiples of the vane passing frequency. The vane passing frequency is equal to the pump rotational speed multiplied by the number of impeller vanes. Accelerometers installed on pumps capture vibration data in the form of acceleration in the time domain. This data is analyzed in the frequency domain to facilitate fault detection. Time domain data is usually converted to the frequency domain with a Fourier transform, and the fast Fourier transform (FFT) is a common discrete approximation for that process [10]. Vibration analysis is used to detect common faults such as cavitation, flow pulsations, bent shaft, shaft misalignment, and bearing wear.

Other research has been done to diagnose the occurrence of faults using pressure measurements from suction and discharge pressure transducers installed on pumping systems [11, 12]. The pressure measurements are used to classify normal and abnormal machine behavior. This process is similar to that of classification using vibration measurements, but without requiring surface treatments to mount accelerometers.

Procedures have been developed for fault diagnosis of pump components through artificial neural networks (ANNs). Characteristic features of vibration signals from normal and abnormal operation are used as inputs to the ANN. The output of the model is the classification of the input features as normal operation or fault occurrence [13].

Research has been done to predict the RUL using physics-based models that describe the behavior of the system [14, 15, 16, 17, 18]. These models account for several different damage processes occurring simultaneously within a component. Recursive Neural Networks (RNNs) have also been developed to combine RUL estimation with failure prediction as a short-term task [19].

Current diagnosis methods do not provide a comprehensive picture of the entire pumping system. Fault classification is mostly based on vibration readings. Furthermore, vibration analysis can only detect mechanical faults. Frequently, the root cause of failure in a system is operational in nature, such as clogged or damaged valves and diffusers. The forecasting models developed are deterministic, preventing the addition of uncertainty in estimation. A probabilistic estimate of the RUL allows the decision maker to weigh their options and select the path with the least risks. Furthermore, there is a need to account for the influence of different faults on the RUL. Each fault will degrade the machine in a unique manner, altering the RUL appropriately.

2.0 Bayesian Networks

Bayesian networks are probabilistic graphical models that represent a set of variables by their conditional probabilities. They allow for various types of information to be incorporated into a common probabilistic framework. The types of information include sensor data, uncertainties, expert opinion, and mathematical equations [20].

Bayesian networks allow us to analyze systems causally. This lets us describe complex and dynamic behavior without requiring intricate physics-based models. The ability to describe the cause and effect relationship between different variables is a key advantage of Bayesian networks. They use statistical inference to estimate the occurrence of phenomenon based on observations or evidence. Inference removes the need to directly observe an activity and helps to identify causes from observed effects.

Bayesian networks also enable risk-based decision making by providing a probabilistic picture of the condition of a system [21]. Using a probabilistic viewpoint rather than a deterministic approach for describing systems enables the addition of uncertainty and risk. This risk can be reduced by optimizing business decisions.

2.1 Bayes' Rule And Network Structure

Bayesian networks make statistical inferences according to Bayes' rule. Bayes' rule describes the probability of an event conditional to some prior knowledge about the event. Bayes rule also allows us to update the event probability based on the arrival of new evidence.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{2–1}$$

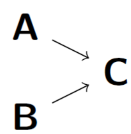
where

- A and B are events and $P(B) \neq 0$.

- $P(A|B)$ is the posterior probability; the probability of event A occurring if B is true.
- $P(B|A)$ is the likelihood; the probability of event B occurring if A is true.
- P(A) is the prior; the probability of event A without having any knowledge of B.
- P(B) is the marginal likelihood; the total probability of the evidence B.

Bayesian networks expand this idea to multiple variables that have a cause and effect relationship with each other. By identifying which variables influence others, conditional probabilities are propagated throughout the network. This lets us determine the probability of an event from the combined probability of its influencing evidence.

In this network,



variables A and B cause event C. The likelihood of event C occurring is affected by the likelihood of A and B both according to the equation

$$P(C) = \sum_{A,B} P(C|A,B)P(A)P(B) \tag{2–2}$$

This lets us determine the probability of C given our knowledge of A and B. We can also infer the probability of A or B given our knowledge of C [20]. The ability to infer unknown probabilities is a key strength of Bayesian networks.

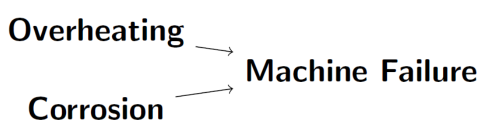
2.2 Building And Reasoning With Bayesian Networks

Bayesian networks are built on the principle of cause and effect. This requires subject matter expertise to model the complex interactions between components of a system. As a result, the developed network provides a comprehensive picture of the entire system, and in-depth analysis can be performed for each part of the system.

Bayesian networks consist of three components; nodes, arcs, and their conditional probabilities. Nodes depict the variables of interest. These variables can be discrete or continuous events that have a causal relation to a system. Examples of variables that can be represented by nodes are phenomenon such as the occurrence of a fault or vibration measurements from sensors. Arcs connect nodes to each other and determine the conditional hierarchy of the network. Arcs are unidirectional and can be properly implemented if we have sufficient knowledge about the cause and effect relations in a system. If event A causes event B, an arc will begin from node A and end at node B. Conditional probabilities between two nodes determine the behavior of the network. These probabilities decide how the likelihood of event B will change according to the likelihood of event A.

The construction of a Bayesian network begins by selecting the variables of interest. This is decided by reviewing the goal of the network and determining what factors affect the operation of the system. Then, the variables are connected by causal arcs. The arcs show cause and effect, and can be drawn using domain expertise or machine learning. Lastly, the conditional probability tables (CPTs) for each parent-child pair are assigned. These values can be determined using data-driven models, physics-based models, or domain expertise.

In this network,



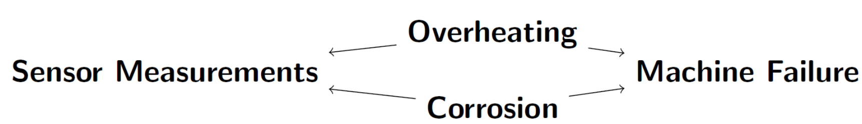
Overheating and **Corrosion** are nodes connected to a **Machine Failure** node via arcs. The likelihood of overheating and corrosion both affect the health of the machine. For this network, we assume that overheating is much more destructive that corrosion and thus reduces machine life faster. The relationship between fault occurrence and machine life is evident in their associated CPT (Table 1).

Once the network is built, we can begin analyzing the behavior of the system. The CPTs define how variables interact with each other. To understand how the system has behaved in the past, or is behaving currently, we can set probability evidence and observe how that evidence is propagated throughout the network. If we know the current state of one variable, we can set that as evidence. Then we can analyze how that known variable affects all the other variables in the network. This method can be used to indirectly estimate the states of hidden variables that cannot be directly measured.

Table 1: The probability of machine failure is affected by the states of both fault A and fault B.

Overheating State	Corrosion State	Machine Failure Probability
Occurs	Occurs	80%
Occurs	Does not occur	60%
Does not occur	Occurs	30%
Does not occur	Does not occur	10%

In this network,



we cannot directly observe the occurrence of faults. We can only infer them based on sensor measurements. Therefore, an additional node is added that relates the sensor measurement values to their associated faults. If we know the current sensor readings, we can set that value as evidence and infer that the machine is most likely experiencing fault A.

2.3 Using Bayesian Networks To Overcome Limits Of Current Practice

Currently, determining the root cause of failure is based on laborious checkups [22, 23, 24]. When a machine fails, service personnel manually inspect the system based on their prior experience. This method can be time-consuming and cost inefficient. Bayesian networks can be used to address challenges for condition diagnosis. Root causes of faults are usually operational in nature, such as a closed valve or maintenance oversight [25]. Bayesian networks can incorporate operational data into fault diagnosis methods since they allow the combination of disparate data sets. Examples of disparate data sets include digital sensor measurements and maintenance reports. Combining disparate data sets provides a large scale picture of the system and the interactions between various phenomenon and activities. This allows for deeper understanding of the condition of the pump and the causes for its degradation. We can infer the root cause of failure by first observing the occurrence of a fault. Then, we can use probabilistic reasoning to determine what caused the fault. Bayesian networks can also be used to address challenges for condition forecasting. Forecasting the health of a pump is not a trivial task since each fault degrades the machine at a different rate. The health forecast is conditional on the type of fault experienced by the pump. This conditional behavior can be modeled using Bayesian networks. If we can provide enough information about how each fault affects a pump's life, we can translate that into conditional probabilities in the network. Therefore, we can first diagnose the fault that is most likely occurring in the pump, and then update the health forecast accordingly.

2.4 Bayesian Network Modeling

To develop a Bayesian network that combines diagnosis and forecasting into one condition monitoring program, we used the GeNIe modeler and SMILE engine from BayesFusion [26]. BayesFusion, LLC provides artificial intelligence modeling and machine learning software based on Bayesian networks. GeNIe Modeler (Graphical Network Interface) is a development environment for building graphical decision-theoretic models. SMILE (Structural Modeling, Inference, and Learning Engine) is a reasoning and learning/causal discovery engine in Python for Bayesian networks.

The condition monitoring Bayesian network is created using a hybrid approach that combines domain expertise and data-driven models. First, we choose the two most common faults that occur in the centrifugal pump. Next, we determine how those faults degrade a pump, i.e., which major component is directly affected by those faults. Then, we determine the common root causes of those faults and where these commonly occur in the piping system. Then, we create the structure of the Bayesian network by setting the appropriate variables as nodes and connecting them using arcs. Finally, we determine the CPTs between all of these nodes by training the network using data-generating models.

3.0 Pump Selection And Model Creation

Nuclear power plants have many different centrifugal pumps installed in various subsystems for different applications [27]. Using domain expertise, we model a pump to simulate normal and abnormal operation to generate data. This data is then used to create the final condition monitoring Bayesian network.

3.1 Pressurized Water Reactors

A pressurized water reactor (PWR) is chosen as the system to analyze since they are widely used in the United States because of their ease of operation and safety [28]. Of the 93 reactors currently operating in the US, 62 are PWRs [29]. Thus, they are appropriate for analysis and for developing advanced asset management procedures.

A PWR consists of two major systems to convert heat generated from fission into electrical power. The primary system consists of the reactor vessel, steam generators, pressurizer, and reactor coolant pumps. The function of the primary system is to transfer the heat from the fuel to the steam generators and prevent fission products from escaping the fuel. The secondary systems in a PWR consist of the main steam system and the feedwater system. The main steam system routes the steam to the turbine then pipes it to the condenser. The steam is condensed into water and then fed through to the feedwater system. The condensate pumps pass the condensed steam through a cleanup process to remove impurities from the water and then through a series of heaters. The feedwater pumps are used to pump water into the steam generator.

3.2 Feedwater System Specifications

The feedwater pumps are chosen as the machine of choice for our analysis. Feedwater pumps are a crucial part of the energy generating process. They are responsible for sending water to the steam generators. Feedwater pumps are also usually very expensive, and improper maintenance can cost a lot of money.

A feedwater system typically contains pumps installed in parallel with common suction and discharge headers. These pumps are usually high-pressure centrifugal type, with one or multiple stages. The piping for feedwater systems includes suction and discharge controls valves that automatically open or close depending on the steam generator supply requirements. The automatic control valves allow the system to accommodate all operating conditions and load transients (Figure 1).

The conditions of service for the selected feedwater pump are 0.38 m^3/s (6000 gpm) at 8.96 MPa (1300 psi). To meet these demands, a single stage horizontal centrifugal pump is configured. The pump performance and design parameters are specified in table 2.

3.3 Pump Fault Mechanisms

For the condition monitoring analysis of our pump, three modes of operation are chosen: normal operation, cavitation, and bent shaft occurrence [30, 31]. Normal operation is the ideal state of the pump and is used as a baseline to train our condition monitoring Bayesian network. Cavitation and a bent shaft are two of the most violent faults that cause serious damage to a pump.

During normal operation, the pump is running at its best efficiency point (BEP) at the desired pressure and flow. Pumps are designed to operate for many years at their best efficiency points without any degradation. The vibrations from a pump are at their lowest magnitude, and there are no unbalanced forces acting on the impeller.

Cavitation occurs when air bubbles get trapped near the top of the pump casing and then implode. The imploding of these bubbles causes shockwaves which can significantly

Table 2: A 2050.68 kW (2750 HP) single stage centrifugal feedwater pump is configured for this research.

Description	**Quantity**		
Flow, rated	0.38	m^3/s	(6000 gpm)
Head, rated	8.96	MPa	(1300 psi)
Speed	59.33	Hz	(3560 rpm)
Impeller diameter	0.46	m	(18 in)
Efficiency	84.05	%	
Temperature	20.00	°C	(68 °F)
Material selected	Carbon steel		
Power, rated	1747.18	kW	(2343 hp)
Power, maximum	2231.14	kW	(2992 hp)
Motor rating	2050.68	kW	(2750 hp)

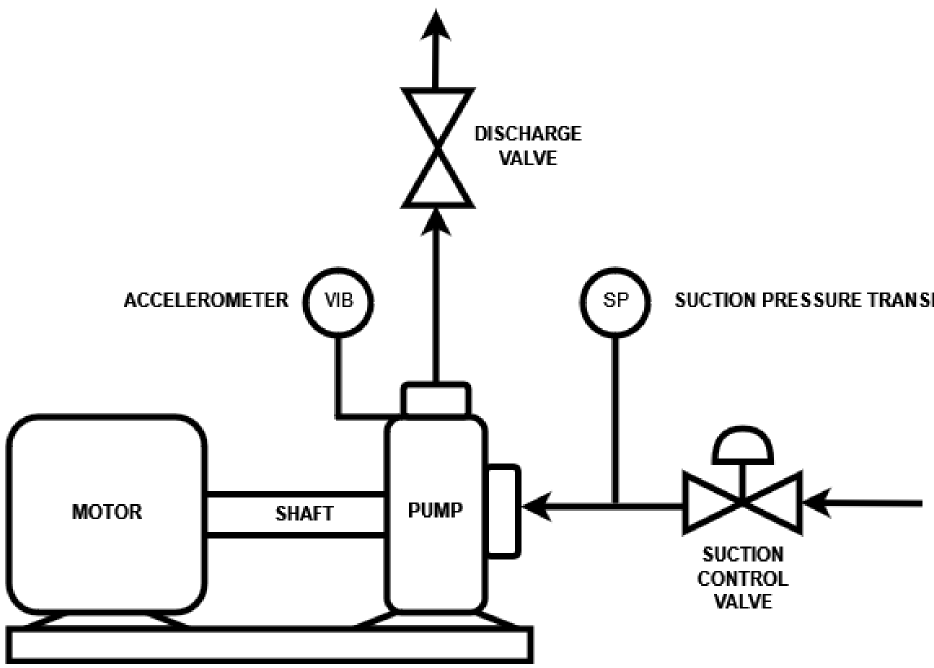


Figure 1: The analyzed pumping system includes a suction valve that controls the flow of water into the pump.

damage the impeller. Cavitation is caused when the suction pressure of the liquid decreases below its vapor pressure, increasing the chances of evaporation and the formation of bubbles. Cavitation causes random high frequency vibrations and is diagnosed using vibration analysis. A bent pump shaft can develop over time and cause premature wear of the shaft and impeller. A shaft will bend over time due to misalignment. Misalignment is one of the most common faults that can occur due to thermal overload. A misaligned shaft will cause complex vibrations that require analysis in the frequency domain.

3.4 Pump Models For Synthetic Data Generation

To create the condition monitoring Bayesian network, the conditional probabilities for each node pair need to be determined. In order to determine the CPTs, we use a data-driven approach. The normal and abnormal operation of the pump are modeled to create synthetic sensor data and operational data. These datasets are used to compute the CPTs by applying a learning algorithm.

3.4.1 Modeling Cavitation Due To Pressure Drop

A harsh change in static pressure in the system can lead to cavitation. System static pressure is usually modulated by control valves, which is a device that regulates the flow of a liquid in a pump system. As the valve opens or closes the pressure drop shifts to the valve and alters the flow in the system. A change in flow velocity leads to a change in static pressure.

If a control valve has malfunctioned or been left partially closed, its surface area will be reduced. When the fluid passes through the reduced area of the valve, its velocity increases. As the velocity increases, the static pressure of the fluid decreases. If the velocity continues to increase, the pressure at the valve will decrease below the fluid's vapor pressure and bubbles will begin to form. As the fluid moves downstream and out of the restricted valve, its velocity decreases and the pressure increases. If the velocity increases sufficiently, the increase in the pressure will cause the bubbles to collapse and implode resulting in cavitation.

Depending on the layout of the pumping system, it is highly likely that the vapor bubbles make their way into the pump casing before they implode. Often, the abrupt increase in area when the bubbles move from the pipe into the pump is the catalyst that makes the bubbles implode. The resulting cavitation causes damage to the impeller and reduces its operating efficiency. If a suction valve closes completely, the pump will be running dry and the pressure will drop to the minimum system pressure which is dependant on various hydraulic considerations. In this research, we assume that the minimum system pressure is lower than the cavitation threshold.

A butterfly-style control valve is chosen for simulating the change in pressure that can cause cavitation. These valves are commonly used throughout industrial piping systems. The control valve is modelled as a circle with a radius r projected on to the viewing plane at an angle θ. When the valve rotates on the viewing plane, it is projected as an ellipse with a height of $2r$ and width of $2r\cos\theta$. The formula for the area of an ellipse is πab, therefore the area of the valve can be calculated as $\pi r^2 \cos\theta$.

The equation for the velocity of a fluid through a pipe is

$$v = \left(\frac{Q}{A}\right) \tag{3–1}$$

Knowing how the surface area changes with valve position, the change in velocity of the fluid through can be determined [32].

Using Bernoulli's equation, the change in pressure due to change in fluid velocity can be calculated [33].

$$P_1 - P_2 = \rho\left(\frac{{v_2}^2 - {v_1}^2}{2g}\right) \tag{3–2}$$

These relations are modeled in MATLAB. A signal is generated to replicate the position of a valve from 0 degrees (fully open) to 90 degrees (fully closed) and the resulting suction pressure values are recorded (Figure 2).

To determine the occurrence of cavitation, a pressure threshold is defined. Cavitation will start occurring when the pressure drops below the vapor pressure of the fluid. The vapor pressure of the fluid at 20 °C (68 °F) is 205.5 kPa (29.8 psi). Therefore, for the purpose of data

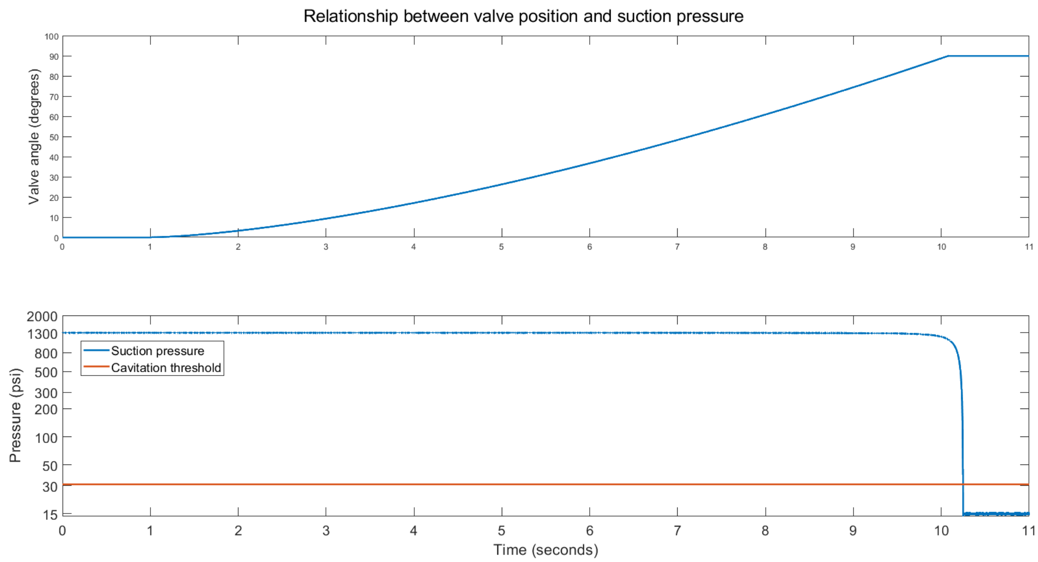


Figure 2: As the suction valve is closed, the pressure through it drops below the liquid vapor pressure.

generation, the pump begins to cavitate when the suction pressure drops below 205.5 kPa (29.8 psi).

3.4.2 Modeling A Bent Shaft Due To Thermal Expansion

The two major components of a pump are the casing and the motor. To convert the electrical energy and transmit it to the fluid, couplings are required to combine the pump shafts and motor shafts together. During coupling installation, extra attention is given to align the two shafts in all dimensions to prevent unbalanced forces. There is also a degree of flexibility built into the couplings to absorb the impact of slight misalignment. Gear couplings are a type of flexible couplings commonly used in pump systems. Shaft mounted external gear teeth mate with internal gear teeth on a housing that contains a lubricant. Lubricated couplings require maintenance like other major components in a pumping system. The relative motion between the shafts and other centrifugal forces cause separation of the grease and leakage from the housing. Periodic checks are required to ensure sufficient lubrication to compensate for leakage. Furthermore, old lubricant is periodically flushed and removed completely and replaced with new application.

Typical relubrication for gear couplings are six months to one year [34]. These lubrication schedules are based on general guidelines and are not informed, i.e., they do not change according to the actual state of lubrication. If there is any deviation from typical pump operation, these schedules can become offset from when they are actually required. Examples of atypical operation can include increased or decreased duration of operation, operating with contaminants, or a pressure leak in the piping.

Failure to keep an optimal maintenance schedule leads to a rapid decrease in lubrication levels in the couplings. Insufficient coupling lubrication causes a drastic increase in friction between the shafts and coupling components. If the friction increase is left unchecked, the temperature in the coupling housing can increase enough to begin altering the mechanical properties of the shaft. If the shaft becomes hot enough, it begins to thermally expand while decreasing its yield strength. The thermal expansion can lead to significant misalignment between the pump and motor shafts.

Excessive misalignment will force a rigid shaft to deflect as they rotate around an axis. This deflection will permanently warp and bend the shaft over time. The bent shaft will lead to unbalanced rotation of the impeller. An unbalanced impeller experiences unbalanced forces inside the pump casing which cause damage and degradation.

To simulate a bent shaft due to insufficient lubrication, the number of cycles since the last relubrication is related to the change in temperature of the shaft. As the shaft is rotated, the processes acting on it wears down the lubrication in the coupling housing. The decrease in lubrication increases the temperature of the shaft and ultimately causes it to misalign and bend.

A shaft begins to warp under a load when it gets hot enough to significantly lower its yield strength. We define a 46% prolonged decrease in yield strength as significant to cause the shaft to bend [35, 36]. For industrial applications, pump shafts are usually made from 304 stainless steel [37]. At room temperature, the yield strength of 304 stainless steel is 186.2 MPa (27,000 psi). A 46% decrease in that value results in a yield strength of 103.4 MPa

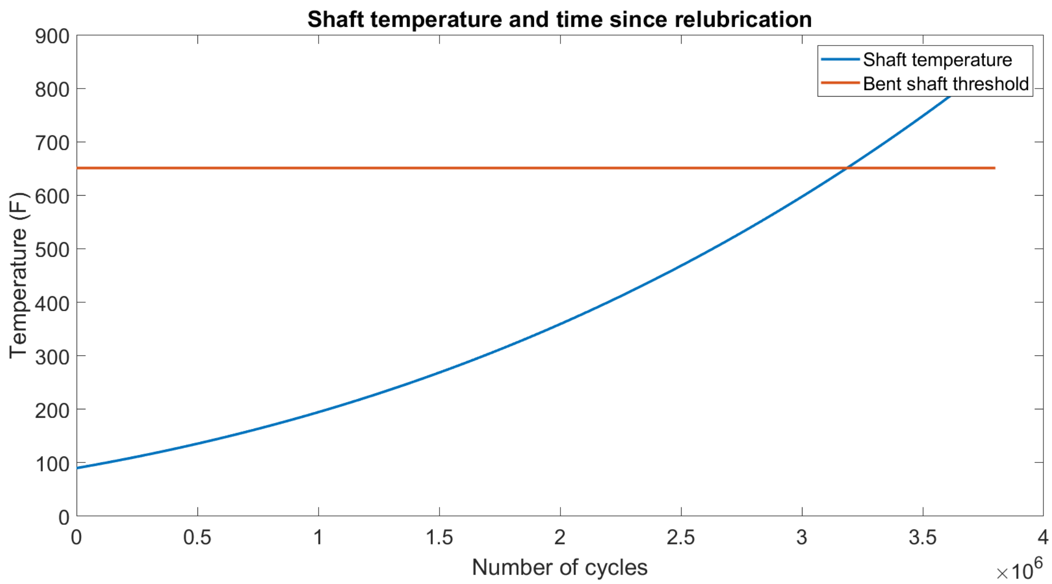


Figure 3: If the pump shaft is not relubricated due to maintenance oversight, it will eventually begin to warp due to thermal expansion.

(15,000 psi), which occurs at 343.3 °C (650° F) [38]. Therefore, a bent shaft is likely to occur when the shaft reaches a temperature of 343.3 °C (650° F). For our data-generating model, we assume that the shaft will reach 650 F due to running for 3,800,000 cycles without applying additional lubrication.

For the purpose of data generation, the date of lubrication is converted to number of operational cycles of the pump. An experiment is simulated in MATLAB where a coupling is lubricated once, then left running until impeller performance begins to decrease. The number of cycles since last lubrication is recorded and used for CPT computation (Figure 3).

3.4.3 Spring-Mass-Damper Model For Simulating Pump Vibrations

To understand a pump's vibration behavior under normal and abnormal operation, a vibration model of the pump is created. The model consists of masses of different sizes that replicate the major parts of a pump. These masses are connected with springs and dampers to model the vibration characteristics of the various pump components [39].

The centrifugal pump is represented by a lumped parameter three-beam model. A representation of this system can be seen in figure 4. The beams are modeled as a series of mass points of varying values, representing the different parts of the pump. The three beams represent the motor shaft, pump shaft, and base plate. The motor and pump shafts are connected by a coupling. The shafts are connected to the base plate by bearings. The base plate is connected to the ground using flexible mounts. The coupling, bearings, and flexible mounts are represented by linear spring and proportional damper combinations.

The number and location of mass points are chosen to replicate the pumps mass distribution and flexibility and to model the interaction of forces and movement between connected components. The motor and pump shafts contain the most mass points due to their ability to significantly bend and endure various forces. The base plate is mostly rigid because it is stiff relative to the shafts. Constructing a model with mass points at these specific locations allows the application of forces to simulate the occurrence of rotating imbalances, coupling misalignment, flow-induced faults, and bearing defects.

The equation of motion for the pump is

$$M\ddot{r}(t) + D\dot{r}(t) + Kr(t) = B_f f(t) \tag{3–3}$$

The number of degrees of freedom is m, and the number of input forces acting on the structure is q. The remaining parameters are described in table 3.

- The mass matrix, M, is

$$M = \mathrm{diag}(m_1, m_2, \ldots, m_{11}) \tag{3–4}$$

- The damping matrix, C, assumes proportional damping,

$$D = \alpha M + \beta K. \tag{3–5}$$

- The input matrix, B_f, is.

$$B_f = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}^T$$

Table 3: The equation of motion for the pump is modeled in state-space using lumped parameters.

Parameter	Vector Size	Description
$r(t)$	$m \times 1$	Displacement vector
$f(t)$	$q \times 1$	Applied force vector
M	$m \times m$	Mass matrix
D	$m \times m$	Damping matrix
K	$m \times m$	Stiffness matrix
B_f	$m \times q$	Input matrix

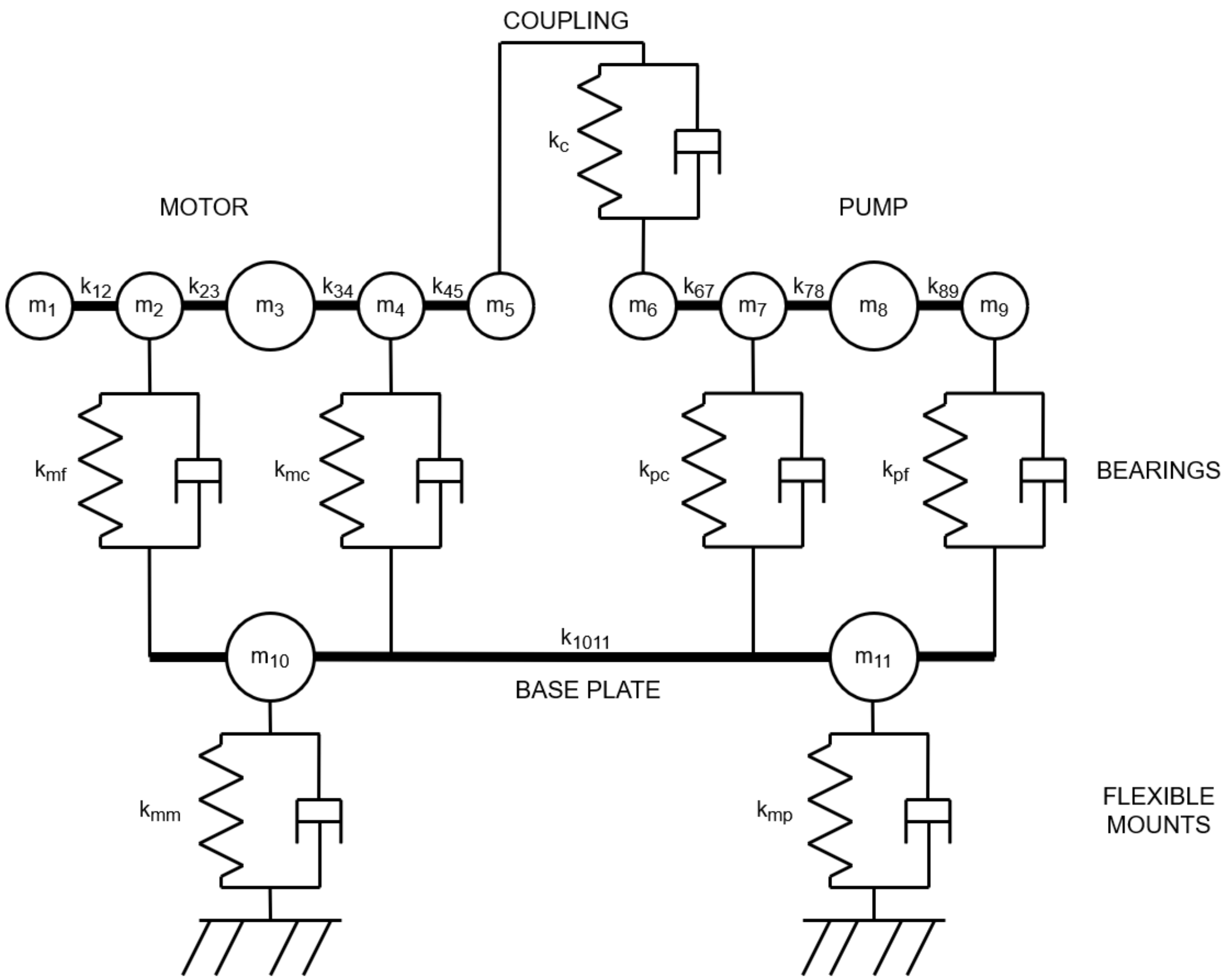


Figure 4: The three beam pump model is used to simulate its response to various input signals

Table 4: The pump model is developed as a spring-mass-damper system with multiple parameter values.

Parameter	Value	Unit	Description
m_1	133.57	kg	Motor fan and part of motor shaft
m_2	440.97	kg	Outboard motor bearing mass, part of motor shaft
m_3	881.93	kg	Inboard motor bearing mass, part of motor shaft
m_4	440.97	kg	Inboard motor bearing mass, part of motor shaft
m_5	224.07	kg	Motor half of coupling, part of motor shaft mass
m_6	732.93	kg	Pump half of coupling, part of motor shaft mass
m_7	1466.3	kg	Inboard pump bearing mass, part of pump shaft
m_8	2532.27	kg	Pump impeller mass, part of pump shaft
m_9	1466.3	kg	Outboard pump bearing mass, part of pump shaft
m_{10}	253.59	kg	Mass of motor stator, motor case, part of base plate
m_{11}	253.59	kg	Mass of pump case and part of base plate
$k_{12}, k_{23}, k_{34}, k_{45}$	755.9	kN/m	Beam stiffness between mass points 1-2, 2-3, 3-4, and 4-5
k_{67}, k_{78}, k_{89}	67.27	kN/m	Beam stiffness between mass points 6-7, 7-8, 8-9, and 9-10
k_{1011}	41.56	kN/m	Beam stiffness between mass points 10-11
k_{mf}, k_{mc}	13500	kN/m	Motor bearing spring rate
k_{pc}, k_{pf}	7880	kN/m	Pump bearing spring rate
k_{mm}, k_{mp}	17500	kN/m	Spring rates of the base-plate mounts
k_c	9000	kN/m	Coupling spring rate

- The stiffness matrix, K, is

$$K = \begin{bmatrix} k_{12} & -k_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -k_{12} & k_{12}+k_{23}+k_{mf} & -k_{23} & 0 & 0 & 0 & 0 & 0 & 0 & -k_{mf} & 0 \\ 0 & -k_{23} & k_{23}+k_{34} & -k_{34} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -k_{34} & k_{34}+k_{45}+k_{mc} & -k_{45} & 0 & 0 & 0 & 0 & -k_{mc} & 0 \\ 0 & 0 & 0 & -k_{45} & k_{45}+k_c & -k_c & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -k_c & k_c+k_{67} & k_c+k_{67} & -k_{67} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -k_{67} & \begin{bmatrix} k_{67}+k_{78} \\ +k_{pc} \end{bmatrix} & -k_{78} & 0 & 0 & -k_{pc} \\ 0 & 0 & 0 & 0 & 0 & 0 & -k_{78} & k_{78}+k_{89} & -k_{89} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -k_{89} & k_{89}+k_{pf} & 0 & -k_{pf} \\ 0 & -k_{mc} & 0 & -k_{mc} & 0 & 0 & 0 & 0 & 0 & \begin{bmatrix} k_{mf}+k_{mc} \\ +k_{1011}+k_{mm} \end{bmatrix} & -k_{1011} \\ 0 & 0 & 0 & 0 & 0 & 0 & -k_{pc} & 0 & -k_{pf} & -k_{1011} & \begin{bmatrix} k_{pc}+k_{pf} \\ +k_{1011}+k_{mp} \end{bmatrix} \end{bmatrix}$$

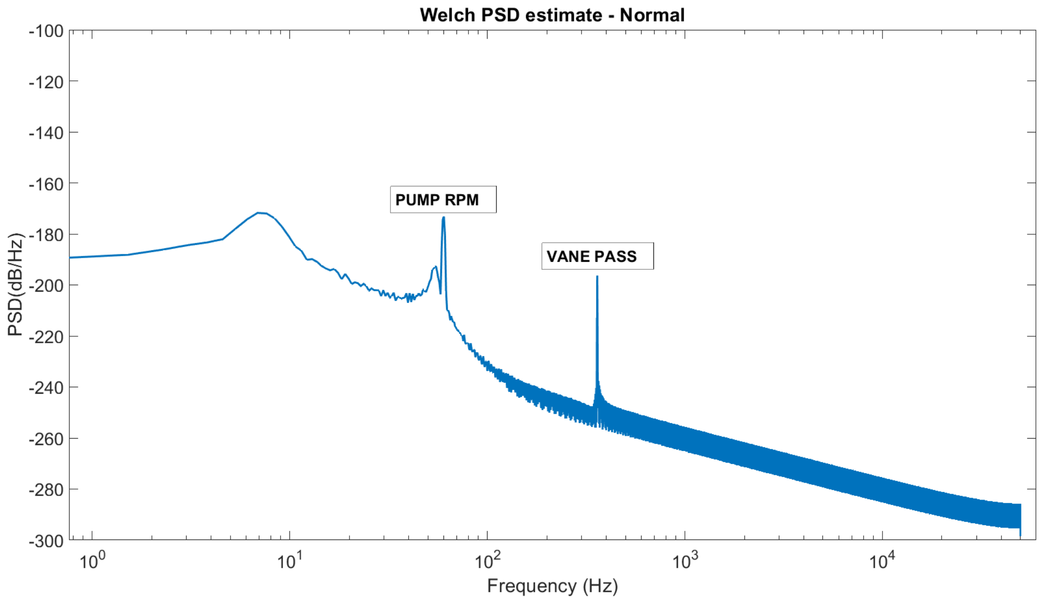


Figure 5: The vibration signal of the pump running during normal operation shows peaks at the vane pass at motor RPM.

For normal operation and cavitation, the external force is applied only on the impeller mass, m_8. This replicated the turbulence experienced by the pump due to the water flowing through the impeller Vibration data is measured with accelerometers placed near the vibration source. To replicate this process, the output state-space equation is developed to obtain acceleration from the pump casing mass (m_{11}). This simulates placing an accelerometer on the pump casing, which is common practice.

To replicate normal operation, sinusoidal signals at 60 Hz (3600 rpm) and at 360 Hz are applied to the impeller mass (m_8 in the model). These frequencies are the impeller rotation, 3600 rpm, and the vane pass frequency (6×3600 rpm). To simulate turbulence in the pump, a white noise forcing function is applied to the impeller mass. Figure 5 shows the vibration spectra of a pump running at 3600 rpm under normal conditions. We clearly see that the vane pass frequency (360 Hz) and the motor RPM (60 Hz) dominate the response.

Pump cavitation occurs when air bubbles get trapped in the pump casing and implode,

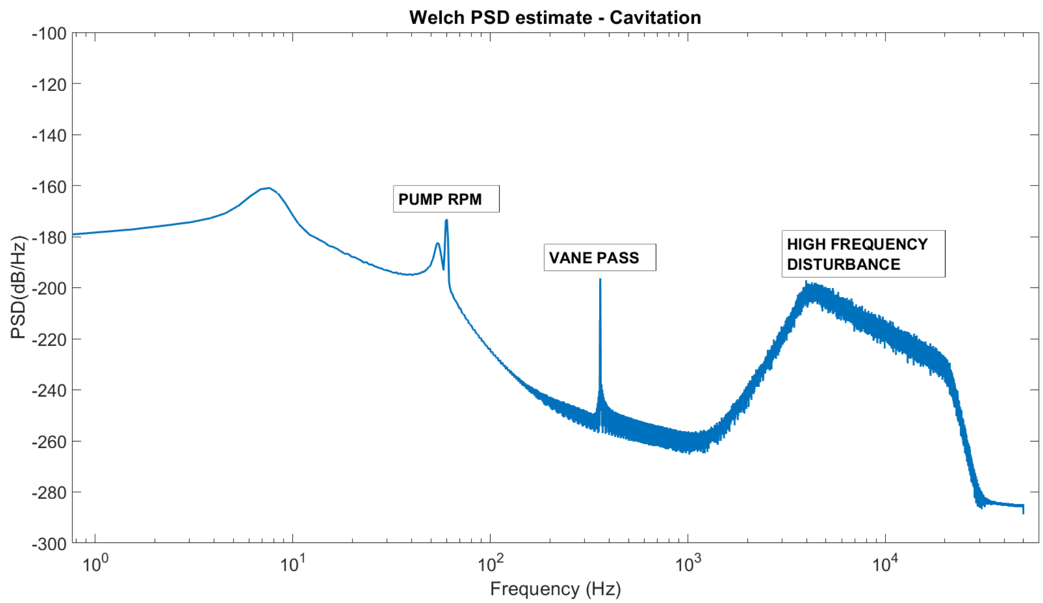


Figure 6: The vibration signal of a cavitating pump shows random high frequency excitation.

causing shock waves. This phenomenon produces random high frequency vibrations between 4 kHz to 20 kHz [3]. To simulate a running pump experiencing cavitation, the input to our pump model is modified to include colored noise in the bandwidth of interest. The cavitation signal is applied to m_8, along with the inputs from the previous section. This simulates a pump running at a certain rate while experiencing cavitation. Acceleration data is gathered from the motion of mass m_{11}. The resulting cavitation vibration signature is shown in figure 6. We clearly see that cavitation causes high amplitude disturbances between 4 kHz to 20 kHz. This disturbance often dominates the vibration response.

A pump shaft with insufficient maintenance can become warped and permanently bent over time. A bent pump shaft causes high axial vibrations that can be diagnosed using spectral analysis. This results in a large amplitude spike at two-per-revolution [3]. To simulate a running pump with a bent shaft, the input to our pump model is modified. A sinusoidal signal with a frequency of two-per-revolution (60 Hz) is applied to mass m_6, the pump shaft mass. The resulting bent shaft vibration signature is shown in figure 7. The

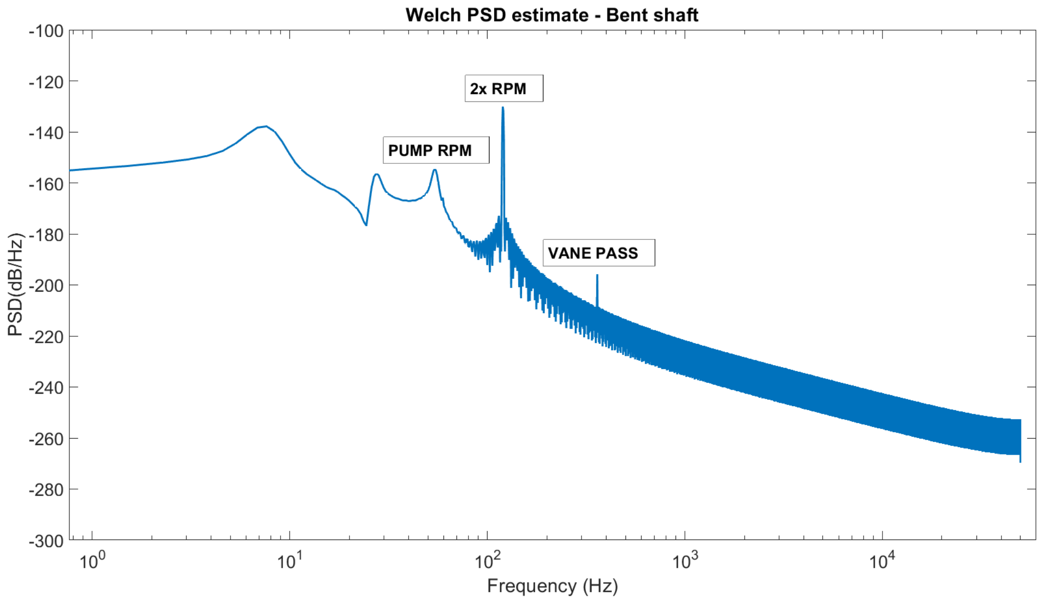


Figure 7: The vibration signal of the pump running running with a bent shaft shows a high amplitude spike at 2× motor RPM.

dominating feature in the vibration response is a large amplitude spike at 120 Hz.

In order to incorporate vibration information in the Bayesian network, feature engineering is performed on the vibration data. Feature engineering is the process of extracting useful variables from a dataset using domain expertise. Using features instead of the raw data can simplify models and improve prediction.

The vibration data is decomposed into three features:

1. *Crest factor:* The crest factor is defined as the ratio of the peak value of a signal to its RMS value (Figure 8). A crest factor value of 1 indicates no peaks. Crest factor is calculated as

$$\mathrm{cf} = \frac{x_p}{x_{rms}} \tag{3–6}$$

where x_p is the maximum absolute value of the signal and x_{rms} is the root mean squared value of the signal.

2. *Skewness:* Skewness is used to measure whether the signal is negatively or positively

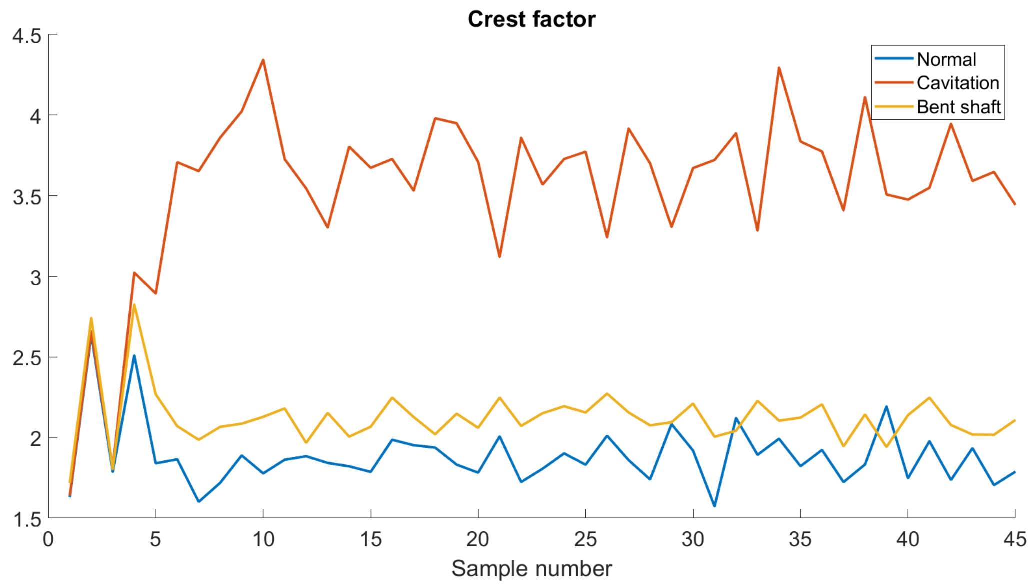


Figure 8: The crest factor values of the signal are distinct for cavitation.

skewed (Figure 10). It is obtained from the mean value of the probability density function of the signal. Skewness is calculated as

$$s = \frac{\mathbb{E}\{x - \mu^3\}}{\sigma^3} \tag{3–7}$$

where μ is the mean of x, σ is the standard deviation of x, and $\mathbb{E}\{x\}$ is the expected value of x.

3. *Kurtosis:* Kurtosis is used to quantify the peakness of a signal (Figure 9). A higher kurtosis value corresponds to a signal with more peaks that are greater than three times the signal RMS. Kurtosis is calculated as

$$k = \frac{\mathbb{E}\{x - \mu\}^4}{\sigma^4} \tag{3–8}$$

These features are dimensionless normalized quantities. In order to analyze the machine state, these values need to be compared to an established baseline. The baseline quantity and the abnormal deviations from it depend on the configuration of the analyzed system. In our research, we determine the state of the pump by computing the features for normal

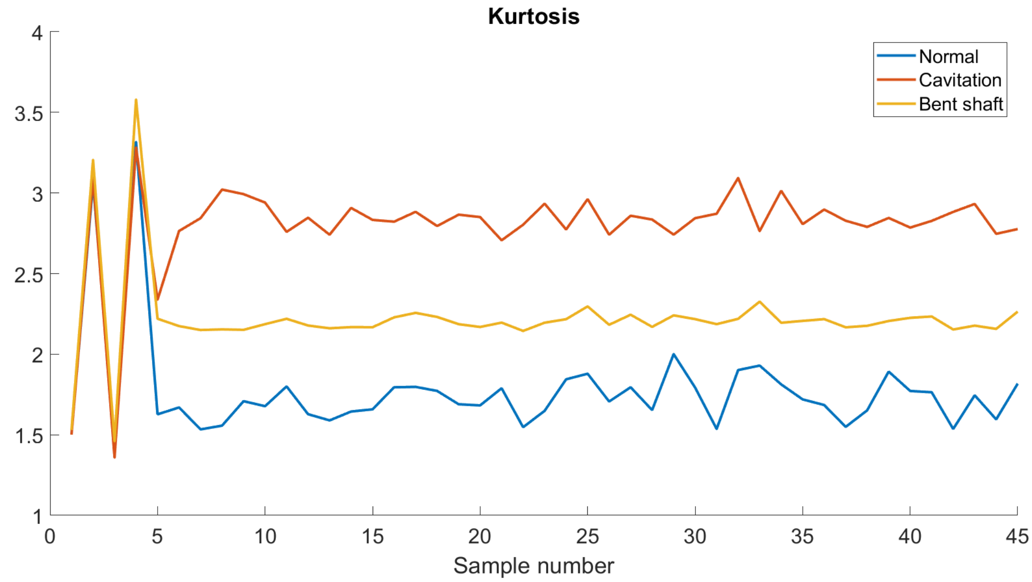


Figure 9: The kurtosis values of the signal are distinct for each of the three modes of operation.

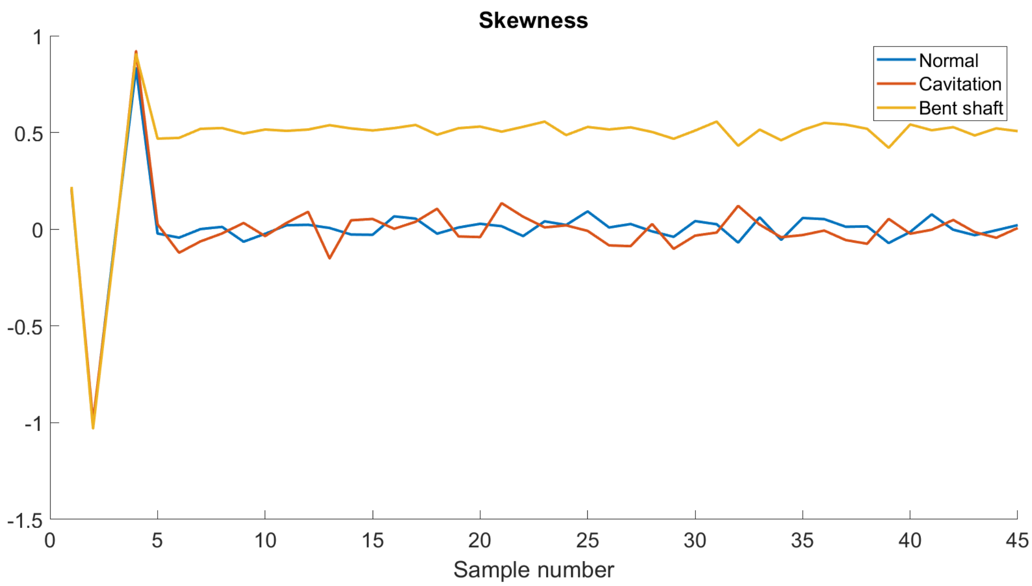


Figure 10: The skewness values of the signal are distinct for a bent shaft.

operation and then comparing them to the values from cavitation and a bent shaft. In figures 8, 9, and 10, we can clearly see the deviations from normal operation when the pump is experiencing a fault. The degree of deviation from the baseline is not considered in this research but it can be investigated in future work.

3.5 Survival Analysis For Conditional Forecasting

Even during normal operation, pump components will degrade over time. The impeller faces constant dynamic forces that cause warping and chipping over its lifetime. Eventually, the impeller wears significantly and stops providing enough energy to the fluid to meet the required duty points. Abnormal operation such as running while cavitating or with a bent shaft will exacerbate this process, and the impeller will significantly degrade at a much faster rate. After a certain threshold, the worn impeller is no longer of use and needs replacing.

Whether the pump is operating normally or abnormally, there is a need to predict when the impeller will degrade and require maintenance. To develop a prediction model, impeller lifetime data is desired. A NASA turbofan dataset [40] is altered to recreate the operation of an impeller rotating inside a pump. The dataset is used to train our predictive models to provide an estimate of the future impeller health.

Survival analysis is a collection of techniques to determine the expected amount of time before an event occurs, and the goal of survival analysis is to develop the survival function for a machine. The survival function is the probability of an event occurring after a specified time. Mathematically, given that a device fails before time T with cumulative distribution $F(T)$ (and probability density $f(T) = F'(T)$), the survival function $S(t)$ defines the probability that failure at time T is after the current time t; i.e, it's the probability that the device survives past time t.

$$S(t) = P(T > t) = \int_t^{\infty} f(\tau)\, d\tau = 1 - F(t) \tag{3–9}$$

For condition monitoring, the event of interest is machine failure. Survival analysis is suitable for forecasting due to its ability to cope with incomplete data sets. Lifetime data for a machine is hard to obtain, but this method specializes in providing a time to failure estimation from collected data.

The most common tool to compute the survival function is the Kaplan-Meier estimator (Figure 13). It is used to compute the Kaplan-Meier survival plot from observational data. It is defined as

$$\hat{S}(t) = \prod_{t_i < t} \frac{n_i - d_i}{n_i} \tag{3–10}$$

where d_i is the number of failure events at time t_i and n_i is the number of machines that have survived up to time t_i.

The Kaplan-Meier estimator has its advantages in determining the survival function, but due to its non-parametric nature it is difficult to implement in a comprehensive statistical model. To facilitate the use of survival functions in analysis, a parametric model is derived that provides similar estimates as the Kaplan-Meier model. In this research, the parametric Weibull model is fit to the lifetime data. the Weibull model is defined as

$$S(t) = \exp\left[-\left(\frac{t}{\lambda}\right)^{\rho}\right] \tag{3–11}$$

where λ is the scale parameter and ρ is the shape parameter.

Survival analysis is performed on a pump dataset to estimate its remaining-useful-life. The Python package `lifelines` is used for computing the survival functions [26]. The dataset contains contains run-to-failure data for a hundred pumps experiencing two different faults. (Figures 11, and 12). The pumps begin operation with normal amounts of initial wear, but develop either cavitation or a bent shaft over time. The faults persist through the time series until total failure.

First, the Kaplan-Meier estimator is used to provide an overview of the survival function (Figures 13, 14). From these plots, we can observe that all the pumps run for at least 130 cycles, and the likelihood of surviving rapidly declines. Second, the Weibull fitter is used for parameterization (Figures 15, and 16). The resulting Weibull coefficients can be used to align the forecasting window to any nuclear plant outage.

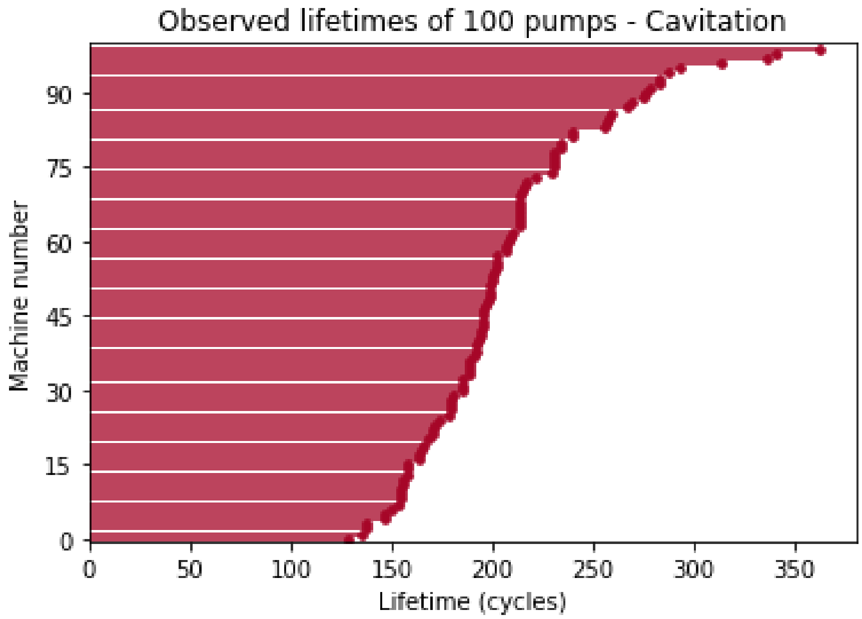


Figure 11: The maximum lifetime of pumps experiencing cavitation is around 400 cycles.

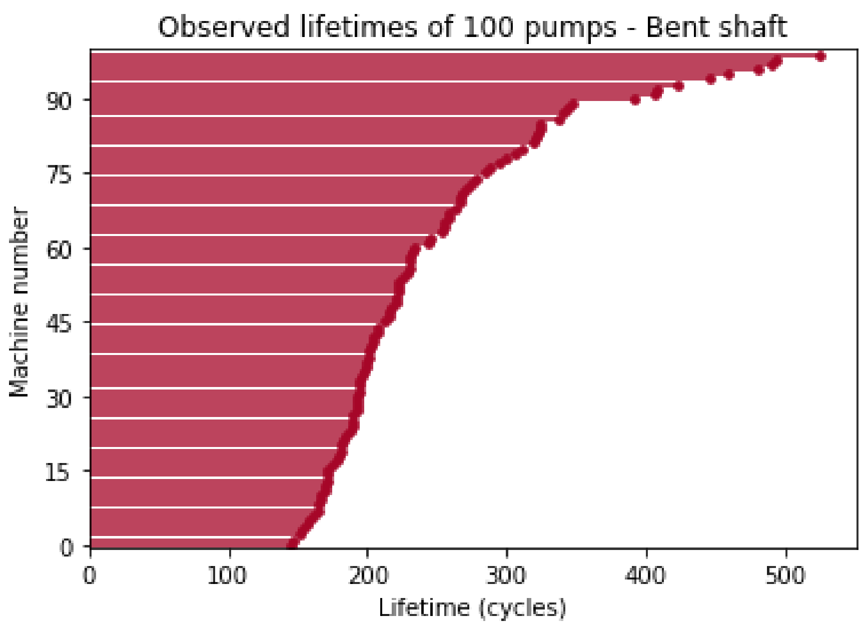


Figure 12: The maximum lifetime of pumps experiencing a bent shaft is around 550 cycles.

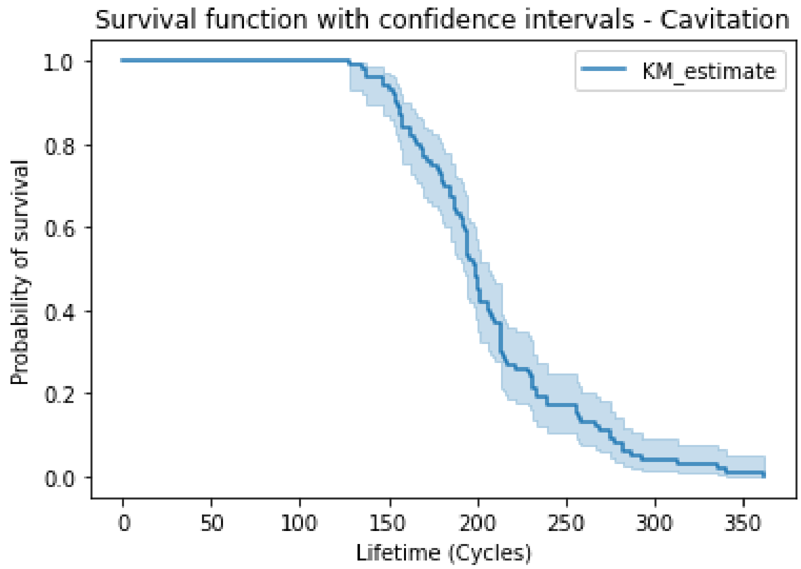


Figure 13: From the Kaplan Meier plot, we determine the median life of cavitating pumps is 200 cycles.

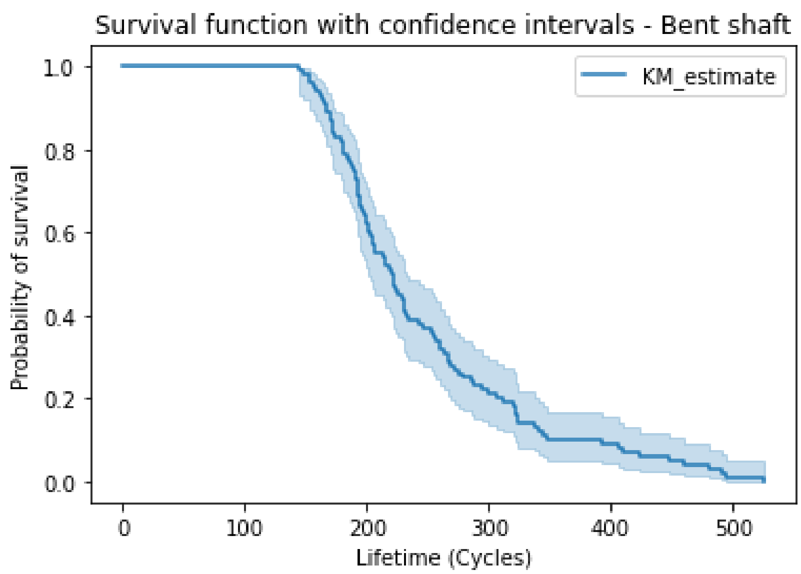


Figure 14: From the Kaplan Meier plot, we determine that half of the pumps fails around 220 cycles while operatign with a bent shaft.

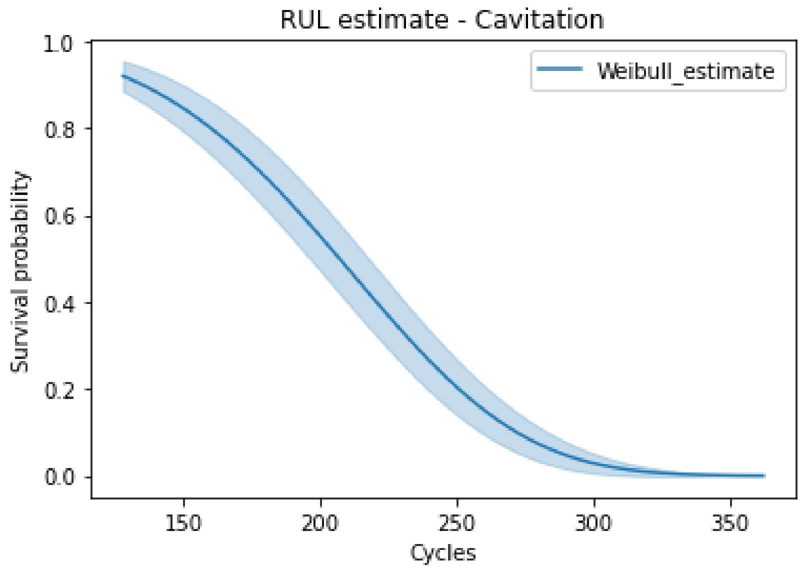


Figure 15: The resulting λ and ρ values for the cavitation Weibull model are 225.03 and 4.41 respectively.

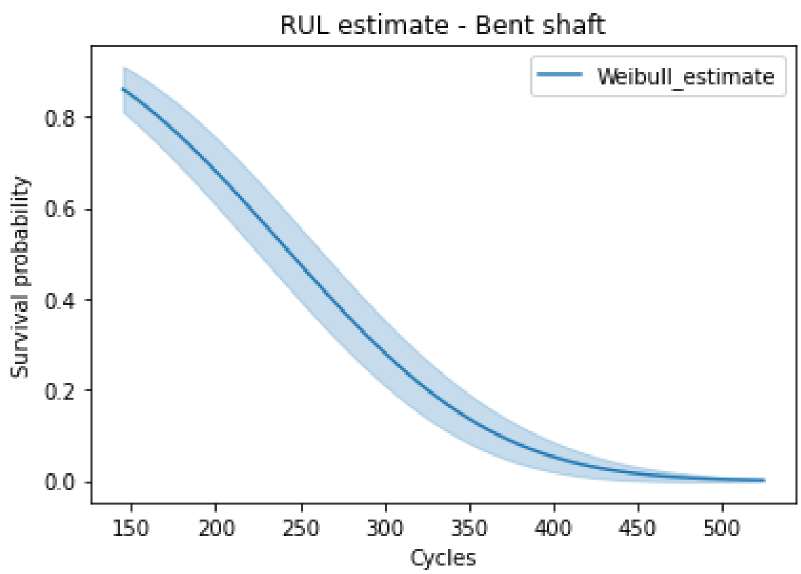


Figure 16: The resulting λ and ρ values for the bent shaft Weibull model are 276.82 and 2.93 respectively.

4.0 Condition Monitoring Bayesian Network Creation

Once we completed the preliminary data generation and RUL analysis, we began creating the Bayesian network. To do so, we first determined the capabilities that we expect from our condition monitoring framework. In order to improve condition monitoring for asset management, we determined three requirements:

1. We need to know the current state of the machine. This would help operators determine whether the machine is in need of any urgent repair that might cause an unplanned outage.
2. We need to know how long the machine will run until it reaches a certain failure threshold. This would help decision-makers determine whether the machine would safely operate until the next planned outage. Knowing the RUL would also allow decision-makers to coordinate with the supply chain to ensure that a replacement is available without delay. This would help in reducing outage duration.
3. We need to know the root cause of machine failure. This would compliment the RUL estimations by allowing decision-makers to order the specific failed component without any redundant inventory. This would also aid in the actual maintenance process by removing the need for trial-and-error root cause determination. This would help in reducing outage duration.

To accomplish these tasks, we combined information from multiple sources: dynamic models, maintenance logs, domain expertise, and machine data in the form of sensor measurements. Using Bayesian networks, we were able to combine all these disparate systems into one cohesive condition monitoring framework (Figure 17):

1. Physics-based dynamic models were developed to create training data for the network. We simulated numerous modes of operation to gather vibration and pressure information about the pump. After some signal processing, we obtained measurements that we would expect to see from a real pump. Finally, we performed data readiness on these

measurements in order to feed them to the learning algorithm to generate conditional probabilities.

2. Maintenance logs provided us with information about the life of the pump. These logs included the date of last service for the pump, the reason for servicing, and the date when the pump was first installed. This information allowed us to compute the lifespan of numerous pumps that failed due to various causes. In turn, this lifetime data was used to develop survival functions for our pump. These survival functions provided us with estimates of the RUL of the pump under normal and abnormal conditions. Once we had the RUL estimates, we structured our dataset appropriately in order to train our network.
3. Domain expertise was used to create the cause-and-effect structure of the network. We designed the Bayesian network such that we could provide evidence to it in the form of current vibration and pressure measurements and infer the current and future condition of the pump. In order to have this capability, we needed to create conditional probabilities between each node in the network. This task was trivial for a node-pair in which a single cause lead to a single effect, such as the interaction between a bent shaft and its root cause. However, CPTs became complex when a single node had multiple causes, or vice-versa. Therefore, the final step in creating the Bayesian network was to feed data from the dynamic models and maintenance logs into the structure defined by our domain expertise. To do so, we used a data-driven machine learning algorithm to simultaneously determine the CPTs for the entire network.
4. Sensor measurements provided us with information about the current state of the machine. Each mode of operation that we modeled has a unique vibration signature. If there were multiple root causes to a failure, the associated pressure measurements would aid in estimating the correct one. These measurements were used to update the estimations of the Bayesian network in order to infer the condition of the pump.

The key to creating a condition monitoring framework that addressed the three requirements determined above was developing CPTs between disparate systems. To do so, we used Bayesian networks along with a data-driven machine learning algorithm. The following sections further explain the network creation process.

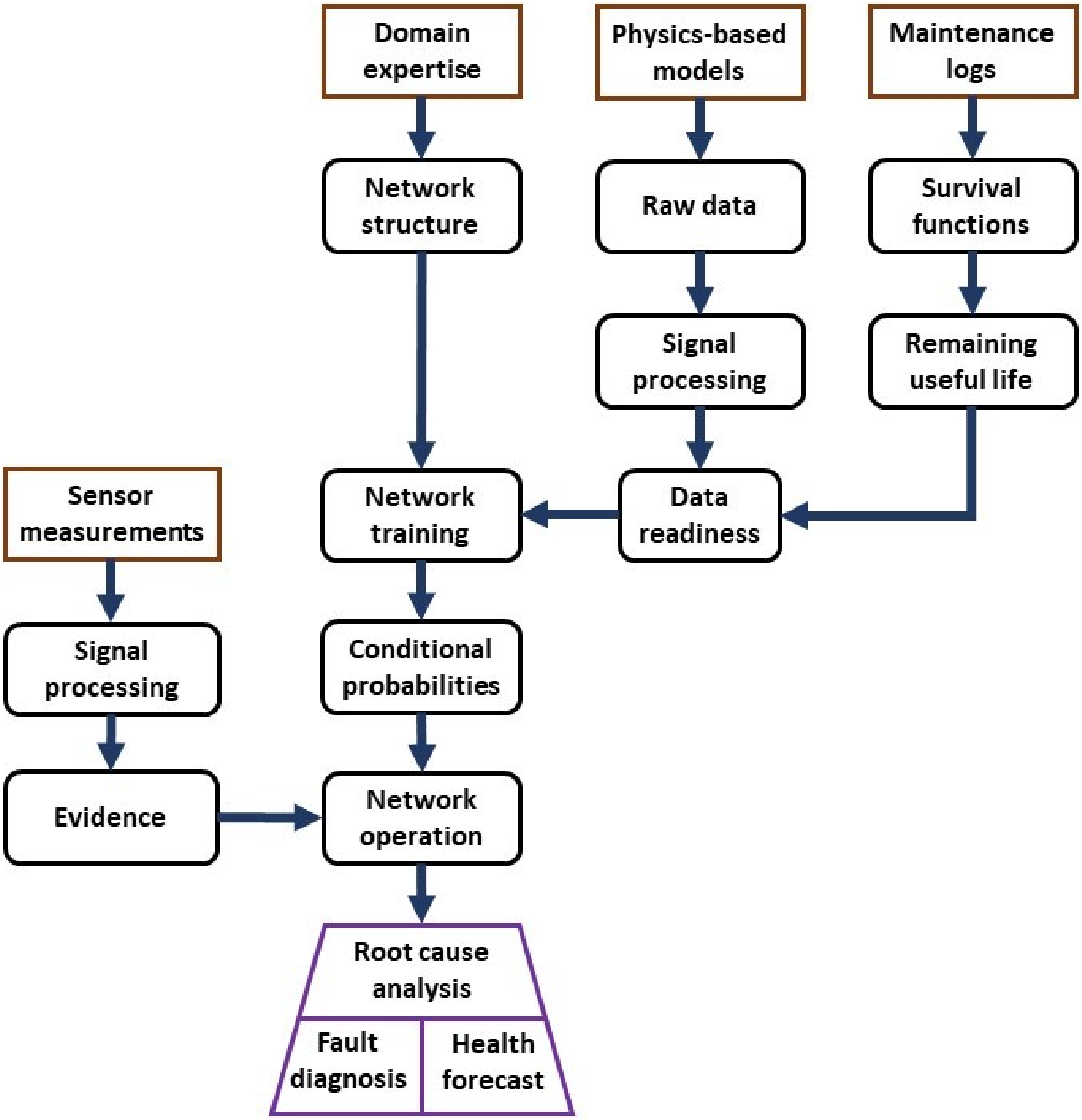


Figure 17: Four disparate systems were combined to develop the final condition monitoring Bayesian network.

4.1 Modeling The Bayesian Network

Using the fault data and lifetime data from previous sections, we created a condition monitoring Bayesian network to overcome the limitations mentioned in section 1.2 (Figure 18). The Bayesian network is developed using figure 1 as reference. The inputs to the network are pressure and vibration measurements. The vibration information is input in the form of features. These features are extracted from the accelerometer measurements. The pressure information is input using measurements from the suction pressure transducer. From these inputs, we can diagnose one of two faults, infer the root cause of failure, and forecast the pump's health.

We define the health of the selected pump as the health of its impeller. The impeller is the rotating part inside a pump that transfers energy from the motor to the fluid. The fluid enters the pump at a certain flow and pressure, and exits with increased energy. The amount of energy transferred to the fluid can be affected if the impeller develops defects due to any pump fault. These defects decrease the efficiency of the pump and motor system and cause the desired conditions of service to not be met.

4.2 Modeling Cavitation In The Bayesian Network

In the selected pumping system (Figure 1), the suction valve controls the suction pressure of the fluid going into the pump. The suction pressure is not observed directly, it is only inferred from the suction pressure transducer measurements. This relationship is modeled in figure 19. The state of the **Valve Position** node affects the **Pressure** node. Similarly, the state of the **Suction Pressure Transducer** node depends on the state of the **Pressure** node.

The occurrence of cavitation is inferred via the actual pressure state of the pump. This relationship is shown in figure 20. The **Pressure** node describes the true pressure state of the pump and it directly affects the state of **Cavitation**.

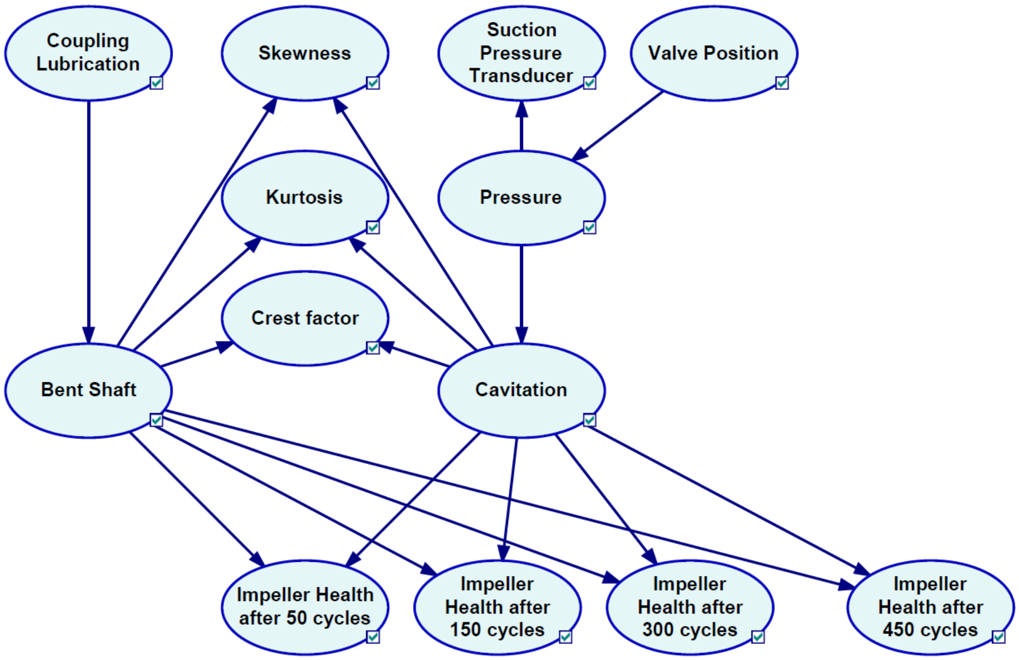


Figure 18: The condition monitoring Bayesian network can diagnose faults, infer root cause of failure, and forecast pump health.

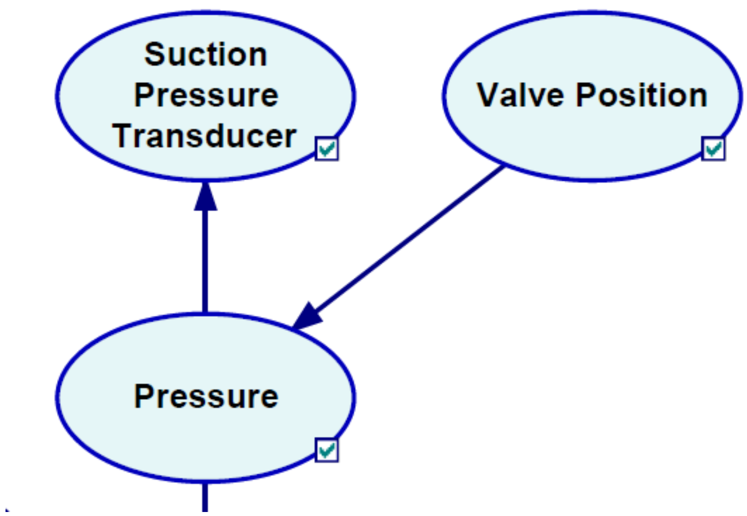


Figure 19: The position of a valve causes a change in the suction pressure.

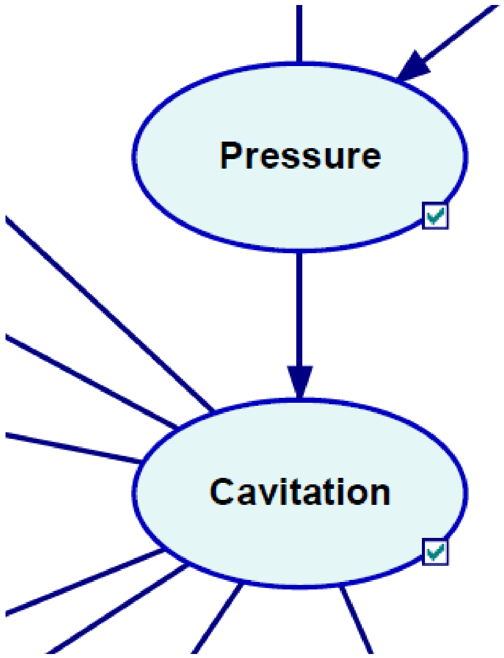


Figure 20: A change in suction pressure causes cavitation.

4.3 Modeling A Bent Shaft In The Bayesian Network

In the selected pumping system, the motor shaft and pump shaft are connected with a coupling. If the coupling is not lubricated on schedule, it can lead to warping and bending of the shafts. This relationship is shown in figure 21. The state of **Coupling Lubrication** directly affects the state of **Bent Shaft**.

4.4 Vibration Analysis Using The Bayesian Network

Based on the analysis in section 3.4.3, the vibration measurements are added into the Bayesian network in the form of features. There is a unique combination of skewness, kurtosis, and crest factor values for each of the three simulated modes of operation. When the appropriate values are entered into these nodes as evidence, the Bayesian network can

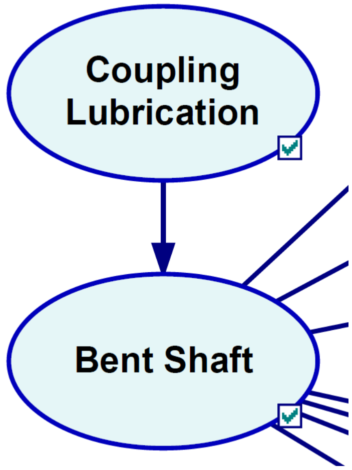


Figure 21: A bent shaft depends on the lubrication state of the coupling.

determine the current state of the pump. This relation is shown in figure 22. The state of **Bent Shaft** and **Cavitation** directly affect the state of the **Skewness**, **Kurtosis**, and **Crest factor**.

4.5 Forecasting Health Using The Bayesian Network

Based on the analysis in section 3.5, the survival models are added into the Bayesian network. Pump health is forecasted for four different operating periods: 50 cycles, 150 cycles, 300 cycles, and 450 cycles. After the appropriate state of the pump is inferred, the Bayesian network can determine how the pump will degrade after each of these cycles. This relation is shown in figure 23. The state of **Impeller Health after 50 cycles**, **Impeller Health after 150 cycles**, **Impeller Health after 300 cycles**, and **Impeller Health after 450 cycles** are directly affected by the states of **Bent shaft** and **Cavitation**.

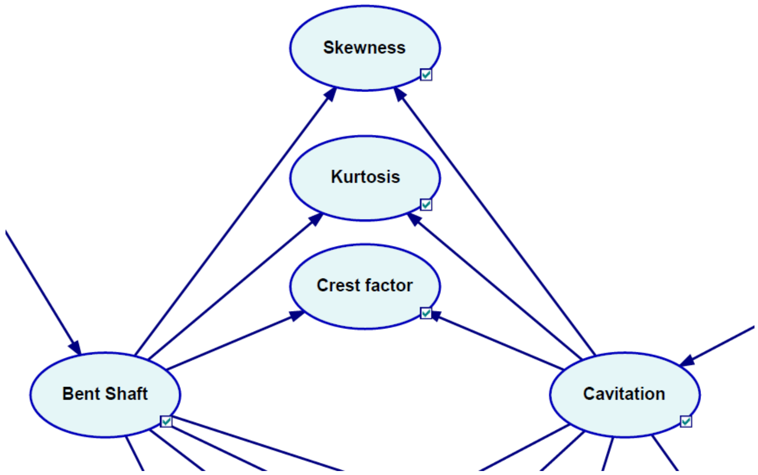


Figure 22: Each operation state of the pump has a unique combination of feature values.

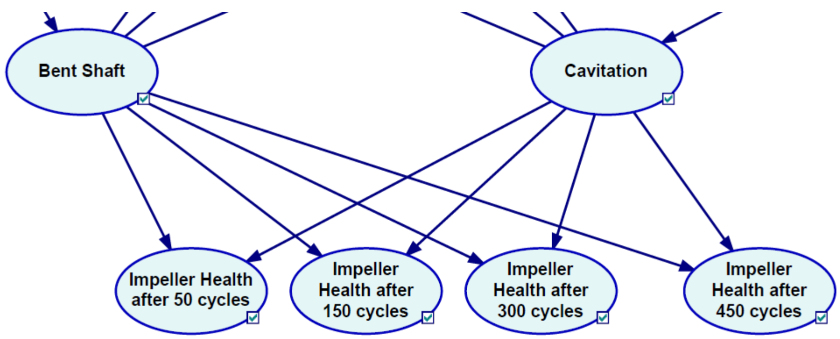


Figure 23: The remaining life of a pump changes conditional to the current diagnosis.

Table 5: The pressure values are discretized in order to create the pressure node.

Pressure range	
0 to 0.21 MPa	(0 to 30 psi)
0.21 to 0.69 MPa	(30 to 100 psi)
0.69 to 2.07 MPa	(100 to 300 psi)
2.07 to 6.89 MPa	(300 to 1000 psi)
6.89 to 7.58 MPa	(1000 to 1100 psi)
7.58 to 8.27 MPa	(1100 to 1200 psi)
8.27 to 8.96 MPa	(1200 to 1300 psi)
8.96 to 9.65 MPa	(1300 to 1400 psi)

4.6 Data Structuring For The Bayesian Network

In order to perform Bayesian inference using GeNIe, the Bayesian network needs to contain discrete states. Discretization also allows parameter learning algorithms to create CPTs from data, as described in the upcoming section.

4.6.1 Discretizing Pressure Information

The nominal operating pressure for the pump is 8.96 MPa (1300 psi). The measurement data ranges from nominal operation at 8.96 MPa (1300 psi) to cavitation at 205.5 kPa (29.8 psi). From the measurement data, we also observe that there are minor pressure fluctuations on the order of 3.4 kPa (0.5 psi). The measurement data was obtained from models developed in section 3.4.1. By analyzing the relationship between pressure and the occurrence of cavitation in those models, discrete pressure states are determined as shown in table 5.

The non-uniform pressure ranges are chosen to reduce the number of pressure states in

Table 6: The valve position states are discretized in order to create the valve position node.

Valve position	Range
Open	0 to 87°
Almost closed	87 to 88°
Closed	88 to 90°

the Bayesian network. During normal operation, the pressure does not fluctuate significantly from its nominal point of 8.96 MPa (1300 psi). A bent shaft reduces impeller efficiency and drops the operating pressure to around 8.28 MPa (1200 psi). Cavitation occurs around 207 kPa (30 psi) and below. Therefore, there is minimal need to model every pressure state between 8.96 MPa (1300 psi) and 0 MPa (0 psi). It is assumed that there is minimal measurement noise in the suction pressure transducer. Therefore, the **Pressure** node is also discretized according to the states listed in table 5.

4.6.2 Discretizing Valve Information

A fully open valve allows unrestricted flow of liquid. During normal operation, the flow and pressure are 0.38 m^3/s at 8.96 MPa. At a certain valve position, the fluid pressure begins to decrease and eventually goes to zero. From the valve model developed in section 3.4.1, we can determine 3 states of valve position that significantly impact the pressure drop (Table 6).

4.6.3 Discretizing Cavitation Information

Cavitation occurs when the operating pressure of the fluid drops below its vapor pressure. The fluid vapor pressure for the analyzed pump is 0.21 MPa (29.88 psi) [41]. During normal operation, the pressure of the fluid is 8.96 MPa (1300 psi). For this research, cavitation

Table 7: The occurrence of cavitation is discretized into binary states to create the cavitation node.

Cavitation	Pressure range
Yes	0 to 0.21 MPa (0 to 30 psi)
No	0.21 to 9.65 MPa (30 to 1400 psi)

is analyzed as a binary phenomenon; it is diagnosed as either occurring or not occurring. Based on the model developed in section 3.4.1, we can determine discrete states for cavitation (Table 7).

4.6.4 Discretizing Coupling Lubrication Information

A lubricated coupling reduces the friction between shaft components and prevents thermal expansion. Over time, the lubrication wears down, increasing friction and causing a bent shaft. Based on the model developed in section 3.4.2, we can determine a threshold when the shaft temperature becomes high enough to cause warping. This temperature is reached when the pump is operated for a certain amount of cycles without any relubrication. By analyzing the number of cycles in our model, discrete lubrication states are determined (Table 8).

Table 8: The coupling lubrication for a shaft is discretized into binary states to create the coupling lubrication node.

Coupling lubrication
Normal
Insufficient

Table 9: The occurrence of a bent shaft is discretized into binary states to create the bent shaft node.

Bent shaft	Temperature range
No	−17.8 to 343.3 °C (0 to 650 °F)
Yes	343.3 to 482.2 °C (650 to 900 °F)

4.6.5 Discretizing Bent Shaft Information

A bent shaft occurs when the coupling lubrication wears out which causes thermal expansion and a decrease in the yield strength of the shaft. The temperature at which these phenomenon become significant is 343.3 °C (650 °F). For this research, a bent shaft is analyzed as a binary phenomenon; it is diagnosed as either occurring or not. Based on the model developed in section 3.4.2, we can determine discrete states for a bent shaft (Table 9).

4.6.6 Discretizing Vibration Information

Vibration data is translated into unique vibration features. These features have distinct values for each mode of operation: normal operation, cavitation, and a bent shaft. Based on the model developed in section 3.4.3 and the vibration feature plots (Figures 8, 9, and 10), we can procedurally determine discrete states for each feature (Table 10).

4.6.7 Discretizing Impeller Health Information

The health of the impeller depends on the operation state of the pump. During normal operation, an impeller can run for years without any degradation. However, its life is reduced when a fault occurs. The impeller states are discretized into two states: **Healthy** and **Failure**. The probabilities of these states are determined using survival models developed in section 3.5.

Table 10: The vibration features are normalized and then discretized to create their respective nodes.

Skewness range		
0.75	to	1.00
0.50	to	0.75
0.25	to	0.50
0.00	to	0.25
-0.25	to	0.00
-0.50	to	-0.25
-0.75	to	-0.50
-1.00	to	-0.75

Kurtosis range		
3.25	to	3.50
3.00	to	3.25
2.75	to	3.00
2.50	to	2.75
2.25	to	2.50
2.00	to	2.25
1.75	to	2.00
1.50	to	1.75

Crest factor range		
4.25	to	4.50
4.00	to	4.25
3.75	to	4.00
3.50	to	3.75
3.25	to	3.50
3.00	to	3.25
2.75	to	3.00
2.50	to	2.75
2.25	to	2.50
2.00	to	2.25
1.75	to	2.00
1.50	to	1.75

4.7 Parameter Learning For CPT Creation

In our research, the conditional probability tables for each node pair are created using learning algorithms. These algorithms are trained on the data that was generated from the previously created models. In order to create CPTs and perform parameter learning, we use the expectation-maximization (EM) algorithm [42]. The EM algorithm is an iterative method to find local maximum likelihood estimates of parameters in statistical models. The EM process alternates between the expectation and maximization step. The expectation step creates a function for the expectation of the log-likelihood from the current parameter expectation. The maximization step computes the parameters that maximize the expected log-likelihood.

The data generated in earlier sections is discretized according to the states described in section 4.6. The discrete data is then used for learning the CPTs using the EM algorithm. Once the CPTs are created, the condition monitoring Bayesian network is complete.

5.0 Using Bayesian Networks To Analyze Normal And Abnormal Pump Operation

The completed condition monitoring Bayesian network is used to analyze three different modes of operation. To begin testing, additional sets of data are created for normal operation, cavitation, and bent shaft occurrence by altering the models from section 3.4. This testing data is then used in case studies in order to diagnose faults, determine root cause, and forecast machine health.

5.1 Normal Operation Case Study

To simulate a pump running at its normal operating point, the vibration and pressure data-generating models are altered. Only those two models are altered because the vibration and pressure measurements are the inputs to the Bayesian network. By doing so, we can generate testing data that simulates normal operation. This deviation from the testing data is necessary to validate whether the Bayesian network can actually diagnose and forecast machine health regardless of the information provided to it.

To generate new vibration testing data, the white noise excitation function is increased by 50%. This is done to simulate normal operation of the pump but with higher turbulence through the impeller. The new normal operation vibration response is shown in figure 24.

To generate pressure testing data, a nominal suction pressure transducer signal is generated at 1,300 psi with some added noise. This is done to simulate the normal operation of the pump when the upstream valve is completely open.

Once the testing data is generated, we can begin the Bayesian network analysis. First, we set evidence for our vibration and pressure input nodes. The **Suction Pressure Transducer** node is set at **1300 PSI** (Figure 28).

The new vibration feature values are not constant throughout each sample (Figures 52, 53, and 54). In order to include information from each sample in the Bayesian network,

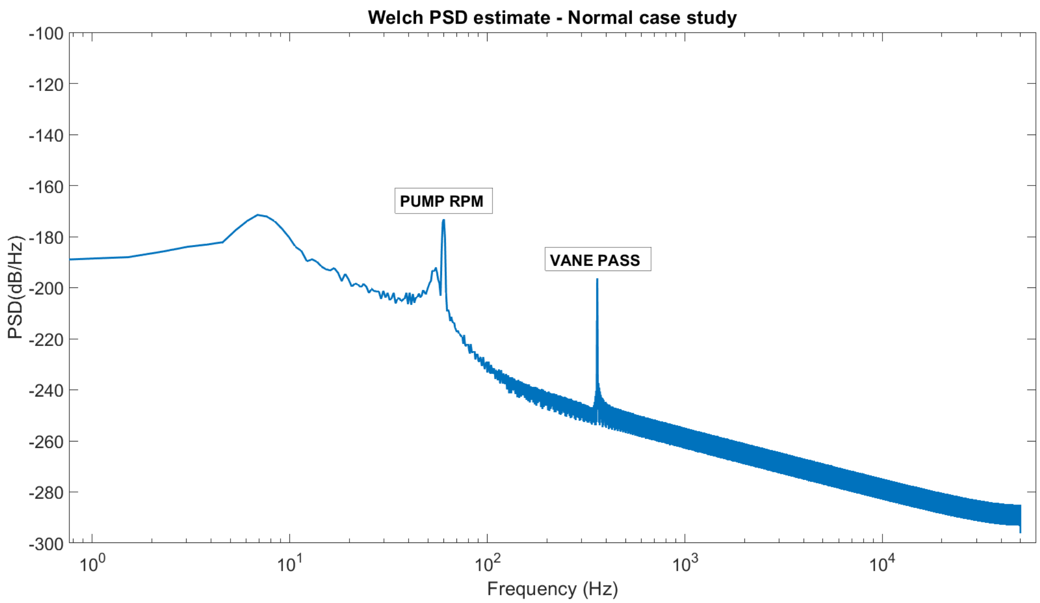


Figure 24: The vane pass and motor RPM frequencies dominate the normal operation vibration response.

the features are translated into a measurement distribution (Figures 25, 26, and 27). These distributions are entered directly into the Bayesian network using the 'virtual evidence' tool in GeNIe.

5.1.1 Normal Operation Diagnosis

The Bayesian network determines that there is no fault occurring based on the normal operation evidence. The state of the **Cavitation** node is inferred as **No** (Figure 29). The state of the **Bent Shaft** node is also inferred as **No** (Figure 30).

5.1.2 Normal Operation Root Cause Determination

Since there is no fault occurring during normal operation, there is no root cause of failure. The root cause of a bent shaft, i.e., the **Coupling Lubrication** node is inferred as **Normal** (Figure 32). The root cause of cavitation, i.e. the **Valve Position** node is inferred

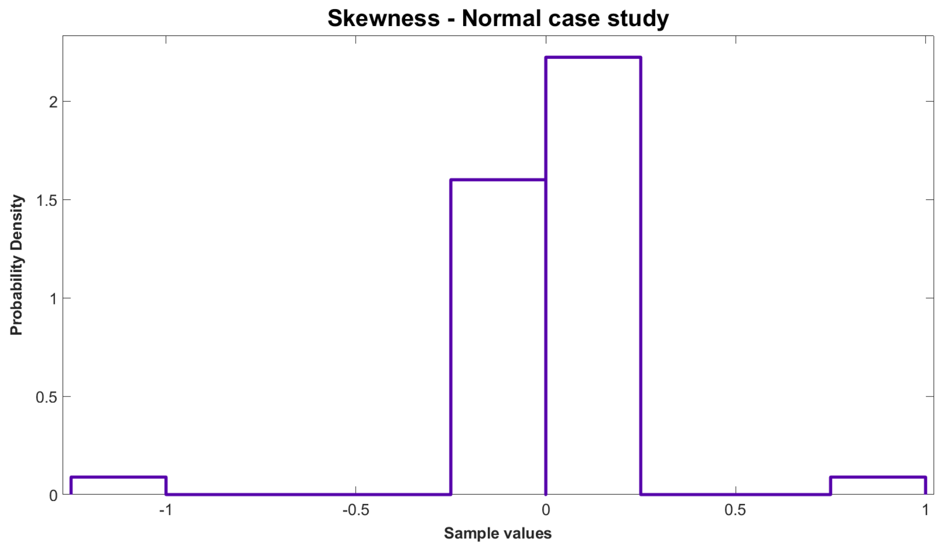


Figure 25: The skewness distribution for normal operation is an input for the Bayesian network.

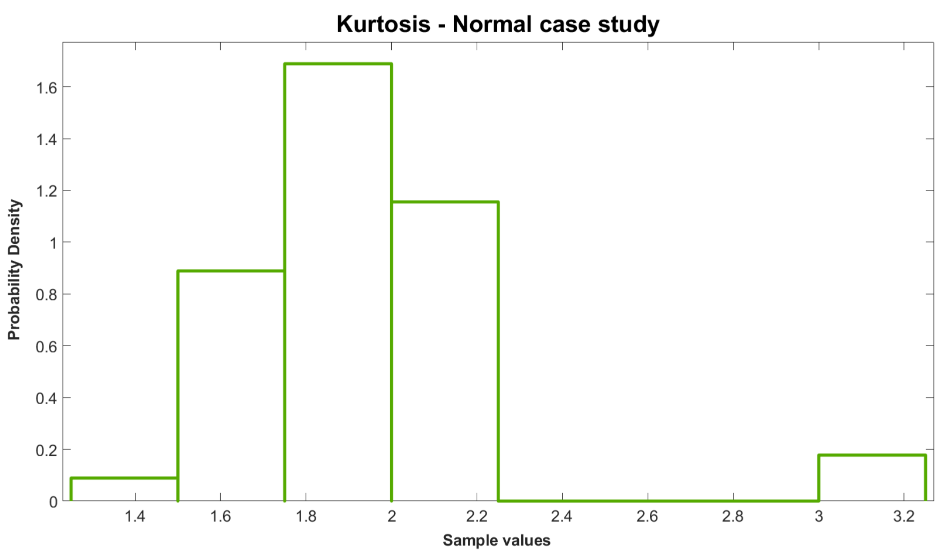


Figure 26: The kurtosis distribution for normal operation is an input for the Bayesian network.

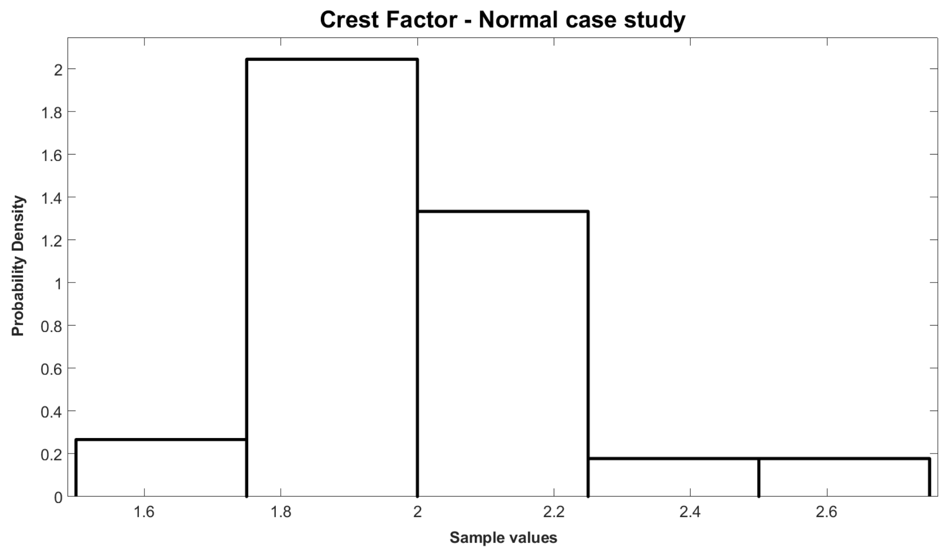


Figure 27: The crest factor distribution for normal operation is an input for the Bayesian network.

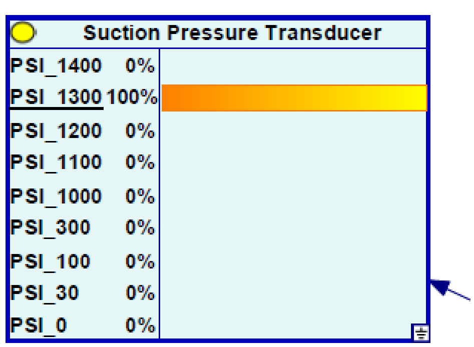


Figure 28: The Suction Pressure Transducer node evidence is set at 1,300 psi.

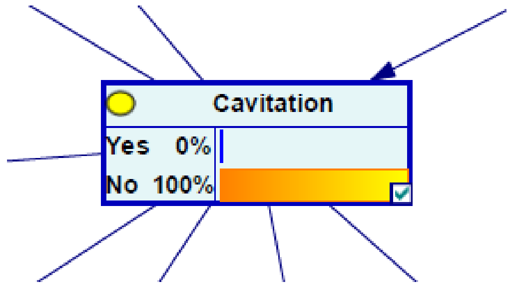


Figure 29: The likelihood of cavitation during normal operation is zero.

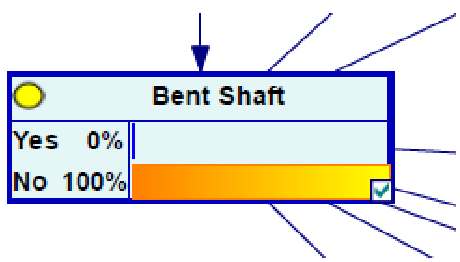


Figure 30: The likelihood of a bent shaft during normal operation is zero.

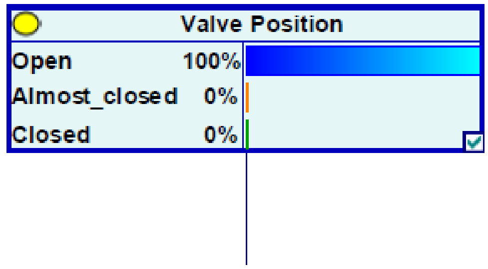


Figure 31: The likelihood of a malfunctioning valve during normal operation is zero.

as **Open** (Figure 31). These inferences are accurate to how the data was modeled for normal operation.

5.1.3 Normal Operation Pump Health Forecast

A pump is designed to run for many years when operated at its nominal conditions of service. During normal operation, there are no faults that significantly degrade the pump at an abnormal rate. Thus, the Bayesian network infers that the pump will be 100% healthy until after 450 cycles (Figure 33).

This forecasted duration can be extended to determine when the pump will actually fail under normal operation. However, we are only concerned with the first 450 cycles for this research.

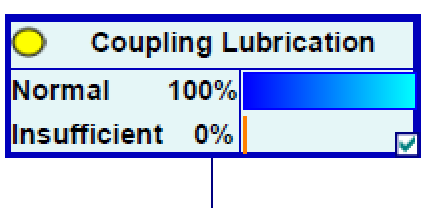


Figure 32: The likelihood of insufficient coupling lubrication during normal operation is zero.

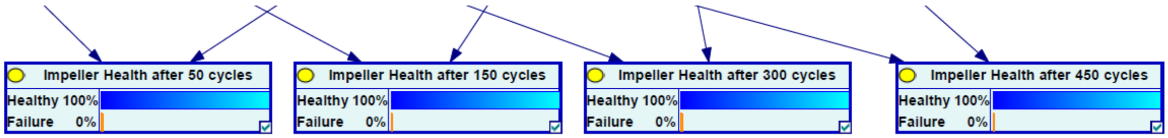


Figure 33: The pump will run without any issues for at least 450 cycles under normal operation.

5.2 Cavitation Case Study

To simulate a pump experiencing cavitation, the vibration and pressure models are altered. To generate new vibration testing data, the excitation function is altered. The cavitation excitation function is a combination of white noise and colored noise. This is done to simulate the high amplitude and frequency disturbances experienced by the impeller due to cavitation. The new cavitation vibration response is shown in figure 34.

To generate pressure testing data, a suction pressure transducer signal is generated at at 1,300 psi which then drops suddenly to 15 psi, with some added noise. This is done to simulate the drop in suction pressure to the minimum system pressure, which can cause cavitation when the upstream valve partially or completely closes.

Once the testing data is generated, we can begin the Bayesian network analysis. The pressure values are not constant throughout the measured data. In order to include information from the entire signal, the pressure values are translated into a measurement distribution (Figure 38). These distributions are entered directly into the Bayesian network using the 'virtual evidence' tool in GeNIe (Figure 39).

The new vibration feature values are not constant throughout each sample (Figures 52, 53, and 54). In order to include information from each sample in the Bayesian network, the features are translated into a measurement distribution (Figures 35, 36, and 37). These distributions are entered directly into the Bayesian network using the 'virtual evidence' tool in GeNIe.

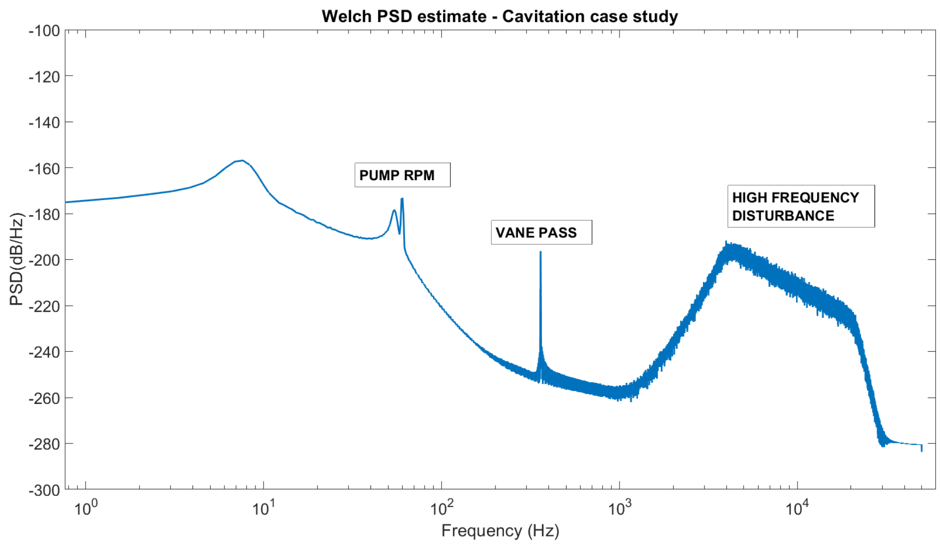


Figure 34: The random high frequencies dominate the cavitation vibration response.

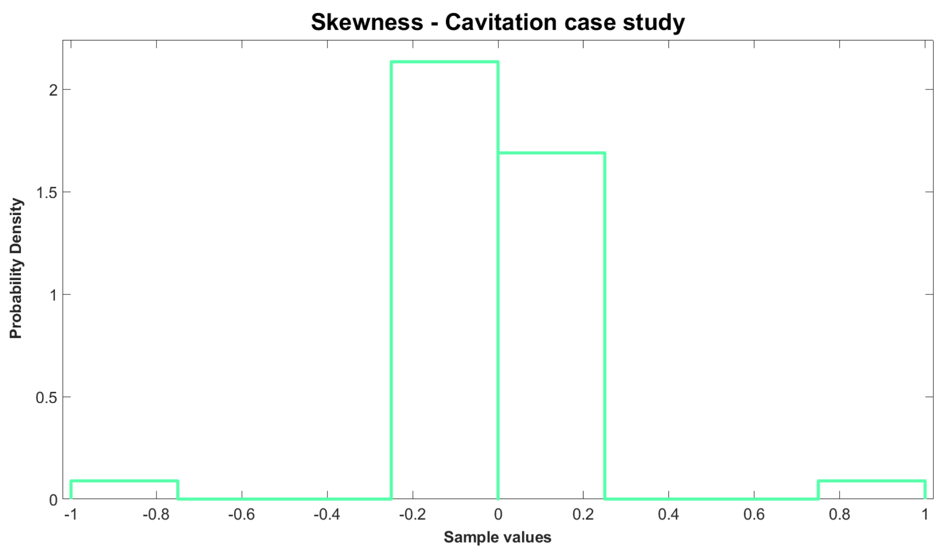


Figure 35: The skewness distribution for cavitation is an input for the Bayesian network.

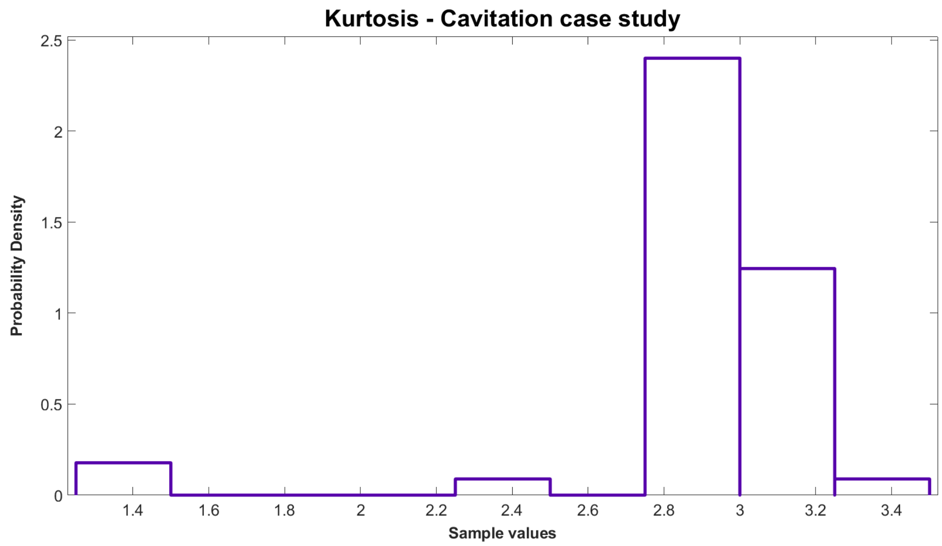


Figure 36: The kurtosis distribution for cavitation is an input for the Bayesian network.

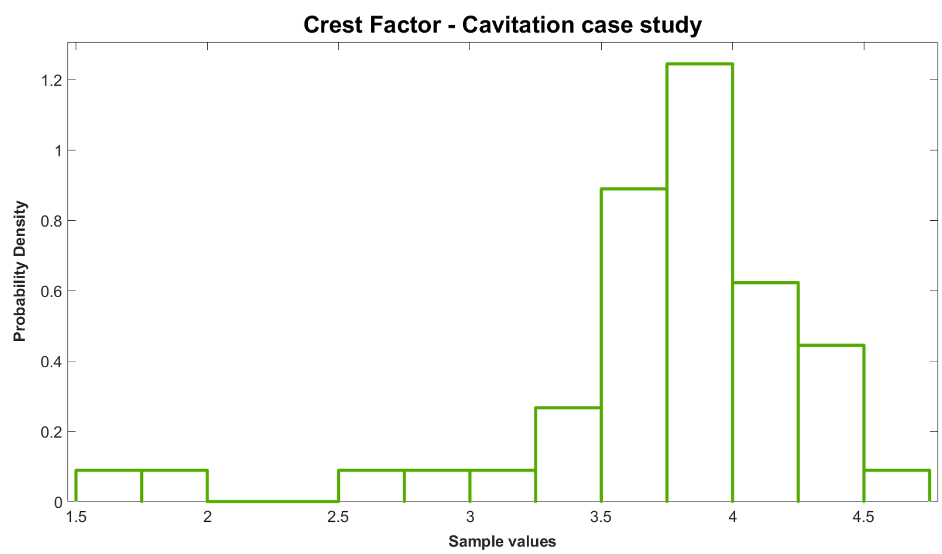


Figure 37: The crest factor distribution for cavitation is an input for the Bayesian network.

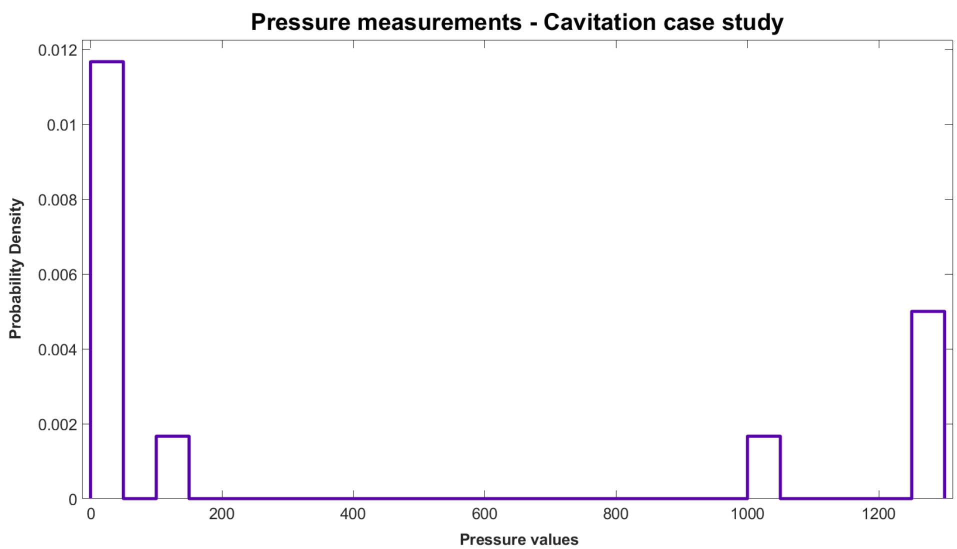


Figure 38: The Suction Pressure Transducer measurements are input as a distribution.

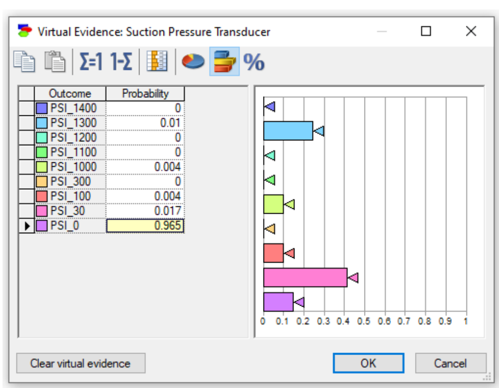


Figure 39: The Suction Pressure Transducer node evidence is set as a distribution.

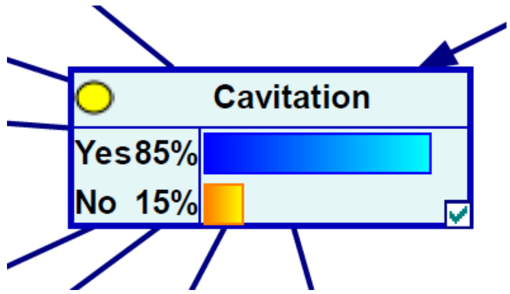


Figure 40: The likelihood of cavitation is 85%.

5.2.1 Cavitation Diagnosis

The Bayesian network determines that there is a 85% likelihood of cavitation (Figure 40). This is the expected probabilistic result based on the testing data generated from the cavitation models.

5.2.2 Cavitation Root Cause Determination

Since we have determined the occurrence of cavitation, we can infer its root cause. The Bayesian network performs inference and determines that a malfunctioning valve is the most likely cause of cavitation. The state of the **Valve Position** node is inferred as having a 85% likelihood of being **Closed** (Figure 41).

Once the Bayesian network determines the likely root cause of cavitation, this information can be used by nuclear plant decision makers. Instead of checking the pumping system via a trial-and-error process, the operators can directly repair the malfunctioning valve. This would speed up maintenance and optimize outages.

5.2.3 Cavitation Pump Health Forecast

Cavitation can cause significant damage to a pump. The rate of degradation from cavitation is very high, as determined by the survival models developed in section 3.5. Thus, the Bayesian network infers that the pump has a 13% chance of failing by 150 cycles, an 83%

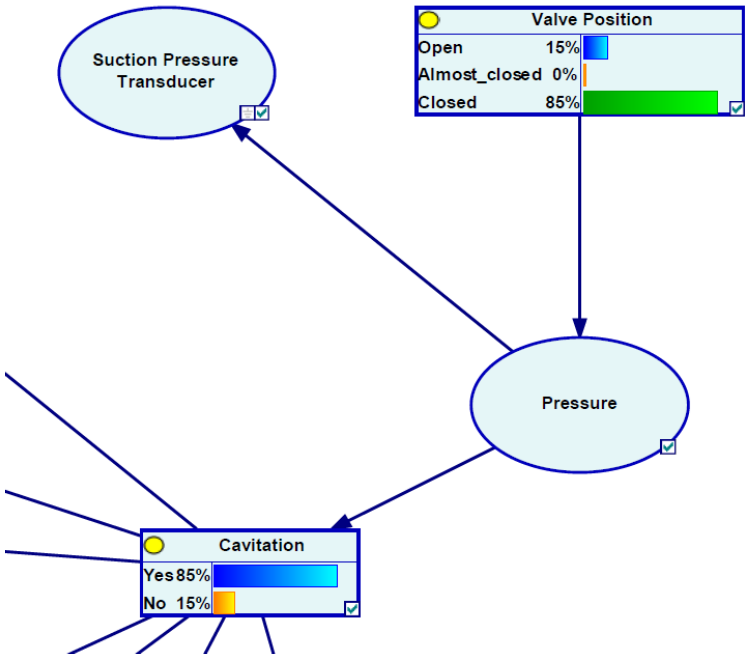


Figure 41: The likelihood of a malfunctioning valve is 85%.

chance of failing by 300 cycles, and an 85% chance of failing by 450 cycles, given the 85% likelihood of cavitation (Figure 42).

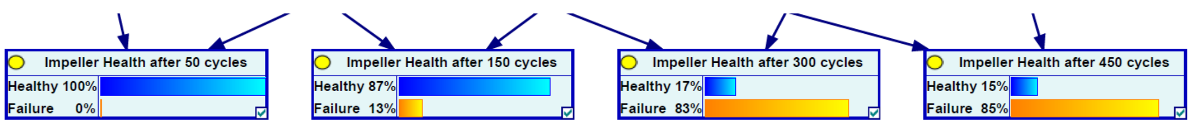


Figure 42: The pump has a 85% likelihood to fail by 450 cycles due to cavitation.

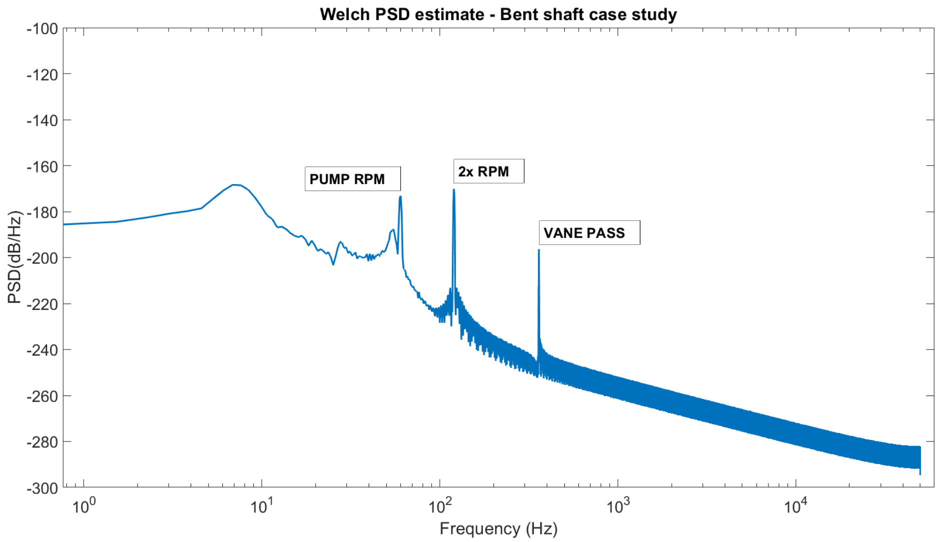


Figure 43: A large amplitude spike at 2× motor RPM dominates the bent shaft vibration response.

5.3 Bent Shaft Case Study

To simulate a pump experiencing a bent shaft, the vibration and pressure data-generating models are altered.

To generate new vibration testing data, the white noise excitation function is changed. The excitation is applied to the impeller mass as well as the coupling mass. This is done to simulate the turbulence through the impeller as well as the disturbances on the pump shaft. The new bent shaft vibration response is shown in figure 43.

To generate pressure testing data, a suction pressure transducer signal is generated at 1,300 psi which then drops to 1,200 psi with some added noise. This is done to simulate the decrease in impeller efficiency due to damage from the bent shaft.

Once the testing data is generated, we can begin the Bayesian network analysis. The pressure values are not constant throughout the measured data. In order to include information from the entire signal, the pressure values are translated into a measurement distribution

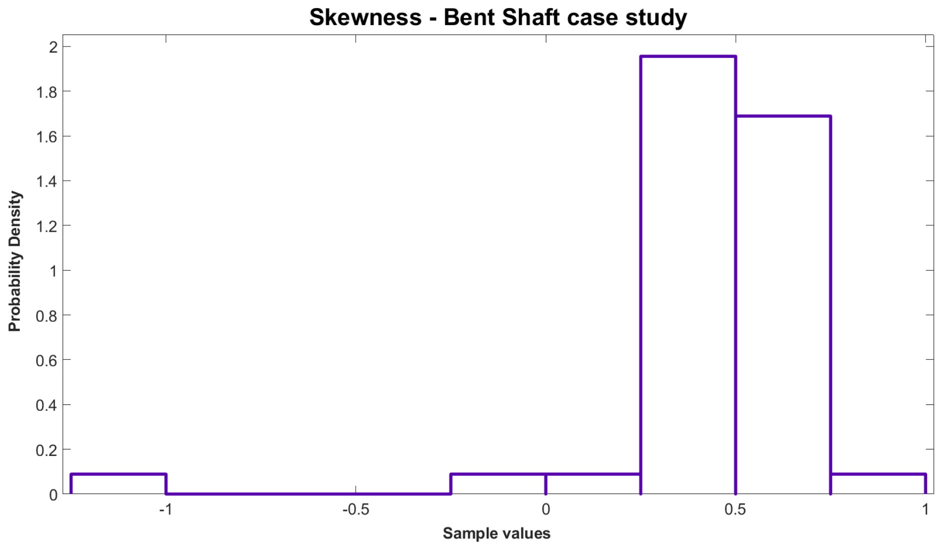


Figure 44: The skewness distribution for a bent shaft is an input for the Bayesian network.

(Figure 47). These distributions are entered directly into the Bayesian network using the 'virtual evidence' tool in GeNIe (Figure 48).

The new vibration feature values are not constant throughout each sample (Figures 52, 53, and 54). In order to include information from each sample in the Bayesian network, the features are translated into a measurement distribution (Figures 44, 45, and 46). These distributions are entered directly into the Bayesian network using the 'virtual evidence' tool in GeNIe.

5.3.1 Bent Shaft Diagnosis

The Bayesian network determine that there is a 95% likelihood of a bent shaft (Figure 49). This is the expected probabilistic result based on the testing data generated from the bent shaft models.

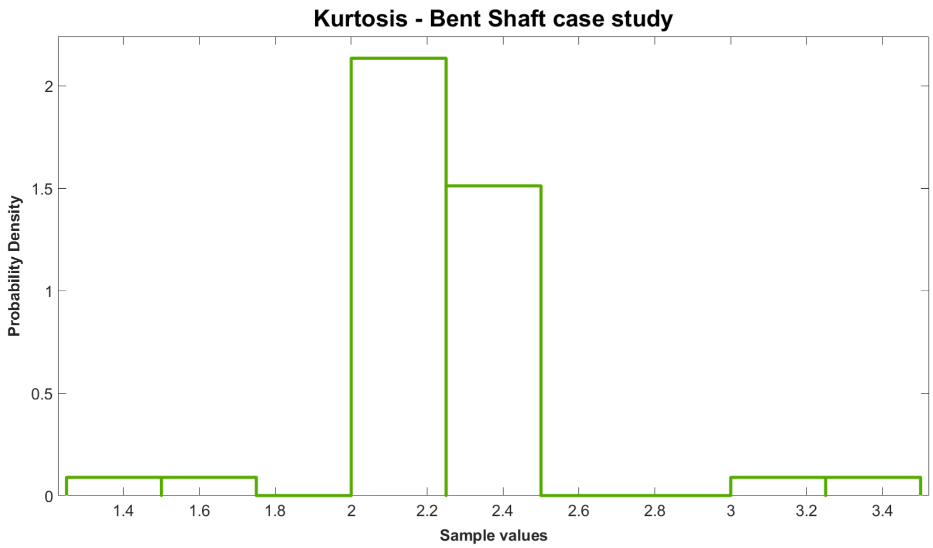


Figure 45: The kurtosis distribution for a bent shaft is an input for the Bayesian network.

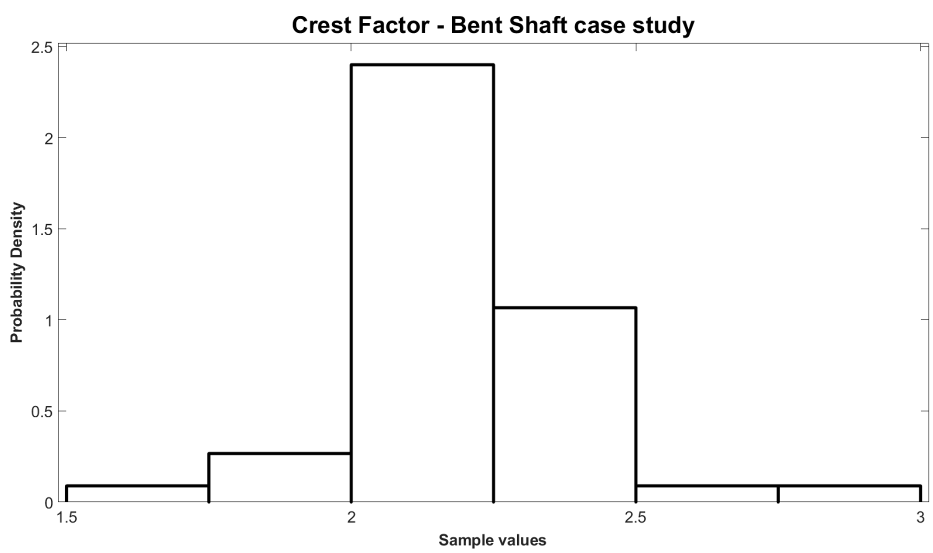


Figure 46: The crest factor distribution for a bent shaft is an input for the Bayesian network.

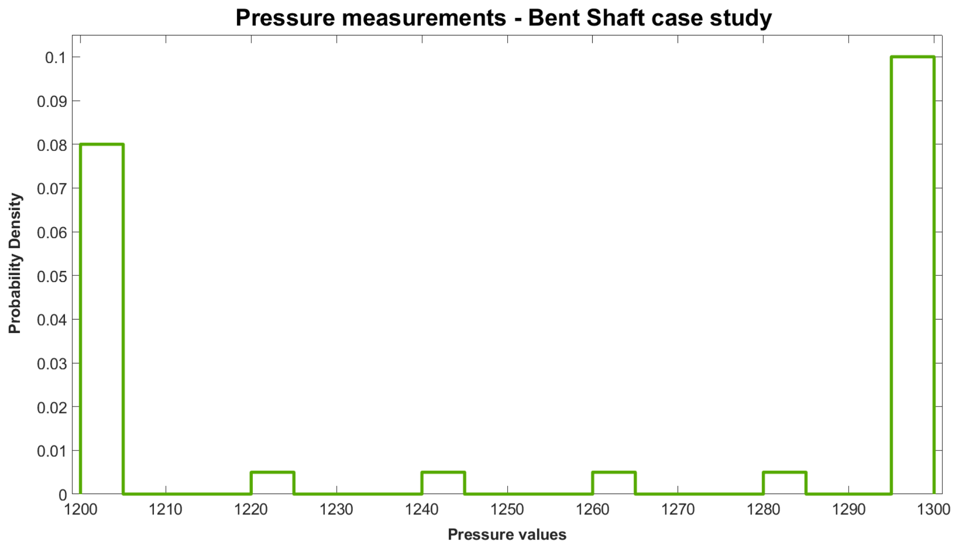


Figure 47: The Suction Pressure Transducer node measurements are input as a distribution.

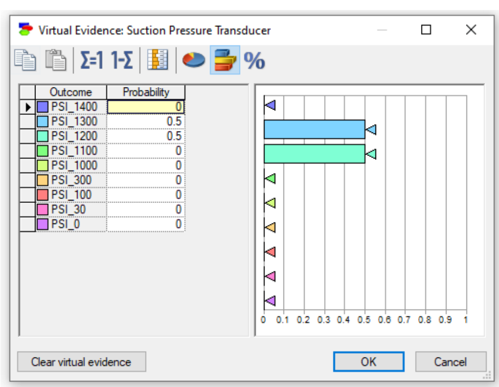


Figure 48: The Suction Pressure Transducer node evidence is set as a distribution.

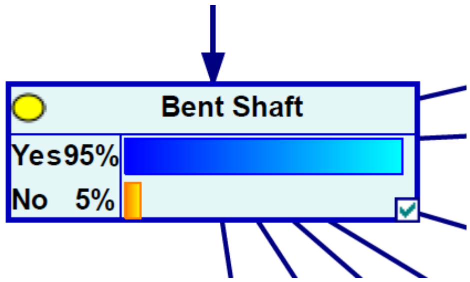


Figure 49: The likelihood of a bent shaft is 95%.

5.3.2 Bent Shaft Root Cause Determination

Since we have determined the occurrence of a bent shaft, we can infer its root cause. The Bayesian network infers that insufficient coupling lubrication is the most likely cause of the bent shaft (Figure 50). The state of the **Coupling Lubrication** node is inferred as having a 95% chance of being **Insufficient**.

Once the Bayesian network determines the likely root cause of the bent shaft, this information can be used by nuclear plant decision makers. Instead of checking the pumping system via a trial-and-error process, the operators can directly relubricate the pump coupling. This would speed up maintenance and optimize outages.

5.3.3 Bent Shaft Pump Health Forecast

A bent shaft causes unbalanced forces to act on the impeller and therefore causes it to wear. Thus, the Bayesian network infers that the pump will have a 1% chance of failing after 50 cycles, a 15% chance of failing after 150 cycles, a 68% chance of failing after 300 cycles, and a 94% chance of failing after 450 cycles, given the 95% likelihood of a bent shaft (Figure 51).

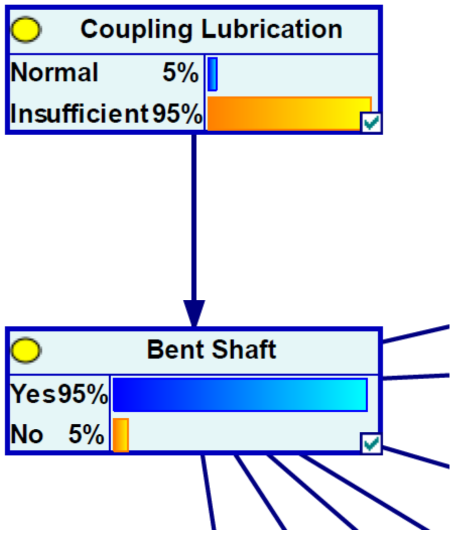


Figure 50: The likelihood of insufficient coupling lubrication is 95%.

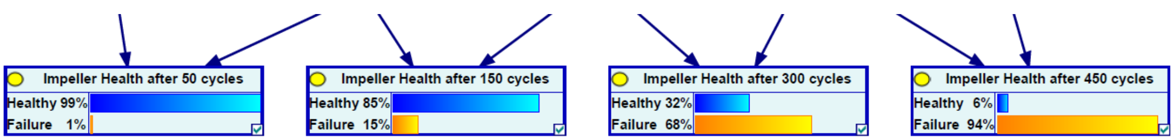


Figure 51: The pump is 94% likely to fail by 450 cycles due to a bent shaft.

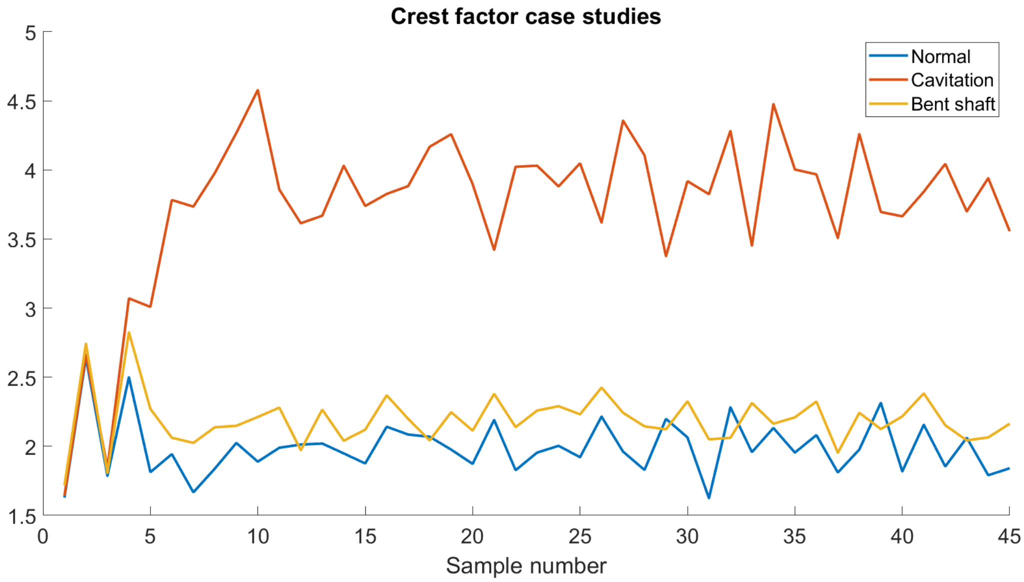


Figure 52: New crest factor values are computed for each case study.

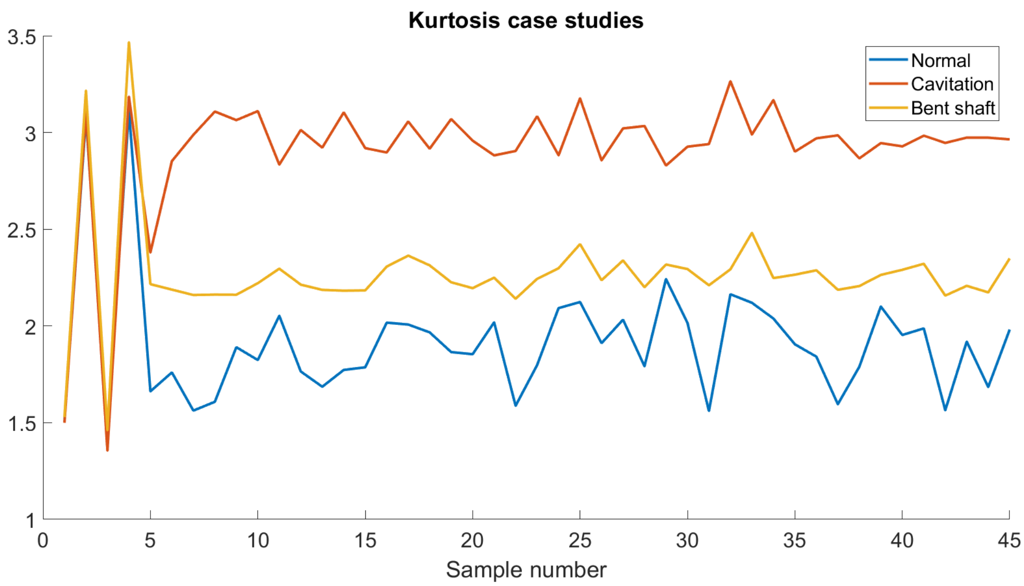


Figure 53: New kurtosis values are computed for each case study.

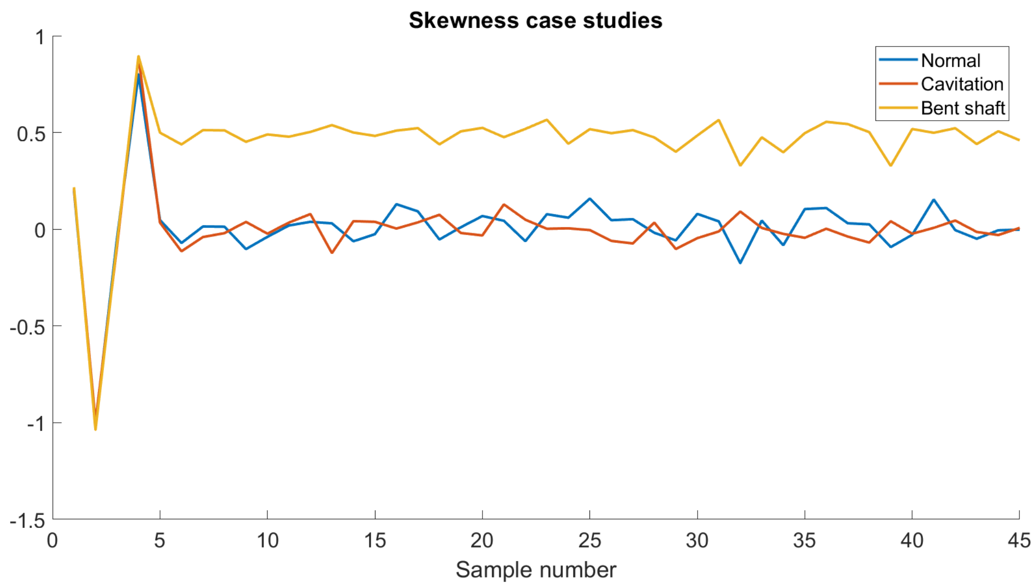


Figure 54: New skewness values are computed for each case study.

6.0 Summary And Conclusions

6.1 Summary

In order to improve the lifespan of nuclear power plants, there is a critical need to develop a proactive condition monitoring platform. In this research, we create a Bayesian network for a centrifugal pump system that estimates the health of the machine from sensor measurements. The Bayesian network is created using a hybrid approach that combines data-driven methods with domain expertise. With this network, we can diagnose the occurrence of two common pump faults, infer their root cause, and forecast the health of the pump in the future.

In order to diagnose faults, we use vibration analysis to determine the state of the pump. The normal and abnormal modes of the operation each have unique vibration signatures, which are learned by the Bayesian network. In order to infer the root cause of faults, domain expertise is leveraged to develop conditional relationships between various pump components and their surrounding piping accessories. The Bayesian network can then infer the most likely cause of failure given the current state of the pump. In order to forecast pump health, we combine survival analysis with Bayesian statistics. This allows the Bayesian network to estimate the health of the pump conditional to its current mode of operation.

Three different case studies are performed on the Bayesian network for normal and abnormal operation. In each case study, we analyze the state of the pump and estimate its remaining-useful-life. The Bayesian network is successful at estimating the current state of the pump based on vibration and pressure measurements. Based on these estimates, the Bayesian network also successfully provides the most likely cause of abnormal operation as well as the conditional forecast for the pump's health.

6.2 Conclusions

In this research, we were able to create a condition monitoring platform using Bayesian networks that can estimate the state of a pump. By doing so, we developed a framework for proactive and preventative maintenance using conditional probabilities, sensor data, and operational information. This framework could be deployed to industrial plants, where it would process real-time sensor measurements and provide machine health estimations to operators. This would aid decision makers optimize the maintenance schedules of a power plant, thus improving their viability.

In this research, we determined that a hybrid approach can be used to provide accurate machine health assessments. Incorporating domain expertise to develop models can significantly decrease the amount of data required, as well as improve the transparency of the model. Domain expertise also allows the addition of conditional dependencies, which can be leveraged to infer hidden information such as the root cause of failure.

6.3 Contributions

By performing this research, we made the following contributions:

- We established the advantages of probabilistic estimation for machine learning by introducing uncertainty that can be leveraged by decision-makers.
- We provided a condition monitoring solution to optimize O&M for nuclear power plants and, by extension, other industrial plants.
- We illustrated the advantages of including domain expertise in machine learning models to improve estimation.
- We demonstrated how to combine survival analysis with Bayesian statistics to conditionally update a machine's remaining-useful-life.

6.4 Research Success

The goal of this research is to develop a condition monitoring system in order to improve asset management. To assess the success of this research, the objectives outlined in section 1.1 are discussed again.

- *Relate disparate systems in a common framework for better forecasting and diagnosis:* Disparate systems are phenomenon that are essentially different in kind. Thus, disparate systems have disparate methods of measurements, which lead to disparate data sets. In our condition monitoring system, examples of disparate systems include the vibrations from the pump and the lubrication state of the coupling. Using Bayesian networks, we were able to relate disparate systems using conditional probabilities. For example, a bent shaft diagnosis was determined from vibration measurements and the root cause was inferred from maintenance reports. By completing this objective, we developed a robust condition monitoring platform, where we were able to diagnose faults, infer their associated root causes, and predict their effect on machine life.
- *Infer the condition of hidden states using data:* Hidden states are processes that are impossible to directly observe. In our condition monitoring system, the occurrence of faults is a hidden state. Using Bayesian networks, we were able to use sensor data and operational information to diagnose faults. Cavitation and a bent shaft were inferred using vibration measurements, and these inferences were reinforced using pressure measurements. By completing this objective, we created a condition monitoring platform that can decrease uncertainty in fault diagnosis.
- *Provide the root cause of machine failure in order to improve decision making in a plant:* For the purpose of asset management, simply diagnosing a fault is not enough. Understanding why the machine failed is also important. Knowing the root cause of failure allows the decision makers to develop prevention and mitigation strategies to reduce risk of future breakdowns. Using Bayesian networks, we were able to determine the root cause of failure for two simulated faults. By doing so, we developed a framework for root cause analysis using conditional probabilities, sensor data, and operational information.

By completing this objective, we developed a condition monitoring system that can aid decision makers optimize the maintenance schedules of a nuclear plant.

- *Predict the condition of components using sensor data and historical trends:* Forecasting machine health is important for proactive asset management. If decision makers know how long until a machine is likely to fail, they can develop strategies to reduce unplanned outages. Similarly, if a scheduled outage is approaching but the machine is working properly, then the maintenance outage can be shortened by delaying the maintenance of that particular machine. Using Bayesian networks, we were able to integrate survival models for normal and abnormal operation to predict the remaining-useful-life of a pump. This integration allowed the health forecast to change conditionally with the state of the pump. By completing this objective, we increased the accuracy of our forecasting tool in order to reduce prediction uncertainty.

6.5 Future Work

Future work in condition monitoring would add on to the research performed for this project. There are three proposed areas for future work.

First, we would include additional faults in the Bayesian network. Initially, cavitation and a bent shaft were chosen because they are common and well understood. However, there are various other faults that cause significant damage to a pump. These include bearing wear, misalignment, and flow pulsations. These faults have their own unique vibration and pressure signatures and will require feature extraction and data manipulation to ensure accurate diagnosis.

Second, we would expand the pump network and include multiple pumps running together in series or parallel. Pumps are usually part of a bigger system, and the disturbances from one can propagate to the others which can lead to false diagnosis from sensors. This issue would be addressed by modeling multiple pumps in the Bayesian network. When expanding the pump network, we would also include additional accessories such as suction diffusers, check valves, and strainers. These components would introduce multiple root causes for a single fault. For example, cavitation can occur due to a malfunctioning valve or a clogged suction diffuser. Adding additional accessories to the Bayesian network will provide a comprehensive picture of the entire pumping and piping system, further benefiting root cause analysis.

Third, we would create dynamic fault models that change the remaining useful life of a pump conditional to various parameters. In the current research, we considered faults as binary processes that either occur or don't occur. However, the wear rate of a pump under abnormal operation is not a static value. The wear rate is not only affected by the operating state but also the mechanisms of the fault: First, what type of fault is occurring? Different faults are caused by different physical phenomena, and their effect on the pump varies. Second, what is the magnitude of the fault? The same fault can have different wear rates based on its intensity. Third, what was the duration of the fault? Faults do not act like impulses. They can occur for short or long periods of time, and the amount of damage done can be proportional to that duration. To address this issue, we would develop forecasting models that update their predictions based on the four mechanisms mentioned above.

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