

A Framework for Reconciling Expert Opinions and Empirical Data for
Hydropower Asset Management Decision-Making

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Dedication

To my family, especially my beautiful wife Ali who supported me throughout this endeavor and to all those who have encouraged me to pursue higher education, I dedicate this work to you.

Abstract

This research develops a framework for reconciling expert opinions of component lifetimes and empirical failure data to predict powertrain failure probabilities for Asset Management decision making purposes. Using probability models of component failures, fleetwide dispatch and component replacement history along with a large hydroelectric utility's powertrain expert elicitation we propose a four use cases. The first use case enables a more detailed calculation of average component life. The second use case provides risk managers the ability to understand how dispatch affects the risk of a single component failure. The third and fourth use cases enables the recommendation of the distribution of generation dispatch at a 2-unit and a 4-unit facility to maximize the reliability of all of the facilities modelled powertrain components for a given timeframe. The third use case uses this information in a historical sense to develop a Reliability Index while the fourth use case recommends future dispatch. Three historic operating years will establish constraints to the future operating scenarios used to assess powertrain risk.

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Acronyms

CDF	Cumulative Distribution Function
Corps	United States Army Corps of Engineers
CRM	Conditional Reliability Model
EPRI	Electric Power Research Institute
ERBA	Economic Risk Based Analysis
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Modes, Effects and Criticality Analysis
GADS	Generating Availability Data System
HAC	Hydropower Analysis Center
MLE	Maximum Likelihood Estimation
MOP	Modes of Operation
NERC	North American Electric Reliability Corp.
pdf	Probability Density Function
RCA	Root Cause Analysis
RCM	Reliability Centered Maintenance
RMC	Risk Management Center
SLM	Strategic Life Model
TVA	Tennessee Valley Authority
USBR	United States Bureau of Reclamation

Nomenclature

a	Cyclic wear coefficient
A_T	Total age of unit
A_{HMOD1}	Age of unit at HMOD
A_{HMOD2}	Age of unit since HMOD
ACV	Average Coefficient of Variation
AL	Average Life
B_L	Lower Bound
B_U	Upper Bound
BR	Bound Ratio
c	Unit cycles
$\vec{c}_{i,j}$	Future expected start-stop cycles
$C_i(s)$	Total unit cycles for plant i, dispatch s
$\tilde{c}_{i,j,k}$	Historical component start-stop cycles
C_p	Cost of planned outage
C_F	Cost of forced outage
CF	Cost Factor
CI	Confidence Interval
CPUT	Cost per unit time
D	Outage data set
E_c	Average Expert Confidence
EOH	Equivalent Operating Hours
EOY	Equivalent Operating Years
$\overrightarrow{EOY}_{i,j,k}$	Future dispatch in EOY
$\overleftarrow{EOY}_{i,j,k}$	Historical EOY
$F(t)$	Cumulative Distribution. Function
$f(t)$	Probability Density Function
$g(x_k)$	Function to optimize
$\vec{h}_{i,j}$	Future expected generating hours
$\overleftarrow{h}_{i,j,k}$	Historical component generating hours
$H_i(s)$	Generating hours for plant i, dispatch s
i	Plant index
j	Unit index
k	Component index
$L(\theta)$	Likelihood of the parameter vector
n	Weighting value
N	Number of stress cycles
$OP_k(\psi)$	Optimal Replacement Point
$R(t)$	Reliability function
$R_{i,max}$	Maximum Reliability for plant i
$R_{i,actual}$	Actual Reliability for plant i
$R_{i,min}$	Minimum Reliability for plant i

RI_i	Reliability Index for plant i
s	Dispatch scenarios
S	Stress
t	Component age
t_e	Expert estimated time
T_P	Expert Time Period
u	Suspended unit index
w	Total number of failed components
$x_{i,j,k,w}(\psi)$	Failure point w
γ	Timeframe of CRM
y_γ	Year of interval γ
Δy	Interval length
$z_{i,j,k,1}$	Suspended/current component age
α	Weibull scale parameter
β	Weibull shape parameter
γ	Index of expert time intervals
$\theta_{i,\psi}$	Data parameter vector
$\theta_{i,4}$	Expert parameter vector
η	Total Expert Intervals
κ	Iteration step of optimization scheme
μ	Number of suspended Components
τ	Total number of units
$\varphi(t_e)$	Expert estimated PDF
$\Phi(t_e)$	Expert estimated CDF
ψ	Failure cases index
$\omega_{i,j,k}(\psi)$	Number of failures

1. Introduction

The proposed research will explore important aspects of hydroelectric powertrain reliability as a function of unit dispatch patterns. The answers to the proposed research questions enable plant owners to choose optimal strategies to maximize reliability, availability and value of the hydroelectric powertrain. The physical scope defines the components covered by the powertrain model. This research is significant as the hydroelectric industry aims to remain a leader in reliable operations as it becomes increasingly burdened by grid fluctuations.

1.1. Problem Statement

This research addresses four Research Questions (RQ's) that focus on four different use cases for probabilistic powertrain reliability models. By developing a framework for our probabilistic powertrain reliability model we can show the sensitivity of the answers to these RQ's as a function of the failure distribution function, current component ages and the expected dispatch patterns.

- Research Question 1 (RQ1) asks to what extent additional start-stop cycling decreases the strategic life of three powertrain components: the thermoset stator windings, rotor windings and Kaplan turbine runner.
- Research Question 2 (RQ2) asks how unit dispatch patterns affect the risk of failure of a single component
- Research Question 3 (RQ3) asks how the reliability of actual distribution of dispatch patterns compare to the reliability of the optimal distribution of dispatch patterns and the least reliable distribution of dispatch patterns
- Research Question 4 (RQ4) asks how optimal unit dispatch patterns for plant reliability are affected by four distinct parameter vectors at a 4-unit facility and a 2-unit facility.

1.2. Scope

Fleet wide operations data and simulated outage events from Tennessee Valley Authority (TVA) will provide a data driven approach to probability of failure. Due to data scarcity, most plant owners only use their specific data and/or expert opinions to guide reliability decisions. The hydropower expert elicitation hosted by the U.S. Army Corps of Engineers (Corps) Risk Management Center and Hydropower Analysis Center provides knowledge from many industry participants for use at Corps facilities. Simulated failure data and the expert estimates will combine to estimate three distinct parameter vectors that will be compared against the expert only case in the sensitivity analyses.

The physical scope of the model encompasses the hydroelectric powertrain, defined broadly as the turbine, generator, exciter, governor, transformer, and circuit breaker. Cyclic stresses affect certain component more than other components. These components will be analyzed first since their results will have greater impact on decision makers. Components that fit this description are stator windings, rotor windings, turbine runner, generator output breaker, wicket gate shear

pins, wicket gate bushings, and generator step up (GSU) transformers. However, the expert elicitation excluded both wicket gate components and therefore they will not be analyzed at this time. The scope is further narrowed specifically to the stator windings, rotor windings and turbine runner for the extent of this research although future work will include more components.

Reliability is defined as the probability that the component will operate as required for of a given horizon time while availability is the percent of calendar time the unit is able to operate.

Recognizing the prevalent failure mechanisms and optimizing maintenance strategies can improve reliability and availability. Important to asset management decision makers is the concept of conditional reliability defined as the probability that the component will operate as required for future time $\overrightarrow{EOY}_{i,j,k}$ given that it has already operated as required for time $\overleftarrow{EOY}_{i,j,k}$. The Weibull distribution is one tool analysts can use to understand how these failure mechanisms and dispatch patterns affect system reliability and availability.

Each component must be analyzed individually before being combined into a series of components where each component must be functioning for the unit to function (1). The current analysis framework requires an expert elicitation to provide useful parameter estimates to the model to be used in conjunction with unit failure data. Therefore, this model will be limited to those components discussed by the Corps expert elicitation or future elicitations.

1.3. Significance of Study

This research looks to narrow the knowledge gap in several of the research opportunities outlined in the DOE Hydropower Vision document released in July 2016. Notably it will aid in the:

- “Development of best practices and justification for acquiring, validating, archiving, analyzing and securing hydropower dispatch, cost, maintenance, condition monitoring, and performance data to maximize hydropower value” (2).
- “Understanding and creating parameters for the correlations and causalities among flexible hydropower dispatch, reliability, and O&M costs, and integrating such information into scheduling and planning processes” (2).
- “Development of risk-based analytics to measure and manage hydropower reliability and hydropower scheduling” (2).

Hydropower provides rapid response to changes in grid power demand improving overall grid stability and preventing grid collapses due to voltage deviation. The varying modes of operation of hydroelectric plants, the ancillary services they provide to the grid, their dispatch patterns and market forces result in an intricate reliability optimization problem. The value of this optimization is dependent upon a significant difference in the cost of forced outages compared to planned outages. Reliability studies are becoming more significant as owners are cautious of how wind power penetration may affect hydroelectric dispatch patterns. Wind power penetration affects the grids’ need for ancillary services and the spatial distribution of hydroelectric plants,

wind power farms and power demand, and the hydroelectric plants Mode of Operation (MOP) determine which units are affected the most.

Wind integration studies concur that the forecast error of the net load, defined as grid load minus wind power, is greater than the forecast error of the load as seen in Figure 1-1 because the wind power forecast error is greater than the grid load forecast error (3) (4) (5) (6) (7). Therefore, wind power penetration into the market affects regulation requirements and reserve capacity requirements that increase as wind penetration levels increase (3) (6) (7) (8) (9).

An extensive analysis of wind penetration in the Bonneville Power Administration (BPA) balancing area found that four hydroelectric power plants exhibited significant negative correlation between Δ Power Output and Δ Wind Generation (10). These were Chief Joseph, Grand Coulee, John Day and The Dalles (10). A similar analysis was performed on the unit level and units belonging to these four plants were the entirety of the top 40 correlated units in BPA's service area (10). The negative correlation suggests that as power from the wind farms diminishes, these hydroelectric plants provide the additional power required by the grid and vice versa (10). System operators cover this change in wind power output by ramping hydroelectric units to increase or decrease power output.

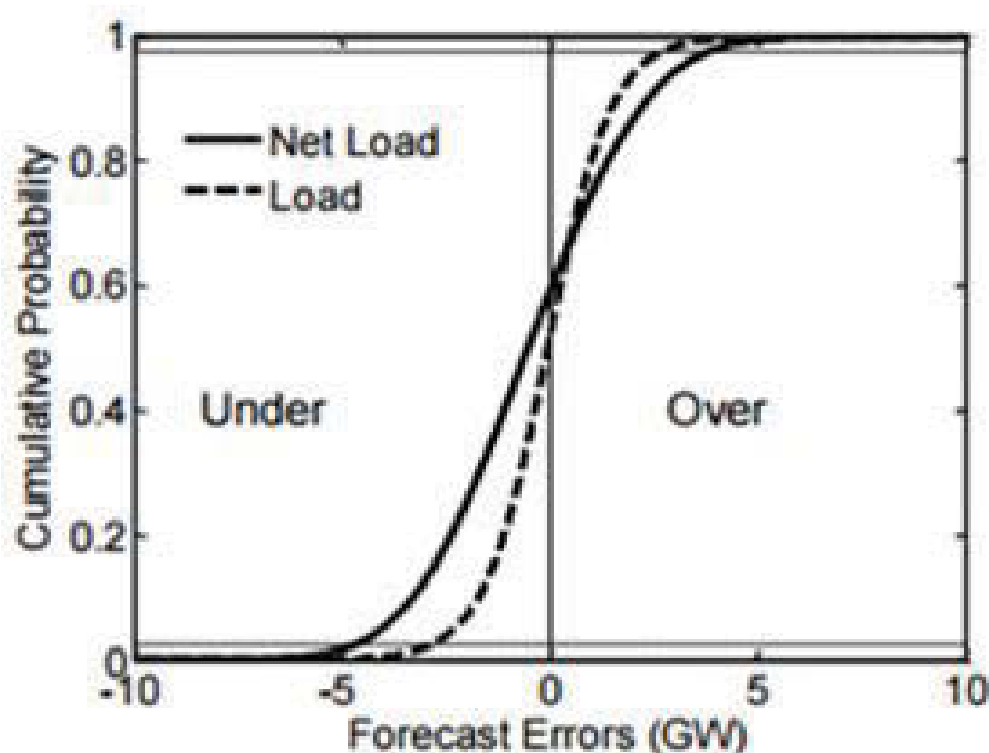


Figure 1-1 Cumulative Distribution Functions of net load errors and load errors. Statistical model fit to data from ERCOT (5).

This increase in unit starts became noticeable on a fleet-wide scale in 2012 as depicted in Figure 1-2. The trend continued in 2013 and 2014. Of concern to system operators is its correlation to increased forced outage hours shown in Figure 1-3 where 2013-2014 have significant increases compared to 2009-2012. The graphs display only the upper quartile of units as (10) found that only a fraction of units ramping and start-stop cycling is affected.

Hydropower's significant flexibility exacerbates the problem of determining the actual cost of an outage. Due to hourly changes in the point price of electricity as seen in Figure 1-4 (11), flexible plants can maximize profits by operating during high value periods. When plant flexibility is lost due to one or more than one unit outages, the remaining units will operate in lower value periods in order to prevent spill. Thus, while plant generation may not necessarily be affected by the outage, plant revenue will decrease.

The length of the outage increases significantly when it is forced rather than planned since design and transportation of the components does not typically happen before the outage occurs. This increases the cost of forced outages as well (12). A forced outage resulting in a complete overhaul of either the turbine or the generator system can last over three years while a planned outage can be resolved in less than a year (12).

The research questions posed in the problem statement aim to determine the significance of the trends visualized in Figures 1-2 and 1-3 and how concerned stakeholders should be with the changing dispatch patterns. The models developed provide a weighting technique that gives more weight to unit failure data as more data points are collected. Weighting the unit failure data verse expert component life estimates allows the estimation of parameter vectors, that when combined with unit dispatch patterns provides a statistical risk of failure calculation.

Each component has technical, economic, and strategic lives that are weakly interconnected making it difficult to distinguish between them in some instances. Ideally, the technical life of component k is described as the mean time to failure for the component. Realistically, utilities estimate the technical life using expert opinion or manufacturer specifications which results in a biased value that is typically an integer multiple of five. The strategic life will be defined as one that incorporates the costs of planned and forced outages with the risk of failure to minimize costs. The economic life is used in depreciation calculations and can equal either the technical or strategic life or be a unique value based on the decrease in efficiency over time. The trend is to focus too much on the technical life, since strategic and economic factors can vary significantly over the hydropower fleet. This research aims to enable plant owners to make informed decisions on strategic life based on how previous components have reached their technical life.

The two models we will use are a Strategic Life Model (SLM) and a Conditional Reliability Model (CRM). The results of these models will be useful to plant and system managers and will inform routine decisions. The CRM can take the form of either a single component, a group of components within a selected unit or a group of units within a selected plant.

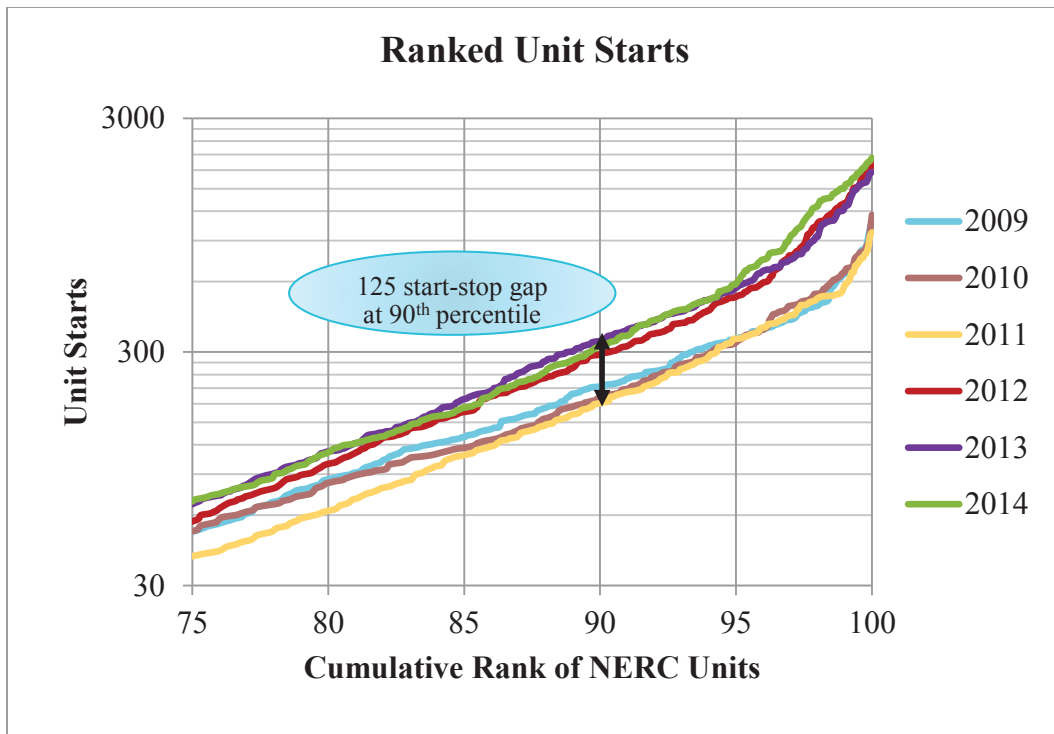


Figure 1-2: NERC GADS Ranked Unit Starts

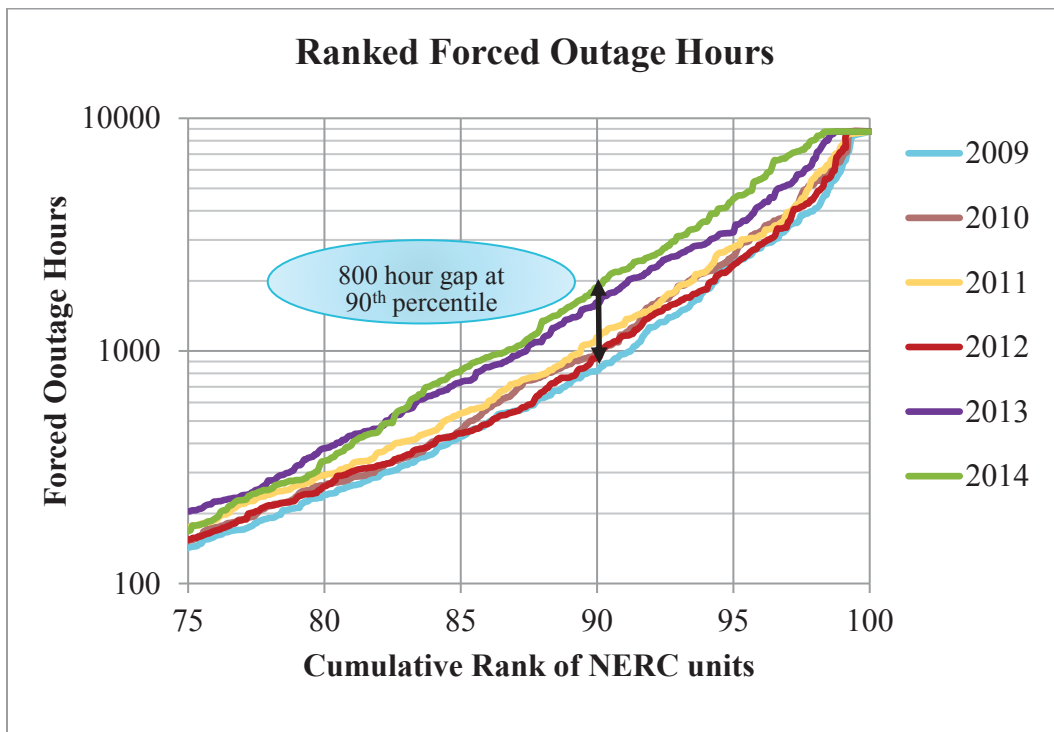


Figure 1-3 NERC GADS Ranked Forced Outage Hours

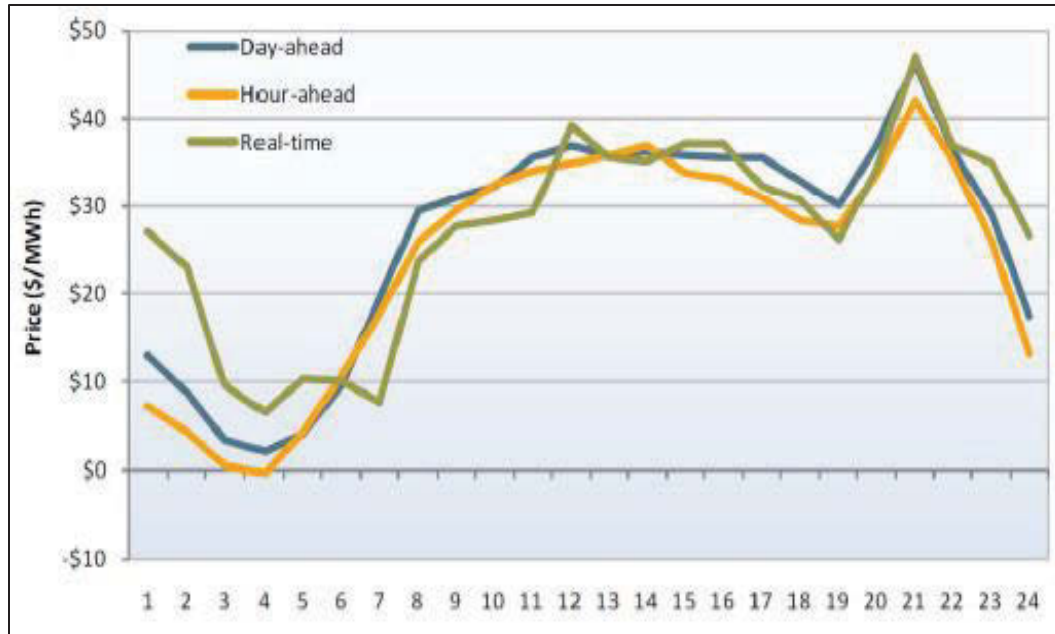


Figure 1-4 Hourly Fluctuations in the California ISO market (11)

The SLM discussed in section 4.3 quantifies the life reduction of the component k , under unique dispatch scenarios s , to answer RQ1. To answer RQ2, the CRM will analyze multiple scenarios as described in section 4.4 to show how altering future dispatch scenarios and parameter vectors $\theta_i(\psi)$ can affect component reliability. RQ3 will focus on three historical dispatch patterns and determine a Reliability Index for each plant based on the optimal and least reliable distributions detailed in section 4.5 using the same parameter vectors $\theta_i(\psi)$. Again, using the parameter vectors $\theta_i(\psi)$, RQ4 will determine plant reliability values if historical hydrologic conditions were repeated and is discussed in section 4.6.

The idea of a cost per unit start is often discussed in the hydroelectric industry (13) (14) (15) since this average cost is incorporated into any power generation bid or ancillary service bid to the market along with overhead, variable O&M, and fuel costs (14). The SLM supports long term planning in determining the average cost of a unit start (15). By predicting the strategic life of each component in RQ1, the system manager can accurately estimate the operational cost of the unit. Surveys from (13) & (14) suggest MW rating correlates with unit start cost, but this is influenced by the increased price of the replacement part and other increases to the outage cost for larger plants (15) with estimates varying from \$130 to \$330 per start based on the nominal rating of the unit with \$330 value representing pumped storage plants (14). Alternatively, the CRM enables asset managers to determine the marginal cost of a unit start for each operating period (15). Hydropower is burdened with increased start stops over other fuel types because the cost of a unit start for hydropower is significantly less than for steam turbine units allowing for hydropower to supply specific ancillary services to the grid as discussed in section 2.1.2 (14).

System managers can use the results of the CRM to make dispatch decisions that optimize component or system reliability as shown by answered RQ2 and RQ4. Utilities may deviate from these optimal reliability dispatch patterns for a variety of reasons, particularly efficiency and environmental requirements but these operations can be justified with the help of the RI to show the extent of the suboptimality of the operations with respect to reliability by answering RQ3. As other generating units on the grid undergo outages, system reliability becomes more important as additional unit outages become more impactful to the grid.

Once outage cost information is acquired from TVA, this model can enable two additional use cases. Future Use Case 1 enables plant managers to alter dispatch patterns to minimize the risk-cost of failures for the system. This requires weighting the reliability of each component by the expected outage cost. Future Use Case 2 determines component replacement priority given budgetary constraints where risk-cost reduction is analyzed for unique scenarios where funds are allocated to different budgetary line items for component replacement in the off-peak season. Similarly, entire units can be compared against each other to determine priority for overhaul work similar to TVA's Hydropower Modernization Program or New York Power Authority's Life Extension and Modernization Program.

2. Background

This review illustrates the complexity of the problem including the complexity of the system of components, how the hydroelectric industry is currently addressing the problem, and how other industries have worked to solve similar problems. Hydroelectric system operations, the design and behavior of hydroelectric powertrain components, and statistical methods used in reliability analyses are described in sections 2.1, 2.2, and 2.3. Optimization methodologies, physics based models and data accessibility are reviewed in sections 2.4, 2.5 and 2.6. Maintenance practices, failure analyses and damage/lifetime analyses used in the hydroelectric industry are discussed in sections 2.7, 2.8 and 2.9.

2.1. Hydropower System, Facility and Unit Operations

Each hydroelectric facility is unique but there are efforts to identify peer groups within the fleet. Typically, these efforts use unit capacity (MW rating) and/or mode of operation. The ancillary services market provides another dividing line as specific plants routinely provide specific services to the grid. The ancillary services the plant provides to the grid, the plant's MOP and plant owner decisions all affect the plant dispatch pattern. These dispatch patterns have changed over time with start-stops becoming more frequent and decreasing ramp times which causes increased ramp rates. These two aspects of modern hydroelectric units mutually enhance the cyclic wear mechanisms (15). This section details the different modes of operation, ancillary services and maintenance strategies that define hydroelectric plants operations and maintenance.

System operations describes the management tools necessary to extract the full potential value from a river system simplified below as four facilities with a total of 14 units. Whether they are owned by one utility or multiple entities system operational planning will benefit all facilities involved. Facility operational planning involves unit commitment decisions that are subject to a variety of forces including power efficiency, water quality, fish passage, and risk-reliability. Annual unit operations, hereafter termed *dispatch patterns*, refers to the annual generating hours and annual unit start-stop cycles each unit is allocated. Other unit operation categories will be discussed in section 2.1.3.

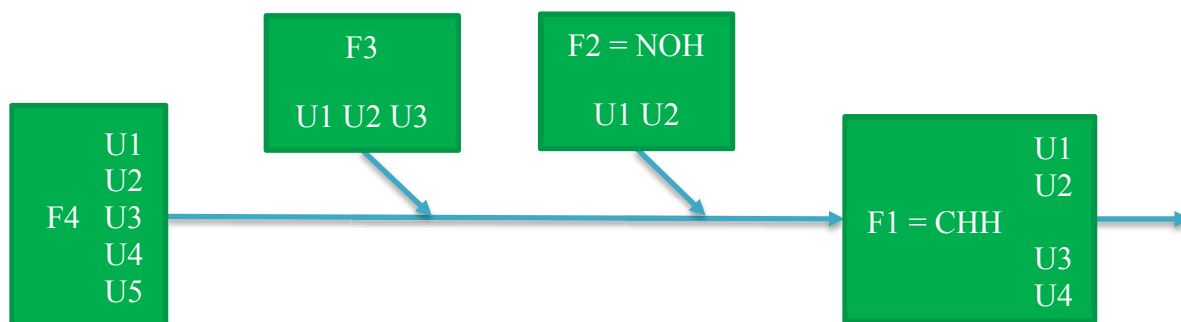


Figure 2-1 Diagram of Hydropower System. Multiple interconnected facilities with a varied number of units at each facility.

2.1.1. Modes of Operation

Hydroelectric facilities are routinely classified as either run-of-river or peaking. In the very early stages of U.S. hydropower, it was not uncommon for run of river plants to start in the autumn and run continuously to the spring (15). The ramp time to full load has also decreased significantly from historical use. It is believed that quick start up times combined with more frequent start-stops both factor into increased component degradation.

As electric grids became more complex, hydroelectric plants that are capable of providing peaking power were increasingly asked to do so. As riverine sojourn time has become more understood and communication between plants on the same river has increased, optimizing the operation schedule has become a priority. This is limited by a plant's MOP. MOPs effectively group hydroelectric facilities as seen in Table 2-1 (16). Reservoir size, residence time and dam height are significant in determining the plant's MOP (16). In addition to run-of river and peaking designations, 4 additional MOP's are used: run-of-river with upstream peaking, intermediate peaking, peaking with seasonal run-of-river, and reregulating plants. Run-of-river plants do not have much temporal flexibility in when they produce power. Therefore, when additional flexibility is required by the grid, the dispatch patterns of peaking and intermediate peaking plants will be increasingly affected.

Table 2-1 Dam Modes of Operation (16)

MOP	Description
Run-of-river	Discharges from the tailrace or dam approximate the sum of inflows to the reservoir at any given time. Hydroelectric generation is dependent upon natural incoming flows. Minimal fluctuation of the reservoir surface elevation
Peaking	Stores and releases water (high flow releases) for hydroelectric generation. Typically, large reservoir fluctuations because of seasonal drawdowns
Run-of-river/upstream Peaking	Operates as a run-of-river facility but harnesses inflows from upstream storage releases or peaking operations to generate electricity.
Intermediate peaking	Stores limited amounts of water for occasional releases or moderates the intensity of peaking for hydroelectric generation.
Run-of-river/peaking	Operates as run-of-river for periods of time or seasons (e.g. during fish spawning) and then operates as a peaking facility the remainder of the time.
Reregulating	Stores and releases water to stabilize flow fluctuations from upstream peaking or storage release facilities and generates electricity. Mitigation facility.

2.1.2. Ancillary Services

Power generation is the primary service, but hydroelectric units' fast ramp times allow the contribution of ancillary services to the grid. Hydroelectric units can provide online regulation through AGC, meet reserve power requirements, and provide voltage control through

synchronous condensing operation. The MW rating of the largest unit on the local grid is typically the minimum amount of reserve capacity required by the system operator.

Online regulation causes increased reliance on AGC in hydropower. Hydroelectric units transitioning from set point dispatch to AGC dispatch may see an increase in unit starts of one to two orders of magnitude (3). Regulation, in the form of AGC causes runner wear and wicket gate wear and tear (13).

Spinning reserve is called into service when there is an under commitment of generation possibly due to a severe over forecast of wind resources (17). If there is an over-commitment of generation due to excess wind power generation, wind power can be curtailed or other resources can be reduced or shut off to maintain system balance (17). Spinning reserve operation of hydroelectric units causes runner wear, generator wear and circuit breaker wear (13).

The differences between supplemental reserve and replacement reserve are the start-up time of the generators and the expected operating time (17). Due to its quick start-up time, hydropower typically acts as supplemental reserve. Supplemental reserve operation causes an increase in generator wear and circuit breaker wear (13).

Synchronous condensing operation enables the hydroelectric unit to provide VAR (volt-ampere reactive) and inertial support to the grid without passing water through the turbine. This reactive power is essential for transmission and distribution of AC power. System inertia helps the grid minimize frequency deviations from 60 Hz.

2.1.3. Dispatch States

The generation mix of the balancing area and the interconnection abilities of the local grid both affect the dispatch patterns of hydroelectric units. The International Energy Agency classified hydroelectric dispatch states into five categories (4). Three of these categories roughly correspond to the ancillary services discussed in the previous section.

- Automatic Generation Control (AGC): The power output of the unit(s) is automatically adjusted to maintain the desired grid frequency.
- Set Point: Online and running at a set power output chosen by the system operator.
- Condensing: The unit runs to provide volt-ampere reactive support without passing water. Instead, air is injected and the generator stator runs as a motor allowing the unit to be synchronous to the grid. This decreases the energy losses in the power system and improves the quality of electric power.
- Standby: Not generating but can be brought online in 5 minutes and up to full power within 10 minutes.
- Unavailable due to Outage: Unit or plant maintenance is occurring.

When quantifying the degradation and failure rates of components, set point dispatch is the assumed dispatch state. With the right data AGC and synchronous condensing operation can be

analyzed to determine the role these dispatch states play in component reliability. “Unavailable due to outage” has various sub-states defined as forced, planned and maintenance outages. Not all outage events affect the value of the hydroelectric project equally. The number of units at the plant, number of other units at the plant experiencing outages, intensity-duration-frequency of precipitation events in the watershed, time of year, type of outage, action required, cost of components and repair time all affect the total cost of the outage.

2.2. Hydroelectric Powertrain Components

The hydroelectric powertrain includes the turbine, governor, generator, exciter, transformer and circuit breaker and their associated subcomponents. The arrangement of each component and the failure modes and mechanisms for components of interest will be discussed herein.

Additionally, actions taken by industry to monitor or reduce the degradation of components will be included. This project will focus only on the current installed levels of technology for each component. As technological advances occur, each component must be analyzed again.

Previous research into failure mechanisms of hydroelectric powertrain components was summarized by the Electric Power Research Institute (EPRI) in (13). Increased operation, ramping, start-stop cycling and/or thermal cycling are noted failure mechanisms for various components including the wicket gates, turbine runner, governor, generator stator bars, stator windings, rotor windings, thrust bearings and main shut off valve. The cost burden of unit start impact is not evenly distributed between components as recent projections suggests the generator stator windings, rotor, thrust bearings, auxiliary equipment and the main shut off valve account for at least 75% of start-stop costs (15). The turbine and governor account for 15-20% of start-stop costs while the excitation system, cooling water system, main transformer and the load breaker have a minor role in start-stop costs (15).

Exciters and governors are critical powertrain components but their low failure rates and low costs of outages compared to turbines and generators discourages discussion of their failure modes at this time. The excitation system ensures that the unit voltage is synchronized to the grid voltage before power generation occurs (18). An excitation system incorporates an exciter, regulator, terminal voltage transducer and load compensator, and a power system stabilizer (18). Exciter technology has evolved from direct current exciters to alternating current exciters to static systems (18). The excitation system controls the voltage of the output electric energy and the VARs provided to the grid (18). The regulator processes and amplifies the control signal for the exciter (18). The transducer converts the terminal voltage into a DC quantity to compare with a reference voltage and the load compensator may be used to keep the voltage at a set point (18). The system stabilizer acts to dampen the input signal to prevent the unit from hunting for the perfect operating point (18).

Governors control the speed and power of the unit by signaling the wicket gate servomotor to adjust the wicket gate opening (18). In adjustable Kaplan turbines, the runner blade servomotor also receives a signal and adjusts the blade angle (18). Droop is required to prevent the unit from

“hunting” the optimal point. Mechanical governors are highly reliable machines but minimal maintenance staff experience and obsolescence of spare parts can sometimes be deciding factors for replacement (18). Digital governors have a much shorter lifespan as the programmable logic controller and the software, whether proprietary or industrial, becomes obsolete quicker (18). The lower cost of the digital governor however makes it the default choice for new hydroelectric installations (18).

2.2.1. Hydroelectric Turbines

There are three main hydroelectric turbine designs for medium and large capacity units, Kaplan, Francis and Pelton. Kaplan and Francis turbines are both reaction turbines while the Pelton is an impulse turbine (18). Specific speed of the turbine and hydraulic head are two criteria used to determine which type of turbine is best suited for the site (19). Selection criteria is shown in Figure 2-2. Due to these variables Pelton turbines represent a minority of the U.S. fleet and were excluded from the Corps expert elicitation and will not be discussed further.

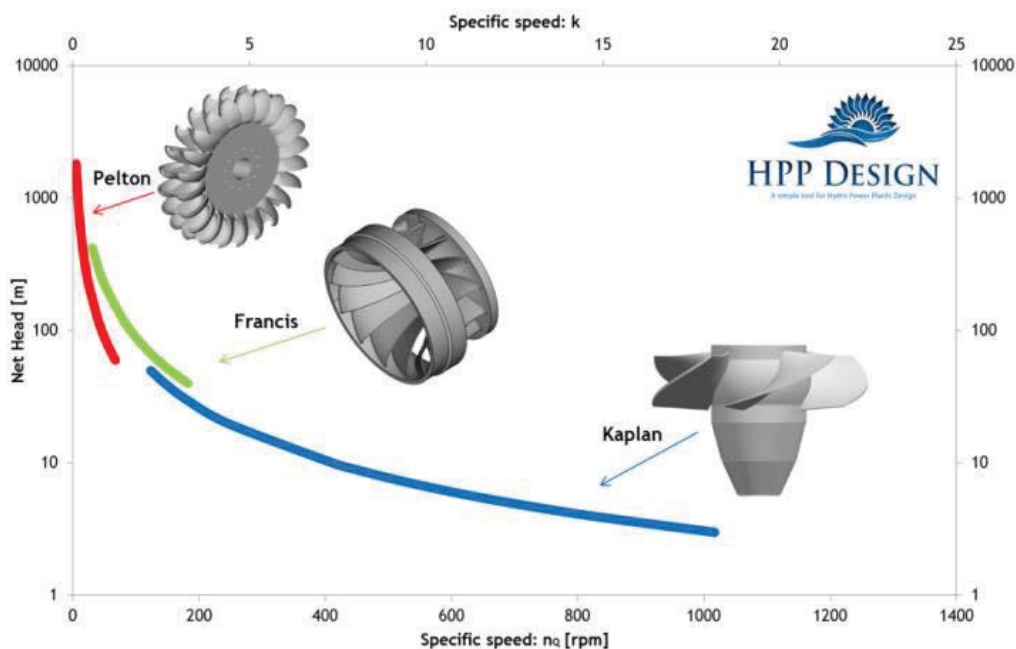


Figure 2-2 Turbine type selection

2.2.1.1. Turbines Types and Associated Components

Kaplan turbine runners are versatile as the newest designs allow for the blade angle to be adjusted (18). Four to seven adjustable blades operate in conjunction with the wicket gates to allow a wider range of efficient operation under varying flow rates (20). Vertically oriented units are the industry norm since horizontal units require a larger footprint (20). Francis turbines

are used for medium and high head projects. The turbine can be oriented vertically or horizontally based on powerhouse design (18). Both Kaplan and Francis units have similar subcomponents that must be discussed. At a minimum, this includes the scroll case, stay vanes, wicket gate assembly and shear pins, turbine runner, turbine shaft, shaft packing, and turbine guide bearings, (18).

The scroll case distributes the water from the penstock to the stay vanes at near uniform velocity (18). The stay vanes guide the flow of water towards the wicket gates (18). The scroll case, stay vanes and wicket gates are designed to minimize head loss. The wicket gates can be adjusted during operation to alter the flow rate or closed to stop flow (18). When open, the wicket gates align very closely to the static stay vanes to reduce cross flow (18). The wicket gate shear pins are designed as a sacrificial part to prevent linkage failures due to overstressing during gate closing (18). The wicket gate assembly provides the structural support for the wicket gate blades while the wicket gate stem rotates within the wicket gate bushing (18). The flow then passes through the turbine runner to generate mechanical energy. The turbine runner is designed for efficiency, fish passage, and cavitation resistance. The turbine shaft transfers the torque from the turbine runner to the generator shaft and then to the generator rotor (18). The shaft packing minimizes water leaking along the shaft surface. The turbine guide bearings keep the turbine and turbine shaft centered by resisting the hydraulic side loads that occur during operation (18).

2.2.1.2. Turbine Failure Modes

Hydroelectric turbines in particular are a critical part of the powertrain, but economic end of life factors, such as efficiency upgrades and fish passage are influential in replacement decisions thus complicating the process of interpreting failure data from outage data. Each type of turbine, has its own failure modes and reliability curve.

Cavitation damage to the turbine runner has been critical to detect due to its effect on unit efficiency and component life (18). Cavitation monitoring systems are now included during most turbine replacements (18). The plant owner can then learn to avoid the cavitation zones in the operating curve (18).

Fatigue crack growth is another prevalent failure mode for hydroelectric turbines. Studies show that ramp events and partial load dispatch are more important than start-stop cycling in estimating turbine degradation where fatigue crack growth is a concern (13) (21). A deterministic answer can be found using structural stress analysis and Miner's cumulative damaged theory (21) (22). A recent EPRI sponsored paper declares likely consequences of unit cycling to include the reduction of the fatigue life of the turbine runner, shaft, and wicket gates and increased wear of thrust and guide bearings and wicket gate bushings (23).

Francis turbine runners constantly encounter unsteady service loads due to the high-frequency pressure fluctuations caused by irregular fluid flow around the guide vanes. These number of small amplitude stress cycles is equal to the number of guide vanes multiplied by the rotational

speed of the turbine (1/min) multiplied by the number of operating minutes for the unit (24). This leads to a large quantity of small amplitude stress cycles which we must then compare to a small quantity of large amplitude stress cycles caused by start-stops (24). The additional stress of overload operation does not reach the amplitude of start-stop stresses and thus has only a minor role in expected lifetime (24).

The typical hydroelectric unit has roughly 20 wicket gates. These gates control the flow of water into the turbine. Wicket gate shear pins are designed as sacrificial parts that break due to mechanical overload on the wicket gate in order prevent damage to costlier components. Increased start-stop events and high ramping rates induce greater fluid and vibrational forces onto the wicket gates, the bushings, and other wicket gate assembly components (23). This causes increased leakage when gates are closed and increased shear pin failures. Shear pins are easily replaced, but if the root cause of the shear pin failure is not addressed, more costly failures may occur.

Complicating this process, there is now increased evidence that fatigue crack propagation may contribute to shear pin failure of older shear pins. Structural stress analyses using ANSYS has produced results for an S-N curve (Stress vs Number of cycles) for AISI 410 shear pins (25). Since this analysis produced significant results showing that bending fatigue is a concern in shear pins, it furthers the need for tracking operations data and lifetime analysis (25). Data analysis of wicket gate movement would provide the necessary values to estimate the occurrence of failure. One start-stop cycle includes opening and closing the wicket gate, but unit ramping can increase wicket gate movement during one start-stop cycle. These failures must be treated independently of shear pin failures not caused by fatigue and are not a primary concern in this research.

2.2.2. Hydroelectric Generators

The generator converts the mechanical energy of the turbine into electrical energy to be distributed by the grid. The two main components are the stator and the rotor. As their names suggest, the stator is stationary and the rotor rotates. The cooling system, thrust bearings and generator shaft are other subcomponents that are critical to reliable operation (18).

2.2.2.1. Generator and Associated Components

The generator is composed of multiple components that convert the rotational energy of the shaft into electrical energy, chiefly the stator and rotor. The generator stator consists of the stator frame, stator windings and the stator core. The stator frame is designed “for high torsional, buckling and vibration stiffness” (26). The stator windings are the electrically insulated copper conductors that are systematically connected to satisfy the design voltage and power requirements (18). The stator winding insulation is a critical subcomponent for reliability analyses due to how suboptimal conditions can greatly affect the degradation of the insulation and the delicate balance designers must consider between increased power output and increased reliability due to the size constraints of the copper wiring and insulation (18). The stator core is comprised of thin laminations of steel that each has a thin coating of insulating varnish (18).

This provides the magnetic circuit path while minimizing eddy current losses and provides the strength necessary to support the stator windings (18). The size of the copper wiring and the volume of insulation is designed to maximize power output while minimize copper losses and withstanding thermal stresses.

The generator rotor must carry the operational loads without producing significant vibration (18). The rotor spider is the structural component that connects to the generator shaft and has the electrical field poles affixed to the perimeter (18). The field poles are connected in series and each copper winding is insulated, establishing the electrical circuit, which upon excitation provides rotor flux to the air gap (18).

Hydroelectric generators typically use direct cooling systems that utilize raw cooling water to reduce thermal stresses. Older, smaller units may have indirect cooling systems installed where air is passed over the components by a fan (18). If continuous monitoring of the stator winding temperature shows an increased operating temperature for normal load and ambient conditions, a maintenance outage is justified to investigate the issue (18). Cleaning the generator of dirt and debris can decrease the operational temperature 5°C (18) leading to smaller thermal stresses on components.

The thrust bearings can be located on either the top side or bottom side of the rotor (18). The thrust bearing carries the downward dynamic operating load of the water and the static load of the rotor (18). An oil film is produced between the rotating collar and the stationary shoes of tolerable thickness and pressure to prevent contact (18). The generator shaft is bolted to the turbine shaft. Proper alignment provided by a second set of guide bearings is necessary to achieve the proper air gap between the rotor and stator and proper bearing loading (18).

2.2.2.2. *Generator Failure Modes*

The main components at risk of failure in the generator are the rotor and the stator and their associated windings, bushings terminals and the stator bars. A survey on generator failures from 1199 hydroelectric generators in Australia, Germany, Norway, Spain, and Sweden concentrated on failures that took 10+ days to repair on units rated greater than 10 MVA in the last ten years (27). Of the 76 failures that met the criteria, 43 of them were caused by insulation damage (56.6%) while mechanical damage accounted for eighteen failures (23.7%), thermal damage for thirteen (17.1%), and bearing damage for two (2.6%) (27).

The study detailed damage categories and root causes of failure. Feedback was provided on what could have prevented the failure from occurring and this is important to have in order to correct the problems at hand. Examples of this included improved detection and alarm systems, increased design requirements, and improved quality control during design, manufacture and assembly (27). This study did not detail the specific subcomponent that endured a failure. This section will summarize knowledge on subcomponent specific failure modes and mechanisms

Dispatch state, component design, and experienced operating incidents all affect the component life of the generator rotor. Frequent start-stops induce mechanical wear on the copper winding insulation reduces the lifetime to 30% to 50% of a similar base load plant (28). Units that operate in synchronous generation mode experience similar degradation rates. If these dispatch states are expected, special design cases, such as body mounted retaining rings and direct conductor cooling, can regain lost life expectancy (28). Contamination of insulating materials with carbon, silicone or oil can lead to premature failure due to overheating and shorted turns (28). Otherwise, the buckling of the laminations is the most critical factor as this can lead to short circuits and/or damage to the stator bars (15).

Shorted turns and field grounds can occur with damaged insulation (18). A short occurs when the copper turns are no longer insulated properly and thus make contact with each other (18). Although shorts are not desirable, a generator can continue to function with a limited number of shorts and repair is only necessary if unit rating cannot be achieved or undesirable levels of thermal sensitivity of the field (28). Field grounds occur when the ground-wall insulation breaks down. This requires immediate removal from service as the occurrence of a second field ground would result in catastrophic damage of the rotor forging, wedges and/or retaining ring (28).

Stator windings are classified based on the voltage rating and the type of insulation. Asphaltic Mica insulation has shown thermal cycling deterioration, but some industry experts believe that newer thermoset insulation does not experience this cyclic deterioration (29). Multiple stakeholders do still find cyclic deterioration to be a culprit in stator winding failures (13) (30) (31) and have estimated cyclic wear coefficients which will be discussed in 3.6.4. Dissenters suggest that adequate knowledge of the thermal age of the unit is not available when the maintenance staff is determining “the difference between delamination and weakly bounded layers of insulation” (29).

A report on thermoset stator windings shows 46% of the symptoms reported involved loose coils and/or loose winding materials (32). Proper installation of wedge and side packing minimizes coil vibration. The thermal expansion of older asphaltic mica insulation systems meant less packing was necessary with the previous technology level (32). They concluded that windings with a MVA rating less than 100 or with a stator core height less than 70” are less prone to loose coils and winding materials that, if left untreated, could result in severe mechanical and electrical degradation (32). To fix loose materials the generator is taken off-line and possibly disassembled. Visual inspection can then determine what subcomponent to repair, replace or refurbish. These problems are caused by the “large and frequent temperature variations occurring due to ‘cold start’” and the differing coefficients of thermal expansion of the two materials. Efficient standstill heating and effective cooling water systems can help reduce the thermal gradients experienced during operation (15).

Thermal cycling is a failure mechanism that traditionally makes increased start-stops concerning. Thermal cycling causes mechanical deformation of the insulation at the slot exits (15). It is

believed that the insulation material and manufacturer of the stator bars contribute significantly to the degradation caused by start-stop cycling. However, breakdowns occurred in both thermoplastic and micadur® insulation during the voltage endurance tests performed (15). It is difficult to distinguish between a reduced lifetime caused by defects in the insulation and a reduced lifetime caused by thermal cycling, but the test performed resulted in bars with reduced lifetimes (15).

Hydroelectric power stations are one of the most heavy-duty applications for thrust bearings, as the bearings must carry both the weight of the turbine and generator as well as the hydraulic down thrust of the turbine. The limiting factor on white metal bearing alloys is fatigue strength, but temperature plays a key role in the strength of the bearing. Bearings, if properly taken care of can have a long component life and most failures are due to issues with the cooling system or the oil system (33). An increased temperature affects the viscosity of the oil and the fatigue strength of the bearings. Maintaining a reasonable oil film thickness is also critical in order to avoid metal on metal interaction (33). Misalignment of the bearing pads can cause uneven wear and thus premature replacement (33). ABB, a Swiss company, field-tested an on-line monitoring system that measures the oil film thickness, pressure and temperature distributions for hydro-generator thrust bearings in 1997 (34). By monitoring these three variables and taking corrective actions, which may include turning off the unit to allow the oil to cool, an owner can significantly reduce catastrophic bearing failure (34).

2.2.3. GSU Transformer

The Generator Step-Up Unit (GSU) transformers are used to increase the voltage so that transmission losses are minimized while distributing the energy to the different load centers (18). They are located in close proximity to the generating unit.

2.2.3.1. Transformer Technology

The insulation, windings, bushings and cooling system consists of similar features as presented in previous sections (18). The transformer core consists of magnetic laminations stacked together (18). Each lamination has a thin layer of insulation to protect the lamination from the adjacent laminations (18). Based on design capacity and other criteria the core can be either single phase or three phase (18).

Insulated wires wound around the core act as the conducting circuit (18). The primary and secondary windings interact to increase the voltage (18). The turn ratio is the ratio between the number of turns on the primary windings and the number of turns on the secondary winding and is equal to the ratio of the voltages on the two lines (18). The increased voltage of the output current decreases line losses.

The bushing in an electrical device consists of a conductor surrounded by insulation to prevent the electrical energy from discharging to a grounded material. The bushing connects the internal windings to the external line connections (18). There are multiple types of insulation materials

available and the insulation includes both a solid insulator and a liquid insulator (18). Solid insulation materials include electrical grade cellulose, wood and insulating varnishes (18). Liquid insulation such as highly processed mineral oil can also be used as a cooling medium for the transformer (18). An external cooling system removes waste heat efficiently to keep the components within design operating temperatures (18). The heat exchanger provides surface area for the insulating fluid to transfer the waste heat to the external system (18). The external system can be either water-cooled or air cooled.

2.2.3.2. *Transformer Failure Modes*

Transformer failures primarily concern three different failure mechanisms: thermal related faults, dielectric related faults and mechanical related faults. Thermal failures occur when the oil or winding temperatures increase and produce localized hot spots. These localized hot spots have deteriorating effects on the insulation due to the different coefficient of thermal expansion. Factors affecting end of life are unit-loading, temperature and the number of short circuits/over-voltages experienced (35).

Partial discharge is a dielectric failure mechanism of the insulation system where voids form thereby deteriorating the insulation system. In order to locate and characterize the type of partial discharge that occurred, a measuring system such as Phase Resolved Partial Discharge Analysis is used. Partial discharges appear as evenly spaced bursts on an oscilloscope whereas arcing has a random pattern (35).

Mechanical failure mechanisms include short circuit forces and vibrations of the core and winding structures. This can lead to deformation of the windings, cleats or leads. Deformations can be detected using leakage inductance because short circuit events decrease the inner winding's diameter and increase the outer winding's diameter giving a higher leakage flux (35).

2.2.4. *Generator Output Circuit Breakers*

The circuit breakers prevent damage from overcurrent and short circuits. In hydropower plant design, there are two major circuit breakers, the generator output breaker and the grid breaker. This research focuses on the generator output breaker.

2.2.4.1. *Circuit Breaker Technology*

The generator output breaker is located between the generator and the GSU transformer (18). The circuit breakers break the circuit when the current exceeds the allowable level in order to prevent damaging overheating of the circuit (18). Types of circuit breakers are differentiated based on the medium used to extinguish the arc. Before 1970, air and oil circuit breakers were the industry standard. Development of vacuum breakers and SF₆ (sulfur hexafluoride) breakers offered alternatives that increased safety and simplified design (18). For worker safety, the circuit breaker is opened during outages to prevent accidental excitation of electrical equipment.

2.2.4.2. *Circuit Breakers Failure Modes*

If a circuit breaker fails to open, larger electrical failures will likely ensue. The best predictor of outage rate for circuit breakers is system voltage and it is known that “failure frequency increases with system voltage” (36). EPRI estimates the SF₆ type circuit breakers replacement period as 7 years based on an estimation of five closures per year. It is suggested by (18) to not leave the circuit breaker in one state for more than two months at a time.

2.3. Reliability Statistics

Reliability describes the probability that the component will remain failure free for a given time period. Conversely, the probability of failure is the chance that the unit will fail in a given time period. The reliability function of choice is the Weibull Distribution which will be introduced and its parameter estimation techniques discussed.

2.3.1. Weibull Distribution

The Weibull distribution models the independent random variable t , which in cases of reliability is commonly referred to as the time to failure. The Two Parameter Weibull Distribution utilizes the shape parameter β , which governs the kurtosis, standard deviation and variance of the model, and the scale parameter α , also called the characteristic life (37). When $\beta = 1$ the Weibull distribution reduces to the exponential distribution and when $\beta = 2$, it reduces to the Rayleigh distribution. These are special cases and show that the Weibull distribution is a more flexible alternative. The cumulative distribution function (CDF) for the Two-Parameter Weibull is:

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^\beta} \quad [2-1]$$

By setting $t = \alpha$ in equation 2-2, α describes the time it takes for 63.2% of the population to fail:

$$F(t = \alpha) = 1 - e^{-\left(\frac{\alpha}{\alpha}\right)^\beta} = 1 - e^{-(1)^\beta} = 1 - e^{-1} = .632 \quad [2-2]$$

The reliability function determines the percent of the population that survives to time t :

$$R(t) = 1 - F(t) = e^{-\left(\frac{t}{\alpha}\right)^\beta} \quad [2-3]$$

The shape parameter β has three unique conditions, $0 < \beta < 1$, $\beta = 1$ and $\beta > 1$. If $0 < \beta < 1$ then the failure rate is decreasing, which is typical of wear in failure and is called “infant mortality”. If $\beta = 1$ then the failure rate is constant. Finally, a $\beta > 1$ means an increasing failure rate and the component has reached the “wear out” stage of its life. It is expected for all components to have $\beta > 1$. Example CDF and probability density function (pdf) curves with various β values are depicted in Figure 2-3 and 2-4. All three distributions have the same α value as changing α only stretches or narrows the distribution. The pdf of the Two-Parameter Weibull Distribution is:

$$f(t) = \frac{\beta}{\alpha} \left(\left(\frac{t}{\alpha} \right)^{\beta-1} \right) e^{-\left(\frac{t}{\alpha} \right)^{\beta}}$$

[2-4]

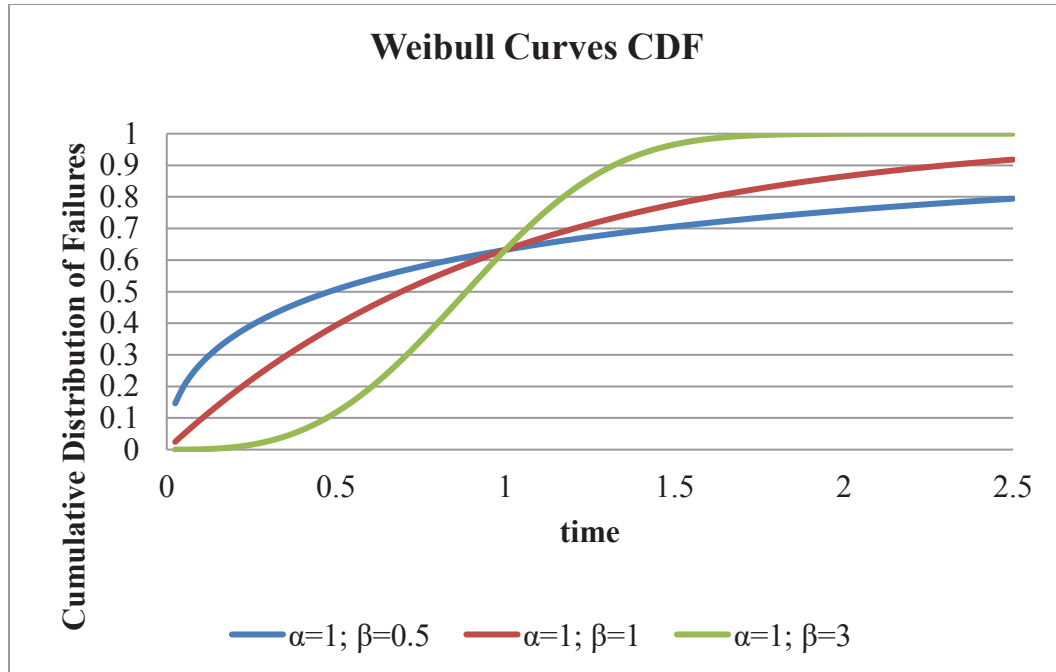


Figure 2-3 Weibull CDF

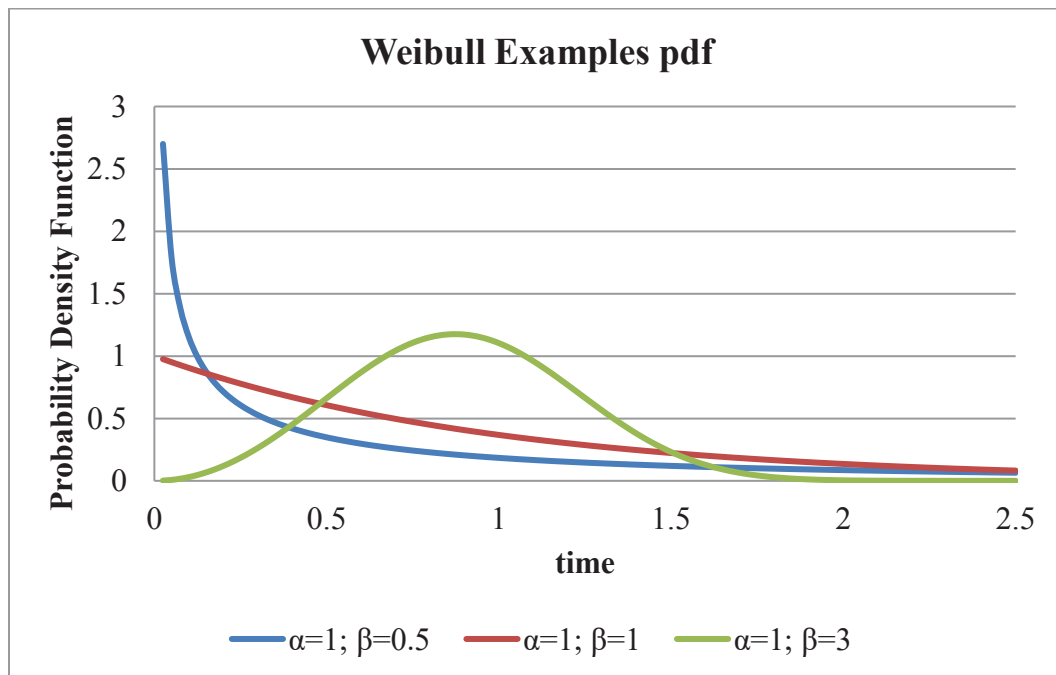


Figure 2-4 Weibull pdf

Conditional reliability defines the reliability of the component given that the component survived to a certain age, T. The probability of A, given that B occurs is expressed as $P(A|B)$. Therefore, the reliability function to replace $P(B)$ as this defines the probability that the unit has survived until time T and the reliability function to replace $P(A)$ signifies the probability that the failure will occur by time T+t.

$$P(A|B) = \frac{P(A)}{P(B)} \quad [2-5]$$

$$R(t|T) = \frac{R(T+t)}{R(T)} = \frac{e^{-\left(\frac{T+t}{\alpha}\right)^\beta}}{e^{-\left(\frac{T}{\alpha}\right)^\beta}} = e^{-\left(\frac{T+t}{\alpha}\right)^\beta + \left(\frac{T}{\alpha}\right)^\beta} \quad [2-6]$$

The Weibull distribution was chosen over other lifetime distribution models, notably the Gamma Distribution and the Exponential Distribution. The Gamma Distribution represents the sum of n exponentially distributed random variables. Similar to the Weibull, it can represent increasing or decreasing failure rates. The Exponential Distribution is a special case of the Gamma Distribution when only one partial failure results in an actual failure. Similarly, the Exponential Distribution is a special case of the Weibull Distribution for when $\beta = 1$. The Gamma Distribution is best utilized in systems where multiple partial failures result in an actual failure. Since this is not the case in hydroelectric powertrain equipment we choose the Weibull Distribution. Determination of Weibull Parameters

To estimate the true distribution parameters that govern the failure rate of each component we collect failure data and expert opinions. The choice to use Maximum Likelihood Estimation (MLE) was made since it can easily combine multiple data sources (38). This method estimates the true distribution parameters by calculating the likelihood that given parameter vector θ , we would obtain each individual failure point $x_1, \dots, x_\omega$ and suspension point $z_1, \dots, z_\mu$. This introduces the likelihood function $L(\theta)$ which is equal to the product of the pdf value for failure point multiplied by the product of the CDF value for each suspended point (39). By maximizing the likelihood function, we find the parameter vector that maximizes the probability that all of the collected information exists within the same distribution.

$$\hat{\theta}_k = [\hat{\alpha}_k, \hat{\beta}_k] = \{\arg \max L(\alpha_k, \beta_k | INFO)\} \quad [2-7]$$

$$L(\theta) = L(\alpha_k, \beta_k | INFO) = \prod_{w=1}^{\omega} \left(\frac{\beta_k}{\alpha_k}\right) \left(\frac{x_w}{\alpha_k}\right)^{\beta_k-1} e^{-\left(\frac{x_w}{\alpha_k}\right)^{\beta_k}} \prod_{u=1}^{\mu} e^{-\left(\frac{z_u}{\alpha_k}\right)^{\beta_k}} \quad [2-8]$$

Survival or censored data points occur when the component is removed from service before failure occurs. MLE can be performed individually on both the expert opinion data and the unit failure data, but the final parameter estimation will maximize the product of the two likelihood functions as shown in equation 2-9 (39).

$$\max L(\theta; INFO) = \max L(\theta; EXP \& DATA) = \max(L(\theta; EXP) * L(\theta; DATA)) \quad [2-9]$$

Negative log likelihood is used in optimization models because it changes the equation from a product of likelihoods to a summation of log likelihoods. This enables faster calculation of partial derivatives providing a quicker optimization. Additionally, the majority of optimization routines are designed to minimize, so we choose to minimize the negative log likelihood, rather than maximizing the log likelihood as these are equivalent arguments.

$$\ln L_{INFO}(\theta_k) = \ln(L_{EXP}(\theta_k)) + \ln(L_{DATA}(\theta_k)) \quad [2-10]$$

$$\min \ln L_{DATA}(\theta_k | x_1, \dots, x_\omega, z_1, \dots, z_\mu) = -\sum_{w=1}^{\omega} \ln \left(\frac{\beta_k}{\alpha_k} \left(\frac{x_w}{\alpha_k} \right)^{\beta_k - 1} e^{-\left(\frac{x_w}{\alpha_k} \right)^{\beta_k}} \right) - \sum_{u=1}^{\mu} \ln \left(e^{-\left(\frac{z_u}{\alpha_k} \right)^{\beta_k}} \right) \quad [2-11]$$

$$\min L_{INFO}(\theta_k) = \min(-\ln L_{EXP}(\theta_k) - \ln L_{DATA}(\theta_k)) \quad [2-12]$$

Although other techniques can be used to convert these expert estimated values into a Weibull distribution, there is no literature available on combining expert values with actual failure data using rank regression on y (RRY) or rank regression on x (RRX) and therefore probability plotting techniques are insignificant. To check the accuracy of MLE though we can compare the resultant parameter vector from the expert elicited values obtained using MLE to rank regression methods by calculating the Mean Squared Error (MSE) to validate that our MLE results in a smaller or similar MSE (38). Methodologies for Weibull RRY and RRX can be found in (38). For linear systems, the MSE will produce the same results as RRY, but since the Weibull distribution is non-linear RRY does not always minimize the MSE. The MSE equation is:

$$MSE = \frac{1}{\eta - 2} \sum_{\gamma=1}^{\eta} \left(1 - e^{-\left(\frac{y_{\gamma}}{\alpha} \right)^{\beta}} - F(y_{\gamma}) \right)^2 \quad [2-13]$$

Where y_{γ} and $F(y_{\gamma})$ denote the time and CDF estimates that are given in the expert elicitation.

2.4. Generalized Reduced Gradient Optimization

Microsoft Excel provides a solver add-in tool for use in solving complex linear and nonlinear functions. The tool provides three different optimization schemes, Simplex LP for linear functions, GRG non-linear for non-linear smooth functions, and evolutionary for non-linear, non-smooth functions. Both our MLE calculations and Dispatch Decision Scheme are non-linear smooth functions and can be solved using GRG non-linear.

GRG nonlinear uses an iterative process to solve smooth non-linear equations. This method requires a feasible starting point, that the analyst provides. Using partial derivatives, the algorithm selects the variable with the steepest descent direction and selects a step size based on imposed constraints (40). The trial step size is continuously halved until certain descent

conditions are satisfied. The function is then solved to ensure $g(x_{k+1}) < g(x_k)$ and finds the value of this variable that corresponds with the local minimum (40). The process is repeated until it converges to a solution. When a constrained variable encounters one of its bounds, movement in that direction is removed from consideration by the algorithm (40).

To ensure a globally maximum solution we use the multi-start capability of Excel's Solver. Using a population size of 1,000, solver uses 1,000 randomly selected initial conditions and determines the global maximum by optimizing each of the 1,000 trials. Other solver options were changed to accommodate specifications of our desired solution. Precision (1.0×10^{-9}) and convergence (1.0×10^{-7}) values govern how the solver perceives a local maximum as the change in the target cell in the last five iterations is compared to the convergence setting and the precision setting indicates the sensitivity of the decision variables. Setting "derivatives = 2", uses central differencing for estimates of partial derivatives and was used since it is a more robust method. Setting "Assume nonneg = TRUE" will keep the decision variables positive. Although there are other constraints on each decision variables, it may be seen as repetitive, but is used regardless. Use of "Automatic Scaling = TRUE" allows solver to rescale the variables to a similar magnitude as the constraints.

2.5. Physics Based vs Statistical Approaches

Physics based approaches to failure mechanisms for turbine runners (22) (23) (24), wicket gate shear pins (25), and stator windings (29) are used throughout the industry as highlighted in 2.1. These include computational modelling and advanced life testing which can both conclude a mean time to failure but are resource intensive. To infer probabilistic reliability from advanced life testing is inconvenient due to cost limitations on sample size. The solution to this sample size issue is to collect actual failure data. This introduces the concern of data quality as data collection is dispersed amongst interested parties.

Our models currently use the Weibull distribution for reliability decisions but to more accurately model each component we must model each relevant failure mechanism that the component experiences using combined life curves (41) that take the same shape as the poly-Weibull distribution. That is, a systems Weibull distribution for three unique components are combined into one reliability equation in the same fashion that three failure mechanisms for one component can be combined into one reliability equation for that component.

$$F(t) = 1 - e^{-\sum_{k=1}^n \left(\frac{t}{\alpha_k}\right)^{\beta_k}} \quad [2-14]$$

$$f(t) = \sum_{i=1}^n \left(\frac{\beta_k}{\alpha_k}\right) \left(\frac{t}{\alpha_k}\right)^{\beta_k-1} e^{-\sum_{k=1}^n \left(\frac{t}{\alpha_k}\right)^{\beta_k}} \quad [2-15]$$

If data quality is low and does not include accurate designations of the dominant failure mechanism, statistical methods to estimate the parameters of combined life curves detailed in (42) can be used to compute these distributions. It is expected that the methodology used to

describe the expert elicited values will have to be altered to use these statistical methods once failure mechanism data is obtained.

If physics based approaches provide a cyclic wear coefficient it can be input into the parameter vector and removed from the MLE and the SLM and CRM will both still operate as designed. A key issue in hydropower currently is the disagreement over these cyclic wear coefficients. A statistical approach provides another source of information for asset managers to consider.

2.6. Sources of Reliability Data

Historically the hydroelectric industry has been data poor. Recent efforts have resulted in utilities increasing their data acquisition and storage capabilities. There is still not a consensus on the time interval used for operational data. TVA has decreased this timestep from 6 hours in the 1970's and 1980's to 5 minutes as of 2004. Additionally, interagency communication is increasing but data sharing is still facilitated through the FERC prescribed mandatory reporting to NERC. Industry groups, including CEATI and EPRI have allowed formalized group settings to discuss industry challenges and how best to face them. Operations and Maintenance "Best Practices" have been disseminated by ORNL (18). While CEATI, EPRI and ORNL are well suited to lead research initiatives, data collection still falls squarely on the shoulders of utilities.

Unit O&M data can be difficult to obtain from utilities because a competitive marketplace produces a "keep it to ourselves" approach (13). Some utilities have developed partnerships to work cooperatively on mutually beneficial analyses. We will discuss the Hydropower Asset Management Partnership (HydroAMP) between Corps, United States Bureau of Reclamation (USBR), Hydro Quebec and Bonneville Power Administration. Data reported to NERC that is available for purchase will also be discussed in this section. In order to make informed decisions while lacking significant unit failure data points, utilities use expert elicitations. The results of the elicitations can be used to validate component life estimates and provide confidence in economic values derived from these component life estimates.

2.6.1. Expert Elicitations

The Corps expert elicitation followed a Delphi method where five to seven experts with "disparate domain knowledge" provide estimates, receive feedback, discuss and provide a second round of estimates (43) (44). The Corps elicitation was not a pure Delphi technique because all of the experts were directly engaged with each other and were moderately acquainted with one another. This was done to speed along the process and increase participation compared to electronic questionnaires while acquaintances were inevitable based on the finite number of qualified experts accessible to the Corps.

2.6.1.1. Delphi Technique

The Delphi technique is one method of collecting expert opinions. First developed by RAND Corporation it is now used in various disciplines to aid decision makers. In its purist form, the Delphi technique will "obtain the most reliable consensus of opinion of a group of experts... by a

series of intensive questionnaires interspersed with controlled opinion feedback (45). This method is not intended to compete with historical data, but is often used when this data is lacking or impractical. There is no consensus that the number of experts used impacts the accuracy of the method, but it inherently uses three experts at minimum. Reference (44) suggests that equal weighting of experts provides a more accurate result than weighting the experts unequally regardless of how weights are distributed. Reference (39) uses a single expert opinion to weigh against historical data, but with access to multiple experts, using a single expert's opinion instead of the median of the expert estimates would theoretically be less accurate.

The Delphi technique instructs the user to elicit information from all experts and to provide feedback to the experts, in our case, by displaying the individual's estimates. Then the experts whose estimates fall outside of the upper and lower quartiles are asked to "give reasons why they believe their selections are correct against the majority opinion". After discussion was concluded, the experts are given the opportunity to change their estimates. This can continue for any number of rounds, but there is no evidence of accuracy improving, so the Corps stopped the process after two rounds.

2.6.1.2. Corps Expert Elicitation

The experts met at Corps offices in Portland, OR for three days with experts joining and departing as their expertise was needed. Starting with generator components moving to electrical components and finally turbines and governors the group of experts went through this Delphi method, estimating five points on the CDF curve for each component.

Routine maintenance, broadly described as maintenance that does not improve the current condition of the component, is assumed to occur for all units during failure curve modelling as exemplified by some of the listed assumptions (46). Routine inspection, greasing, cleaning, calibration etc. may reduce the degradation rate and failure to perform these tasks as prescribed may lead to premature failure but performing them does not improve the current condition of the component (46). Major maintenance tasks are assumed to improve the technical state of the component by rehabilitation or repair to "as good as new" condition. Detailed information on maintenance best practices for specific equipment can be found in (18) & (47).

In order to convert this data into a parameter estimation, we must use this information to estimate the probability of failure from $(0, T_p]$. More importantly, as discussed in section 2.9.4 there are methods that combine this data with failure data to achieve a combined solution. These curves will provide more industry confidence in the findings until the unit failure data sets are sufficiently large.

2.6.2. Unit Failure Data

Plant owners collect operations and maintenance data for their personal records and mandatory reporting to NERC. Operations data includes flow rate, gross head, net head, wicket gate opening, runner blade angle, and unit power, the latter of which is used to determine the number

of unit starts. Maintenance data includes predictive maintenance monitoring data, outage event data, and condition assessment data. The unit failure data will require mining the operation and maintenance history to determine the operating time to component failure, $x_{i,j,k,\omega}$.

2.6.2.1. HydroAMP project

HydroAMP started in 2001, provides a cohesive effort to develop a formalized method to guide condition assessment at hydroelectric power plants. HydroAMP's goals are outlined as:

- Development of long-term investment strategies
- Prioritization of capital investments
- Coordination of O&M budgeting processes and practices
- Identification and tracking of performance goals (48)

HydroAMP meets these goals by establishing a single database to house equipment condition monitoring data in a standardized format from all participating organizations and established assessments and analyses used to help inform decision makers (48). HydroAMP concerns both major powertrain components (governor, turbine, generator, exciter, transformers and circuit breakers) and specific auxiliary components that are mission critical (Batteries, Compressed Air Systems, Cranes, Emergency closure gates and valves, and surge arresters) (48).

There are two tiers of assessments in HydroAMP and two types of analyses. Tier 1 assessments include collecting information to determine equipment condition (48). This includes physical inspection and any maintenance testing results as well as operational history and component age (48). Each component is scored from zero to ten and a data quality indicator score is used to determine how reliable the information is (48). Tier 2 assessments are non-routine and generally require special equipment, expertise or extended time (48). After performing these additional tests, adjustments to the condition index score can be made (48).

A Type 1 analysis considers total cost, condition index score, the current year cost, incremental annual maintenance difference, the phase the project is in and the achievability of the project (48). The achievability is ranked as high, medium or low based on the "ability to undertake the project in the immediate timeframe" (48). The four phases of project completion are study, engineering, procurement or construction.

The Type 2 analysis introduces additional factors relating to "the consequence of undertaking or not undertaking a repair or replacement action" (48). Type 2 analysis is used for expensive pieces of equipment when there are several alternative action items based on budgetary constraints (48). The additional factors used in the type 2 analysis can include (48):

- Total outage duration
- Marginal Value of Generation
- Business, environmental, legal and safety issues
- Risk Map Score

- Revenue at Risk
- Priority Rank

Each component receives a score based on the consequence of failure, which is then combined with the condition index rating to determine the risk map score. The risk map score is the primary way to rank capital projects, although current year budget limits sometimes overrule the risk scores (48). Additional economic analyses can be performed to determine the need for a horizontal replacement programs for specific components (48). The risk map score does not however take into account the expected dispatch patterns, and therefore risk incurred, if replacement is delayed, a gap that we are working to fill.

2.6.2.2. North American Electric Reliability Corporation

The North American Electric Reliability Corporation (NERC) collects information from all power producers within the North American electric grids (Eastern Interconnect, Western Interconnect, Texas Interconnect, and Quebec Interconnect), which includes the continental United States and the southern provinces of Canada, for the Generating Availability Data System (GADS). The software systems pc-GAR SI (standard issue) and pc-GAR MT (mean time) enable users to access this data, although it protects against unit identification. Utilities report data on either a voluntary or a mandatory basis based on plant size. Before 2011 all reporting was voluntary, and in 2012, it became mandatory for power generating plants larger than 50 MW. Since 2013, all power-generating plants greater than 20 MW are now required to report to NERC. This was a much-needed step that will provide a more comprehensive data set for future failure-analysis research. There are however multiple shortcomings with the pc-GAR SI and pc-GAR MT software and the way in which the data is presented.

Data collected for GADS includes O&M data that details the amount of time spent in certain dispatch states and the number of occurrences for each dispatch state including attempted unit starts and actual unit starts. The reliability statistics as explained in appendix F of NERC's data reporting instructions are then calculated using this data. Our experience with the GADS database has not been without complications. A report was submitted to the GADS Hydro working group detailing some of these complications and solution strategies that NERC or utilities can use to create a better data system. These include, but are not limited to incorrect or incomplete designation of turbine type and orientation, turbine manufacturer and generator manufacturer.

2.7. Hydroelectric Maintenance Strategies

Maintenance strategies currently used in the hydroelectric industry vary by plant owner and component. Each owner uses a combination of management practices. The majority of the hydropower industry has accepted the comprehensiveness of reliability centered maintenance (RCM) as the best way to monitor critical components. Economic risk based assessment (ERBA) is the most statistically inclined approach. Corrective maintenance, preventative maintenance and predictive maintenance are incorporated into these two state of the art

approaches, but still have roles for non-critical components that do not require the comprehensiveness of RCM or ERBA as determined by the plant owner.

2.7.1. Corrective Maintenance

Corrective Maintenance requires action only in the case of component failure. Thus, it is known by many as “run to failure”. The components that are assigned corrective maintenance can usually be repaired on very small timescales, have redundant equipment, or are ancillary equipment in the hydroelectric plant since the component failure can occur at any time thereby reducing unit availability (47). If repair time and outage costs for planned and forced outages of a component are similar, the strategic decision is to run the component until failure occurs.

2.7.2. Preventative Maintenance

Preventative Maintenance calls for routine maintenance at predetermined time intervals. The time intervals are often provided from the original manufacturer, but can be changed based on operating experience or to account for inactivity (47). Examples of time based maintenance (TBM) activities for the generating unit include “visual inspections, cleaning, functional tests...lubrication, oil tests, and governor maintenance” (49).

Visual inspections from TBM allow for condition assessments, which score the components on equipment age, O&M history and other relevant condition indexes (CI). The CI score combined with test results inform decision makers about necessary maintenance tasks (48). Condition assessments are used in HydroAMP’s tier 1 analyses discussed in section 3.4.2.1. Condition assessments are used throughout the industry to make fleet wide decisions on replacement priority.

2.7.3. Predictive Maintenance

Predictive maintenance uses on-line monitoring systems to effectively track and predict component degradation and ultimately failure. Examples of predictive maintenance monitoring are cavitation measuring in turbines, temperature probes on insulated materials, rotor speed measurement, partial discharge analysis for stator windings and air gap monitors that measure the distance between the rotor and stator while in use (50). Use of predictive maintenance reduces the dependence on preventative maintenance that requires intermittent scheduling of inspections and assessments. These systems do require acquisition and installation costs that are small compared to the cost of an outage (50).

2.7.4. Reliability Centered Maintenance

RCM was originally developed in the late 1960’s by the airline industry. RCM focuses on preventing failures with the largest consequences. RCM determines the maintenance intervals using actual unit data and component criticality (51). Since RCM is performed proactively, it pairs well with Root Cause Analysis (RCA) that is done reactively because organizations can “learn from reactive responses to become more proactive” (52). Accurate RCM decisions

require a well-executed failure mode, effects and criticality analysis (FMECA) to be available. RCA and FMECA are discussed in section 3.7.

EPRI began using RCM to optimize maintenance tasks at Nuclear Power Generation Facilities in 1984 (51). The definition used by the EPRI RCM Users Group is:

“RCM analysis is a systematic evaluation approach for developing or optimizing a maintenance program. RCM utilizes a decision logic tree to identify the maintenance requirements of equipment according to the safety and operational consequences of each failure and the degradation mechanism responsible” (51).

RCM asks the following seven questions in order to understand possible future failures:

- What are the functions of the equipment or process?
- How can it fail to provide the function?
- What causes each functional failure?
- What are the effects of each functional failure?
- How does each failure influence the goals?
- What action should be taken to predict and prevent each failure?
- What action should be taken if a proactive task cannot be determined? (52)

The answers to these questions may influence current preventative and predictive maintenance strategies by eliminating old or establishing new inspections, functional tests and monitoring devices (51). In this way, RCM optimizes the use of reactive, preventative and predictive maintenance techniques at a plant.

2.7.5. Economic Risk Based Analysis

ERBA uses seven measures to determine the best economic decision but the significance of each measure changes for each plant and for each component. These seven measures are representative age, failure-probability curves, frequency of failure, type, extent and cost of the repair method, value of lost revenue from downtime, extent of renewal introduced by the repair and the economic discount rate (53). The Corps and Acres International developed ERBA independently.

Representative age reflects the current condition of the part relative to expected calendar age of components in similar condition. Weibull distribution curves are the failure-probability curves used in their example. The frequency of failure can be derived from the failure-probability curves. The extent of renewal introduced by the repair is the reduction in representative age that occurs once the repair is complete. The type, extent and cost of the repair method, the value of lost revenue from downtime and the economic discount rate all affect the total cost of the outage (53). The lowest level elements considered in the analysis were generators and turbines and not stator windings, wicket gates etc. ERBA offers comprehensive analysis but this tool has failed to

spread outside of the Corps (53). Our models use similar underlying concept to determine strategic life and optimal dispatch patterns.

2.8. Failure Analyses

Failure analyses are tools owners can use to understand the causes and effects of component failures to help make informed decisions for future components maintenance and to determine what signs of failure maintenance workers can expect. Root Cause Analysis and Failure Mode, Effect and Criticality Analysis will be discussed within this section.

Without both an RCA and an FMECA neither RCM nor ERBA would not be possible. These analyses can be performed independently in order to determine which components in the system require additional attention. At that point, either RCM or ERBA can facilitate increased reliability of the system.

2.8.1. Root Cause Analysis

After a failure occurs, RCA looks to identify the root cause(s) of the unit failure. RCA asks what was the problem, what were the causes of the problem, and what actions should be taken to prevent the problem from occurring (52)? Similar to RCM, RCA requires an understanding of the function of the component, its operating history, critical failure modes and their failure mechanisms (52). Once root causes are determined, analysis of each root cause provides updated information to decision makers. An RCA can segregate failures to determine the propensity of that failure mechanism to arise or to aid advanced statistical analyses (52).

One must be careful to distinguish between the failure mode and the failure mechanism. While failure modes are the effects by which a failure is detected, failure mechanisms are the mechanical, electrical, physical and chemical processes that cause failures to occur (54). NERC lists possible failure modes as leaks, cracks, or fractures and failure mechanisms as erosion, corrosion, or vibration (55). RCA will identify the failure mechanism that resulted in the occurrence of failure.

2.8.2. Failure Mode, Effect, and Criticality Analysis

A Failure Mode, Effect, and Criticality Analysis is a five-step process with the goal of identifying all possible failure modes and their effects on the system “in terms of financial, safety and functional consequences” (56). This process indirectly determines which parts are failing more often than expected and which parts could benefit from better monitoring. It is now common practice in the nuclear power industry. The hydroelectric industry performs both FMECA and the less laborious failure modes and effects analysis (FMEA).

The nuclear power industry is one of the most developed industries concerning reliability analysis along with the airline industry. Nuclear power plants operating restrictions differ significantly from fossil fuel plants as they have routine shutdowns every 18 to 24 months for refueling. It is wise for them to perform their maintenance tasks during this refueling window to reduce the number of forced outages.

As part of implementing a Reliability Centered Maintenance program at San Onofre Nuclear Generating Station in 1991, an FMEA was performed. Preventative maintenance recommendations were used for non-critical components. The probability of failures that were published were annualized values where high reliability is characterized by a value less than or equal to 1.0×10^{-4} and a high probability of failure is characterized by a value greater than 1.0×10^{-3} (57).

2.9. Damage and Lifetime analyses

A majority of models in use currently presuppose the ability to identify the exact moment of unit failure. Damage models accumulate damage expenses, sum the expenses and when the total reaches 1.0, the component is said to have failed. Similarly, current equivalent operating hour models set a failure threshold. Each operation counts towards that threshold differently based on the coefficient for that operation. Once the threshold is reached, the component is said to have failed.

2.9.1. Airline Industry Variable Selection

The airline industry offers an important case study on the importance of variable selection in reliability modelling. By comparing the Weibull distributions using operating hours verses a Weibull distribution using number of flights we can see that a more pronounced peak of failures occurs when using number of flights (56). This bunching of failures enables clearer maintenance decision making.

The difference is due to the correct assumption that airlines use planes to repeat routes. This means that certain planes always take longer flights and other planes always take short flights. The occurrence of the majority of airplane failures happens during takeoff and landing which theoretically affirms this model. The components critical to these tasks are used twice per flight independent of the total flight distance.

Similarly, for hydropower, a unit's past and future dispatch patterns depend heavily on its MOP as discussed in section 3.5.1. Specific plants endure a higher amount of flexible operations, realized in higher unit starts per year and a large number of ramping events per year (10). Since each hydroelectric unit's operating-year is unique, equivalent operating hours, as discussed in sections 3.8.4 and 4.2.1, offers an opportunity to normalize the unit failure data to account for these differences in dispatch patterns.

2.9.2. Semi-Markov multi-nodal Deterioration Model

Once individual component failures are well understood, stakeholders look towards developing analysis techniques that allow for a multi-unit or plant based approach. These techniques are concerned with establishing decision-making schemes in order to analyze how to best spend monetary resources to reduce financial risks. Both SINTEF Energy Research in Norway and Hydropower Asset Management Partnership (HydroAMP) require large amount of condition

monitoring data for their respective approaches but both incorporate expert estimates into their deterioration models.

(39) introduced a semi-Markov multi-nodal deterioration and failure model for powertrain components in hydropower plants. A lognormal distribution was used to model sojourn time between the five states of component deterioration and thus the likelihood function takes the form of the lognormal PDF.

The expert elicitation proposed is different from the expert elicitation hosted by Corps' RMC and HAC. It relies on the experts to estimate two data points instead of five, asking for the time it takes for 10% of the population to move to the next state and for the average sojourn time of the population. Assuming that there are systematic biases the 10th percentile changes to the 25th and the average is taken as the 50th (median). The expert opinions and the failure data are combined by maximizing the likelihood of all information obtained. A lognormal distribution is also used instead of a Weibull distribution, but how the likelihood equations are combined is not affected.

$$L(\theta; INFO) = L(\theta; EXP \& DATA) = L(\theta; EXP) * L(\theta; DATA) \quad [2-16]$$

One goal in developing this maintenance model was to break the vicious circle where “missing data causes a lack of models, and missing models cause a lack of data [collection]” (39). A covariate model where the distribution's parameter vector, $\theta_{i,\psi}$, can be fine-tuned based on the parameters below is suggested with the acknowledgement that this information is currently scarce and/or hard to acquire.

- Year of construction
- Manufacturer
- Material properties
- Manufacturing method
- Operating conditions (service hours, cycles, loading)
- Type* and exact design of the equipment
- Ambient conditions (silt in the water) (39)

2.9.3. Life Extension of Combined Systems

(10) details a deterministic damage model that can be used for energy storage systems used in conjunction with a hydroelectric model. The example uses a three-unit hydroelectric plant that has access to both a flywheel and a flow battery for energy storage purposes. A deterministic model was used to incorporate damage coefficients for multiple co-variants (10). For hydroelectric operation, these included time spent operating in the “rough zone” defined as 30-50% capacity, start-stop events and small, medium and large ramping events defined as less than 10%, between 10% and 20%, and greater than 20% of capacity based on five-minute interval power output data (10).

The premise behind this life extension project is that one can extend the life of a unit by preventing it from operating in more damaging dispatch states (AGC, start-stop cycling, high ramp rates) near the end of the life. While this idea is similar to our goal, we understand that we can only reduce the risk of failure rather than know the precise moment each component will fail.

2.9.4. Applications of Equivalent Operating Hours

A study was presented to the Industrial Application of Gas Turbine Committee discussing life cycle impact of steam injection on gas turbines. Steam injection increases mass flow and power output of the unit but the negative effects are reduced thermal efficiency and component life. Gas turbine baseline operating life curves assume no steam injection. When assuming oxidation life as the critical failure mechanism it was determined that a 3% steam injection rate led to a 20% reduction in component life, but that this was economically viable due to the increased power output (58).

A Lehigh University study developed a maintenance cost model for a combined cycle power plant based on various operating scenarios. As with hydropower, the “variable O&M cost is not always directly proportional to unit output but may also be impacted by operating mode” (59). Therefore, based on current industry standards, equivalent operating hours (EOH) are used to evaluate steam turbines. ABB, a power technology firm, uses equivalent operating hours for their maintenance calculations on motors and gas and diesel generators. They value one cycle as 20 EOH and value one hour of variable speed drive operation as 1.2 EOH (60). Therefore, we introduce a cyclic wear coefficient, a into our parameter vector that will convert the number of cycles into EOH.

$$\hat{\theta}_l(\psi) = [\hat{\alpha}_k, \hat{\beta}_k, \hat{a}_k] = \{\arg \max L(\alpha_k, \beta_k, a_k | INFO)\} \quad [2-17]$$

In hydroelectric plants, generator stators and their windings are commonly using EOH. EPRI’s 2001 report suggests a 40-year component life for the stator windings and determines that increasing the number of unit starts by 150 per year would decrease the expected life to 31.5 years. It does not specify the baseline unit starts or the operating hours per year.

The coefficient used to convert unit starts to equivalent operating hours has been debated for years. A 1984 EPRI study suggested that one unit start is equal to 10 EOH (13) (31). More recently, a “rule of thumb” of five EOH per unit start has been used (30). Some dissenters in the industry believe technological advances make this entire conversation null and void for pumper storage units. (29) cites a 1980’s General Electric thermal aging test concluded that “cyclic aging of the Class B and Class F insulation systems is less damaging than continuous isothermal aging” (61). (29) reasons that in pump storage plants the thermal cooling time is too large and therefore each start-stop doesn’t account for a full thermal cycle (29). However, our analysis seeks to find the difference in degradation rate between a large number of cycles and a small number of cycles and the “always on” continuous isothermal aging is not a condition of interest.

Additionally, the example used by (29) are pump storage plants, while our research seeks answers for conventional hydroelectric units and explicitly excludes pumped storage units where the downtime may not be long enough.

(29) then seeks to disprove previous research that cites one start-stop event as equal to 16 service hours. The 105-megavolt ampere Mt. Elbert Pumped Hydro Storage plant is used as an example. (29) states these units have been “stopped and started once or twice a day for 26 years” and that the two units have over 6,600 and 9,100 starts (29). For reference, 300 starts a year for 26 years equals 7,800 starts. (29) then converts the units’ starts to equivalent operating hours (EOH) and converts these EOH to calendar years at a rate near 2920 operating hours per year. The result is that the age of the windings is calculated as 58 and 74 years. The flaw here is that industry instinctively accounts for a certain number of unit starts per year in their current idea of unit age.

At the Corps’ expert elicitation, the assumption was made for daily start-stop and this is taken to mean 300 start-stops per year. Therefore, over 26 years, each start less than 7,800 adds to the remaining life while each start over 7,800 decreases the remaining life of the component. Using this approach to EOH, the units are aged 23.5 and 28.7, a more reasonable estimate of the current age of the windings since compared to the calendar age of 26, since as (29) noted, “the windings are far from end of life” (29).

3. Methods

The methodology discussed below outlines the models used to answer RQ1 and RQ2. RQ1 asks to what extent additional start-stop cycling decreases the expected component life. RQ2 asks how optimal unit dispatch patterns for plant reliability are affected by distinct parameter vectors.

The first step is to collect data from all sources. For this study, we will use TVA hydro data for 29 of their conventional hydroelectric plants and an expert elicitation. The Corps' HAC and RMC hosted a hydropower component expert elicitation in Portland, OR in January 2016. The experts provided insight into the failure rates of six key powertrain components and multiple technologies of each component. Notes taken from these meetings will be used in conjunction with the unit-level failure data using methodology outlined by (39) and (62).

The analysis will be performed on two TVA units. The four-unit Chickamauga Hydropower Facility (CHH) and the two-unit Norris Hydropower Facility (NOH) were selected based on the criteria below:

- All units at a facility must have similar capacity ratings
- Kaplan turbines
- Desire for one 2-unit facility and one 4+ unit facility

Nomenclature in this section uses i, j, k to denote the plant, unit, and component, for $i = 1 = CHH$ and $i = 2 = NOH$, $j_1 = 1$ to 4 or $j_2 = 1$ to 2 and $k = 1$ to 3. The parameter vectors used in this study and the optimal replacement point are denoted as $\theta_k(\psi)$ and $OP_k(\psi)$ to show that they are unique to the physical component discussed but are also a function of the failure scenarios $\psi = 1$ to 4 used in this sensitivity analyses. Likewise, the dispatch categories $c_j(\psi, s)$ and $h_j(\psi, s)$ are unique to each unit but are a function of the failure scenarios $\psi = 1$ to 4 and dispatch scenarios $s = 1$ to 3 that represent different hydrologic and grid demand scenarios. The reliability index is denoted $RI_i(\psi, s)$ as it is unique to the plant but is a function of the selected failure scenario and dispatch scenario. The current component age $T_{i,j,k}(\psi)$ is unique to the specific plant, unit and component, but is a function of the failure scenario due to changes in the cycling coefficient.

3.1. Data Collection

Expert Elicitation data was collected from the USACE elicitation. Utilities have been slow in providing their unit outage data as the data is disparate and not easily accessible or transferable. In lieu of this data, we have imitated a fleetwide data set for the purpose of showing the model's capabilities. Although a component's probability of failure depends on a variety of factors, current O&M strategies only consider component age, visual inspections and on-line monitoring systems and some rudimentary estimates for unit cycling damage. This project provides a framework for measuring the significance of other easily measurable variables such as unit cycles and service hours on all components.

3.1.1. Utility O&M Databases

USBR, TVA and the Corps have been contacted about providing unit level dispatch data on a small timescale. TVA has provided unit level operations for 29 hydroelectric plants (109 units) with five-minute intervals. USBR provided hourly unit level dispatch data for the three-unit Flaming Gorge plant for a previous research effort. No cost or maintenance data has been provided by either utility. The Corps extended an invite for their expert elicitation but did not provide any unit level data.

Hydroelectric utilities vary widely in the amount of data that is tracked and how easy it is to access such data for research purposes. Although non-disclosure agreements are common and expected in this field, there were still significant delays in the data acquisition phase of this project. Reasons for delays are two-fold. Although the data is stored for internal use, it is immobile when moving in large quantities. Additionally, the data is disparate and requires data from multiple divisions of the utility. The data itself needs to be specific enough to determine unit dispatch patterns over a length of time and show significant outage events. However, once the time to failure values are calculated, the data no longer is attached to a certain unit and thus the data set becomes anonymous before it is used to estimate the distribution parameters. Similarly, the data published will not explicitly show what unit is each data point. This will protect each utility from criticism if their components have experienced shorter lives but also allow the industry to gain from these experiences.

Due to the significant delays in the acquisition of outage data, we proceeded with a simulated fleetwide data set. This section details the methodology used to produce these estimated failure data sets for each of the three replacement cases for each of the three modelled components. Using the TVA fleet as an example fleet, we were provided with unit in service dates and HMOD (Hydropower MODernization) dates. Using TVA blue books, the extend of HMOD work was determined for each unit. For plants whose Blue Book publishing date precedes the plants' HMOD date some assumptions were made.

3.1.2. Expert Opinion Elicitation

Expert elicitation is commonly used in data weak industries to help guide decisions. They can range from eliciting the most likely outcome to eliciting a range of outcomes. One function of the Corps' elicitation is to compare the expert estimates to their unit failure data to evaluate the process to justify using the elicitation process for components where failure data is unavailable.

3.1.2.1. Expert Opinion Elicitation Process

The Corps' HAC and RMC hosted an in-person hydropower component expert elicitation in Portland, OR in January 2016 and invited experts from multiple utilities. The event was spread out over three days. To allow experts to attend only their area of expertise, the schedule was sent out in advance with the first day covered generators and exciters, the second day covering circuit breakers and transformers and the third day covering turbines and governors. Though there was a small group of interested parties gathered, only five to seven experts were given voting rights

(46). The technical integrator facilitated the event. The rest of the group was designated as either observers or listeners based on their role (46). After a brief overview of how the Corps would be using the elicited values included example elicitations, the technical integrator began the exercise by having the experts and observers review the critical component list for that day (46). Then for each component, the technical integrator requested a list of assumptions that the experts wished to use for the component (46). While these changed slightly between components, the assumptions of 50% duty cycle, daily start-stop interpreted as 300 unit starts per year, and to not include pumped storage units were used for all components. Assumptions used for one or more components are:

- Normal and adequate maintenance
- Clean, sheltered, no water
- No extreme loading
- No economic considerations
- Exclude ancillary services
- Installed properly
- Normal environmental conditions
- Clean air quality
- No variable speed units
- Annual IR inspections
- Annual gas in oil testing
- No asphaltic mica insulation
- No alkali-aggregate interaction
- Torque checked at each rewind
- Operate within air balance gap
- SF6 gas is properly handled
- Double electrical diagnostic testing every 6-7 years
- Transformer loading at 30% nameplate capacity
- Failure of transformer occurs in service or during testing
- No “act of god” failures (electrical strikes)
- Stator frame welds inspected periodically
- GSU transformers load at 60% nameplate capacity
- Bushing replacement qualifies as normal maintenance
- Delivered and installed correctly
- Replacement of breaker parts is not considered a failure
- 4-10-year interval for circuit breaker testing
- Electrical testing on circuit breaker contacts every 9-10 years
- Operates within design considerations
- Technology has not become obsolete

- Mechanical and magnetically balanced
- Time based maintenance for circuit breakers
- Cooling system provides even temperature distribution

The experts then established the total time period, T_P . The selection criteria for the total time period were:

- $T_P \leq 100$ to ensure a reasonable timeframe for asset management.
- $F(T_P) > .632$ to ensure that enough information was collected to be useful in developing Weibull parameter estimates.
- $F(0.8 \times T_P) < .99$ to ensure that all five, and not just four, data points gathered were of significance.

Of the 25 components analyzed, only three did not meet the second criteria. The time period of stator frames and rotor spiders were capped at 100 years to meet the first criteria while SF₆ circuit breakers were capped at 50 years due to the absence of historical use. Experts were asked for five data points on the Cumulative Distribution Function, that as (63) suggests, were equally spaced by $\Delta y = \frac{T_P}{5}$. Thus $y_\gamma = \gamma * \Delta y$ for $\gamma = 1, \dots, 5$. For convenience experts used a total time period, T_P , value that is easily divisible by 5 so that Δy is an integer. T_P values selected included 25, 40, 50, 60, 75, and 100. Each expert submitted estimates of five points on the CDF curve to the nearest 1/100 using 0.0 to represent no chance of failure and 1.0 to represent certain failures. These five estimates represent $F(y_\gamma)$ for $\gamma = 1, \dots, 5$. The median of the final estimates was recorded for future use and for obscurity of each expert's individual estimate. Use of the median in place of the mean aligns with the Corps plans to use the median values for their analysis and gives less weight to outliers. The median values for select components for each interval is in Table 3-1.

Table 3-1 Corps Expert Elicited Values: the 3 components analyzed are shown, 25 were elicited

Corps Expert Elicitation Jan 2016		CFD Median Estimates				
Component	Part or Description	F(20)	F(40)	F(60)	F(80)	F(100)
Rotor	Windings	0.01	0.05	0.25	0.4	0.65
Turbine	Kaplan	0.05	0.15	0.4	0.6	0.95
Component	Part or Description	F(10)	F(20)	F(30)	F(40)	F(50)
Stator	Windings >6900, multi-turn	0.03	0.1	0.3	0.65	0.93

Experts submitted five values to the technical integrator along the CDF curve expressing their opinion of the probability a unit would normally fail by time y_γ for $\gamma = 1, \dots, 5$. These values were then shared with the group by the technical integrator and then the room was opened for a

guided discussion led by the technical integrator (46). This discussion included the experts recounting failures at particular plants that informed their opinions and developing additional assumptions. The experts were asked to once again estimate the CDF if their opinion changed during the discussion (46). After the second round of estimates was complete, the moderator recorded how confident each expert was in the median estimates of the group (46). Acceptable responses were low, medium-low, medium, medium-high, and high. These confidence values will be used to weight the failure data against the expert elicited values (46).

3.1.2.2. *Transforming Expert Opinions into a Parameter Vector*

There are many methods for using expertly elicited values in reliability engineering, but our options are limited by our desire to use MLE to combine expert opinions with actual failure data. Methodology used by (63) for maintenance intervals assumes a uniform distribution of failures within each interval. The uniform distribution says that if $\Delta y = 10$, the probability of failure is constant from $(0, 10]$ and $(10, 20]$. The failure probability within each interval is equal to the fraction of the population that is expected to fail in the interval divided by the total time of the interval per the expert elicitation. Using γ to designate the interval number, the failure rate is expressed as:

$$\varphi(t_e) = \frac{F(y_\gamma) - F(y_{\gamma-1})}{\Delta y} \quad \text{if } y_{\gamma-1} < t_e \leq y_\gamma, \quad \gamma = 1, \dots, 5 \quad [3-1]$$

Since we desire to integrate $\varphi(t_e)$ it is useful to visualize the piecewise equation.

$$\varphi(t_e) = \begin{cases} \frac{F(y_1) - F(y_0)}{\Delta y} & \text{for } y_0 < t_e \leq y_1 \\ \frac{F(y_2) - F(y_1)}{\Delta y} & \text{for } y_1 < t_e \leq y_2 \\ \frac{F(y_3) - F(y_2)}{\Delta y} & \text{for } y_2 < t_e \leq y_3 \\ \frac{F(y_4) - F(y_3)}{\Delta y} & \text{for } y_3 < t_e \leq y_4 \\ \frac{F(y_5) - F(y_4)}{\Delta y} & \text{for } y_4 < t_e \leq y_5 \end{cases} \quad [3-2]$$

To perform an MLE of expert estimates we need to estimate artificial failure points. In determining that 100 data points would be the simplest amount to estimate, these failures will correspond to the each $1/100^{\text{th}}$ of the probability estimates. As with all pdf curves, the area under the curve is equal to unity. That is $\int_0^\infty \varphi(t_e) dt = 1$. Thus, at any point in time t_e , the area under the curve to the left of t_e is expressed as $\int_0^t \varphi(t_e) dt$ is equal to the fraction of the population expected to fail.

Therefore, each estimated failure, x_w , occurs at some point t where $\frac{w-1}{100} < \int_0^t \varphi(t_e) dt \leq \frac{w}{100}$. However, in order to accurately estimate where the artificial failure occurs we assume it occurs at the midpoint.

$$x_w = t_e \text{ where } \int_0^t \varphi(t_e) dt = \frac{w-0.5}{100} \text{ for } w = 1, \dots, 100 \quad [3-3]$$

This results in the use of $\Phi(t_e) = \int_0^t \varphi(t_e) dt$ to simplify this process. Since each piece of $u(t_e)$ has a uniform failure rate the integral is easy to calculate. Using the piecewise notation, the integrated function for the first three intervals can be written as:

$$\Phi(t_e) = \begin{cases} \left(\frac{F(y_1)-F(y_0)}{\Delta y} \right) (t_e - y_0) & \text{if } y_0 < t_e \leq y_1 \\ \left(\frac{F(y_2)-F(y_1)}{\Delta y} \right) (t_e - y_1) + \frac{F(y_1)-F(y_0)}{\Delta y} (\Delta y) & \text{if } y_1 < t_e \leq y_2 \\ \left(\frac{F(y_3)-F(y_2)}{\Delta y} \right) (t_e - y_2) + \frac{F(y_2)-F(y_1)}{\Delta y} (\Delta y) + \frac{F(y_1)-F(y_0)}{\Delta y} (\Delta y) & \text{if } y_2 < t_e \leq y_3 \end{cases} \quad [3-4]$$

In long form, this gets out of hand quite quickly. However, the terms without t can be simplified:

$$\Phi(t_e) = \begin{cases} \left(\frac{F(y_1)-F(y_0)}{\Delta y} \right) (t_e - y_0) & \text{if } y_0 < t_e \leq y_1 \\ \left(\frac{F(y_2)-F(y_1)}{\Delta y} \right) (t_e - y_1) + F(y_1) - F(y_0) & \text{if } y_1 < t_e \leq y_2 \\ \left(\frac{F(y_3)-F(y_2)}{\Delta y} \right) (t_e - y_2) + F(y_2) - F(y_1) + F(y_1) - F(y_0) & \text{if } y_2 < t_e \leq y_3 \end{cases} \quad [3-5]$$

With the assumption that $F(y_0) = 0$ the equations can be simplified further.

$$\Phi(t_e) = \begin{cases} \left(\frac{F(y_1)-F(y_0)}{\Delta y} \right) (t_e - y_0) & \text{if } y_0 < t_e \leq y_1 \\ \left(\frac{F(y_2)-F(y_1)}{\Delta y} \right) (t_e - y_1) + F(y_1) & \text{if } y_1 < t_e \leq y_2 \\ \left(\frac{F(y_3)-F(y_2)}{\Delta y} \right) (t_e - y_2) + F(y_2) & \text{if } y_2 < t_e \leq y_3 \end{cases} \quad [3-6]$$

Upon expanding for use in all five intervals the reduced CDF equation is:

$$\Phi(t_e) = \begin{cases} \left(\frac{F(y_1)-F(y_0)}{\Delta y} \right) (t_e - y_0) & \text{if } y_0 < t_e \leq y_1 \\ \left(\frac{F(y_2)-F(y_1)}{\Delta y} \right) (t_e - y_1) + F(y_1) & \text{if } y_1 < t_e \leq y_2 \\ \left(\frac{F(y_3)-F(y_2)}{\Delta y} \right) (t_e - y_2) + F(y_2) & \text{if } y_2 < t_e \leq y_3 \\ \left(\frac{F(y_4)-F(y_3)}{\Delta y} \right) (t_e - y_3) + F(y_3) & \text{if } y_3 < t_e \leq y_4 \\ \left(\frac{F(y_5)-F(y_4)}{\Delta y} \right) (t_e - y_4) + F(y_4) & \text{if } y_4 < t_e \leq y_5 \end{cases} \quad [3-7]$$

The next step is to convert this into a concise equation that represents all five intervals. This is done by introducing γ to represent the intervals.

$$\Phi(t_e) = \frac{(F(y_\gamma) - F(y_{\gamma-1}))}{\Delta y} (t_e - y_{\gamma-1}) + F(y_{\gamma-1}) \quad \text{if } y_{\gamma-1} < t_e \leq y_\gamma \quad [3-8]$$

By setting $\Phi(x_w) = \frac{w-0.5}{100}$ we can obtain the estimated time to failure. We must re-arrange the equation such that x_w is isolated.

$$\frac{(F(y_\gamma) - F(y_{\gamma-1}))}{\Delta y} (x_w - y_{\gamma-1}) + F(y_{\gamma-1}) = \frac{w-0.5}{100} \quad \text{step 1: substitute } \Phi(x_w) \quad [3-9]$$

$$\frac{(F(y_\gamma) - F(y_{\gamma-1}))}{\Delta y} (x_w - y_{\gamma-1}) = \frac{w-0.5}{100} - F(y_{\gamma-1}) \quad \text{step 2: subtract } F(y_{\gamma-1}) \quad [3-10]$$

$$(x_w - y_{\gamma-1}) = \left(\frac{w-0.5}{100} - F(y_{\gamma-1}) \right) * \frac{\Delta y}{(F(y_\gamma) - F(y_{\gamma-1}))} \quad \text{step 3: multiply by } \frac{\Delta y}{(F(y_\gamma) - F(y_{\gamma-1}))} \quad [3-11]$$

$$x_w = \left(\frac{w-0.5}{100} - F(y_{\gamma-1}) \right) * \frac{\Delta y}{(F(y_\gamma) - F(y_{\gamma-1}))} + y_{\gamma-1} \quad \text{step 4: add } y_{\gamma-1} \quad [3-12]$$

Now that the bounds "if $y_{\gamma-1} < x_w \leq y_\gamma, \gamma = 1, \dots, 5$ " are not useful since we are solving for x_w we must define new bounds. We propose:

$$x_w = \left(\frac{w-0.5}{100} - F(y_{\gamma-1}) \right) * \frac{\Delta y}{(F(y_\gamma) - F(y_{\gamma-1}))} + y_{\gamma-1} \quad \text{if } F(y_{\gamma-1}) < \frac{w-0.5}{100} \leq F(y_\gamma) \quad [3-13]$$

These time to failure values, x_w , can be input into the likelihood function such that the parameter vector can be maximized. However, we must still account for suspended data. There are $100 * (1 - F(T_p))$ suspended data points. All of these data points have a suspension time of T_p as this is the latest date that we have an estimate of survival.

The parameter vector, $\theta_i(\psi)$, will be calculated using the expert values in conjunction with the data driven approach. It is important for researchers to compare their proposed model against human experts, $\theta_i(\psi = 4)$, or other current techniques instead of simply comparing against a dumb procedure such as run to failure (64). For this reason, the importance of the expert elicitation is two-fold as it both informs the combined distribution and offers a baseline of knowledge for comparison.

3.2. Statistical Methodology

The statistical methodology will incorporate data from a variety of sources as seen in Figure 5. Using data package 1, the expert parameter vector can be estimated. Data package 2 includes all unit level data collected. More significantly, by using data packages 1 and 2, we can arrive at our final parameter estimation that will incorporate unit start-stop events into the distribution.

3.2.1. Weibull Distribution and Equivalent Operating Years

A statistical model will be created using the Weibull distribution. The model will convert unit starts to equivalent operating hours using equation 3-14. Using the assumption of 50% duty cycle and 300 unit starts per year as discussed at the expert elicitation. The EOHs are then converted to Equivalent Operating Years (EOY) using equation 3-15. Figure 3-1 shows the flow of information in determining the final parameter estimations.

$$EOH_{i,j,k} = a_k * c_{i,j,k} + h_{i,j,k} \quad [3-14]$$

$$EOY_{i,j,k,\psi} = \frac{EOH_{i,j,k}}{300 * a_k + \frac{8760}{2}} = \frac{a_k * c_{i,j,k} + h_{i,j,k}}{300 * a_k + 4380} \quad [3-15]$$

In future analyses, when using more than two covariates equation 3-14 will be modified as shown in equation 3-16 and equation 3-15 will be modified based on the assumptions made by the intended user.

$$EOH_{i,j,k,\psi} = a_{k,1} * c_{i,j,k,1} + \dots + a_{k,n} * c_{i,j,k,n} + h_{i,j,k} \quad [3-16]$$

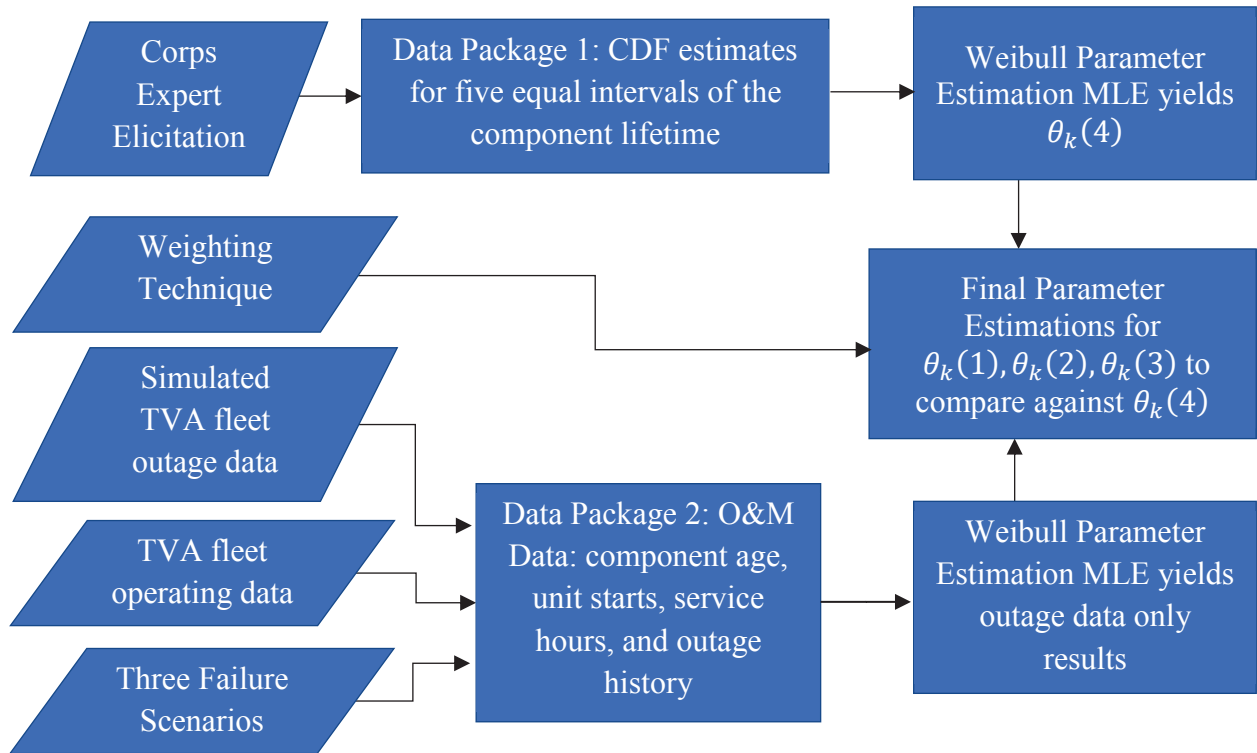


Figure 3-1 Flow of Data Inputs

3.2.2. Parameter Estimation Techniques

MLE is used to estimate the Weibull distribution parameters, α , β , and a , the coefficient of cyclic wear. The expert estimated likelihood function uses the artificial failure and suspension times x_w and z_u :

$$L_{EXP}(\theta_k(4)) = L(\alpha, \beta | EXP) = \prod_{w=1}^{\omega} \left(\frac{\beta_k}{\alpha_k} \right) \left(\frac{x_w}{\alpha_k} \right)^{\beta_k-1} e^{-\left(\frac{x_w}{\alpha_k} \right)^{\beta_k}} \prod_{u=1}^{\mu} e^{-\left(\frac{z_u}{\alpha_k} \right)^{\beta_k}} \quad [3-17]$$

The TVA fleet imitation failure and suspension data is converted to EOY using equation 3-15 and then input into equation 3-19 (62).

$$L_{DATA}(\theta_k) = L_{DATA}(\alpha_k, \beta_k, a_k | D) = L_{DATA}(\alpha_k, \beta_k, a_k | x_1, \dots, x_{\omega}, z_1, \dots, z_{\mu}) \quad [3-18]$$

$$L_{DATA}(\theta_k) = \prod_{w=1}^{\omega} \left(\frac{\beta_k}{\alpha_k} \right) \left(\frac{\frac{a \cdot c_w + h_w}{300 \cdot a_k + 4380}}{\alpha_k} \right)^{\beta_k-1} e^{-\left(\frac{\frac{a \cdot c_w + h_w}{300 \cdot a_k + 4380}}{\alpha_k} \right)^{\beta_k}} \prod_{u=1}^{\mu} e^{-\left(\frac{\frac{a \cdot c_u + h_u}{300 \cdot a_k + 4380}}{\alpha_k} \right)^{\beta_k}} \quad [3-19]$$

While performing MLE using Microsoft Excel's solver, bounds will be given to the parameters α , β , a to speed up computational efforts. Bounding β between 0.1 and 5 for all components. Bounds for α provides adequate space to find the global maximum and vary significantly by component. The cyclic wear coefficient a will have an upper bound of 10 and a lower bound of zero to prevent negative values because they would suggest that start-stop cycling enhances the effective life instead of diminishing it.

3.2.3. Confidence Weighting

Our proposed model is dependent on two unique, though dependent sources of information that are used in the parameter estimates. Current industry best practices rely solely on the expert elicitation. With an aging workforce, it is important that a dependable unit failure data driven model is functional in the short term. To ensure industry confidence in the models, the data sources must be weighted to favor expert opinion when little unit failure data is available and favor unit failure data when it is abundant. The accuracy of the statistical models is very dependent on the sample size of the data. Thus, unit failure data will be weighted by calculating the Average Coefficient of Variation, ACV, based on the number of data points available. In literature, experts are weighted using the reciprocal of the standard deviation of the estimate of the mean (39). Since expert estimates of the Weibull distribution does not estimate a mean like the log-normal distribution, we choose to weight the expert values using the average expert confidence, E_C since it is the "only available measure of the quality of a decision" (44) and increasing the number of participating experts does not improve model accuracy (44).

Accuracy of models are shown through the upper and lower confidence bounds, known jointly as the confidence interval, $CI = [B_L, B_U]$ and bound ratio, $BR = B_L/B_U$. The confidence bounds are dependent upon what percent of possible outcomes are to be included within the bounds.

80%, 90%, 95% and 99% confidence levels are typical in statistical modelling and one-sided and two-sided bounds have specific purposes. There is no prior work in statistical failure modelling in the hydroelectric industry, so we will use 80% two-sided confidence bounds for our work, which suggests that there is a 10% probability that the actual parameter value is lower than the lower bound of the parameter estimate and a 10% probability that the actual parameter value is higher than the upper bound of the parameter estimate.

Where ACV is the average coefficient of variation. From (65) and (66) we can assume the β parameter takes a lognormal distribution around the MLE β parameter. ACV is a measure of the relative uncertainty of the estimated β parameter. From simulations performed by (66) the input value of α had no bearing on the estimated β parameter and the standard deviation of β increases proportionally with β when sample size is constant. By plotting the results of the sample size analysis, a power function equation for ACV is determined.

$$ACV = \frac{\sigma}{\hat{\beta}} = 1.4818 \times n^{-.654} \quad \text{for all } \beta \quad [3-20]$$

To isolate the standard deviation, we bring the β value to the left-hand side of the equation.

$$\hat{\beta} \times ACV = \sigma \quad [3-21]$$

Since the standard deviation is present in the log normal distribution used in (39) but not in our Weibull distribution, we must alter our likelihood equation 3-12 to include standard deviation.

$$\ln L_{INFO}(\theta_{i,\psi}) = \frac{-1}{\hat{\beta} \times ACV_{EXP}} \ln(L_{EXP}(\theta_{i,4})) + \frac{-1}{\hat{\beta} \times ACV_{DATA}} \ln(L_{DATA}(\theta_{i,\psi})) \quad [3-22]$$

Factoring out β and moving it to the left-hand side of the equation does not affect the results of the MLE. We leave ACV in the equation to provide weights to the two sets of knowledge.

$$\ln L_{INFO}(\theta_{i,\psi}) = \hat{\beta} \left[\frac{-1}{ACV_{EXP}} \ln(L_{EXP}(\theta_{i,4})) + \frac{-1}{ACV_{DATA}} \ln(L_{DATA}(\theta_{i,\psi})) \right] \quad [3-23]$$

$$\frac{\ln L_{INFO}(\theta_{i,\psi})}{\hat{\beta}} = \frac{-1}{ACV_{EXP}} \ln(L_{EXP}(\theta_{i,4})) + \frac{-1}{ACV_{DATA}} \ln(L_{DATA}(\theta_{i,\psi})) \quad [3-24]$$

Now that we can insert standard deviation into our equation through using ACV which is dependent only on sample size, it is convenient to use when comparing the variability of multiple data sources. Thus, in our modelling of multiple hydroelectric powertrain components, we use ACV to provide guidance for the relative weight given to the expert opinions and unit failures.

As experts' confidence increases, we assume that the CI decreases. Thus, a higher confidence should correlate with a smaller BR and a lower confidence with a larger BR. Expert confidence was provided on a 5-point subjective scale that we converted to quantifiable values between 1 and 9. There may be some ambiguity here as it was not until part way through the elicitation process that experts started using medium-low and medium-high to express their confidence.

Each participating expert gave their confidence and using the values above we convert E_C to a number of failure points for an 80% confidence interval simply, $n = 5 * E_C$. This result can then be used to calculate ACV and BR. Furthermore, this provides a method to compare the expert confidence in the median of the groups estimates to the confidence the unit failure data will provide based on the number of data points that are collected.

To determine which data set has more weight we must look beyond ACV because the expert opinions always give 100 artificial data points but the size of the unit failure data is constantly changing. Figure 3-3 depicts the number of actual failure points needed to give equal weight to the two data sources. This is determined by equating the total weight of all unit failure data to the 100 artificial failure data points which are weighting by the average expert confidence. Since ACV is present in the denominator and the number of failure data points required is dependent of the average expert confidence this equation takes the shape of a square root function.

This would suggest at the utility level more weight is given to experts but when unit failure data is shared, it can become powerful enough to use for asset management decision making purposes. As the number of actual failure data points collected increases, the weight of L_{EXP} decreases. The influence of expert opinions will never disappear, but rather will become less influential as the correct data is collected.

A coefficient of 5 is used as a rule of thumb. The goal was for there to be a significant difference between $ACV(E_C = 1)$ and $ACV(E_C = 9)$. Figure 3-2 graphs equation 3-20. A different value for the coefficient can be chosen based on how an Asset Manager desires to weight the two knowledge sources. Based on the desired confidence level, one can determine the number of actual failures required for the results to be statistically significant (66). Until that required number of failures occurs, it is justifiable to put more weight towards the expert opinions.

Figures 3-4 through 3-11 depicts how the failure curve will change based on the weight given to each data source and the sources original estimates. Given the same α , but different β , equal weights will produce a parameter estimate that is near the arithmetic mean but the results are more complex when α varies between data sources.

These graphs were computed by first selecting the α and β values and then using Monte Carlo method to create failure data. Using the Monte Carlo failure data from the two distributions the weighting method was used to determine seventeen possible weighting scenarios which are shown for each of the four initial pairs of distribution parameters. The weighting scenarios express the result of two experts when expert one expresses their confidence as a nine, and expert two varies their confidence from one to nine and then is repeated for expert one's confidence varies from one to nine and expert two's confidence is constant at nine. This method was repeated for four different sets of parameter estimates, when α is constant but β varies, when α varies but β is constant, and two sets where both α and β vary. $\alpha = 1$ and $\beta = 3$ were used as the median for which the estimates are centered around.

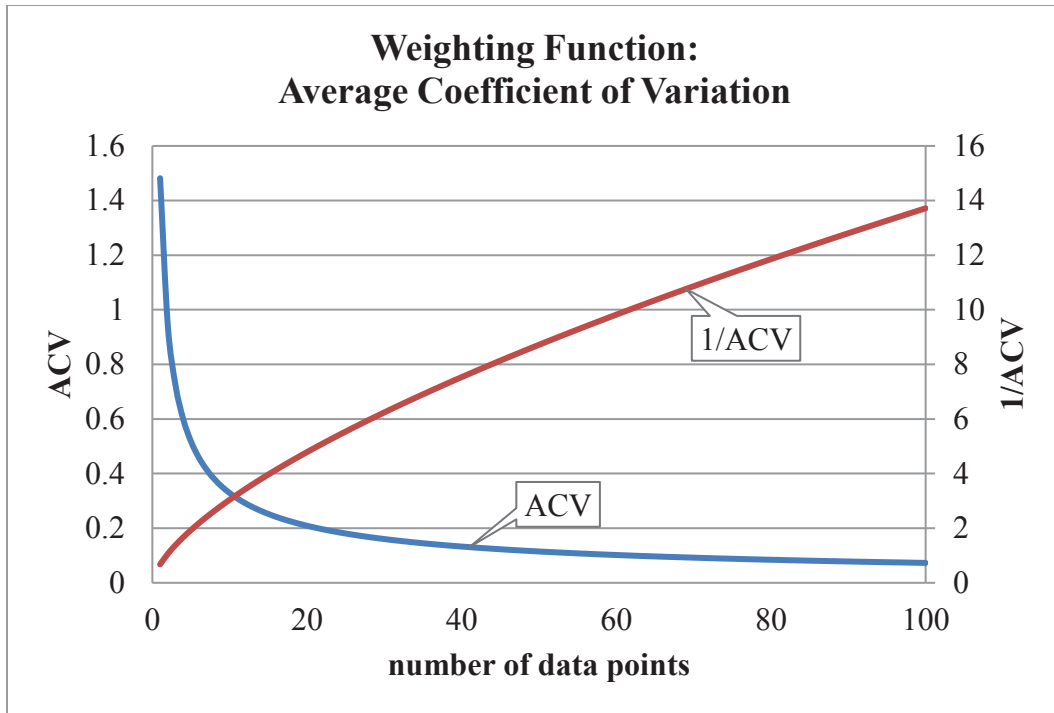


Figure 3-2 Weighting Function

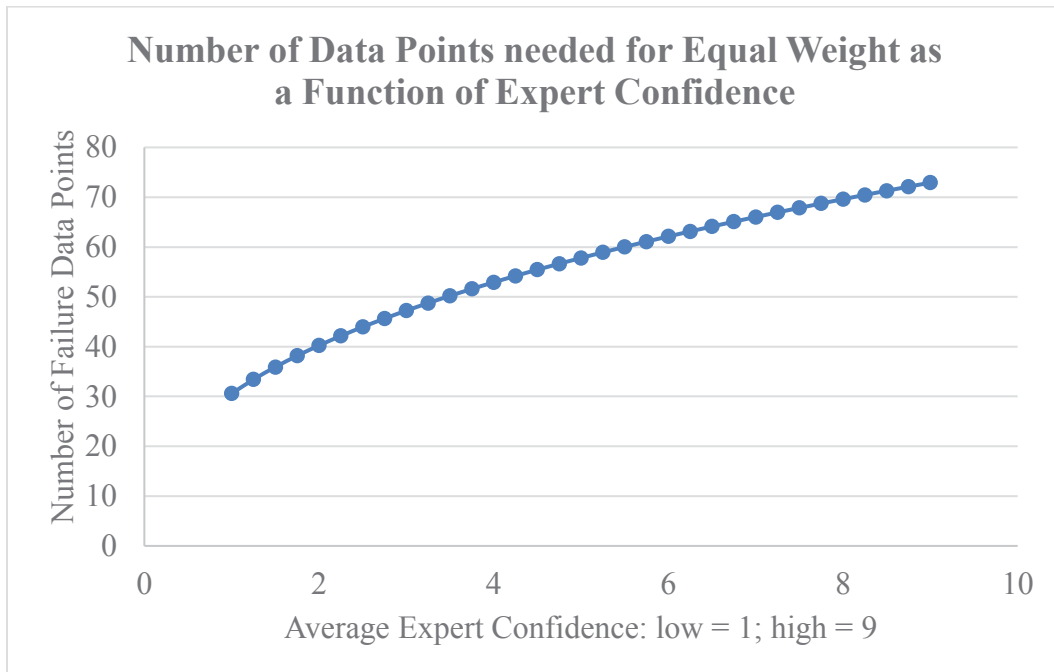


Figure 3-3 Break Even Point between Expert Opinions and Unit Failure Data Found by Solving the equation:

$$\frac{100}{(5 * E_C)^{-0.654}} = \frac{n}{n^{-0.654}}$$

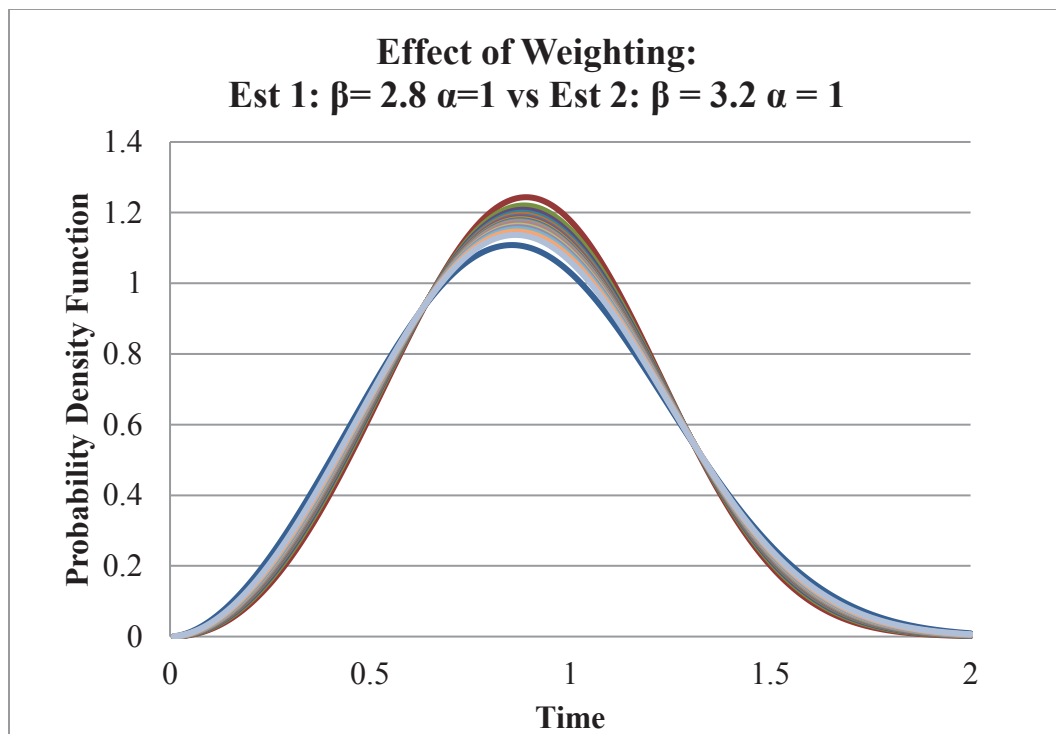


Figure 3-4 Weighting pdf: Constant Scale, Varying Shape

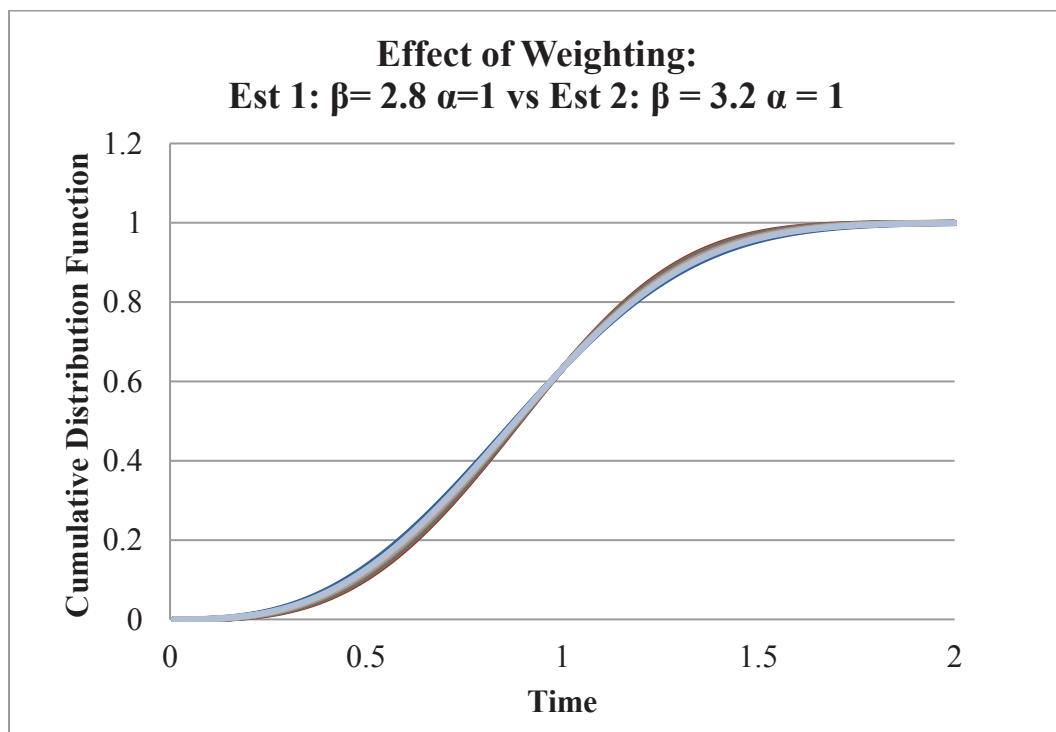


Figure 3-5 Weighting CDF: Constant Scale, Varying Shape

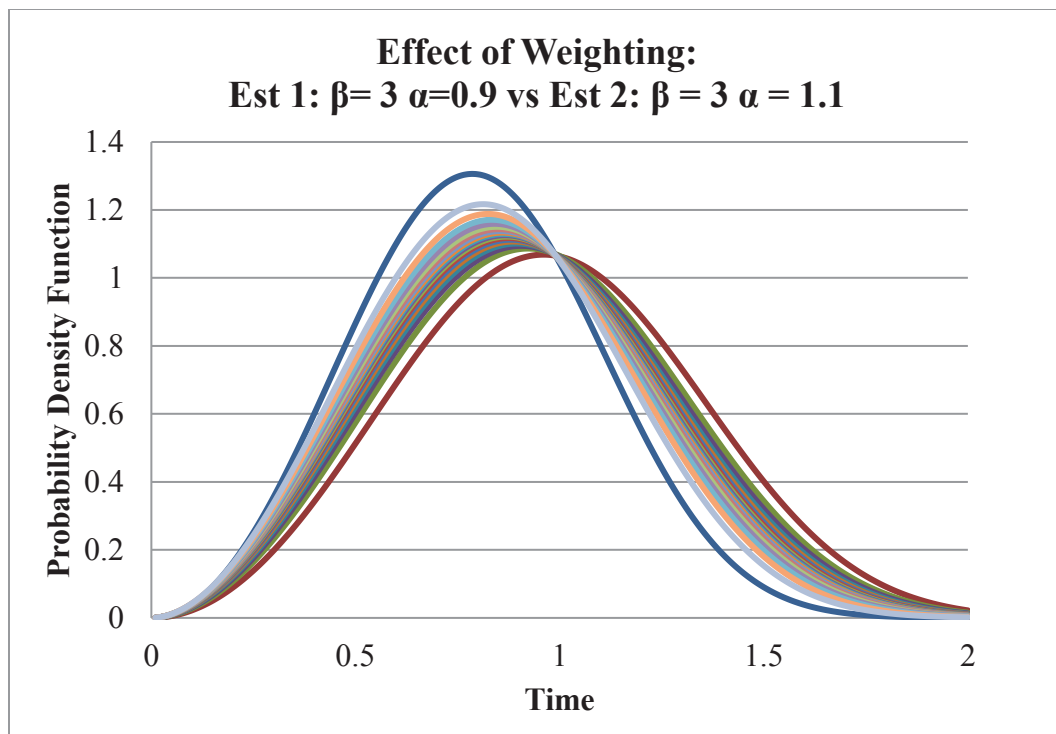


Figure 3-6 Weighting pdf: Varying Scale, Constant Shape

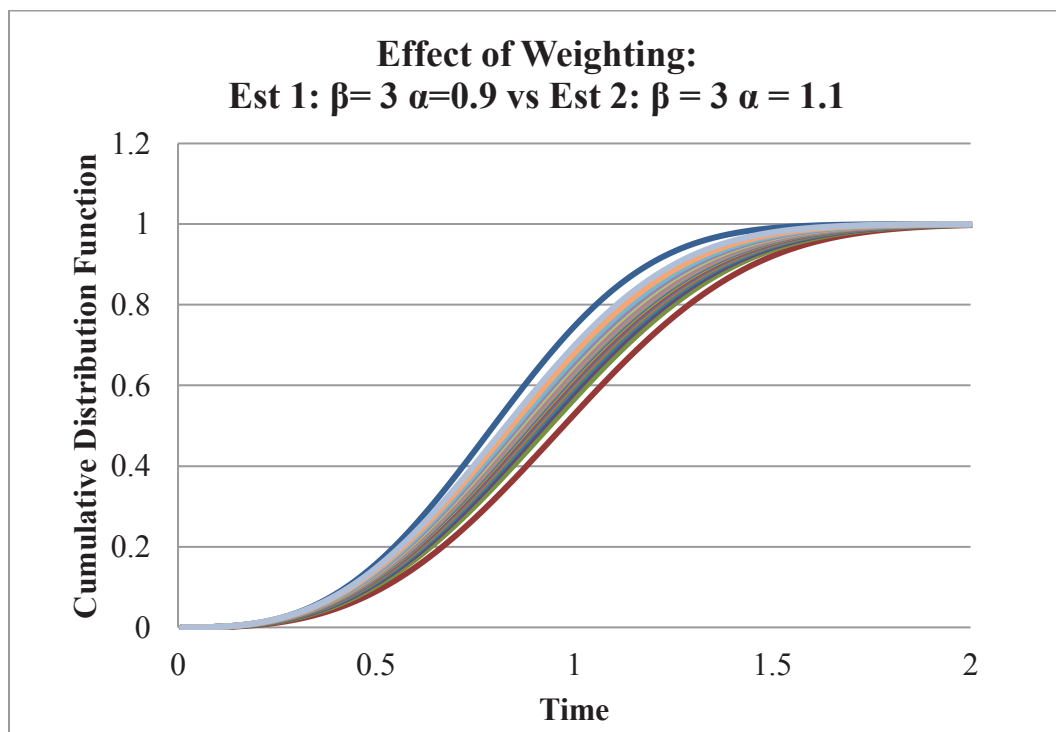


Figure 3-7 Weighting CDF: Varying Scale, Constant Shape

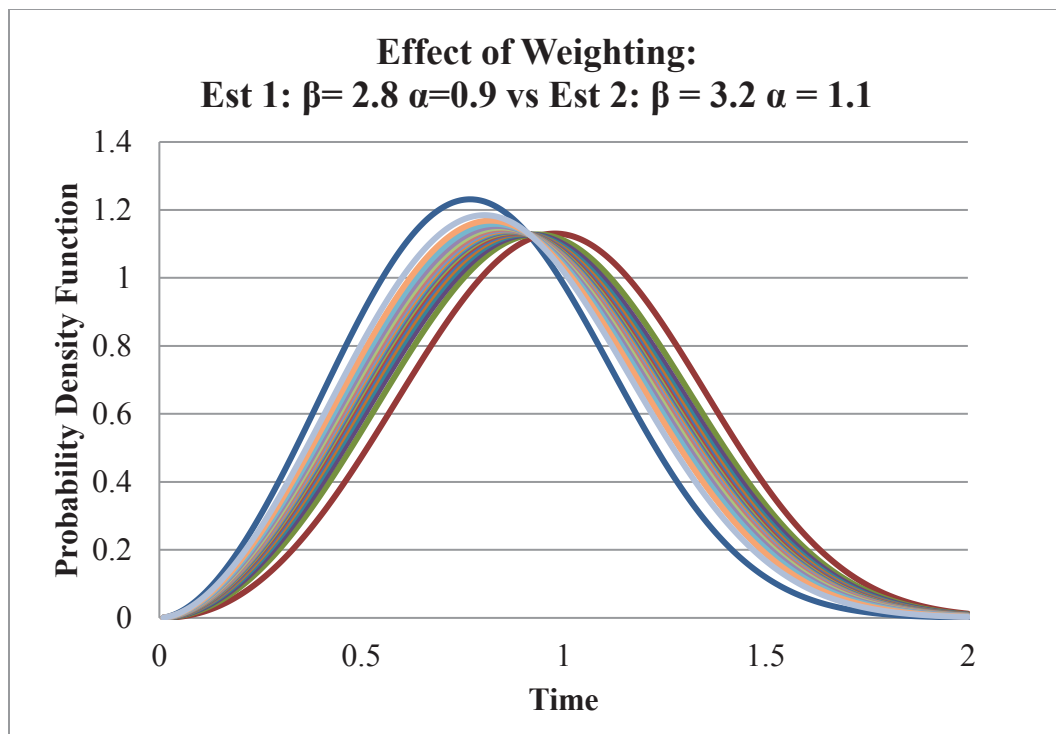


Figure 3-8 Weighting pdf: Increased Scale, Increased Shape

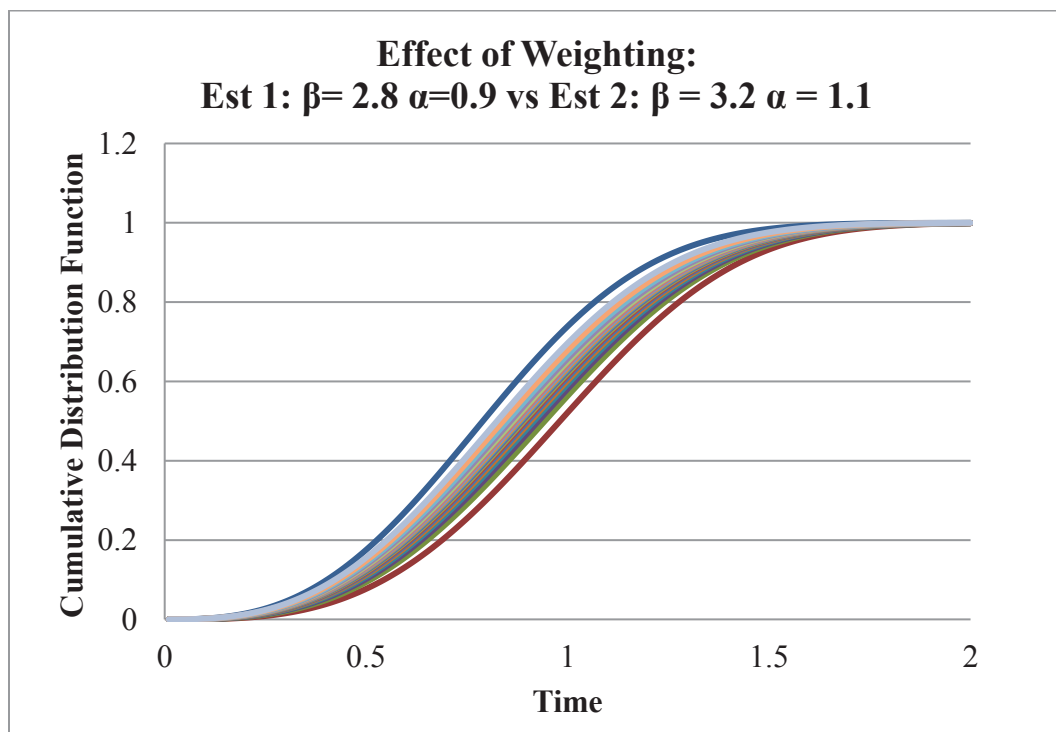


Figure 3-9 Weighting CDF: Increased Scale, Increased Shape

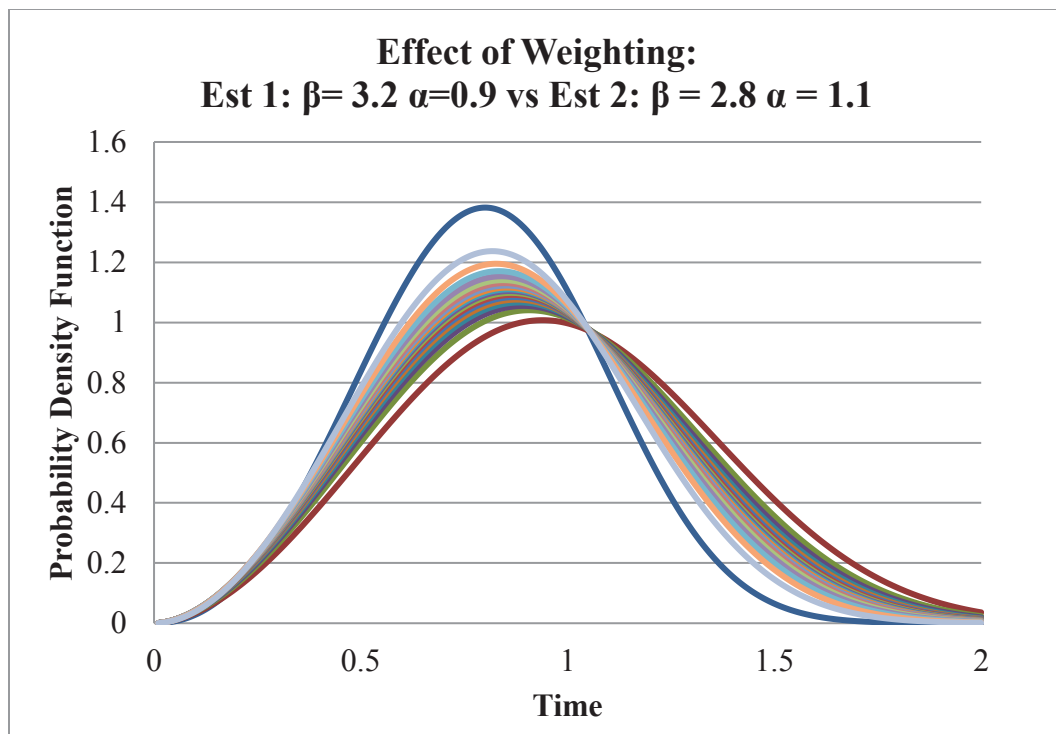


Figure 3-10 Weighting pdf: Increased Scale, Decreased Shape

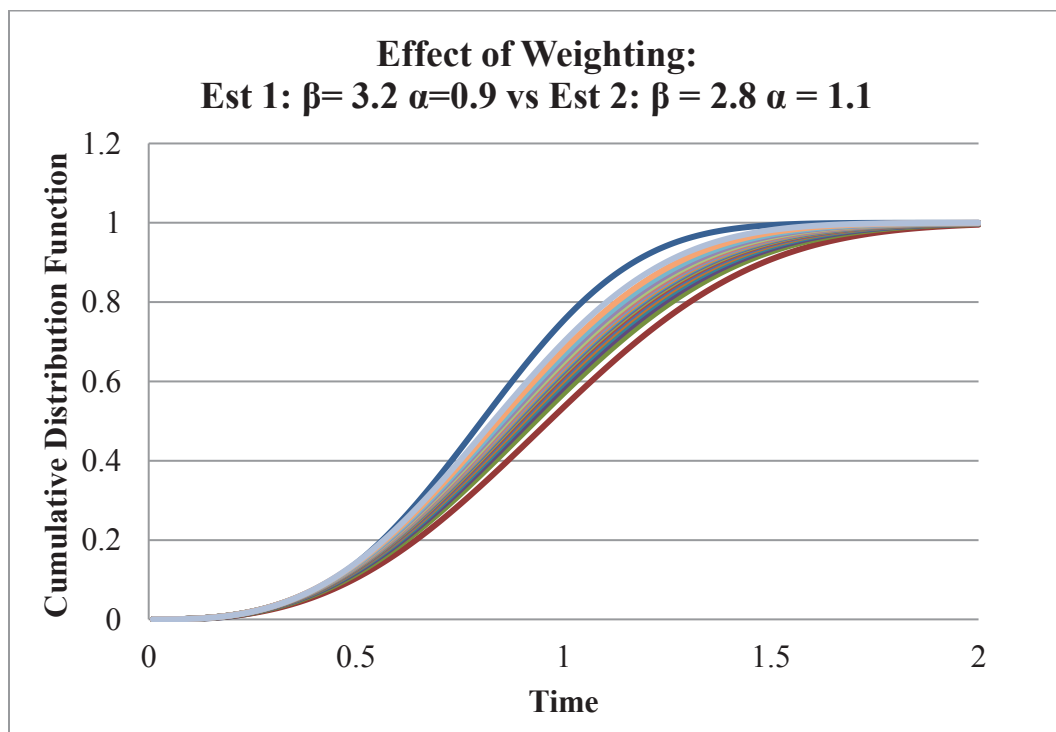


Figure 3-11 Weighting CDF: Increased Scale, Decreased Shape

3.2.4. Failure Scenarios

The failure scenarios are built on imitating the TVA fleet's outages. Three failure scenarios will allow for unique parameter vectors that can be compared against the expert only knowledge base. These failure scenarios will present a case of very rare failures, base case, and very common failures. Using the TVA HMOD data we attained three values, total in service age, A_T , age since HMOD, A_{HMOD1} , and age until HMOD, A_{HMOD2} , and yes/no results on if work was performed on the stator windings, rotor windings and turbine runner during HMOD.

$$A_T = \frac{\text{current date} - \text{in service date}}{365.25} \quad [3-25]$$

$$A_{HMOD1} = \frac{\text{HMOD date} - \text{in service date}}{365.25} \quad [3-26]$$

$$A_{HMOD2} = \frac{\text{current date} - \text{HMOD date}}{365.25} \quad [3-27]$$

$$\therefore A_T = A_{HMOD1} + A_{HMOD2} \quad [3-28]$$

Next, to divide A_T into component lifetimes, requires an estimate of the number of component replacements each unit has endured. The number of total components used at a unit, is equal to one plus the number of replacements, $\omega_{i,j,k}(\psi)$.

If work was performed on the component at HMOD, then it is easy to calculate $z_{i,j,k,1}(\psi)$, but we must still estimate the lifetime of previous components $x_{i,j,k,1}(\psi), \dots, x_{i,j,k,\omega}(\psi)$. If work was not performed at HMOD then we must calculate the ages of components $x_{i,j,k,1}(\psi), \dots, x_{i,j,k,\omega}(\psi), z_{i,j,k,1}(\psi)$.

The expert elicitation estimated 65% of stator winding failures occur by 40 years. To determine the number of stator windings that a unit has had we used nested if statements to assign ω components to each unit. If $A_{HMOD1} > 50$, $\omega_{i,j,1}(2) = 2$, if $25 < A_{HMOD1} < 50$, $\omega_{i,j,1}(2) = 1$ and if $A_{HMOD1} < 25$, $\omega_{i,j,1}(2) = 0$. If the stator windings were replaced at HMOD, $\omega_{i,j,1}(2)$ was increased by one. Similarly, with rotor windings the expert elicitation estimated 65% of failures occur by 100 years. Thus, we used 90 years as the cutoff between $\omega_{i,j,2}(2) = 0$ and $\omega_{i,j,2}(2) = 1$ and again increased ω by one if the rotor windings had work done during HMOD. For Kaplan turbines, the expert elicitation estimated 40% of failures by 60 years. Although potentially low, we used 60 years as the cutoff between $\omega_{i,j,3}(2) = 0$ and $\omega_{i,j,3}(2) = 1$ and again increased ω by one if the turbine runner had work done during HMOD. Additionally, it was assumed that all TVA units were Kaplan turbines and had multi-turn stator windings 6900+kV as a specific list of unit specifications has not yet been made available.

The component lives $w(\psi) = 1, \dots, \omega_{i,j,k}$ were then assigned lifetimes using MLE and the expert estimated Weibull parameters. This was performed using Microsoft Excel's solver add-in as discussed in section 2.4. If age, z_1 was unknown, it was used to unify the sum of component

ages to the unit age. If z_1 was known via HMOD, then $x_{i,j,k,w}(\psi)$ was used to unify the sum of component ages to the unit age. Though not ideal, in order to reduce repeat values $x_{i,j,k,w}(\psi) = x_{i,j,k,w-1}(\psi) + 1$. These ages, $x_{1,1,1,1}(\psi), \dots, x_{i,j,k,w}(\psi)$, along with their 2004 operating history were used in the MLE to determine the parameter vector while noting the current component age, $z_{i,j,k,1}$, as right censored since a failure has not occurred.

To determine the sensitivity of the model, as described earlier, we must alter the base case to reflect a best replacement case and a worst replacement case and then use MLE to once again determine $x_{i,j,k,w}(\psi)$. To do this, the number of replacements was decreased by one to reflect the best replacement case or increased by one to reflect the worst replacement case.

$$\omega_{i,j,k}(\psi = 1) = \omega_{i,j,k}(\psi = 2) - 1 \quad [3-29]$$

$$\omega_{i,j,k}(\psi = 3) = \omega_{i,j,k}(\psi = 2) + 1 \quad [3-30]$$

This method does require some assumptions but for our purposes the possible errors induced by the assumptions are minimal. These include using a small operating history to describe the entire operating history. This can be impacted by minor outages, but 2004 was chosen since it is the first full year of 5-minute operating data and for CHH, NOH and two other TVA plants the generating hours fall within the interquartile range for data collected from 2000-2015. We also assume that no major outages have occurred to a component since HMOD if work was performed on the component at HMOD. These estimates also do not take into account repair time for any component. Without more impactful data outage length data from TVA, we cannot make assumptions about repair time. In this case we also assume that all historical failures are relevant to the current components. It is known that this is false, yet it is difficult to establish a cut-off date and thus for this sensitivity analysis all component failures were deemed relevant.

3.3. Strategic Life Model Methodology

The SLM depicted in Figure 3-2 will answer RQ1 by determining the strategic life of the component in calendar years based on the expected dispatch patterns. “Design Reference Missions” can be used to determine the impact of a unit changing from set point dispatch to flexible operations (23). The model can also be used to compare the expert estimated strategic life and our newly obtained prediction for strategic life based on the same set of future dispatch patterns. The SLM requires the estimation of select coefficients from cost databases and expert judgement. The cost of a forced outage (C_F) and the cost of a planned outage (C_P) for specific components would be optimal, but determining the ratio between the two will suffice. The model determines the optimal planned replacement interval by locating the minimum cost per unit time based on the parameter vector, C_F and C_P (67).

$$CPUT(EOY|\alpha, \beta, a) = \frac{C_P * R(EOY) + C_F * (1 - R(EOY))}{\int_0^{EOY} R(m) dm} \quad [3-31]$$

$$R(EOY_{i,j,k}|\theta_k(\psi)) = 1 - F(EOY_{i,j,k}) = 1 - \left[1 - e^{-\left(\frac{EOY_{i,j,k}}{\alpha_k}\right)^{\beta_k}} \right] = e^{-\left(\frac{\alpha_k * C_{i,j,k} + h_{i,j,k}}{\alpha_k}\right)^{\beta_k}} \quad [3-32]$$

This cost function evaluates the effect of using distinct dispatch patterns and the opportunity cost of using one instead of another. The denominator of equation 3-29 is found using numerical integration's midpoint rule with a convergence value of 1.0×10^{-6} . Equation 3-29 is evaluated in 0.1 EOY increments. This increment will produce clear and precise results while resolving the global minimum in an efficient manner.

The SLM does not explicitly use repair time, rather repair time is one part of the outage costs. Current economic input variables are only rough estimates as the author expects a plant owner to have access to accurate estimates of outage costs that are specific to the hydroelectric unit being examined. This model does not differentiate between labor costs and component costs as labor costs can be complicated based on if salaried in-house staff is used or if sub-contractors are hired on a job by job basis.

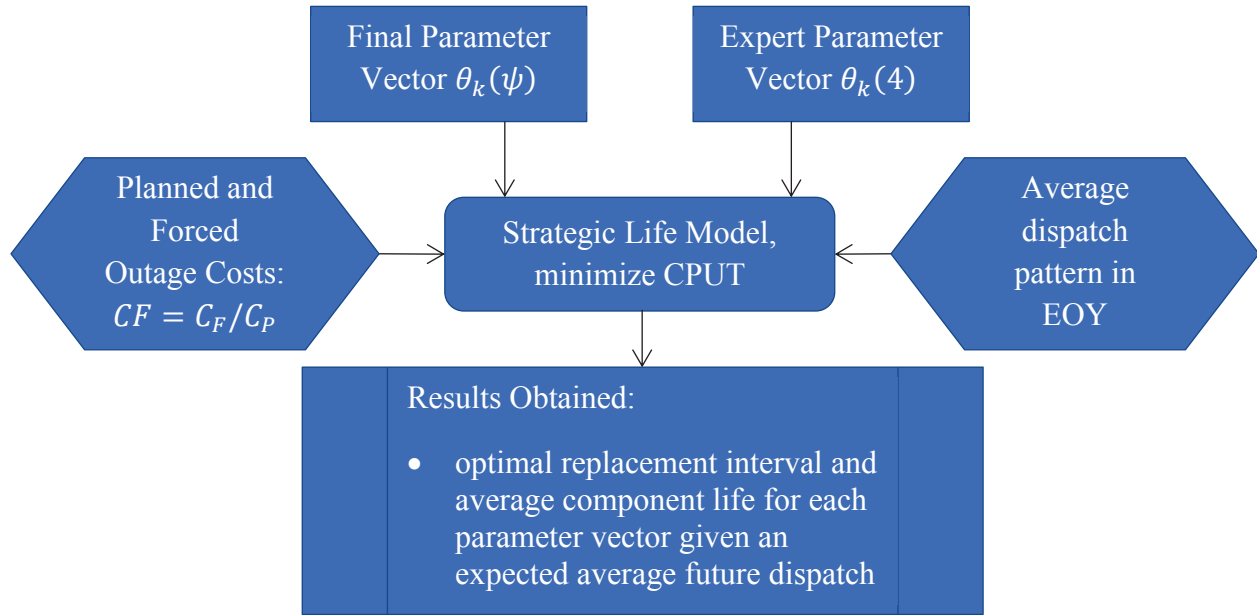


Figure 3-12 Strategic Life Model

3.4. Conditional Reliability Model Methodology

Conditional reliability determines the probability that a component will remain failure free over time $\overline{EOY}_{i,j,k}$, given that it has been failure free for $\overline{EOY}_{i,j,k}$. Figure 3-3 shows how the Weibull distribution with the θ_i parameter vector will be used alongside other data inputs. After

providing data on historical unit starts and service hours endured, this model requires the user to input two additional parameters:

- Operating Horizon: y : the length of future time that this risk analysis considers
- Future dispatch pattern (unit starts per year and service hours per year)

The conditional reliability for individual components can be multiplied together to determine the system reliability envisioning the entire plant as a system of components in series. This value describes the probability that all modelled components at plant i will be failure free for the given horizon time. Our sensitivity analyses incorporated four different Weibull parameter vectors for each of the three components. These parameter vectors were then used to influence dispatch decisions at both four-unit CHH and two-unit NOH using three historical dispatch scenarios.

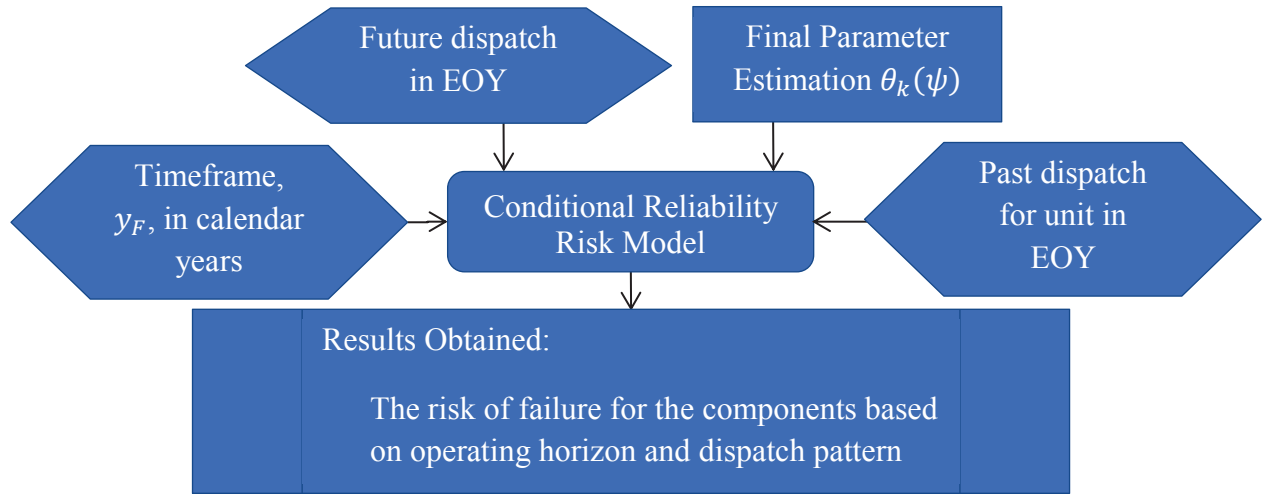


Figure 3-13 Conditional Reliability Model

3.4.1. Single Component Conditional Reliability Model

The single component model output is the risk incurred by the component based on a spectrum of dispatch patterns using equations 3-31, 3-32, and 3-33. $\overrightarrow{EOY}_{i,j,k}$ and $\overleftarrow{EOY}_{i,j,k}$ respectfully represent the equivalent operating years of the component in the future time frame and in the historical sense. $\vec{c}_{i,j}$ and $\vec{h}_{i,j}$ represent the expected number of cycles per year and the expected operating hours per year for the timeframe of the analysis. By calculating the risk of failure using conditional reliability and expected dispatch patterns we can use a poly-Weibull distribution to assess multiple components at once for a unit level reliability calculation. This requires using the k^{th} component's unique α , β , and a values (41). The historical dispatch, $\vec{c}_{i,j,k}$ and $\vec{h}_{i,j,k}$ vary by component based on the component in service date. In addition to

$\tilde{c}_{i,j,k}$ and $\tilde{h}_{i,j,k}$ the component's age, $\overrightarrow{EOY}_{i,j,k}$ varies by the components coefficient of cyclic wear, $a_k(\psi)$.

$$risk_k = 1 - R(\overrightarrow{EOY}_{i,j,k} | \overrightarrow{EOY}_{i,j,k}) = 1 - \frac{R(\overrightarrow{EOY}_{i,j,k} + \overrightarrow{EOY}_{i,j,k})}{R(\overrightarrow{EOY}_{i,j,k})} \quad [3-33]$$

$$risk_k = 1 - e^{-\left[\left(\frac{\overrightarrow{EOY}_{i,j,k} + \overrightarrow{EOY}_{i,j,k}}{\alpha_k} \right)^{\beta_k} - \left(\frac{\overrightarrow{EOY}_{i,j,k}}{\alpha_k} \right)^{\beta_k} \right]} \quad [3-34]$$

$$\text{Given: } \overrightarrow{EOY}_{i,j,k} = y * \frac{\tilde{c}_{i,j} * a_k + \tilde{h}_{i,j}}{300 * a_k + 4380} \quad [3-35]$$

$$\overrightarrow{EOY}_{i,j,k} = \frac{a_k * \tilde{c}_{i,j,k} + \tilde{h}_{i,j,k}}{300 * a_k + 4380} \quad [3-36]$$

3.4.2. Multi-component Conditional Reliability Model

To step from a single component calculation to a plant level model, we first must understand the unit level model. Using poly-Weibull conditional reliability shown in equation 3-37, is useful when analyzing a single unit and suffices for one-unit plants which includes 6 of TVA's 29 plants but only a small fraction of their total generating capacity. Upon acquiring detailed outage information that includes the prevalent failure mechanism, Weibull parameters can be calculated for each individual failure mode of a component in a similar fashion.

$$risk_j = 1 - R_j(t, \theta_k(\psi)) = 1 - \prod_{k=1}^v R_k = 1 - e^{-\sum_{k=1}^v \left(\left(\frac{\overrightarrow{EOY}_{i,j,k} + \overrightarrow{EOY}_{i,j,k}}{\alpha_k} \right)^{\beta_k} - \left(\frac{\overrightarrow{EOY}_{i,j,k}}{\alpha_k} \right)^{\beta_k} \right)} \quad [3-37]$$

To maximize the reliability of the CHH facility, we seek the dispatch pattern that optimizes the reliability of the 4-unit, 3-component system while meeting a required generation total. This increases the number of unique reliability equations from 3 to 12 for CHH. Likewise, for the NOH facility, we have a 2-unit, 3-component system with 6 unique reliability equations. Implementation of this model requires knowledge of previous operating history, our Weibull parameter estimation, and an operating horizon for the study.

3.4.3. Dispatch Scenarios

After reviewing CHH's and NOH's operating history, operating years 2004, 2005, and 2007 will be used to describe three unique operating scenarios. The unit starts and operating hours recorded in each operating year will be used as bounds in the Multicomponent CRM sensitivity analysis as the most reliable operation is no dispatch, the model must force all dispatch hours and unit starts to be assigned.

$$C_i(s) = \sum_{j=1}^{\tau} c_j(\psi, s) \quad [3-38]$$

$$H_i(s) = \sum_{j=1}^{\tau} h_j(\psi, s) \quad [3-39]$$

The total number of unit starts and operating hours for the plant for each operating scenario are distributed among the units bounded by plant specific operating ratios $r_{1,i}$ and $r_{2,i}$ such that the least active unit must provide a portion of the load that the most active unit provides. This establishes real world flexibility scenarios as the closer those bounds are to unity, the closer we move to equal run time and increased flexibility.

3.4.4. Problem Setup

We will use the multicomponent CRM to produce two separate groups of results. First, we will determine how close the actual dispatch patterns were to the recommended reliable dispatch patterns for each of the three dispatch scenarios and the subsequent change in reliability predicted by the expert case, $\psi = 4$, and the base case, $\psi = 2$, given $T_{i,j,k}$ are set accordingly to represent the component age at the beginning of the dispatch scenario. Secondly, we will determine how the dispatch patterns should be allocated if they were to occur in calendar year 2017, as operating data goes through September 2016.

The problem can be described as $2 \times j$ decision variables that are optimized to maximize the plant reliability function. Input values include the study horizon, $y = 1$, component specific equivalent operating ages, $\overline{EOY}_{i,j,k}(\psi)$ and component specific Weibull Parameters α_k, β_k, a_k

$$\max R_i(h_{i,j}, c_{i,j}, \psi, s | y, \overline{EOY}_{i,j,k}(\psi), \alpha_k, \beta_k, a_k) = \prod_{j=1}^4 \prod_{k=1}^3 \frac{e^{-\left(\frac{\overline{EOY}_{i,j,k} + y \cdot \frac{a_k \cdot c_{i,j} + h_{i,j}}{300 \cdot a_k + 4380}}{\alpha_k}\right)^{\beta_k}}}{e^{-\left(\frac{\overline{EOY}_{i,j,k}}{\alpha_k}\right)^{\beta_k}}} \quad [3-40]$$

For the historical reliability model, we can calculate a Reliability Index value to quantify the increased risk associated with how plant's units were actually dispatched. This RI results in a value between 0 and 100 and uses the actual dispatch patterns, the optimal dispatch for reliable operations and the worst-case dispatch for reliable operations while keeping the dispatch totals constant.

$$RI_i(\psi, s) = \frac{R_{i,actual}(\psi, s) - R_{i,min}(\psi, s)}{R_{i,max}(\psi, s) - R_{i,min}(\psi, s)} \quad [3-41]$$

4. Results

Results of the historical dispatch analysis of CHH and NOH that were used to determine the current component ages is described in section 4.1. The resultant parameter vectors are discussed in section 4.2. The results of the SLM for use in operating cost calculation is found in section 4.3. Section 4.4 details the results of the single component CRM while sections 4.5 and 4.6 detail the results of the Historical and Future multicomponent CRM.

Nomenclature in this section uses i, j, k to denote the plant, unit, and component, for $i = 1 = CHH$ and $i = 2 = NOH$, $j_1 = 1$ to 4 or $j_2 = 1$ to 2 and $k = 1$ to 3. The parameter vectors used in this study and the optimal replacement point are denoted as $\theta_k(\psi)$ and $OP_k(\psi)$ to show that they are unique to the physical component discussed but are also a function of the failure scenarios $\psi = 1$ to 4 used in this sensitivity analyses. Likewise, the dispatch categories $c_j(\psi, s)$ and $h_j(\psi, s)$ are unique to each unit but are a function of the failure scenarios $\psi = 1$ to 4 and dispatch scenarios $s = 1$ to 3 that represent different hydrologic and grid demand scenarios. The reliability index is denoted $RI_i(\psi, s)$ as it is unique to the plant but is a function of the selected failure scenario and dispatch scenario. The current component age $T_{i,j,k}(\psi)$ is unique to the specific plant, unit and component, but is a function of the failure scenario due to changes in the cycling coefficient.

4.1. Historical Dispatch Analysis

In order to understand how TVA has previously operated CHH and NOH units we analyzed previous operating years. Wet (2013) and dry (2007 & 2008) years have a significant impact on the generating hours that a plant can provide. The first goal was to discern inter-unit trends to provide values for $r_{1,k}$ and $r_{2,k}$. Secondly it was necessary to choose three dispatch scenarios.

By analyzing unit operations data from 2000-2016. We notice that all four units at CHH have had years of over 300 unit starts, years over 7000 generating hours, years under 100 unit starts, and years under 4000 generating hours so there does not appear to be much unit preference. Analyzing historic $r_{1,k}$ and $r_{2,k}$ values, we see an average of $\overline{r_{1,CHH}} = 1.89$ and $\overline{r_{2,CHH}} = 1.40$. To provide greater lenience in our model outcomes we increased these values to $r_{1,CHH} = 2.0$ and $r_{2,CHH} = 1.5$. Between 2000-2016 both NOH units have had years of over 550 unit starts, years over 5700 operating hours, years under 100 unit starts, and years under 2000 operating hours so there does not appear to be much unit preference. Analyzing historic $r_{1,k}$ and $r_{2,k}$ values, we see an average of $\overline{r_{1,NOH}} = 1.68$ and $\overline{r_{2,NOH}} = 1.17$. Again these values were slightly increased, this time to $r_{1,NOH} = 1.75$ and $r_{2,NOH} = 1.25$.

The goal in selecting the three dispatch scenarios to use in the multicomponent conditional reliability sensitivity analysis were to select dispatch cases for both CHH and NOH that encountered low and high total generating hours and a significant change in total unit starts. Additionally, it could be beneficial for the dispatch scenarios to be viewed as historical such that the historical component age is significantly different in the Historical Reliability Analysis

compared to the Future Reliability Analysis. CHH's 2004 and 2006 operating years were viewed as too similar and with NOH's 2006 and 2007 operating years also very similar it was decided to use 2004, 2005, and 2007 as our three dispatch scenarios.

4.2. Weibull Parameter Vectors

The determination of Weibull Parameters is paramount to the accuracy of the models. As described previously, the shape and scale parameters will be unique to each component and are determined using MLE which is dependent on the failure data and expert elicitation values provided. This research also introduces a cyclic wear coefficient to relate the damage incurred from unit cycling to the damage incurred from one generating hour. For the sensitivity analyses we determined four parameter vectors for each of the three components studied by altering the imitation TVA fleet outage values shown in Table 4-1. Although literature describes cyclic damage for all three components, the stator windings were the only component where a cyclic wear coefficient was found in literature. Therefore, the expert parameter vector has $a_{2,\psi} = 0$ and $a_{3,\psi} = 0$. The twelve parameter vectors are shown below in the format of equation 4-1 and can be visualized in Figures 4-1 through 4-6.

$$\theta_i(\psi) = [\alpha_i(\psi), \beta_i(\psi), a_i(\psi)] \text{ for } i = 1 \text{ to } 3 \text{ and } \psi = 1 \text{ to } 4 \quad [4-1]$$

$$\theta_1(1) = [56.27, 2.47, 0.68]; \theta_2(1) = [114.36, 2.54, 0.00]; \theta_3(1) = [2.74, 96.06, 0.00]$$

$$\theta_1(2) = [43.54, 3.12, 0.93]; \theta_2(2) = [82.71, 2.76, 0.77]; \theta_3(2) = [63.92, 2.79, 0.00]$$

$$\theta_1(3) = [35.86, 2.11, 0.61]; \theta_2(3) = [50.49, 2.14, 1.28]; \theta_3(3) = [53.49, 2.66, 1.39]$$

$$\theta_1(4) = [38.78, 3.22, 5.00]; \theta_2(4) = [98.62, 2.80, 0.00]; \theta_3(4) = [75.02, 2.70, 0.00]$$

The failure scenarios ensured $\alpha_{i,1} > \alpha_{i,2} > \alpha_{i,3}$ for all components. A significant decrease in the shape parameter β seen in $\psi = 3$ will infringe on a utilities ability to effectively preempt forced outages as this is a result of greater spread in the data. The changes in cyclic wear coefficient are intriguing as these values will play a large role in determining the optimal unit dispatch patterns that are the focus of RQ3 and RQ4 in sections 4.5 and 4.6.

Table 4-1 Failure Scenario Summary Data

Number of Failures per scenario. 109 suspensions per scenario not included.	Stator Windings	Rotor Windings	Kaplan Turbine Runner
$\omega(\psi = 1)$	128	7	37
$\omega(\psi = 2)$	236	115	129
$\omega(\psi = 3)$	345	224	238

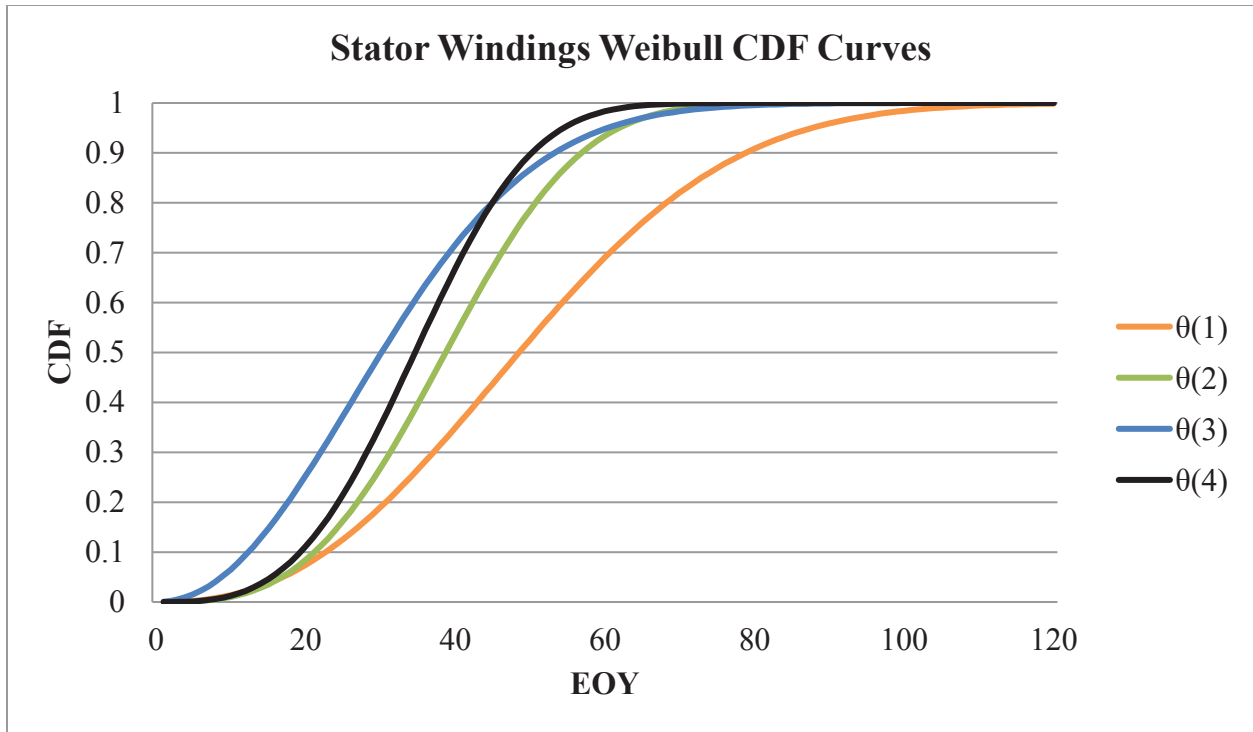


Figure 4-1 Stator Winding CDF

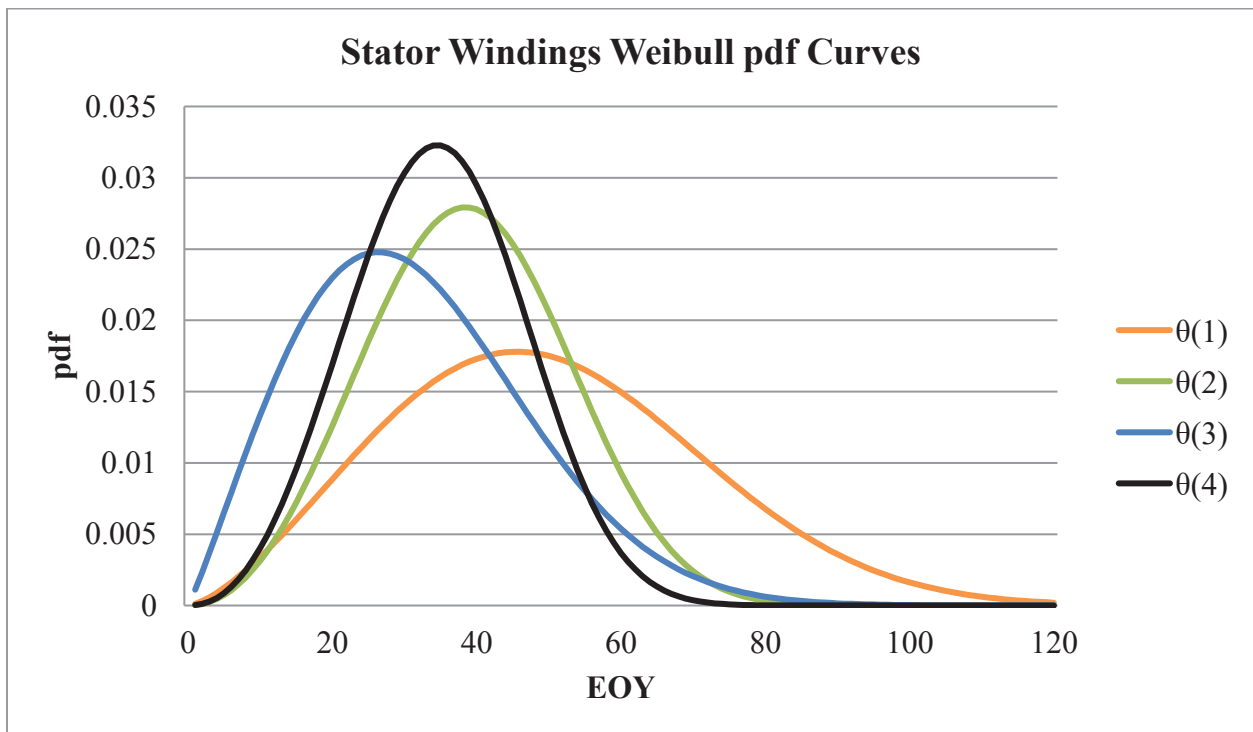


Figure 4-2 Stator Winding pdf

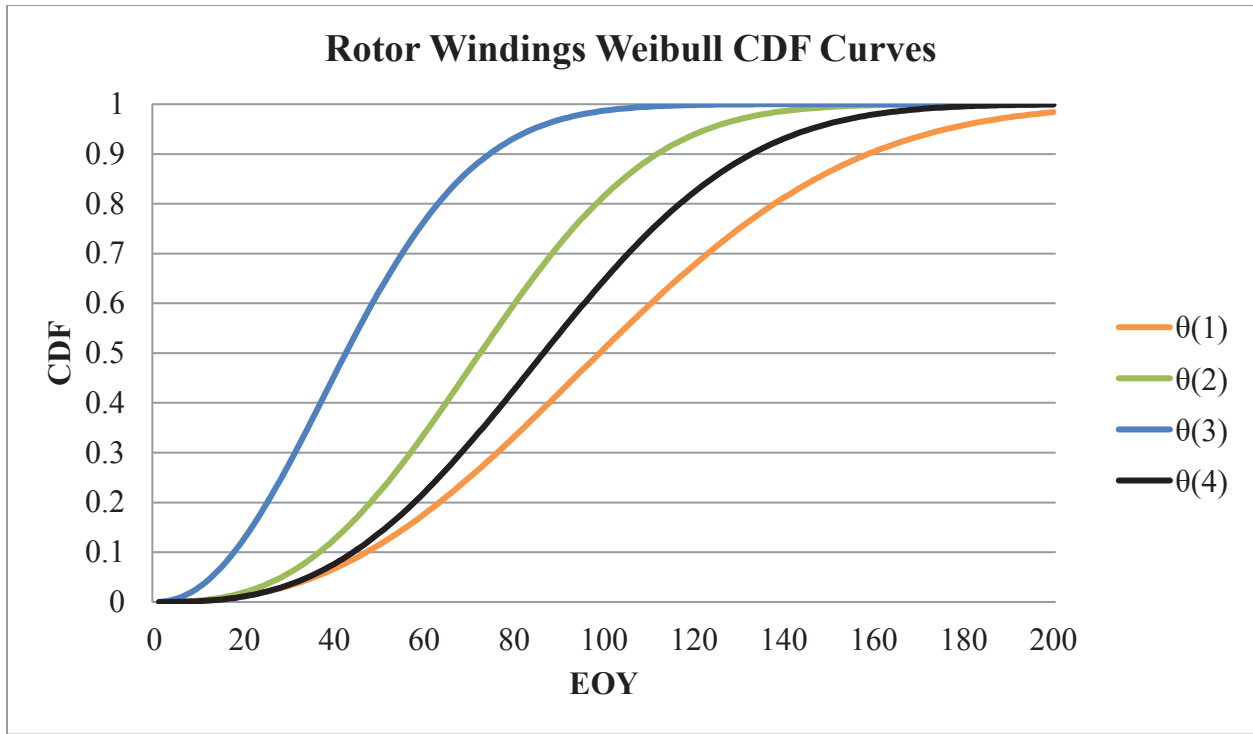


Figure 4-3 Rotor Winding CDF

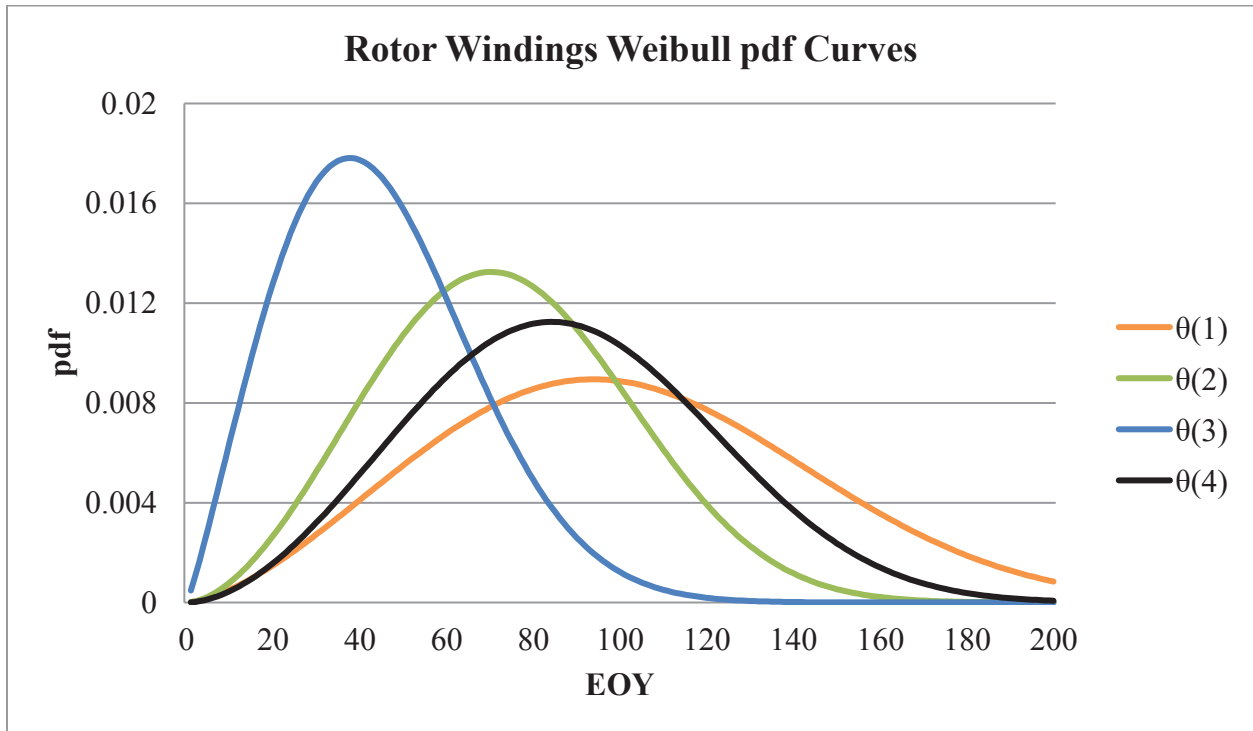


Figure 4-4 Rotor Winding pdf

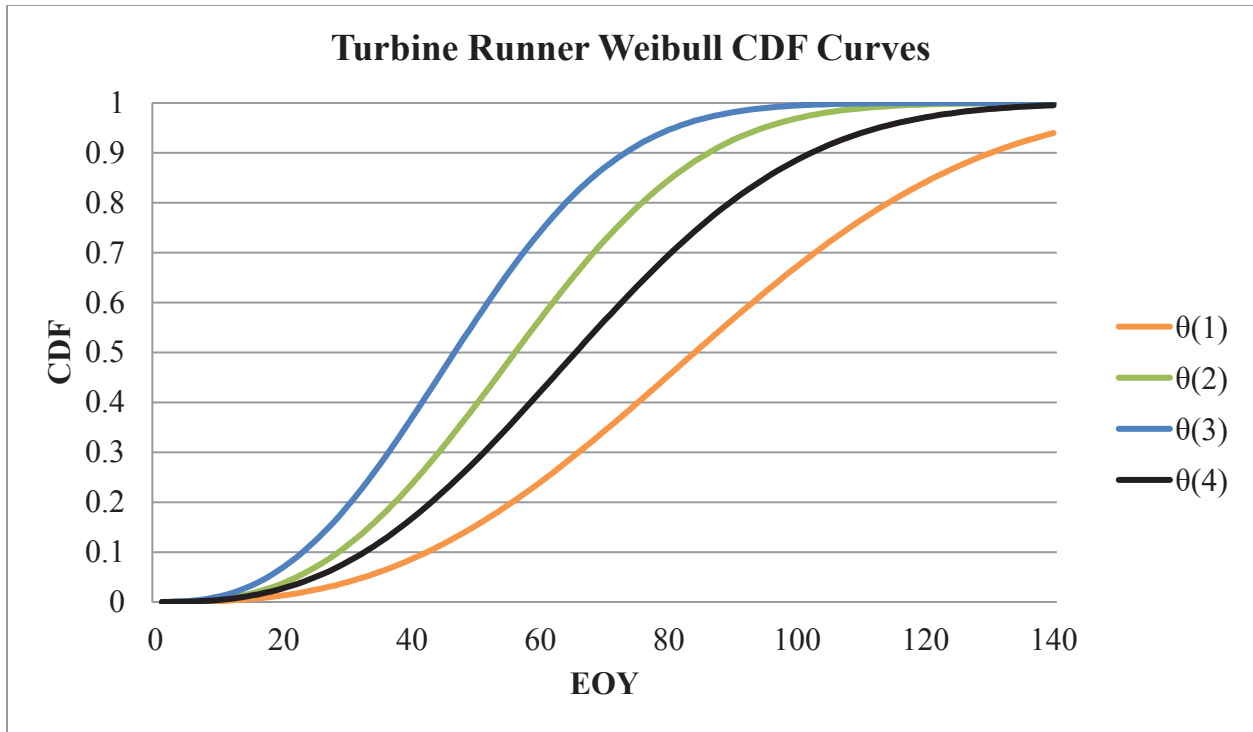


Figure 4-5 Kaplan Turbine Runner CDF

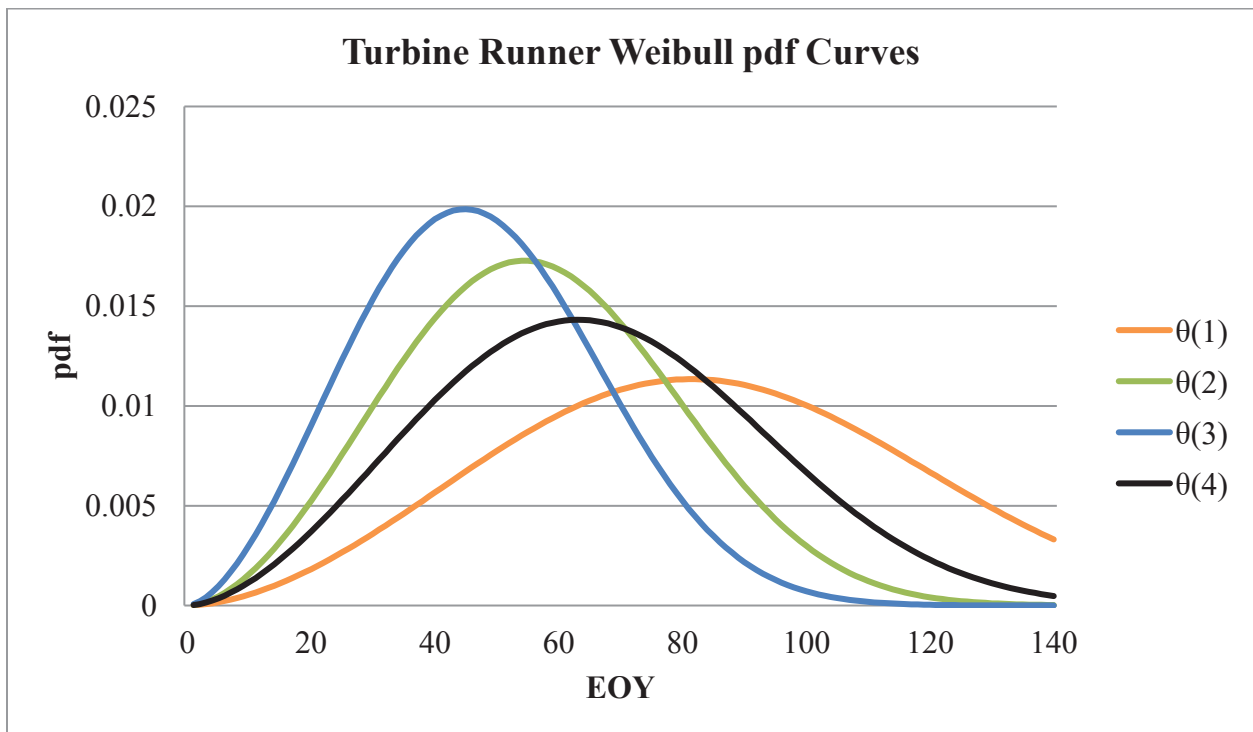


Figure 4-6 Kaplan Turbine Runner pdf

We must then verify the accuracy of these estimates by comparing the MLE results with other parameter estimation techniques. RRX and RRY are commonly used for Weibull parameter estimation (38). Three probability plotting techniques, median rank, mean rank and symmetric rank were used for comparison as suggested by (38). We used the Stator Winding expert elicitation to compare the methodology outlined above to six rank regression methods and MLE outperforms all six in minimizing MSE. The MSE and resulting α and β are in Table 4-2.

Table 4-2 Expert Parameter Estimation Technique Comparison for Stator Windings

Parameter Estimation Method	α : scale	β : shape	Mean Squared Error
MLE of Artificial Failure Points	38.782	3.225	9.64E-04
Median Rank RRY	39.834	2.807	2.39E-03
Median Rank RRX	39.374	2.886	1.99E-03
Mean Rank RRY	39.923	2.738	2.79E-03
Mean Rank RRX	39.399	2.825	2.29E-03
Symmetric RRY	39.772	2.858	2.13E-03
Symmetric RRX	39.355	2.931	1.79E-03

4.3. Strategic Life Model

The SLM provides the asset manager the ability to convert a component's parameter vector into a strategic life that can be used in determining the total cost of operation and thus the price at which a unit's generating capacity is bid. The forecasted average dispatch patterns, α , and expected outage costs impact the strategic life of a component. Table 4-3 depicts the optimal replacement time and the average component life for $i = 1$ to 3 and $\psi = 1$ to 4. The difference in the replacement interval and the average component life is highly dependent on β and CF. We selected $CF = 2$ for each component. The range between $\psi = 1$ and $\psi = 3$ provide a wide range of possible cost outcomes for this component with $\psi = 1$ providing the lower bound and $\psi = 3$ providing the upper bound. The variation between $\psi = 2$ and $\psi = 4$ shows a more likely range of outcomes and possible room for improvement. The shape of the curve is a cost function that reaches infinity as replacement interval approaches zero. The curve hits its minimum and then approaches the run to failure cost.

Interestingly, for stator windings, the $OP_1(2)$ and $OP_1(4)$ are both lower than $OP_1(3)$, yet $\psi = 3$ has the shorter average life. This is influenced by the significant difference in the shape

parameter that also results in a flatter shape for $\psi = 3$. The difference between $OP_1(2)$ and $OP_1(4)$ is a result of $\alpha_1(2) > \alpha_1(4)$ while $\beta_1(2) \sim \beta_1(4)$. The stator windings do show close replacement timing harmony between $OP_1(2)$, $OP_1(3)$, $OP_1(4)$ as shown in Figure 4-7.

For rotor windings, the low value of $\beta_2(3)$ which has led to a higher OP in the stator windings is overcome by the low value of $\alpha_2(3)$. The significant increase in the cost function of $\psi = 3$ compared to the other failure scenarios, shown in Figure 4-8, is a result of nearly double the amount of failures in $\psi = 3$ compared to $\psi = 2$. Although the run to failure costs are lower for rotor windings the 22% difference between $\psi = 2$ and $\psi = 4$ is the largest of the components thus making it very important to find the correct parameter vector for economic analyses. The flatness of the curves however show that there is less opportunity cost forfeited by allowing rotor windings to exceed the optimal replacement point than for other components.

The Kaplan turbine runners show the closest agreement in the cost curves, Figure 4-9, but there is still a significant gap since $OP_3(2) - OP_3(4) = 10.2 \text{ EOY}$ and the difference in average life is 9.18 EOY. Increased data acquisition will result in more accurate parameter vectors and strategic life estimates. The majority of these curves are flatter after the optimal point which can be interpreted as it being more strategic to be a year later on replacement than to be a year early but not to the extent of rotor windings. These curves and $OP_k(\psi)$ are not meant to be used for outage priority decisions as those decisions will be covered by the CRM once outage cost data is collected. These curves allow us to more accurately predict average component life to be used in operational cost estimates used in determining power service bids.

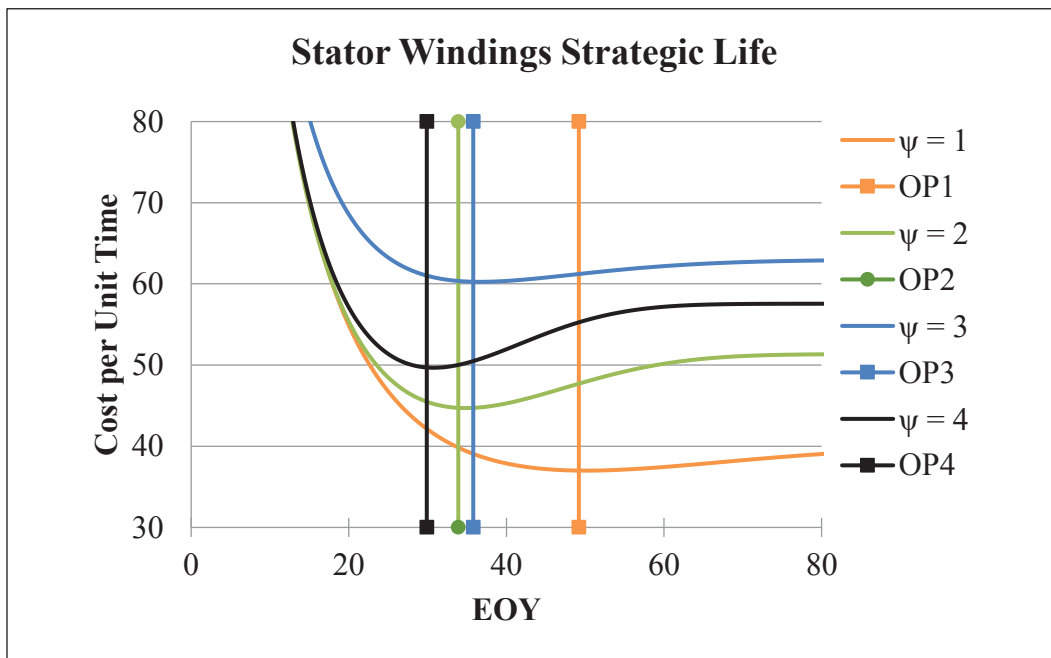


Figure 4-7 SLM Stator Windings

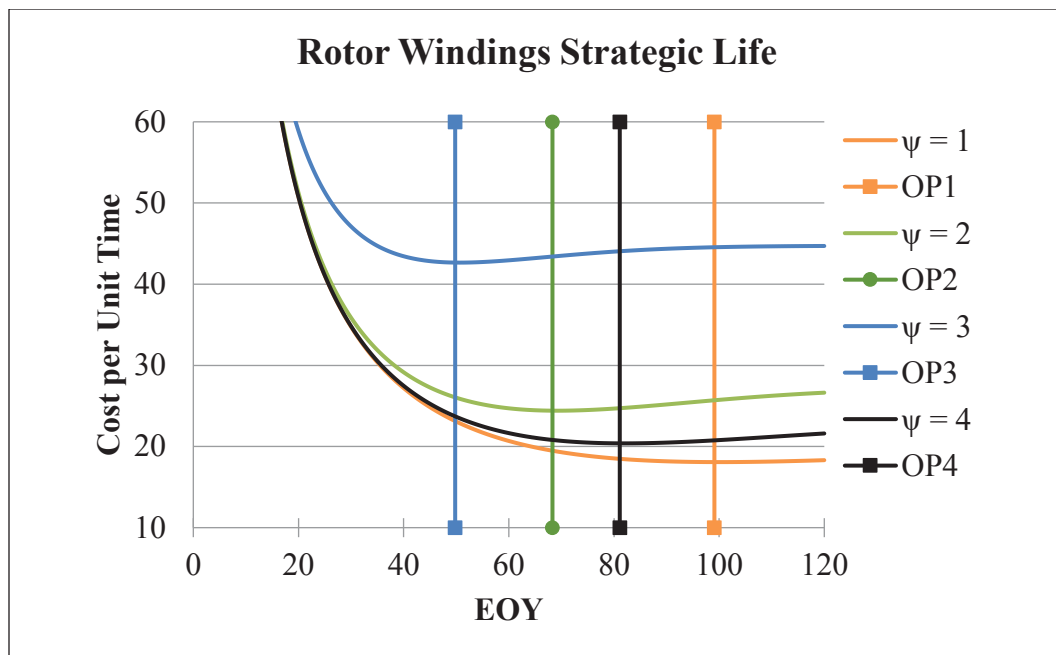


Figure 4-8 SLM Rotor Windings

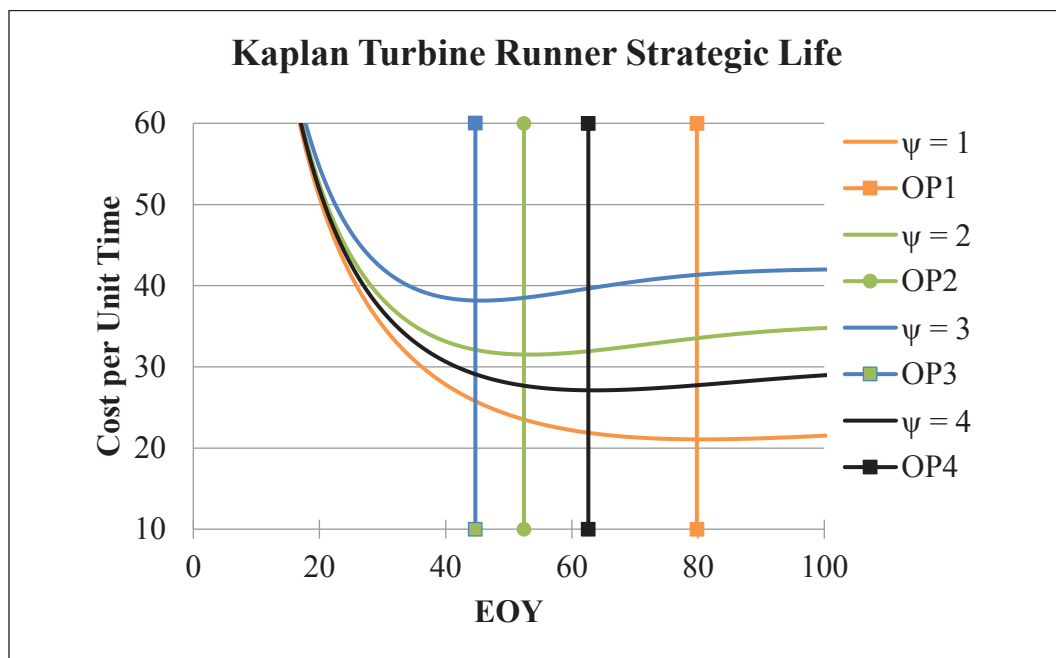


Figure 4-9 SLM Kaplan Turbine Runner

Table 4-3 Strategic Life Model results of average component life

	Failure Scenario	Optimal Replacement Point	Average Lifetime
Stator	$\psi = 1$	50.1	41.43
	$\psi = 2$	34.8	31.31
	$\psi = 3$	36.7	27.49
	$\psi = 4$	30.8	27.94
Rotor	$\psi = 1$	100.0	83.61
	$\psi = 2$	69.2	59.85
	$\psi = 3$	50.7	38.45
	$\psi = 4$	82.0	71.24
Turbine	$\psi = 1$	80.7	69.58
	$\psi = 2$	53.3	46.27
	$\psi = 3$	45.6	38.45
	$\psi = 4$	63.5	54.45

4.4. Single Component Conditional Reliability Model

The results of the single component CRM allow asset managers to visualize the potential risk incurred for various dispatch patterns specific to a unit's operating history. When budgetary constraints prevent replacement work from occurring in the current year, visualizing the component level risk of failure allows asset managers to understand the risk-cost they are incurring and determine a plan for minimizing this risk cost by decreasing operations at this unit. Since these results vary based on the current age of the component, CHH4 will be used for all k, ψ scenarios for $k = 1$ to 3 and $\psi = 1$ to 4 because of its significant work at HMOD that enables more accurate $T_{i,j,k}(\psi)$.

When $a_k(\psi) = 0$, as it does for five of the twelve parameter vectors, we see flat risk lines since risk of failure only increases with generating hours and not with unit starts. No risk map is steeper than $\theta_1(4)$ as $a_1(4) = 5.0$ which is 3.57 times greater than the next $a_k(\psi)$. The risk maps also show that the stator windings and rotor windings at CHH4 are roughly two to four times as likely to fail as Kaplan turbine runners based on the different $\theta_k(\psi)$. The relative age of the stator and rotor windings will therefore guide future dispatch decisions more than the Kaplan turbine runner ages in sections 4.5 and 4.6.

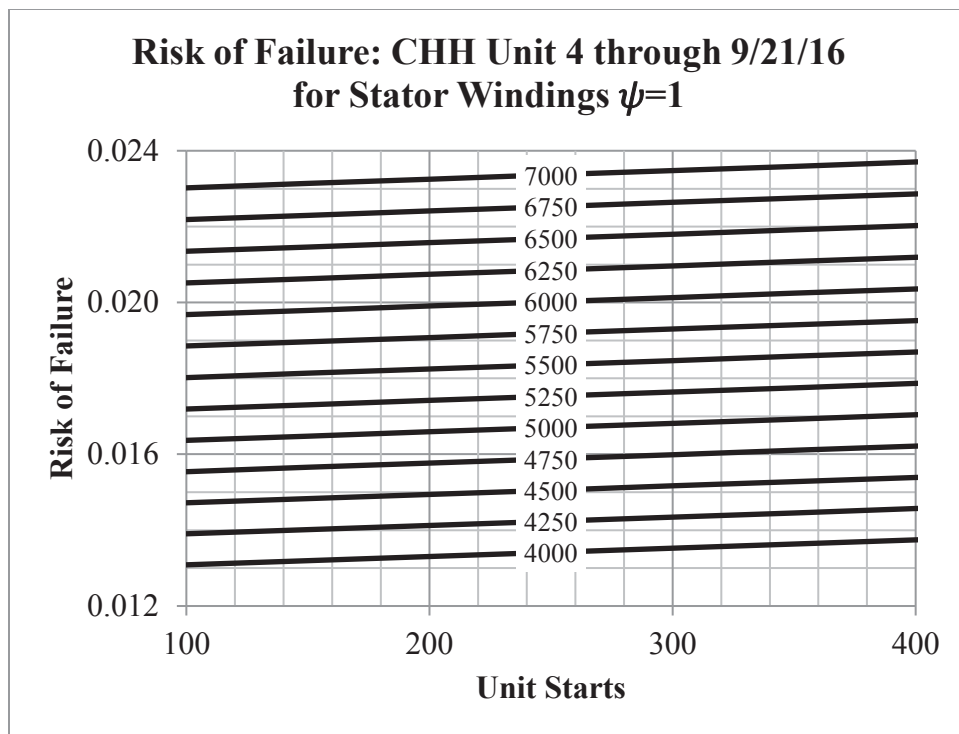


Figure 4-10 Stator Winding Risk of Failure $\psi = 1$

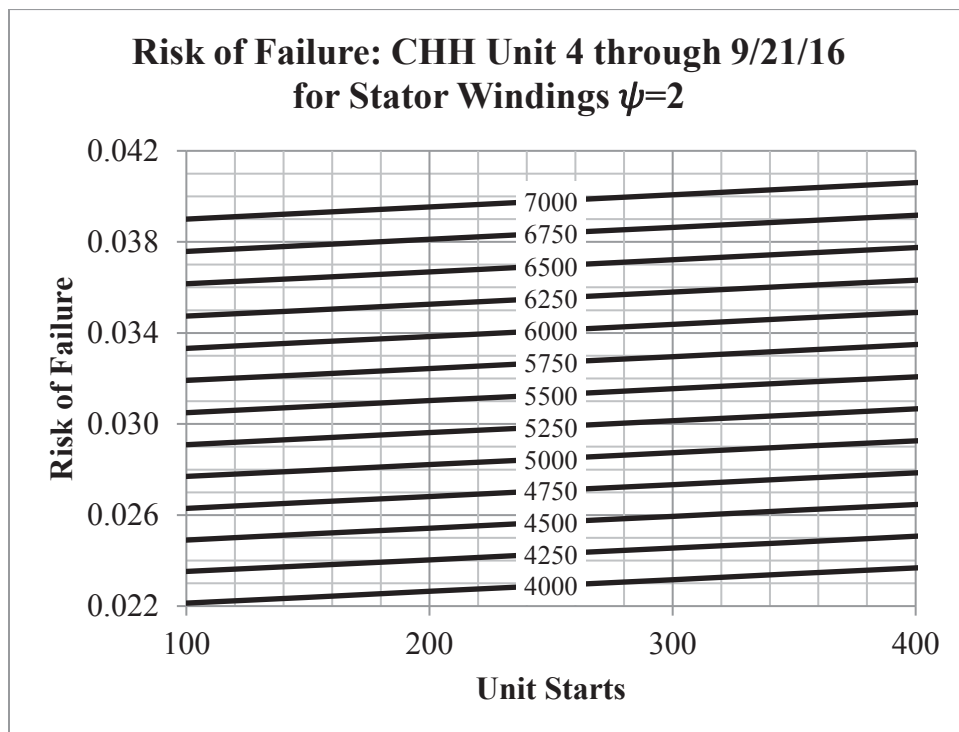


Figure 4-11 Stator Winding Risk of Failure $\psi = 2$

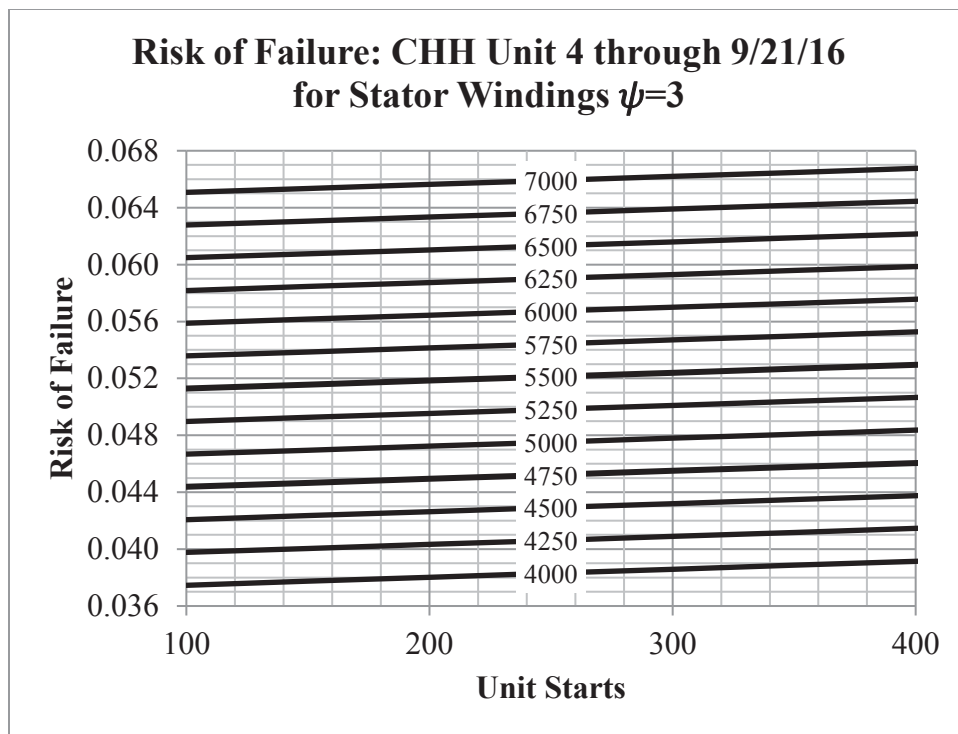


Figure 4-12 Stator Winding Risk of Failure $\psi = 3$

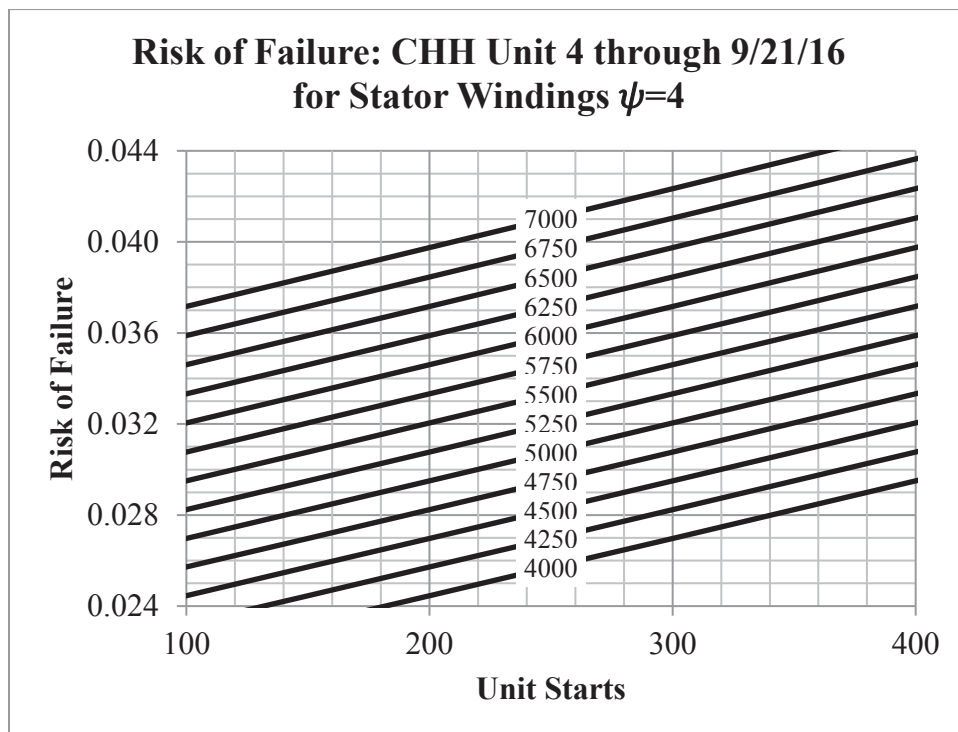


Figure 4-13 Stator Winding Risk of Failure $\psi = 4$

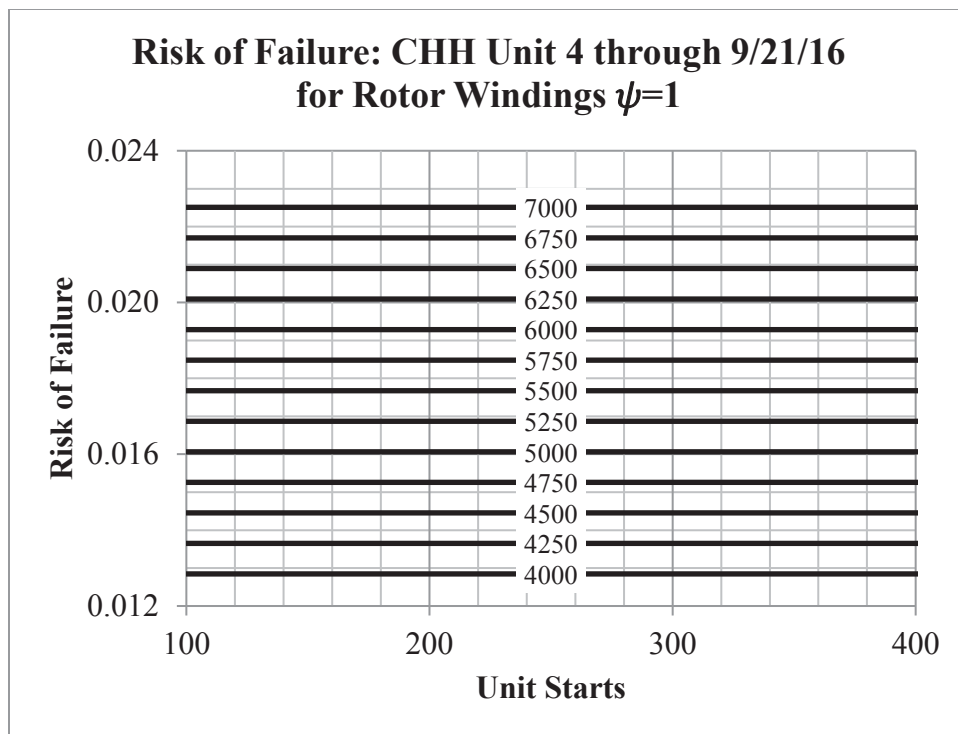


Figure 4-14 Rotor Winding Risk of Failure $\psi = 1$

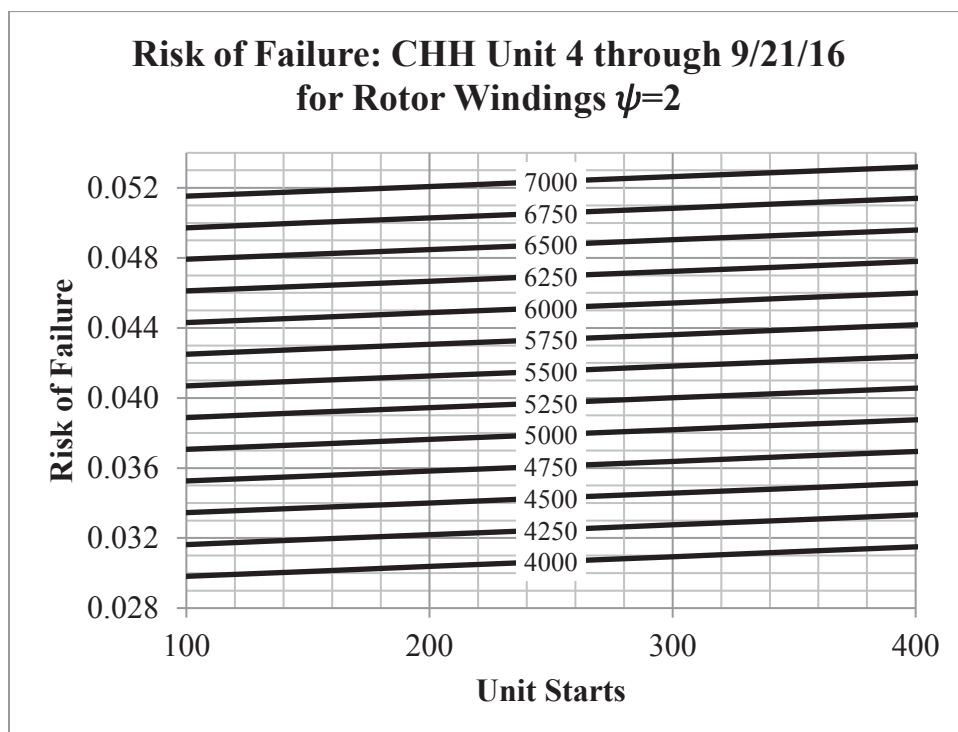


Figure 4-15 Rotor Winding Risk of Failure $\psi = 2$

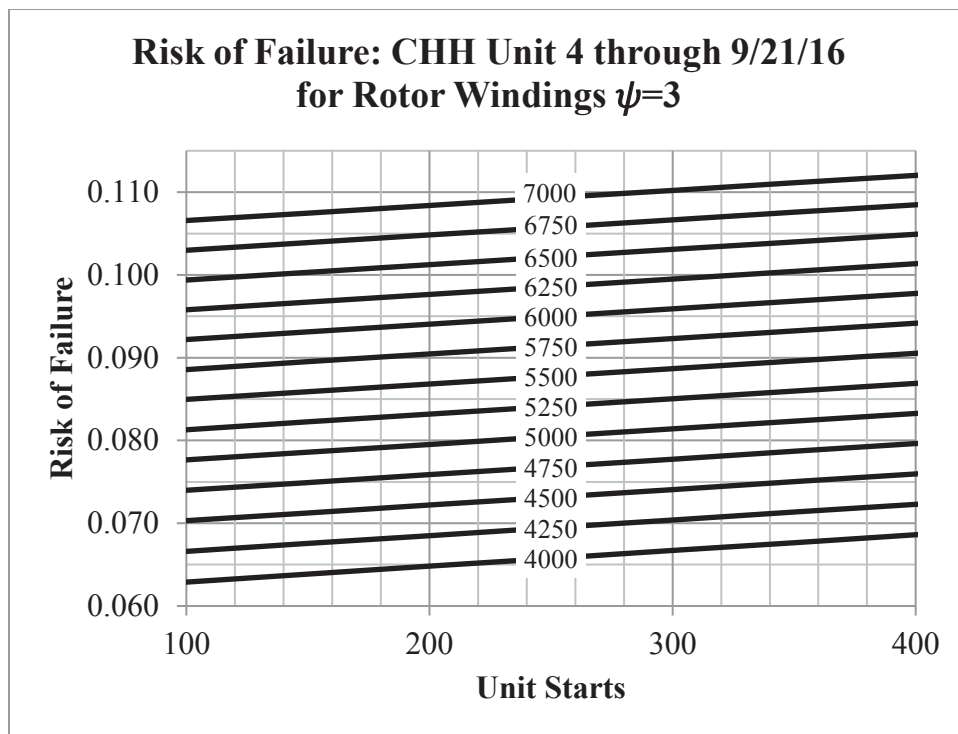


Figure 4-16 Rotor Winding Risk of Failure $\psi = 3$

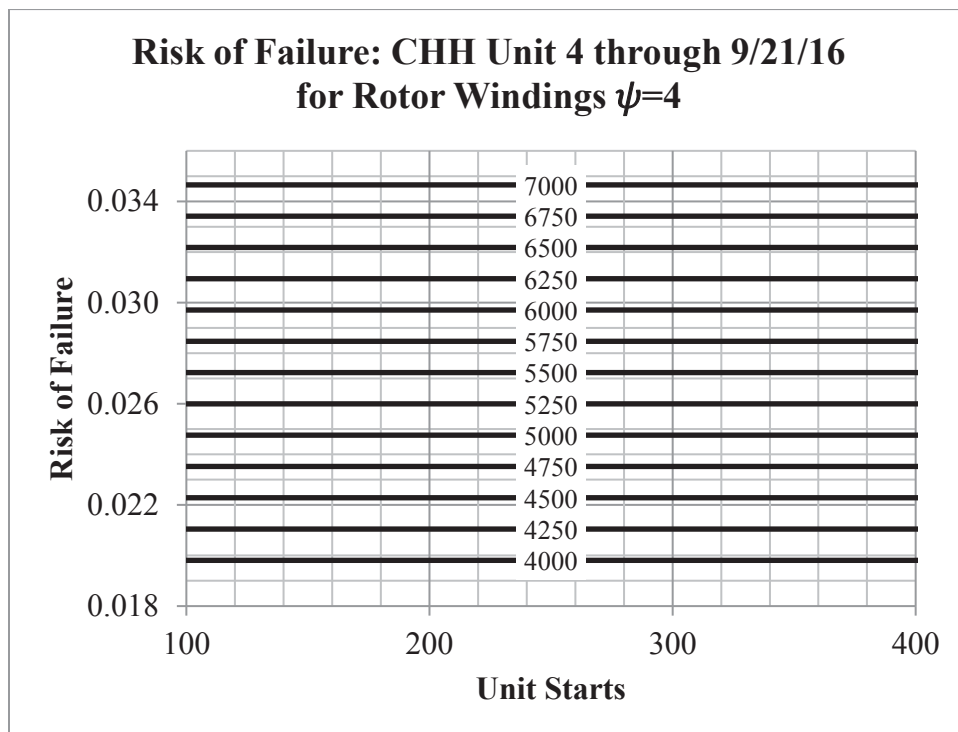


Figure 4-17 Rotor Winding Risk of Failure $\psi = 4$

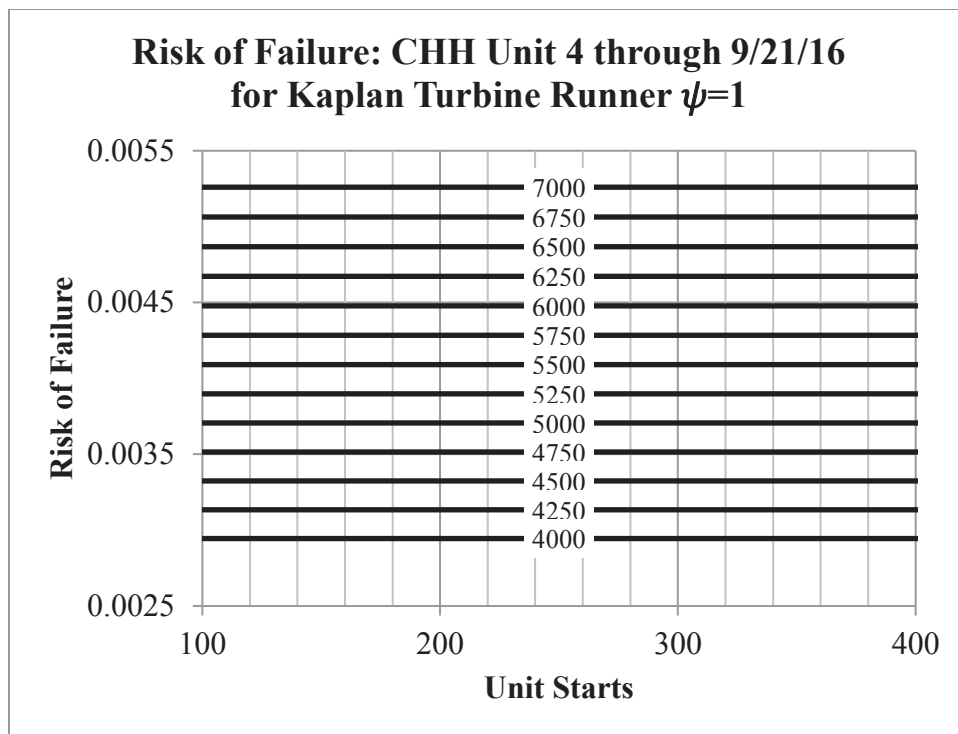


Figure 4-18 Kaplan Turbine Runner Risk of Failure $\psi = 1$

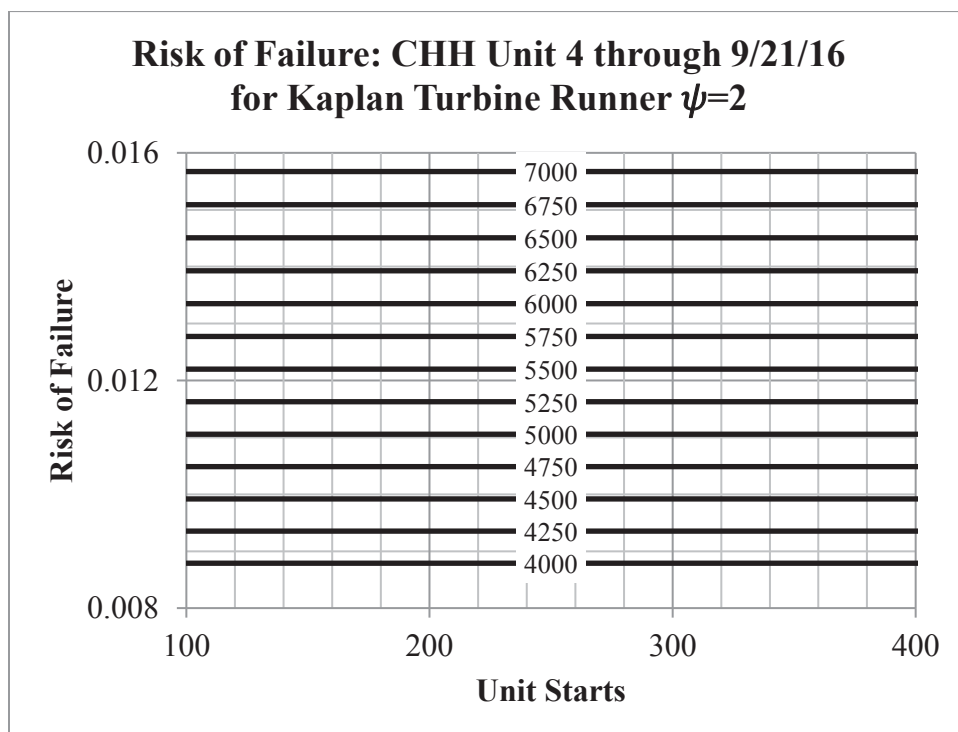


Figure 4-19 Kaplan Turbine Runner Risk of Failure $\psi = 2$

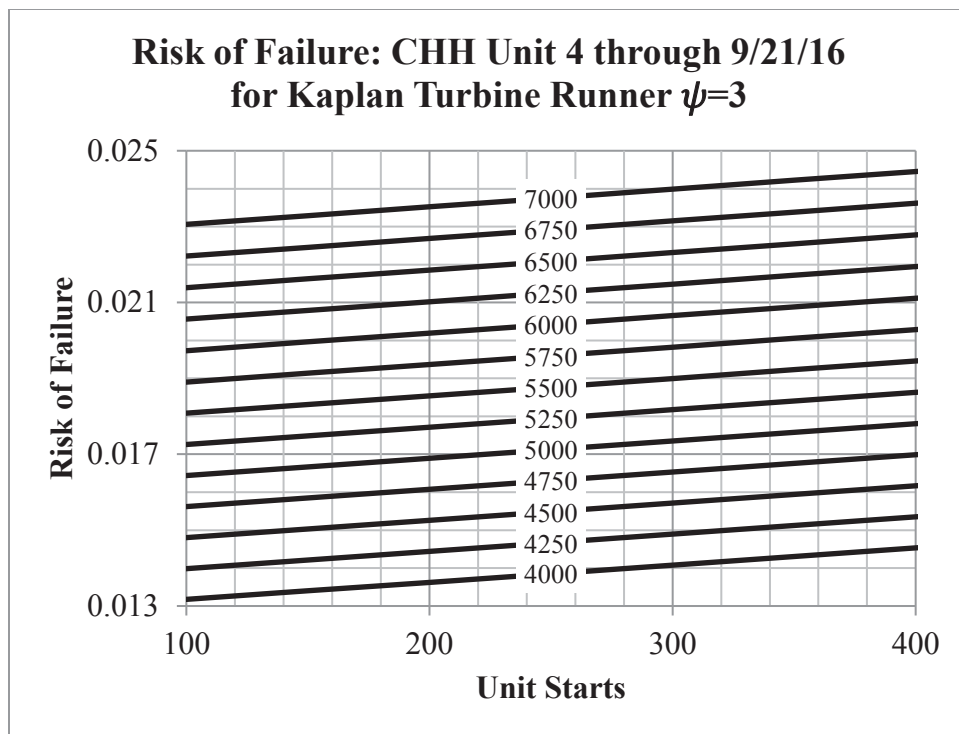


Figure 4-20 Kaplan Turbine Runner Risk of Failure $\psi = 3$

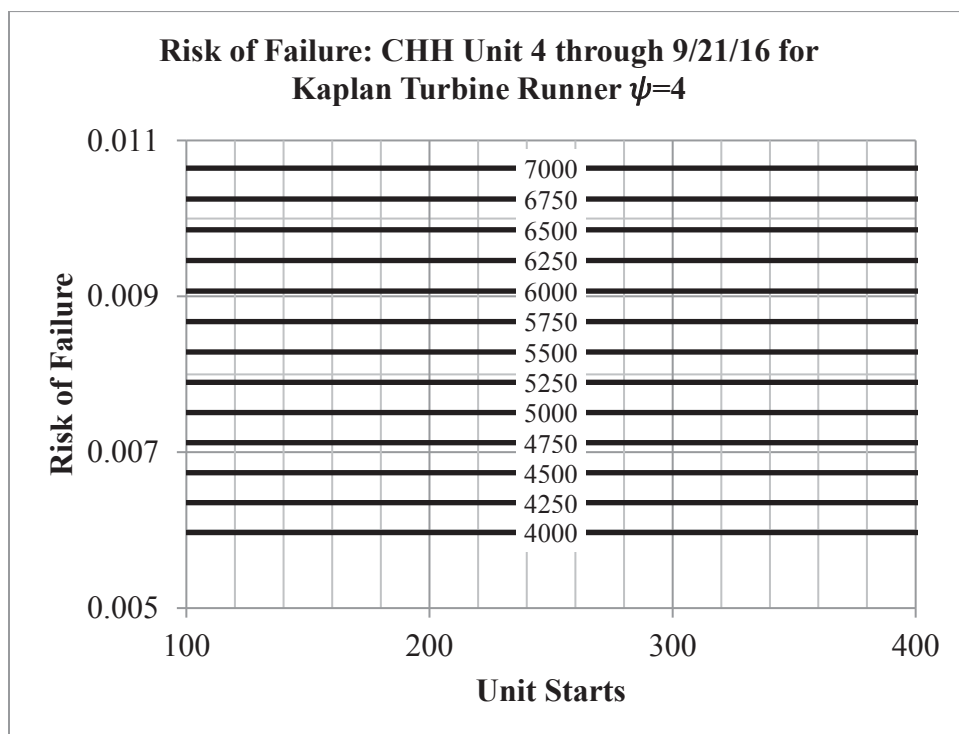


Figure 4-21 Kaplan Turbine Runner Risk of Failure $\psi = 4$

4.5. Historical Reliability Analysis

By reviewing historical operations and running the model set to each of these historical ages we can determine the deviation from actual operations that would have needed to occur to maximize reliability. This enables the calculation of a reliability index, RI. To determine the sensitivity of the multicomponent CRM the model was run using $\theta_k(2)$ and $\theta_k(4)$ for CHH & NOH in historical years 2004, 2005, & 2007. Table 4-4 shows the quantitative results for $\psi = 2$ while Table 4-5 shows the quantitative results for $\psi = 4$.

For 2004, $\psi = 2$ agrees with $\psi = 4$ with how best to dispatch generating hours. However, they disagree on how unit starts should be distributed. This is a result of the significant differences in cyclic wear coefficients $a_k(\psi)$ where $\psi = 2$ spreads cyclic wear to all components yet $\psi = 4$ suggests that only the stator windings incur this cyclic wear. In actuality, NOH unit starts were distributed in excess of $r_{1,NOH}$, but $\psi = 4$ was going in the correct direction.

For 2005, $\psi = 2$ again agrees with $\psi = 4$ with how best to dispatch generating hours and $\psi = 4$ is very similar to the actual dispatch of unit starts at NOH. As in 2004, the unit starts at CHH3 & 4 are suppressed in $\psi = 4$ due to the relative ages of $T_{CHH,3,1}(4)$ and $T_{CHH,4,1}(4)$ to other stator windings. In $\psi = 2$ the reliability of other components overrides the advanced age of $T_{CHH,4,1}(2)$ leading to CHH4 being recommended for an increase in unit starts.

For 2005, $\psi = 2$ again agrees with $\psi = 4$ with how best to dispatch generating hours. There is significant difference in how the models recommend the unit starts are distributed. Both $\psi = 2$ and $\psi = 4$ show that the unit starts at NOH should be concentrated at one unit but disagree as to which unit should handle the majority. This is a common theme with all dispatch scenarios.

The plant's reliability index, $RI_i(\psi, s)$ can be used to measure the reliability of actual operations compared to optimal dispatch and to worst case dispatch. The worst-case dispatch values were determined by minimizing the reliability function while maintaining all bounds and are found in Table 4-6. RI ranges from 0-100 if all optimization constraints are met during actual operation. $RI_{NOH}(4,1)$ exceeds a value of 100 because actual operation violated the unit start ratio $r_{1,NOH}$.

Table 4-4 Historical Recommendation for $\psi = 2$

	Dispatch Scenario 1				Dispatch Scenario 2				Dispatch Scenario 3			
$\psi = 2$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$
CHH1	5760	168	.9625	.8495	5977	241	.9585	.8380	4831	141	.9635	.8820
CHH2	5377	167	.9550		5408	241	.9522		3221	88	.9691	
CHH3	5377	168	.9643		5408	247	.9621		3221	168	.9746	
CHH4	8066	335	.9584		8113	481	.9542		4831	175	.9691	
NOH1	4360	167	.9790	.9555	3647	229	.9812	.9596	2664	341	.9843	.9657
NOH2	5449	291	.9761		4559	400	.9780		3331	598	.9811	

Table 4-5 Historical Recommendation for $\psi = 4$

	Dispatch Scenario 1				Dispatch Scenario 2				Dispatch Scenario 3			
$\psi = 4$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,\max}$	$R_{i,\max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,\max}$	$R_{i,\max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,\max}$	$R_{i,\max}$
CHH1	5650	278	.9752	.8973	5744	403	.9732	.8893	4772	188	.9754	.9183
CHH2	5408	276	.9696		5249	403	.9689		3182	188	.9792	
CHH3	5410	145	.9761		6041	202	.9719		3377	103	.9822	
CHH4	8112	139	.9721		7873	202	.9703		4772	94	.9789	
NOH1	4360	291	.9869	.9711	3647	400	.9881	.9735	2772	598	.9890	.9764
NOH2	5449	167	.9840		4559	229	.9853		3223	341	.9873	

For CHH the RI as are follows for the three dispatch scenarios and used two failure scenarios:

$$RI_{CHH}(2,1) = 92.07; RI_{CHH}(2,2) = 92.54; RI_{CHH}(2,3) = 96.32$$

$$RI_{CHH}(4,1) = 91.89; RI_{CHH}(4,2) = 92.31; RI_{CHH}(4,3) = 96.20$$

For NOH the RI as are follows for the three dispatch scenarios and used two failure scenarios:

$$RI_{NOH}(2,1) = 66.80; RI_{NOH}(2,2) = 33.25; RI_{NOH}(2,3) = 87.00$$

$$RI_{NOH}(4,1) = 127.0; RI_{NOH}(4,2) = 81.33; RI_{NOH}(4,3) = 9.14$$

This shows that CHH was operated close to the optimal dispatch for reliability purposes. However, NOH was not consistent in their RI values. The need for minimum flows at a 2-unit facility like NOH can make optimizing reliable operations difficult, yet these are the facilities that stand the most to gain from reliable operations.

Table 4-6 Minimal possible values for Historic Reliability

	$R_{1,\min}(\psi,1)$	$R_{1,\min}(\psi,2)$	$R_{1,\min}(\psi,3)$	$R_{2,\min}(\psi,1)$	$R_{2,\min}(\psi,2)$	$R_{2,\min}(\psi,3)$
$\psi = 2$	.7978	.7857	.7705	.9550	.9592	.9653
$\psi = 4$	.8603	.8516	.8368	.9708	.9732	.9759

4.6. Future CRM Analysis

The next use for the model is to determine how CHH and NOH units should have been dispatched at the present time if specific historical hydrologic years were repeated. Table 4-7 shows the raw data values while Figures 4-22 through 4-27 present a graphical view.

The results for CHH are greatly influenced by the parameter vector and the current component ages. The models agree that generating hours should be distributed first to CHH4 and CHH1 with a wide gap before CHH3 and CHH2. The sensitivity analysis shows that the unit start distribution is not as simple. $\psi = 2$ shows a near equal distribution of unit starts while $\psi = 1$ and $\psi = 4$ agree that CHH1 and CHH2 should be used for cyclic operations. $\psi = 3$ deviates and suggests CHH4 take the majority of unit starts. This is caused by all components having non-zero cyclic wear coefficients.

The results for NOH show good agreement in dispatching NOH1 with more hours and more unit starts which culminates in a lower average run time for NOH1 than NOH2. The results deviate in $\psi = 3$ as all three components have non-zero cyclic wear coefficients. This shifts the brunt of unit starts to NOH2 while still burdening NOH1 with the larger amount of generating hours.

The reliability values for CHH are significantly below those of NOH. The variation in $R_k(\psi, s)$ is due to the size of the system doubling. The differences in $R_{CHH,j}(\psi, s)$ and $R_{NOH,j}(\psi, s)$ values are due to the differences in component ages. Dispatch totals vary by plant and dispatch scenario and affect both $R_k(\psi, s)$ and $R_{k,j}(\psi, s)$.

Table 4-7 CHH & NOH Dispatch Recommendations

	Dispatch Case 1				Dispatch Case 2				Dispatch Case 3			
$\psi = 1$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$
CHH1	7363	279	.9448	.8263	7247	307	.9456	.8234	4831	191	.9638	.8834
CHH2	4919	278	.9602		4996	304	.9596		3221	191	.9739	
CHH3	4919	142	.9616		5170	301	.9593		3221	95	.9749	
CHH4	7379	139	.9472		7493	298	.9460		4831	95	.9655	
NOH1	5449	291	.9758	.9550	4559	400	.9796	.9621	3331	598	.9849	.9718
NOH2	4360	167	.9787		3647	229	.9821		2664	341	.9867	
$\psi = 2$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$
CHH1	6839	212	.8922	.6595	6916	308	.8900	.6530	4433	145	.9294	.7634
CHH2	5044	208	.9112		5121	298	.9088		3327	142	.9409	
CHH3	5131	209	.9136		5188	301	.9117		3353	142	.9431	
CHH4	7566	210	.8880		7681	303	.8854		4990	143	.9256	
NOH1	5449	291	.9496	.9096	4559	400	.9569	.9226	3331	598	.9666	.9403
NOH2	4360	167	.9579		3647	229	.9642		2664	341	.9727	
$\psi = 3$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$
CHH1	7284	159	.7974	.4603	6999	379	.7984	.4499	4824	115	.8614	.6031
CHH2	4942	159	.8473		5116	208	.8409		3222	114	.8977	
CHH3	4942	203	.8508		5116	208	.8459		3222	114	.9010	
CHH4	7412	317	.8008		7674	416	.7922		4834	229	.8656	
NOH1	5449	167	.8854	.7998	4559	229	.9015	.8251	3331	341	.9234	.8596
NOH2	4360	291	.9033		3647	400	.9153		2664	598	.9309	
$\psi = 4$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$	$\vec{h}_{i,j}$	$\vec{c}_{i,j}$	$R_{j,max}$	$R_{i,max}$
CHH1	7374	237	.9124	.7305	7354	352	.9106	.7215	4830	166	.9423	.8158
CHH2	4916	280	.9346		4997	318	.9330		3221	194	.9569	
CHH3	4916	182	.9368		5061	284	.9330		3221	115	.9586	
CHH4	7374	140	.9144		7495	256	.9102		4831	97	.9438	
NOH1	5449	291	.9601	.9246	4559	400	.9649	.9336	3331	598	.9710	.9449
NOH2	4360	167	.9630		3647	229	.9675		2664	341	.9731	

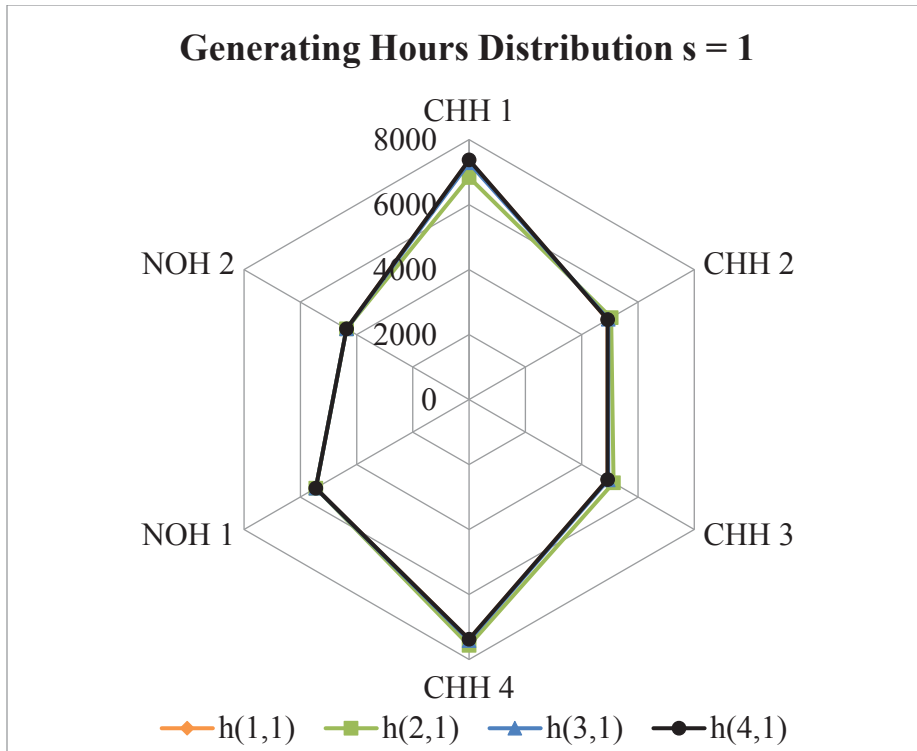


Figure 4-22 CRM Generating Hours Distribution $s = 1$

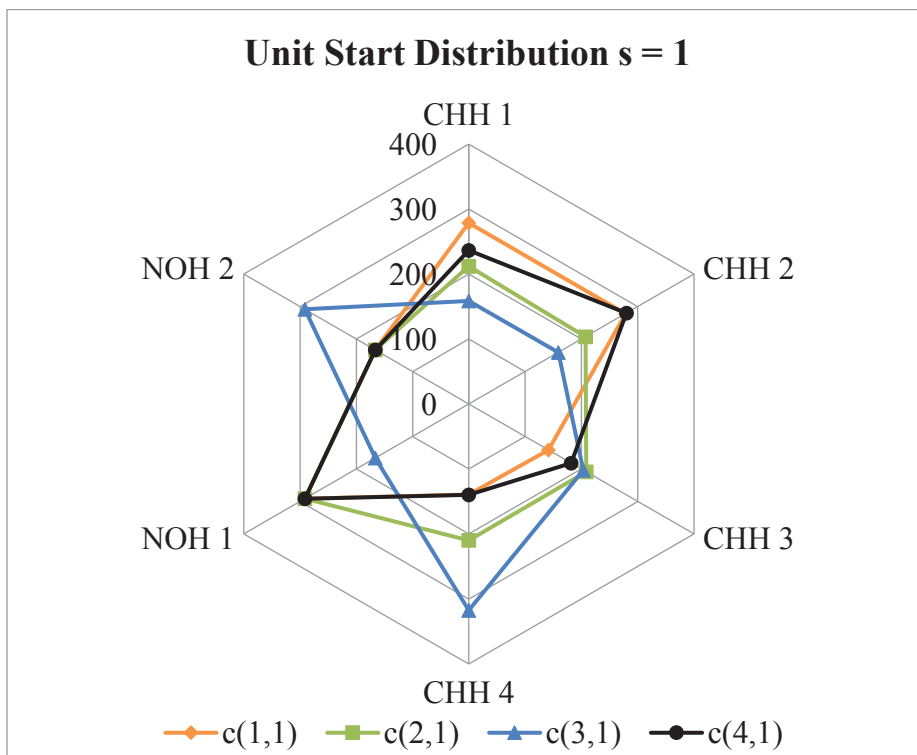


Figure 4-23 CRM Unit Starts Distribution $s = 1$

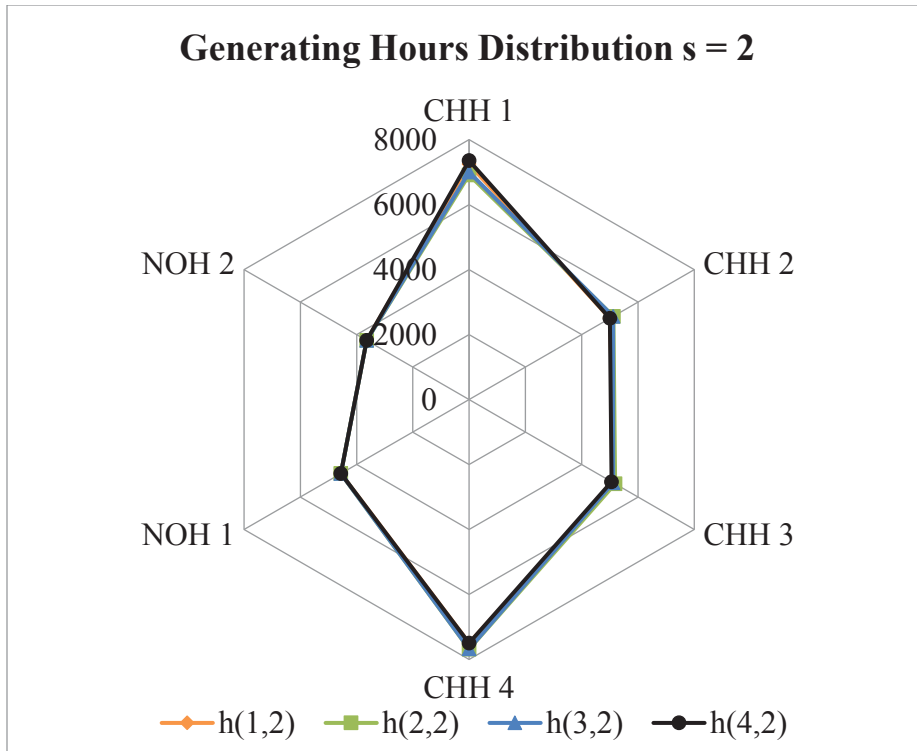


Figure 4-24 CRM Generating Hours Distribution $s = 2$

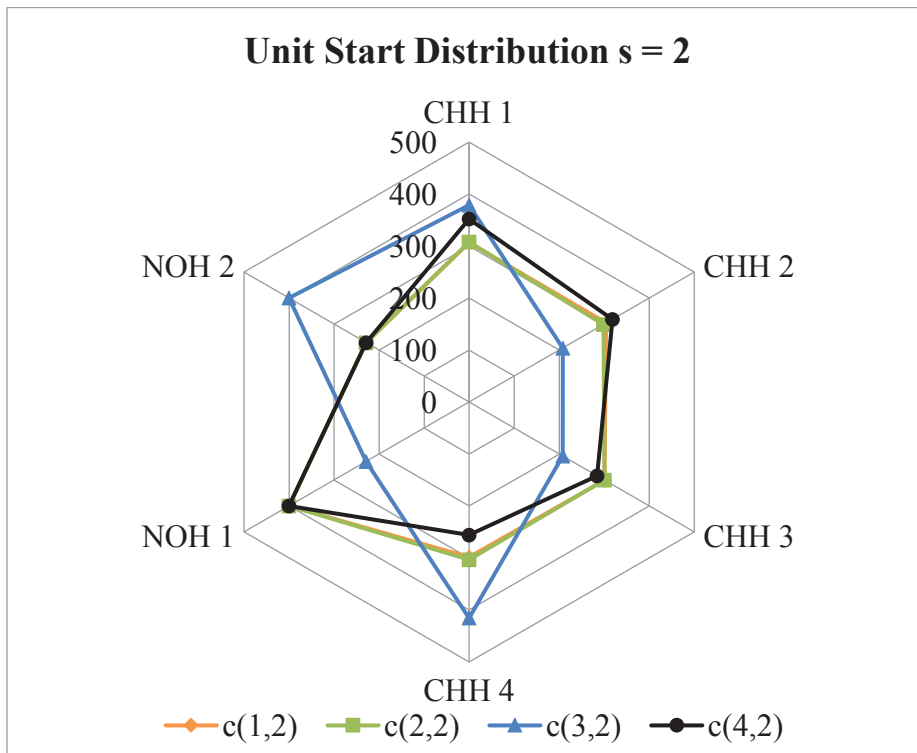


Figure 4-25 CRM Unit Starts Distribution $s = 2$

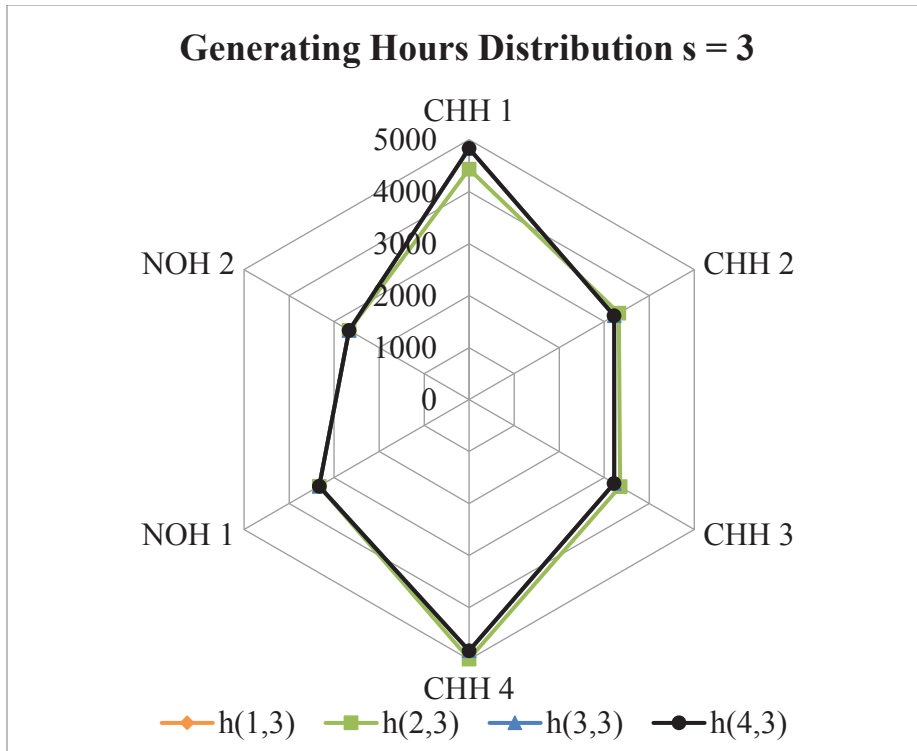


Figure 4-26 CRM Generating Hours Distribution $s = 3$

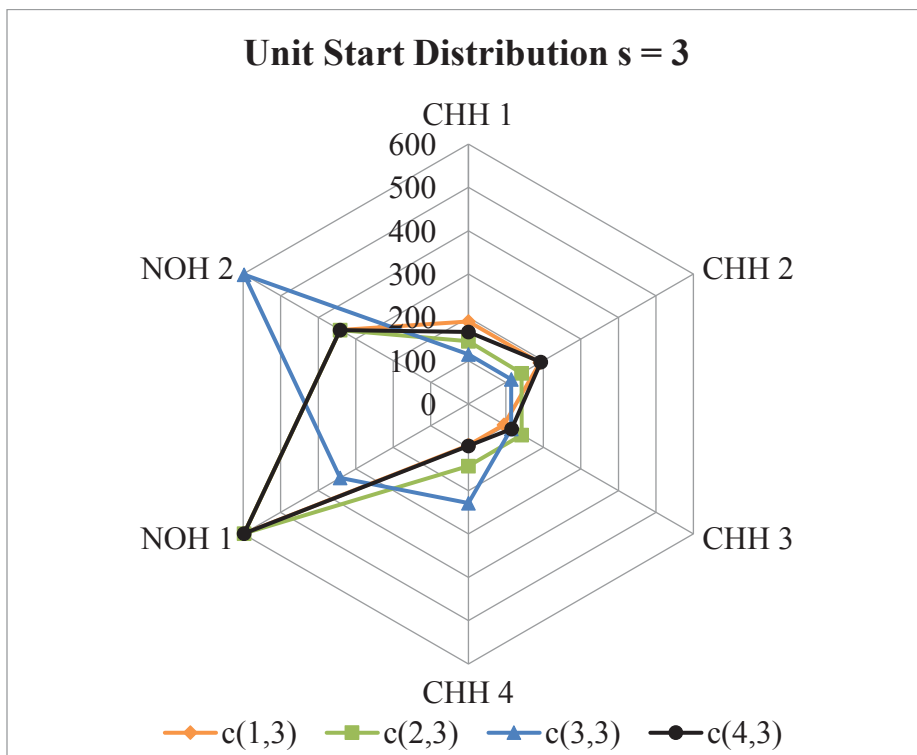


Figure 4-27 CRM Unit Starts Distribution $s = 3$

5. Conclusions and Future Work

The sensitivity analyses show that our model will adapt to fit the data acquired from utilities. The failure data will mold the parameter vectors using the expert elicitation as a baseline and will increase in weight as additional data is acquired. The SLM, single component CRM, and multicomponent CRM have shown they can be used to inform Asset Managers of reliability leaning decisions. The RI can be used to justify dispatch patterns that focus more on efficiency or other operating goals and are sub-optimal with respect to reliability.

This research establishes the EOH/EOY approach to risk-reliability calculations for hydroelectric powertrain components that is necessary to quantify the total cost of a unit cycle. As additional components are added to the model and outage data is acquired, this calculation will become possible. The value to cost ratio for unit starts is currently not a well-informed area and future work in this area can help establish better understanding using the outlined methodology.

The immediate horizon for future work is to scale the model to increase the number of components and to optimize dispatch patterns for an entire fleet. Optimizing a fleet, the size of TVA's 109-unit, 29-plant fleet for 10 components of interest shows the scale of the problem now that a three component, four-unit plant can be optimized. The multicomponent CRM developed in this work can, in future research, be used to compare the optimal dispatch patterns for meeting specific needs. In this work, we focused on maximizing reliability. One could also choose to minimize the risk-cost incurred or weight the units based on efficiency or other metrics of import. This model also assumes that all units at a plant have similar generating capabilities. Future work will adapt this model to perform at plants where units vary in generating capacity.

Future work also includes establishing RI values for the TVA fleet for the past decade to establish pareto distribution curves for the relationship between RI and an efficiency metric. These metrics should transcend MW, hydraulic head and other grouping variables. However, in order to achieve this, $r_{1,i}$ and $r_{2,i}$ must be set the historic ratio for each operating year to prevent RI values in excess of 100 instead of setting one value based on all historic dispatch.

Communicating to system operators the importance of small interval on-line operating data and outage data will be a continued effort and this research can be used as an example of the importance of data collection and the knowledge that can be extracted from this. Future work will include obtaining TVA outage history and using that information to inform the Weibull parameter vectors that govern the reliability calculations. Small interval on-line operating data can provide information on ramp events in order for a ramp event covariate to be added to the model.

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