INL/JOU-23-74413-Revision-1

# A Hybrid Reliability Model using Generalized Renewal Processes for Predictive Maintenance in Nuclear Power Plant Circulating Water Systems

December 2023

Changing the World's Energy Future

Ryan Matthew Spangler, Vivek Agarwal, Daniel Cole

Idaho National Laboratory

INL/JOU-23-74413-Revision-1

# A Hybrid Reliability Model using Generalized Renewal Processes for Predictive Maintenance in Nuclear Power Plant Circulating Water Systems

**Ryan Matthew Spangler, Vivek Agarwal, Daniel Cole**

**December 2023**

**Idaho National Laboratory**
**Idaho Falls, Idaho 83415**

**http://www.inl.gov**

**Prepared for the**
**U.S. Department of Energy**
**Under DOE Idaho Operations Office**
**Contract DE-NE0008909**

IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 19 October 2023, accepted 8 November 2023, date of publication 1 December 2023, date of current version 11 December 2023.

*Digital Object Identifier 10.1109/ACCESS.2023.3338716*

RESEARCH ARTICLE

# A Hybrid Reliability Model Using Generalized Renewal Processes for Predictive Maintenance in Nuclear Power Plant Circulating Water Systems

**RYAN M. SPANGLER[1,2], VIVEK AGARWAL[1], AND DANIEL G. COLE[2], (Member, IEEE)**
[1]Idaho National Laboratory, Idaho Falls, ID 83402, USA
[2]Department of Mechanical Engineering and Materials Science, University of Pittsburgh, Pittsburgh, PA 15213, USA

Corresponding author: Ryan M. Spangler (ryan.spangler@inl.gov)

This work was supported in part by the Nuclear Regulatory Commission (NRC) under Grant 31310018M0048, in part by the University of Pittsburgh Nuclear Engineering Graduate Fellowship Program, and in part by the U.S. DOE Office of Nuclear Energy's Nuclear Energy University Program under the Nuclear Energy Enabling Technologies Advanced Sensors and Instrumentation Program under Grant DE-NE0008909.

**ABSTRACT** The nuclear industry's economic viability is challenged by significant operations and maintenance (O&M) costs. Although maintenance strategies are often risk-averse, many maintenance programs rely on schedule-based strategies that perform repairs and replacements regardless of the asset's condition, leading to unnecessary repairs and high costs. Predictive maintenance can help alleviate these costs through condition monitoring and risk-informed decision-making. In this article, we show that the use of improved reliability models can help reduce the total cost of ownership (TCO) for a high-value repairable asset. Current risk-informed methods used in the industry today rely on mean-time-between-failure (MTBF) models that may oversimplify failure likelihood estimation. Improvements can be made by integrating condition monitoring, operational history, and maintenance effectiveness into a hybrid reliability model. In contrast with conventional MTBF methods, the generalized renewal process uses recurrent event analysis and historical repair data to quantify the effectiveness of maintenance repairs and estimate the likelihood of failure. During a case study on a nuclear power plant's circulating water system, a hybrid reliability model was fitted to the historical data and shown to have improved likelihood estimations when compared to a MTBF model. Monte Carlo simulations were then used to simulate and compare TCO for various maintenance strategies, showing that an extended replacement interval can reduce overall costs by upwards of 10.7%. The successful results of the improved reliability models showcase the ability to aid decision-making and reduce overall operations and maintenance costs in the nuclear power industry.

**INDEX TERMS** Circulating water system, decision-making, general repair, generalized renewal process, maintenance, Markov model, nuclear, operations, predictive maintenance, prognostics.

## I. INTRODUCTION

In the nuclear industry, the cost of operations and maintenance (O&M) is a large burden for nuclear power plants (NPPs), accounting for upward of 66% of annual operating expenses [1]. While the wholesale electricity market prices are about \$22/MWh, costs are much greater for NPPs with an industry average of approximately \$34/MWh [2]. To ensure long-term economic viability and competitiveness of the nuclear power industry, these costs must be reduced.

Total cost of ownership (TCO) is a crucial factor in evaluating the economic performance of a particular system. The TCO encompasses not only the upfront acquisition costs, but also the operational costs, maintenance expenses, and future investments required over the operating life of a

The associate editor coordinating the review of this manuscript and approving it for publication was R. K. Saket.

system. Due to the longevity of a typical NPP, with operating licenses being extended past 60, 80, or even 100 years, the TCO over the lifetime of a plant can be significant. In fact, studies in the aviation industry have shown initial acquisition costs make up only 20% of the overall TCO [3]. Therefore, operational costs, reliability, and maintenance are critical considerations when evaluating the overall costs of a system. Although different from the aviation industry, the nuclear industry can draw many similar parallels to the level of safety and performance necessary to operate mission critical systems.

One of the key challenges for ensuring a low TCO is optimizing the balance between repairing and replacing expensive repairable assets. As systems begin to age, it becomes essential to assess if continued repairs are cost-effective or if replacement is a more viable option. Maintaining performance and reliability by deciding to repair or replace an asset becomes a difficult task that must consider remaining useful life, the effectiveness of repairs, the cost of replacement, and the potential benefits of a replacement with an improved design. Optimizing critical decisions requires finding the right balance of reliability and performance that minimizes the TCO of the plant.

To help reduce TCO and optimize maintenance strategies, a shift to predictive maintenance (PdM) is necessary. Currently, a large portion of the maintenance in an NPP is preventive, reactionary to failures, and schedule-based. Although risk-averse, these strategies can result in high O&M costs due to labor-intensive methods, overly conservative repairs, and unexpected failures. Furthermore, the decision to repair or replace is made based on a time-dependent schedule, resulting in the replacement of an asset regardless of the actual health or reliability. PdM can help NPPs alleviate the high cost of O&M by enabling condition-based and risk-informed decisions that utilize the latest condition monitoring and reliability estimates to justify lifetime extensions [4], [5], [6].

To achieve a successful PdM strategy, robust decision-making tools must be created. While there are several ongoing efforts within the nuclear industry to achieve risk-informed decision-making [7], [8], [9], [10], [11], [12], current methods often rely on mean-time-between-failure (MTBF) models. Widespread adoption of these models is largely driven by model simplicity and data availability in industry databases [13]. However, MTBF oversimplifies the estimation of remaining useful life, required maintenance resources, and TCO.

Since maintenance and repairs are critical to restoring the condition of many systems, the effect of repairs should be included when estimating reliability. Current MTBF models do not account for the effectiveness of the repair, assuming the repair is perfect and returns the health of the system to an as-good-as-new condition (AGAN). Since many systems in an NPP are large, high-value assets, they are typically repaired before they are replaced, possibly several times. For large systems that undergo partial or imperfect maintenance, the AGAN assumption may not hold true and can cause MTBF models to become unreliable. During imperfect maintenance or partial repairs, the reliability of the system is improved by a factor that is dependent on the type, quality, and effectiveness of the repair. To accurately estimate the reliability of the system after repair, it is imperative that the repair effectiveness is quantified and included in the model.

To include the repair effectiveness in risk-informed models, several common renewal process models were investigated for use within repairable systems. There is abundant research focused on the reliability of repairable systems, with notable studies in the aviation, oil and gas, automobile, and several other industries [14], [15], [16], [17]. As part of this research, repairable system models that did and did not include a quantifiable effect of maintenance were investigated. For models that do not include repair effectiveness, the homogeneous Poisson Process (HPP) [18], the non-homogeneous Poisson Process (NHPP) [19], [20], [21], [22], and MTBF models were also considered. Although these models are common for modeling the renewal process for repairable systems, they do not include a variable repair effectiveness, assuming minimal or perfect repair. These assumptions simplify the models but can lead to inaccurate reliability estimations [23]

To address these concerns and include repair effectiveness, the generalized renewal process (GRP) model was evaluated for performance. The GRP model can estimate the underlying time-to-event (TTE) distribution and quantify the effect of imperfect maintenance [24]. This renewal process model provides improved risk-analysis for repairable and aging equipment. Several industries and recent studies have found the GRP model and virtual age (VA) estimation to be a suitable method for integrating recurring failures and imperfect maintenance for risk-informed decision-making [25], [26], [27], [28], [29], [30]. Although the GRP model is criticized due to the absence of a closed form solution [31], numerical solutions through Monte Carlo simulations are easily achievable with modern processors, alleviating such concerns. Although difficult to initially model due to complex governing equations [32], the GRP model is easily scalable, making it a good choice in the nuclear industry. The benefits of fitting a GRP model to data outweigh the complications due to the improved reliability estimations and repair effectiveness insights provided by the solution.

The focus of this research was the creation of a reliability model of an important NPP system—the circulating water system (CWS). The CWS in this plant is unique in that it is currently monitored and the degradation level estimated through vibration sensors, the results of which have been discussed in previous research reports [8], [9], [10]. The condition monitoring efforts have been able to use multimodal analysis, combining data from different sensors to classify the state of the CWS as healthy or unhealthy, along with a diagnosis. However, what is missing from this work is the estimation of event likelihood during periods of healthy operation and the effects from imperfect repair.

To address this gap, this article presents the novel integration of VA, condition monitoring, and imperfect maintenance to create a hybrid data-driven reliability model that can simulate and estimate the likelihood of failure events. The contributions of this article can be summarized as:

1) Using condition monitoring data and maintenance history, both of which are common in the nuclear industry, a hybrid stochastic model was created that can estimate the likelihood of failure and the effectiveness of maintenance. The results of the developed model have been compared to current reliability estimation approaches and provide an improved fit.
2) The framework used to create the reliability model provides the nuclear industry with a higher fidelity model that uses common data types. When compared with conventional modeling approaches, the GRP-based solution provides improved reliability estimates for repairable nuclear assets.
3) Numerical simulations using the developed model have shown that extended replacement intervals can reduce TCO over the operating life of the plant. The simulations have also been used to validate previous maintenance cycle extensions for this particular CWS [10].

NPPs will be able to use this model to estimate their specific system reliability based on their own repair effectiveness and operational history. This model will also enable the nuclear industry to make risk-informed decisions that will allow them to optimize their maintenance strategies and reduce overall TCO. Through the data-driven modeling and cost optimization, the GRP model can help operators reduce O&M costs and ensure the long-term economic viability of the nuclear industry.

This article is organized as follows: Section II discusses the why and how of modeling repairable systems, recurrent event data analysis, and repair process models. Section III presents the CWS as the case study for the methods to analyze the typical states, phases, and observations over the lifetime of the CWS. It also creates the hybrid reliability model used to model these phenomena, data-driven parameter fitting using operational data, and presents an analysis on the repair effectiveness and optimization of the replacement cycle on the CWS TCO through Monte Carlo simulations. Section IV concludes the research and discusses the impact of this work on the nuclear industry and the O&M costs.

## II. MODELING REPAIRABLE SYSTEMS

Much of the structures, systems, and components (SSC) in an NPP are large and high-value, requiring preventive and corrective maintenance (CM) during the operational life. Preventive maintenance focuses on the cyclic maintenance required to continue successful operation, such as inspections and oil changes. CM is performed whenever there is a degradation event or failure and is used to restore the condition of the SSCs to an acceptable performance level [8], [9], [10].

Since CM is usually a partial repair of this system, an AGAN or perfect repair assumption may not be accurate because the portion of the system that was not repaired remains the same condition and of the same reliability. Conversely, assuming the system returns to a ''bad-as-old'' (BAO) state, or minimal repair, may also be an inaccurate assumption since the system has undergone repairs that improve the condition of the overall system. The true effect on reliability from a partial repair lies somewhere between AGAN and BAO assumptions, otherwise known as ''younger-than-old-but-older-than-new.'' To accurately predict the reliability of a system after partial repair, a GRP model can be used to quantify the effects of maintenance and underlying TTE distribution.

A combination of Markov models [33], phased-mission system modeling [34], and recurrent event data analysis [35], [36] have been used to create a hybrid reliability model that can simulate and forecast instances of a repairable system.

### A. HYBRID MARKOV RELIABILITY MODELS

Markov models or Markov chains are popular modeling tools for reliability and availability research due to their simplicity, low computational cost, and generality. In this research, hybrid phased-system Markov models were developed to model degradation and reliability.

#### 1) MARKOV CHAINS

Markov chains are stochastic models that describe dynamic systems containing randomness or uncertainty. Markov chains are composed of two elements: states and transitions. The states describe the system and the transitions define the probability of changing from one state to another. The states and transitions determine the system dynamics and are used to study the response. In this research, discrete-time Markov chains (DTMC) are used, where the states are discrete and finite.

One of the assumptions for Markov models is that the system is Markovian or ''memory-less,'' meaning the next state is only dependent on the current state and not the entire history of previous states. Most repairable systems can be modeled as Markovian by including the history, such as age or number of repairs, in the state of the system.

#### 2) MARKOV RELIABILITY MODELS

Abundant research has focused on the creation of simple Markov reliability models for economic analysis of maintenance strategies. [9], [37], [38], [39].

By creating a system with two states, operational and maintenance, it is easy to predict average maintenance costs by estimating transition probabilities between the two states and solving for expected operational and maintenance costs.

This is a very common modeling choice when time-between-event data is unavailable. Even if time-between-event data is limited, having historical data that provide number of failures and operational time can provide an MTBF estimation that can be a transition probability for solving the expected maintenance costs for the repairable system. An example can be seen in the Markov model in Fig. 1.

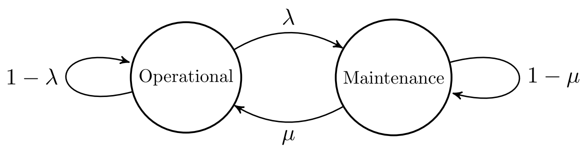


**FIGURE 1. A simple Markov model that describes the reliability of a system.**

In Fig. 1, the transition probability from operational to CM, $\lambda$, and the transition probability from CM to operational, $\mu$, are both constants. When failure data is available, it is common to use MTBF and the average repair time as the transition probabilities during the next timestep, such that $\lambda = 1/\mathrm{MTBF}$ and $\mu = 1/\mathrm{MTTR}$, where MTTR is the mean-time-to-repair.

Since each of these transition probabilities are a function of time, a common sample rate can be defined, such that the transition probability defines the likelihood of transition during the next sample period. By doing so, these become discrete time Markov chains (DTMC) that are defined using transition probabilities. For example, the probability of transitioning from an operational state to a maintenance state within the next sample period is defined as

$$\Pr[\text{ maintenance} \mid \text{operational }] = \lambda = 1/\mathrm{MTBF}. \quad (1)$$

Although simple and effective, caution must be used when using MTBF for reliability analysis and decision-making. MTBF is not recommended for anything other than an average TCO cost or reliability calculation [40]. MTBF is estimated using a fixed failure rate that does not include the effects of early-failure, degradation, or repair effectiveness. As the system begins to age or undergo several repairs, the time between events may change as the systems wear out. After a partial repair, the reliability of the system may not return to an AGAN condition, which results in inaccurate reliability estimations. MTBF models assume that the time between event distributions are independent and identically distributed (i.i.d.), meaning that the time between events is assumed constant over the life of the system, regardless of repairs or age. For large systems that undergo partial repair or wear out, the i.i.d. assumption may not hold true, making MTBF models inaccurate for reliability estimations. Systems that undergo partial repair or exhibit different operational phases over their lifetimes require the use of models with greater complexity to accurately capture this behavior.

#### 3) PHASED-MISSION SYSTEMS

Although Markov models provide inherently flexible modeling capabilities, not all systems can be fit with typical Markovian assumptions, and thus require hybrid modeling methods. For example, systems may undergo healthy and unhealthy operational periods that contain a variety of different degradation processes that are not easily modeled with transition probabilities.

When a transition between two states is a well-known process, such as an observable degradation process, the need for a stochastic transition rate assumption can be removed and replaced with a more representative transition method. This type of modeling is useful when the time it takes for a degradation process to occur from start to finish is known. For example, data may not exist that suggests how long a system will remain in a healthy period; however, data may exist to support a degradation process model that occurs over a set amount of time. In this case, the uncertain transition from healthy to unhealthy can be modeled as a random transition rate, but the degradation process would be modeled as a time-dependent failure process.

To integrate the various operational processes, a hybrid modeling method known as phased-mission systems can be used to characterize and integrate disparate models [34]. The transition between these different phases is no longer a random probability, but can be a deterministic, "mission-completed" requirement. This allows enhanced modeling flexibility that can vary depending on the underlying system process.

In the simple phased-mission model above, the system has three phases: healthy, unhealthy, and failed. For a repairable system, the transition from healthy to unhealthy can be modeled as a time-dependent stochastic process with TTE distributions fit to the data. Conversely, the unhealthy phase of a degrading system behaves differently and can be modeled with various degradation processes. The transition from an unhealthy to a failed phase is not a probabilistic transition, but rather a deterministic function of a degradation limit that can be modeled as a stochastic degradation process. Once the system reaches the threshold of its degradation limit, it can no longer perform its function and enters the failed phase.

### B. RECURRENT EVENT DATA ANALYSIS

As a high-value asset degrades or fails, CM must be performed to restore the system to an acceptable operating condition. The system then continues to operate until another failure event requires CM. This pattern continues until the system is neither repairable nor worth further repair. This pattern is known as a recurring event and can be analyzed to estimate the reliability of the system.

Recurrent event data analysis studies the effects of a system that undergoes several events in its lifetime [35], [36]. The main features studied in this analysis are the number of events, $N$, and the TTE distributions that can be used for reliability estimations or finding the rate of occurrence of failure (ROCOF), also known as the cumulative intensity function.

Recurrent event data analysis is a counting process where a unit or system is monitored and both the number of events the system undergoes and the time between each event are recorded. For example, a repairable system may fail several times over its lifetime and require maintenance to return it to service. Each failure is recorded along with the interval between each failure. As time continues and the system records more events, the interval between events may change. An increasing or decreasing change in TTE duration can be quantified and analyzed for a trend. An increasing or decreasing trend means that as time continues, the time between failures is changing with the system's age, failing more or less often. Once this trend is fitted to the data, a posterior TTE distribution for the next event can be estimated given the history of failures and repairs. Using this TTE distribution of remaining useful life can be estimated and used to plan maintenance.

To perform recurrent event data analysis, there are two main analysis tools used: abacus plots and cumulative intensity functions. An abacus plot visualizes the data and time between events. A cumulative intensity function visualizes and models the number of expected events for a system over time. The cumulative intensity function (CIF) becomes the model for the number of expected failures given the operating history and number of failures. An abacus plot showing one sample path with inter-arrival times can be seen in Fig. 2, while the same data can be seen on a cumulative failure plot in Fig. 3. In Fig. 4, the dashed lines represent the cumulative failures for multiple systems and the CIF is the average number of failures for a set of several systems.

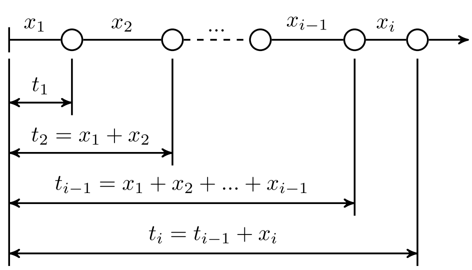


**FIGURE 2.** An example of an abacus plot showing the failures and inter-arrival times for a single repairable system. In this figure, $t_i$ is the event time and $x_i$ represents the inter-arrival time between events.

### C. REPAIR PROCESS MODELING

Renewal processes are a group of recurrent event models that use different techniques to estimate the parameters of various recurrent processes. For repairable systems, there are five types of repairs that can be modeled, each with their own level of maintenance effectiveness [41], [42]:

1) Perfect repair: the maintenance action returns the system to an AGAN condition.

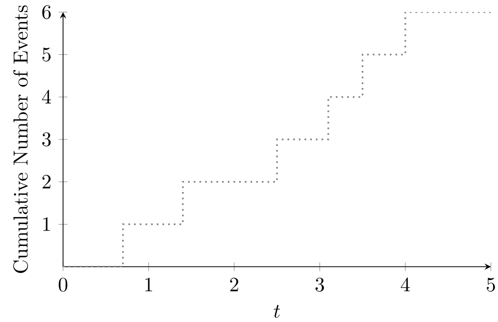


**FIGURE 3.** This plot shows cumulative failures of a single repairable system as a function of time.

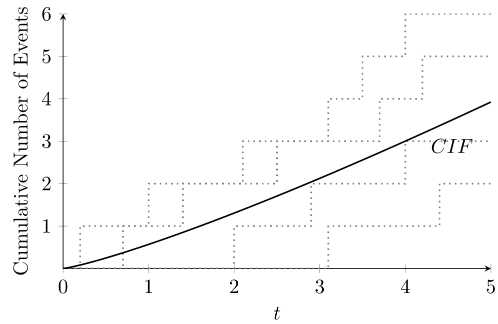


**FIGURE 4.** An example of a cumulative intensity plot showing the expected number of failures for a system that is derived from the operational data of several systems. In the figure, the dashed lines represent the cumulative failures for a single system and the CIF is the parameterized model for the average number of failures for a set of several systems.

2) Minimal repair: the maintenance action restores the system to the same condition before repair, resulting in a BAO condition.
3) Imperfect repair: the maintenance action restores the system to an improved—but not perfect—condition, resulting in a condition that is between an AGAN and a BAO condition.
4) Worse repair: the maintenance action restores the system to a worse condition than before the repair, resulting in a "worse-than-old" condition.
5) Worst repair: the maintenance action causes the system to immediately fail or break down.

With each of these different types of repairs, there are different methods for modeling the effects. The most common models are the renewal process (RP), the NHPP, and the GRP type I and type II [43]. The difference between these models is the underlying effect of maintenance. The RP is a perfect repair model where system condition is returned to AGAN condition after every repair, the NHPP model is a minimal repair mode that returns the system to a BAO condition after repair, and the GRP model restores the condition of the system to an intermediate level after repair. To do this, the GRP model operates on the notion of VA, meaning that the VA of the system determines the reliability and is the method used for tracking operating time and effectiveness of maintenance. The GRP introduces a variable for quantifying repair effectiveness, denoted as $q$. Plots representing the different types of repair process models can be seen in Fig. 5.

#### 1) RENEWAL PROCESS

A common repair assumption is that any repair, even a partial repair, will return the system reliability to an AGAN condition. This is a simple model that needs relatively little data to perform so it is a common first choice for modeling reliability. To model this, RP models were used to estimate the reliability of systems after perfect repair. The RP model requires one major assumption: the TTE distributions are i.i.d.; that is, the number of failures or operational history have no effect on the TTE distribution and assumes that maintenance restores the condition of the system to AGAN.

The underlying TTE distribution is commonly modeled as an exponential distribution that is a result of a constant failure rate. This particular model is a special case of renewal process called the homogeneous Poisson process (HPP). This is a simple reliability model selected if there is limited TTE data. Since HPP only requires a constant hazard rate or mean-time-between-failures, it is a very common industry choice. HPP also provides a closed-form solution for the process, allowing for trivial analysis.

Although common, the constant failure rate and resulting exponential distribution of failure times is not always a good choice for high-value assets. This is due to the fact that high-value assets abide by strict quality controls and testing before going into service, a normal practice in the nuclear industry. A better choice for TTE distributions in high-value asset industries is the Weibull distribution. This is a common choice for reliability distributions due to its ability to fit systems that do not immediately fail upon installation, but have a delayed event date with a right-tailed skewed distribution.

#### 2) NON-HOMOGENEOUS POISSON PROCESS

The NHPP is another common stochastic process model that operates under the assumption of minimal repair, unlike the RP model. In the NHPP model, each repair is minimal and returns the system to service with the same condition as before the repair. This model fits well for very large and complex systems that have many components that are repaired to a minimal operating level before returning to service.

The NHPP models do not fit well in the nuclear industry because the systems are not repaired to a minimal level, but to an acceptable condition or better. The extensive maintenance abides by the strict operating requirements set by the industry and regulations. This results in reliability improvements to the system that will extend remaining useful life and a repair process that does not fit well with the NHPP.

#### 3) GENERALIZED RENEWAL PROCESS

The generalized renewal process was developed by Kijima et al. [24], [43] to fill the gap between perfect repair and minimal repair processes. The GRP model is based on the idea of VA, $V$. As the real age of the system, $S$, increases, the VA of the system also increases. The VA of the system will increase with wall-clock time or the amount of time the system has been operational, depending on the dominating degradation factors being modeled. When partial maintenance or a repair is performed, the VA of the system is reduced by the repair effectiveness, $q$, which is quantified using operational data of the system. When the system is replaced, the real age and the VA of the system are reset to zero. The result of this model is a reliability rate and TTE distribution that is dependent on the operational history of the system and the number and quality of repairs.

There are two GRP models called the Kijima Type-I and the Kijima Type-II. The Type-I model assumes that repairs only reduce damage that has occurred since the previous failure. The Type-II model assumes that all damage accumulated up to the current state is reduced by the repair effectiveness. For this research, only the Kijima Type-II model is evaluated.

To describe this model mathematically, the repairable system event times are defined as $t_1, t_2, \ldots, t_n$, where $n$ is the $n$th event. The inter-arrival times between events can be defined as $x_1, x_2, \ldots, x_n$, such that

$$x_i = t_i - t_{i-1}, \quad i = 1, 2, \ldots n. \tag{2}$$

Following the $n$th event and repair, the VA becomes

$$V_n = q(V_{n-1} + x_n) = q(q^{n-1}x_1 + q^{n-2}x_2 + \ldots + x_n) \tag{3}$$

Assuming a VA after the $(n-1)$th repair is $V_{n-1} = y$, $n$th failure time distribution, $X$, can be described with the following cumulative probability function

$$F(X|V_{n-1} = y) = \frac{F(X+Y) - F(y)}{1 - F(Y)} \tag{4}$$

Using the inter-arrival time distribution as the conditional Weibull distribution, the conditional probability distribution function of the time to the next event can be described as

$$f(t_i|t_{i-1}) = \lambda\beta(x_i + v_{i-1})^{\beta-1} e^{-\lambda[(x_i+v_{i-1})^{\beta} - v_{i-1}^{\beta}]} \tag{5}$$

where $\beta$ and $\lambda$ are the shape and rate parameters of the Weibull distribution, respectively.

To fit the GRP model to failure data, the parameters $\beta$, $\lambda$, and $q$ are optimized through maximum likelihood estimation [41]. The likelihood function is

$$L(\text{data}|\lambda, \beta, q) = \lambda^n \beta^n (e^{-\lambda[(T-t_n+v_n)^{\beta} - v_n^{\beta}]})^{\delta} \prod_{i=1}^{n} \times [(x_i + v_{i-1})^{\beta-1} e^{-\lambda[(x_i+v_{i-1})^{\beta} - v_{i-1}^{\beta}]}], \tag{6}$$

where $\delta = 1$ if the data is time-truncated or $\delta = 0$ if the data is failure-truncated. Taking the natural log of both sides, the

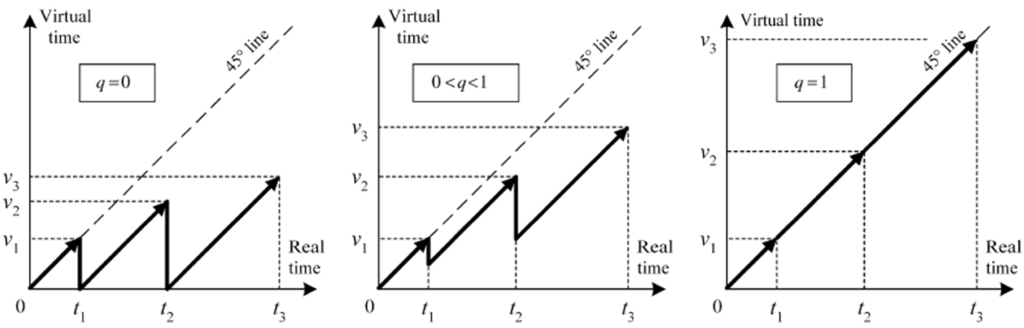


**FIGURE 5.** Repair process models and their effect on VA, where $q$ represents the repair effectiveness. The plots, from left to right, show the RP with perfect repair, the GRP with imperfect repair, and the NHPP with minimal repair [44].

log-likelihood function becomes:

$$\log L(\text{data}|\lambda, \beta, q) = n(\ln \lambda + \ln \beta) - \lambda\delta[(T - t_n + v_n)^\beta - v_n^\beta] - \lambda \sum_{i-1}^{n}[(x_i + v_{i-1})^\beta - v_{i-1}^\beta] + (\beta - 1)\sum_{i-1}^{n} \ln(x_i + v_{i-1}) \quad (7)$$

Extending this to an arbitrary number of systems, $k$, the log-likelihood function becomes:

$$\log L(\text{data}|\lambda, \beta, q) = \sum_{l=1}^{k} n_l(\ln \lambda + \ln \beta) - \lambda\delta \sum_{l=1}^{k}[(T_l - t_{l,n_l} + v_{n_l})^\beta - v_{n_l}^\beta] - \lambda \sum_{l=1}^{k}\sum_{i-1}^{n_l}[(x_{l,i} + v_{l,i-1})^\beta - v_{l,i-1}^\beta] + (\beta - 1)\sum_{l=1}^{k}\sum_{i-1}^{n_l} \ln(x_{l,i} + v_{l,i-1}) \quad (8)$$

Since there are three variables and no closed-form solutions to the GRP equation [45], a numerical optimization algorithm must be used to maximize the log-likelihood equation.

Once the parameters of the GRP model are identified, the reliability and TTE distributions can be calculated using the parameters of the Weibull distribution and the operating history of the system. Furthermore, the models can be used to estimate the reliability and TTE distribution of the system after repair, allowing for predictive maintenance actions to be evaluated for cost-effectiveness.

## III. MODELING CIRCULATING WATER SYSTEM

To accurately model the plant degradation data, it must first be analyzed and broken down into the various operating regions typically seen during plant operation. The overall flow of this modeling effort can be seen in Fig. 6. This section presents the analysis of a repairable system in an NPP and the parameter estimation for the GRP model.

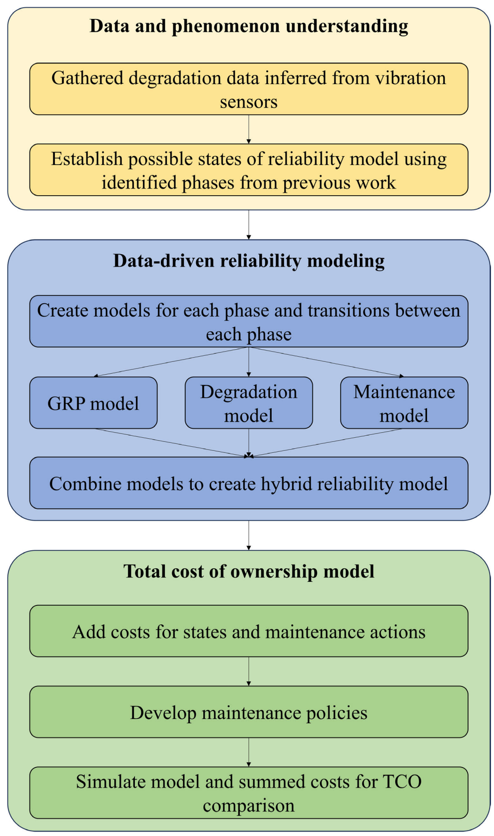


**FIGURE 6.** Overall flow diagram of analysis steps for creating the data-driven reliability model for the CWS.

### A. CIRCULATING WATER SYSTEM

For this research, several circulating water pumps (CWPs) that make up the CWS at an NPP have been selected as the modeling and analysis case study. The CWPs are good candidates for numerous reasons, including condition monitoring data availability, reliability concerns, and low-risk profile to plant safety since they are one of the non-safety plant systems.

As part of a previous research effort, wireless vibration sensors had been placed on 12 CWPs located in the plant. Additional monitoring equipment, already installed, consisted of sensors collecting internal motor temperature data and electrical current data. Using the data collected over numerous years, researchers were able to create machine-learning models that can predict the state of the pump as healthy or unhealthy, as well as to predict a relative level of degradation. The experimental setup, including the CWPs and sensor locations can be seen in Fig. 7. The data collected from the sensors was analyzed using signal processing methods, in combination with machine-learning algorithms, to predict a relative level of degradation. For more information regarding the degradation estimation from plant data, please see references [8], [9], [10].

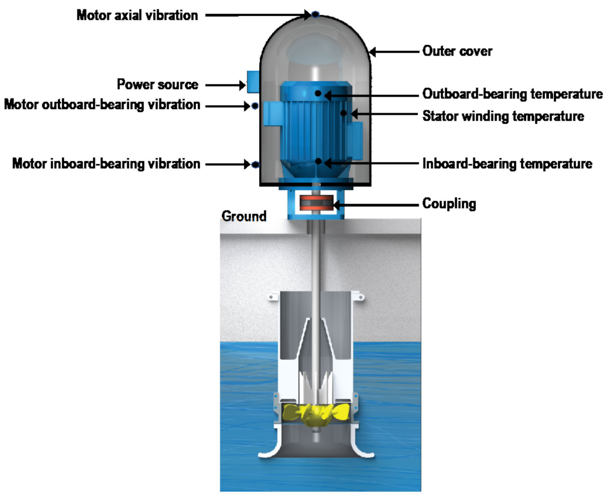


**FIGURE 7.** CWP diagram showing the vertical motor driven pump configuration with measurement locations. Figure reproduced from [8].

A plot of a typical degradation path observed in plant data is shown in Fig. 8. In that plot, two distinct regions can be observed: one where the degradation level remains stationary and nominal, and another where the degradation level starts to rise. Such a degradation path is typical of a diagnosed fault that has occurred in the CWP. This degradation process, which is characterized by a healthy period followed by an increase in degradation level and then a shutdown and corrective maintenance, will be represented by the created model. A third region, offline, can be added, resulting in three distinct phases: healthy, unhealthy, and offline. Both the healthy and unhealthy phases are considered operational, whereas the offline phase represents times when the pump isn't running due to maintenance, outage, or lack of necessity.

### *B. MARKOV RELIABILITY MODELING*

Using those three phases—healthy, unhealthy, and offline—a phased-mission hybrid Markov model that governs the transition from one state to another has been created. A figure representing the CWP model can be seen in Fig. 9. The figure shows a model of the degradation process where the

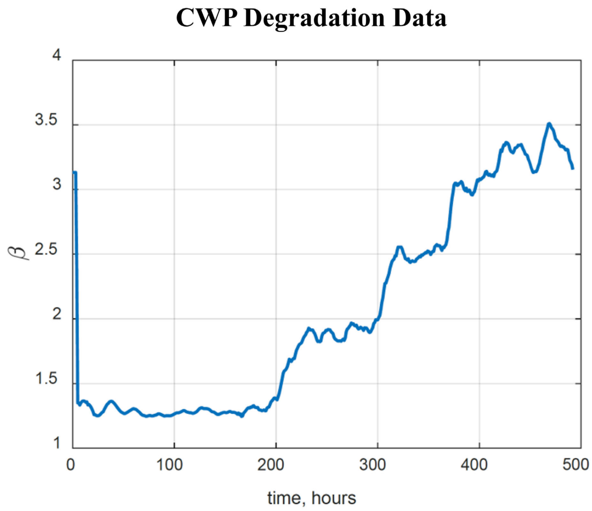


**FIGURE 8.** A typical degradation path observed in plant data. The data first contains a healthy period with no relative increase in estimated degradation, which is followed by an unhealthy period that contains an increasing amount of estimated degradation. Plot reproduced from [10].

phases of healthy and unhealthy have time spans governed by various transition rates and phase-mission processes. In the model, the healthy period is followed by an unhealthy period where the degradation level increases with time. The unhealthy period is then ended by an offline period where the CWP enters a period of corrective maintenance. Once the CWP completes the corrective maintenance, it will become operational and the degradation level will return to zero.

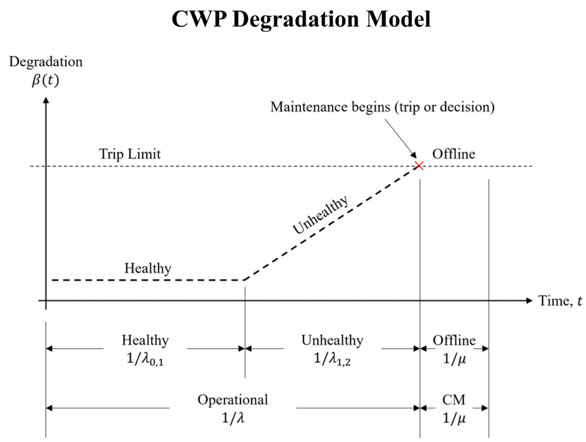


**FIGURE 9.** A model depicting the degradation phases of the CWP. The time spent in each phase, and corresponding transition rates, are inferred from plant data [10].

The Markov model created for the degradation process can be considered a phased-mission model due to the differences of the various phases and their transition descriptions. During the healthy and offline phases, the model is a simple Markov model with transition probabilities, since there is a lack of sensor data to precisely determine these transitions using stochastic modeling and distributions fit to the data to estimate the duration of these phases. In contrast, when the system is in the unhealthy phase, it no longer depends on transition probabilities, but rather has a degradation process that can be monitored and modeled. In the unhealthy phase, the degradation level of the system continually increases until a manual trip by an operator is initiated or an automatic trip limit is reached. Once the trip limit is reached, the system transitions into the offline phase. In this research, the unhealthy phase will be modeled as a linear increase in degradation (with added noise) until the automatic trip limit is reached.

The Markov model transition probabilities are derived from nuclear industry data [13] or inferred from NPP data reports [8], [9], [10]. However, the nuclear industry data only show average failure rates for the CWP system and do not show reliability rates using recurrent event data analysis. This means that the rates from the industry data are constant failure rates that result in exponential distributions of failure times. This is not a valid assumption for modeling the reliability of complex systems and will result in poor decision-making.

Although not shown in the model, Fig. 9 depicts the effect of maintenance on the transition rates. As the system receives more repairs and the VA continues to increase, the transition probabilities will change accordingly. As the system ages, the inter-arrival time between healthy periods will begin to decrease as the VA of the system continues to increase. The transition from healthy to unhealthy will vary depending on the operational history of the system and the number of repairs. This transition rate will be determined using the fitted GRP model discussed previously.

### C. PARAMETER ESTIMATION

Using the reliability data and operational history, data-driven parameter estimations for more accurate transition probabilities have been performed.

#### 1) HEALTHY TO UNHEALTHY

For the healthy to unhealthy transition, $\lambda_{0,1}(t)$, a parameter optimization based on the GRP model was performed to identify the underlying TTE distribution and the effectiveness of maintenance, $q$. To do this, the average time spent in unhealthy periods and during repairs was removed due to the point process assumption (instantaneous repair) required by renewal processes. Once the data were ready, the GRP model parameters were fit to the data using maximum likelihood estimation [41] by maximizing the log-likelihood. A summary of the steps taken when computing the GRP parameters can be seen below:

**Algorithm 1** Fit GRP Parameters to Data

**Data:** Failure and repair times for CWS, $T$
**Output:** GRP Params: $\beta, \lambda, q$

**Function** `LogLikelihood(`$T, \beta, \lambda, q$`)`:
  $T = [t_i, t_{i+1}, \ldots, t_{n-1}, t_n]$
  $X = [t_i, t_{i+1} - t_i, \ldots, t_{n-1} - t_{n-2}, t_n - t_{n-1}]$
  $X = X - \frac{1}{\mu}$ `// subtract time in maintenance`
  $X = X - \frac{1}{\lambda_{1,2}}$ `// subtract time in degraded state`
  $L = LogL(X|\beta, \lambda, q)$
  **return** $-L$
$\beta, \lambda, q$ = minimize(LogLikelihood)

Using the GRP parameters and the log-likelihood, the fit for the model can be compared to other models, such as the RP and NHPP. To do this, the repair effectiveness was fixed to $q = 0$ or $q = 1$ while performing the MLE.

The best fitted model was the GRP model with a log-likelihood of $-36.90$, while the RP and NHPP had log-likelihood values of $-38.22$ and $-37.08$, respectively. The final parameters of the RP, NHPP, and GRP models are listed in Table 1 and Table 2.

**TABLE 1. Optimized parameters estimates for repairable models using MLE.**

| Parameter | RP | NHPP | GRP (Type II) |
|---|---|---|---|
| $\lambda$ | 0.1724 | 0.0800 | 0.0780 |
| $\beta$ | 1.38 | 1.71 | 1.80 |
| $q$ | 0 | 1 | 0.642 |

**TABLE 2. Log-likelihood estimates for each of the repairable models.**

| Model | Log-likelihood |
|---|---|
| RP | -38.22 |
| NHPP | -37.08 |
| GRP (Type II) | **-36.90** |

Since there is no closed-form solution to calculate the mean cumulative intensity function, Monte Carlo simulations were performed to ensure the fit of the GRP model with the actual data. The Monte Carlo simulations were run for 8 years and with 500 pumps. Creating a cumulative intensity function, it can be seen in Fig. 10 that the simulated data using the fitted GRP model performs well when compared to the actual data.

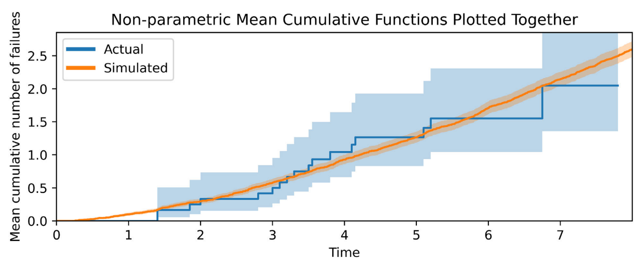


**FIGURE 10. Comparison of the CIFs of actual vs simulated data. The simulated data were created using 500 Monte Carlo simulations of the fitted GRP model.**

### 2) UNHEALTHY TO OFFLINE

The transition from an unhealthy state to an offline state is not a transition probability, but rather a degradation process that can be monitored and modeled as such. In other words, as the level of degradation increases, it approaches a physical level of failure that can be monitored using sensors. This could be an over-current trip, over-temperature trip, or an exceeded level of physical damage, such as a broken shaft.

Modeling this degradation process required establishing a degradation limit. Since data shows the system can operate above $\beta = 3$ and has only been stopped by operator intervention, a slightly higher automatic trip limit has been established. However, since there is limited data to suggest what the exact trip limit would be, the automatic trip-limit has been set to a degradation threshold of $\beta = 5$. A linear fit was performed using the mean time to trip once in an unhealthy phase. The slope of the line was found to be approximately $0.011\beta$ per hour. In addition to the linear line, an added factor of Gaussian noise with zero mean and variance of $\sigma = 0.05$ was used to simulate the stochastic degradation process. Realizations of the beta degradation process can be seen in Fig. 11.

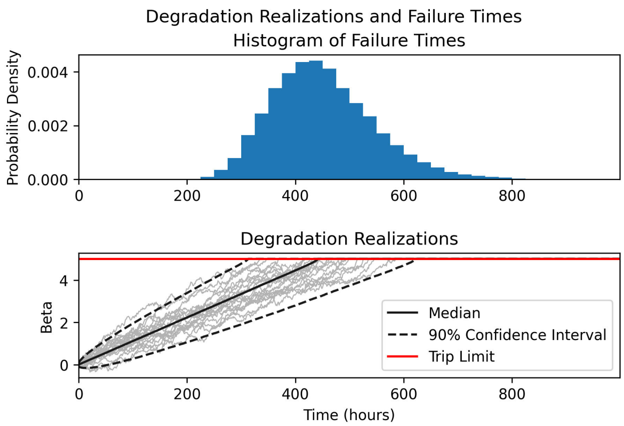


**FIGURE 11.** Realizations of the degradation process plotted with the degradation limit (red), the median, and the 90% confidence interval bounds.

### 3) HEALTHY TO OFFLINE

Although there is condition monitoring data for various fault mechanisms, there is still a possibility from an unknown or unexpected failure. Therefore, a random failure transition has been added that goes directly from a healthy operating condition to an offline state.

The transition from healthy to offline, $\lambda_{0,2}(t)$, can be described as a random failure probability from an unexpected failure mode. The random failure rate is a constant with small probability. For this modeling effort, the random failure rate was estimated at $10^{-6}$ per hour. A plot representing the random failure and the probability density function of expected failure times can be seen in Fig. 12.

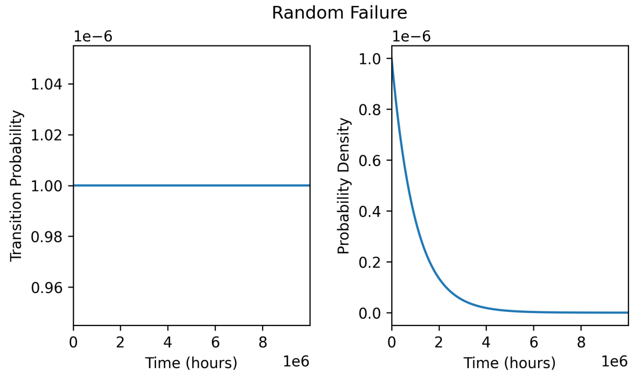


**FIGURE 12.** Random failure rate and the PDF of expected failure date.

### 4) REPAIR RATE

For the rate of repair, the mean of the historical repair times was used to create a Weibull distribution. The Weibull distribution was used due to its improved fit for expected repair duration when compared to an exponential distribution. The previously assumed exponential distribution is a poor fit for repair time data due to the possibility of an immediate repair, which is unlikely. The shape parameter was assumed to be $\beta = 2$, and then, using the mean of 55 hours, the scale parameter was found to be $\lambda = 62.7$. The resulting repair rate and probability density function of expected repair times can be seen in Fig. 13.

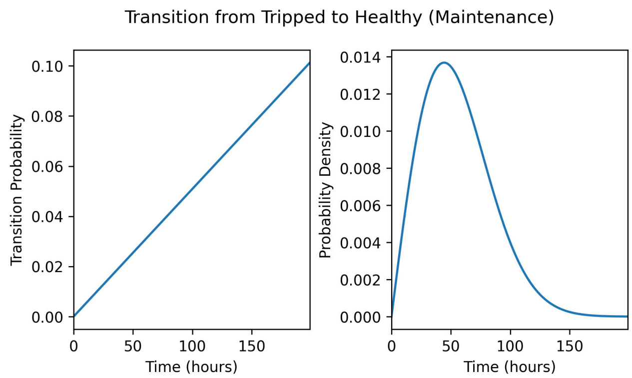


**FIGURE 13.** Repair rate and the probability density function of expected repair date.

## D. ANALYSIS OF PHASED-MISSION SYSTEM PERFORMANCE AND COST COMPARISONS

Once the model parameters were established, the phased-mission system was completed and simulated to analyze its performance.

To calculate the cumulative intensity function for the entire integrated model, Monte Carlo simulations were performed that included the entire phased Markov model with repairs for 8 years, or 70,080 hours. During simulations, repairs were started immediately after the system had reached the degradation limit. There were no delayed maintenance actions, premature shutdowns, or operator interventions, and all failures had reached the degradation limit.

To calculate the cumulative intensity function for a MTBF model, this can be approximated with a linear relationship where the slope of the line represents expected failures per time. The slope of the MTBF line was calculated using the number of failures divided by the total operating time of the pumps. The MTBF for the industry average was also found using the Nuclear Regulatory Commission's Industry Average Parameter Estimation database [13]. The results of the simulations compared to the actual data, the MTBF model, and the industry average MTBF model can be seen in Fig. 14.

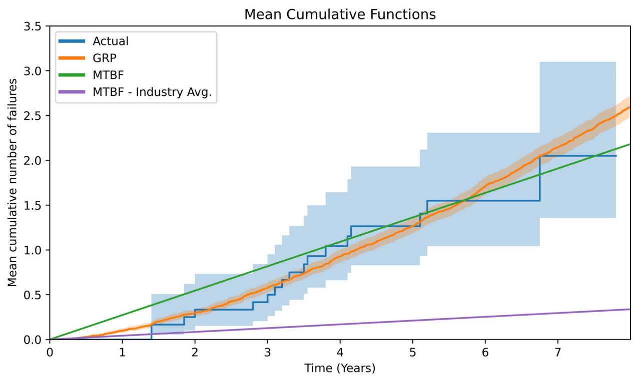


**FIGURE 14.** **The mean cumulative number of events for the actual data, the GRP model, the MTBF model, and the industry average MTBF model.**

In the simulations, the degradation of the CWP and its operational status are illustrated in a snapshot that can be viewed in Fig. 15. Just as an increase in system degradation over time was observed in the data from the plant, the same is reflected by the model.

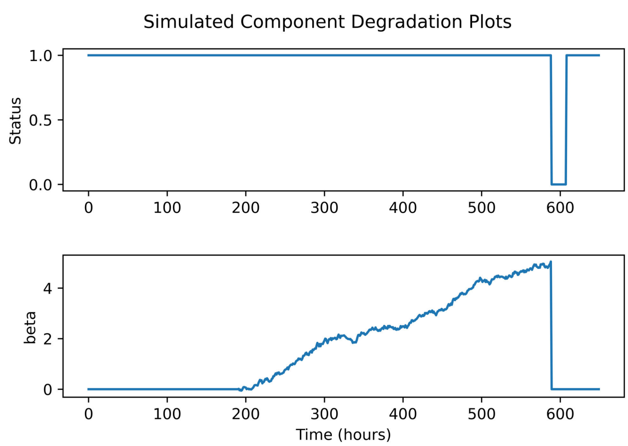


**FIGURE 15.** **A snapshot in time of the degradation process and repair time. The top plot is the operational status of the pump, 1 is operation and 0 is failed/in-repair. The bottom plot is the degradation level of the system.**

The transition probability of major importance is the healthy to unhealthy rate, $\lambda_{0,1}(t)$, that was defined by GRP optimization. As the system continued to age and receive repairs, the VA and corresponding transition probability changed according to the GRP model. A plot showing the VA and the transition probability as it changed over the course of the simulation can be seen in Fig. 16, when maintenance occurred as drops in VA and transition probability.

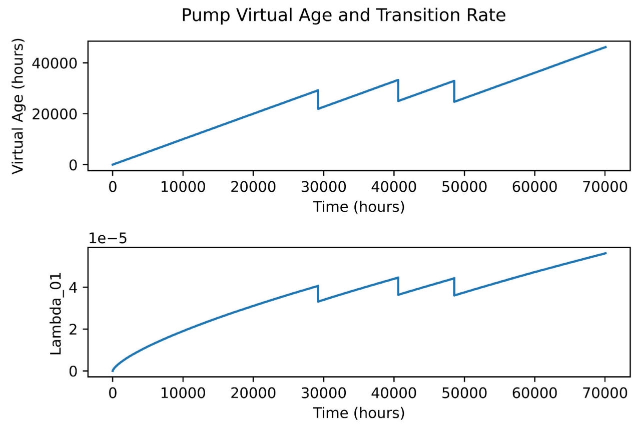


**FIGURE 16.** **Plots of the simulation results for one system. The top plot is the VA of the system and the bottom plot shows the corresponding transition probability from healthy to unhealthy, $\lambda_{0,1}(t)$.**

Further simulations were conducted with a group of 12 CWPs operated for a period of 8 years to replicate real operational and failure data observed in the NPP. The events that occurred can be seen in comparison with the actual data in the form of an abacus and CIF plots in Fig. 17. Since the currently operating CWPs have various ages and operational history, the collected data is censored. This means that the CWP did not fail at the end of the data collection period. This can mean CWP was replaced without failure at the end of its life or the CWP is still operational. To recreate a similar abacus plot, the simulated data were censored with the same dates as the actual data for more similar representation and comparison.

### *E. OPTIMIZATION OF REPLACEMENT INTERVAL*

Although this work is focused on the application of condition-based decision-making, the current maintenance strategy of many operating plants is still schedule-based and can be optimized further, or at least validated, with the created GRP models. For most of this plant's operational life, the replacement of the CWPs occurred every 6 years, regardless of condition. Recent work, using MTBF models, has led to a suggested extension of this interval from 6 years to 9 years [10]. Using the created GRP model and adding cost information from the plant, the interval extensions can be validated. Furthermore, the model can be used to investigate the effect of extending the interval even further and its impact on the TCO.

To do this, Monte Carlo simulations were performed with the CWP model combined with a simple reactive maintenance strategy. The maintenance policy repaired the

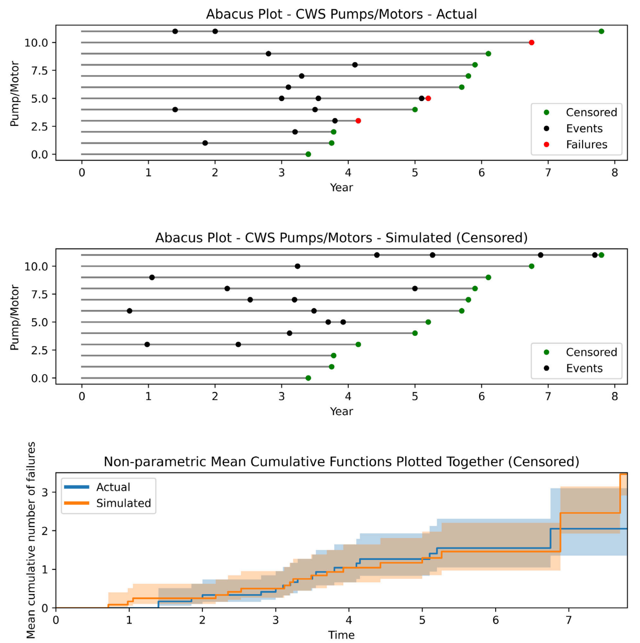


**FIGURE 17. The top two plots show the individual systems as abacus plots, comparing the actual data to the simulated data with one instance of manually censored data. The bottom plot compares the cumulative intensity functions between the actual and simulated data.**

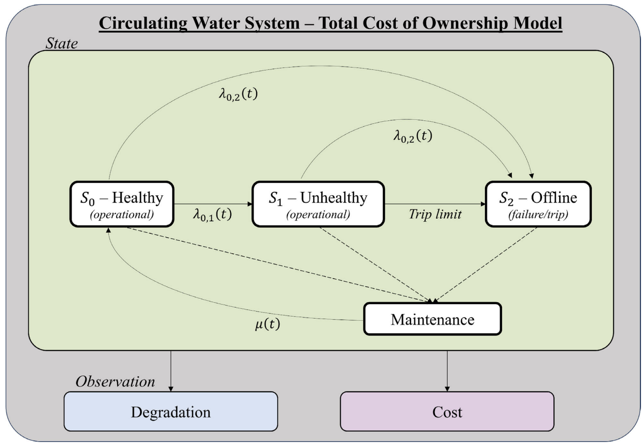


**FIGURE 18. A representation of the circulating water system total cost of ownership model. The state dynamics are modeled using a hybrid Markov and phased-mission system framework where the transitions are determined using data-driven methods. The observation of the state is an estimate of the degradation level that is dependent on the state. The costs are determined by historical estimates of hourly costs multiplied by the time spent in each state.**

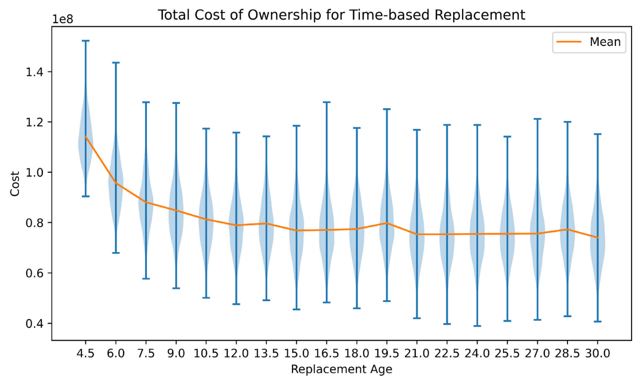


**FIGURE 19. The economic cost analysis was completed with Monte Carlo simulations performed using the completed model and varying lengths of replacement intervals. The blue lines represent the distribution of the simulated costs and the orange line is the expected value.**

system as needed and replaced the system every $X$ number of years, during an outage. For this analysis, the replacement interval was varied from 4.5 to 27 years, aligning with outages that occurred every 1.5 years. The costs used in this analysis were actual historical costs from the plant for labor, materials, foregone revenue due to inoperable CWP (plant derating), and replacement/overhaul costs. The dollar amounts for each of these costs are listed in Table 3 and a graphical representation of the completed degradation model with the corresponding transition rates, observations, and costs can be seen in Fig. 18.

**TABLE 3. Costs for decisions and time spent performing actions.**

| Description | Cost |
|---|---|
| foregone revenue | \$3,127 /hour |
| labor | \$100 /hour |
| materials | \$333 /hour |
| replacement | \$500,000 |

Using the model and integrated costs, instances of the repairable CWP were simulated, each with a length of 60 years, typical for an extended-life NPP. Fig. 19 shows a significant amount of uncertainty over a period of 60 years, but there is a trend of reduced costs that improves as the replacement interval is increased.

Through this analysis, as shown in Fig. 20, extending the replacement interval results in lower TCO. The results indicate that previous efforts to extend the replacement interval from 6 to 9 years have been validated. Fig. 20 shows the percentage change when extending from a 6 year replacement interval. This extended replacement interval, for 12 pumps over 60 years, can be expected to reduce costs by 10.7%, or approximately \$10 million. If the replacement interval is extended even longer to 12 or 15 years, expected savings can be upwards of 17.2% or 19.2%, respectively. These results are summarized in Table 4. However, it should be noted that while the model can be used to forecast extended replacement intervals, extensive data has not been collected at these interval lengths to verify this claim since CWPs have been replaced historically every 6 years. Additional studies would be needed to confirm this hypothesis.

### *F. REPAIR EFFECTIVENESS*

One of the main benefits of using the GRP model is its ability to quantify repair effectiveness. Once a GRP model is fit to the data, this enables the evaluation of repair effectiveness on the overall performance and degradation

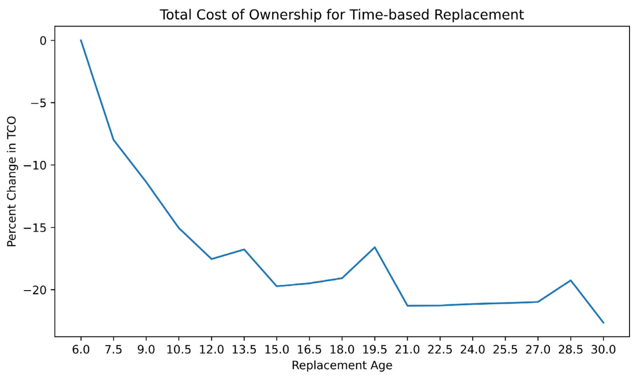


**FIGURE 20.** This plot shows the expected percent reduction in TCO for 12 CWPs over a 60-year period. The percent reduction is in reference to the historical, 6-year replacement interval. The TCO goes down the longer you extend the life of the CWP. The spikes in TCO, seen in years 13.5, 19.5, and 28.5, are due to the operating life being 60 years and the replacement intervals, resulting in a recently replaced CWP just before the end of plant life.

**TABLE 4.** Reduction in TCO when extending replacement interval past 6 years.

| CWP Replacement interval | Reduction in TCO |
|---|---|
| 6 | - - |
| 9 | 10.7% |
| 12 | 17.2% |
| 15 | 19.2% |

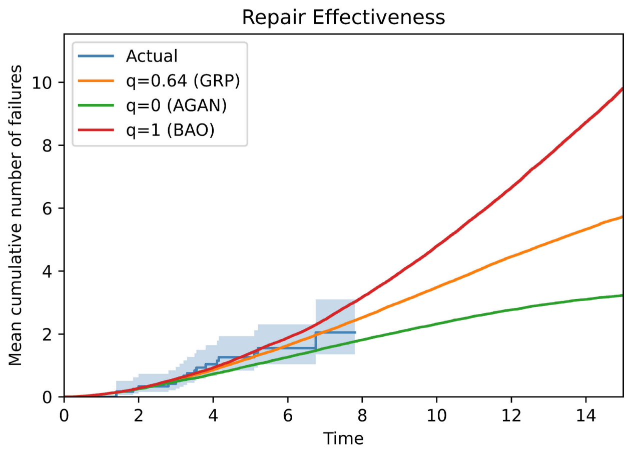


**FIGURE 21.** The differences in repair effectiveness can vary greatly over time and have a profound impact on the number of failures expected during operation of the CWS. The AGAN condition returns the CWS to perfect condition and results in a minimal number of failures, while the BAO repair assumption sees an increasing number of failures.

trajectory of the system. As NPPs are constantly evaluating maintenance practices and improving performance, a balance can be found where the cost of maintenance is balanced with the effectiveness of repair, and ultimately, the reliability of the system. By varying the repair effectiveness variable, $q$, simulations can show how this affects the expected number of failures in the CWS. A plot of the resulting change in the number of expected cumulative failures over time, as a function of varying repair effectiveness, can be seen in Fig. 21.

From the plot, the differences in repair effectiveness become vastly different as the CWS begins to age and the expected number of failures increases with the BAO repair assumption and decreases with the AGAN or perfect repair assumption. This is due to the fact that the AGAN returns the CWS to perfect condition while the BAO does not restore any health or reliability to the system.

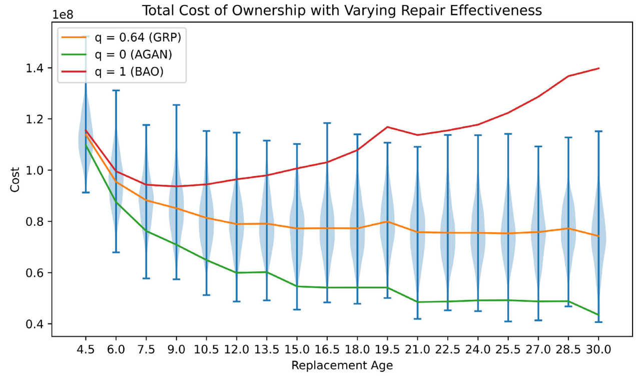


**FIGURE 22.** The change in TCO compared for different values of repair effectiveness.

## IV. CONCLUSION

This article presented the development of a hybrid reliability model for the CWS in an NPP that incorporated repair and failure history, condition monitoring, and the quantification of maintenance effectiveness. When compared to commonly used risk-based models, such as MTBF, the developed model using GRP provides a more complete reliability model that can be used to estimate the likelihood of failure given the maintenance history of an asset.

After fitting the model to the plant data, numerical simulations have shown that the replacement interval used in the current time-based maintenance strategy can be extended to reduce the TCO by more than 10%. These results also validate recent findings in which the replacement interval was increased from 6 years to 9 years in an effort to reduce costs [10]. Simulations indicate that the replacement interval could be extended even further than 9 years while still expecting cost reductions; however, this conclusion should be considered to have uncertainty due to the lack of data with a replacement interval greater than 7 years.

Although assumptions to create the model were limited, uncertainty in the results could still be reduced. As the replacement interval is extended in the future, the data created will need to be analyzed to ensure the model's accuracy when extrapolated. The model could then be fitted to the new data to improve accuracy. Uncertainty could be further reduced with more data that supports higher fidelity models. Examples of this would be specific data to support independent failure modes, different types of repair and the corresponding repair effectiveness, and data from multiple plants. However, although there remains uncertainty, a simple model allows for the transfer to a multitude of systems that undergo repair. Given the numerous types of SSCs that make up an NPP, the developed model provides a risk estimation improvement at a large scale. Future research directions include the expansion of this model to more components and systems, and the analysis of the CWS data after replacement cycles have been extended.

In conclusion, the results of the GRP model are promising as they provide more accurate modeling and simulation when compared to current risk-based approaches. As critical systems in nuclear power continue to age and more data is generated, an analysis should be performed with the best models the data can support. Given the availability of current data that can support a GRP model, there is significant potential to improve risk-informed decision-making and reduce maintenance costs across the nuclear industry.

## REFERENCES


[1] *Nuclear Power Economics | Nuclear Energy Costs—World Nuclear Association*. Accessed: Oct. 1, 2022. [Online]. Available: https://www.world-nuclear.org/information-library/economic-aspects/economics-of-nuclear-power.aspx

[2] Energy Information Administistration (EIA). (Jan. 2021). *Wholesale US Electricity Prices Were Generally Lower and Less Volatile in 2020 Than 2019*. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=46396

[3] A. G. Jacopino, *Generalisation and Bayesian Solution of the General Renewal Process for Modelling the Reliability Effects of Imperfect Inspection and Maintenance Based on Imprecise Data*. College Park, MD, USA: Univ. Maryland, 2005.

[4] J. Zhang, Y. Jiang, X. Li, H. Luo, S. Yin, and O. Kaynak, "Remaining useful life prediction of lithium-ion battery with adaptive noise estimation and capacity regeneration detection," *IEEE/ASME Trans. Mechatronics*, vol. 28, no. 2, pp. 632–643, Apr. 2023.

[5] J. Zhang, C. Huang, M.-Y. Chow, X. Li, J. Tian, H. Luo, and S. Yin, "A data-model interactive remaining useful life prediction approach of lithium-ion batteries based on PF-BiGRU-TSAM," *IEEE Trans. Ind. Informat.*, pp. 1–11, Apr. 2023, doi: 10.1109/TII.2023.3266403.

[6] J. Zhang, J. Tian, A. M. Alcaide, J. I. Leon, S. Vazquez, L. G. Franquelo, H. Luo, and S. Yin, "Lifetime extension approach based on Levenberg–Marquardt neural network and power routing of DC–DC converters," *IEEE Trans. Power Electron.*, vol. 38, no. 8, pp. 10280–10291, May 2023, doi: 10.1109/TPEL.2023.3275791.

[7] R. Appiah, M. Muhlheim, P. Ramuhalli, J. Nistor, T. Gruenwald, C. M. Walker, and V. Agarwal, "Development of a cloud-based application to enable a scalable risk-informed predictive maintenance strategy at nuclear power plants," Idaho National Lab. (INL), Idaho Falls, ID, USA, Tech. Rep. INL/RPT-22-70543-Rev000, 2022.

[8] *Integrated Risk-Informed Condition Based Maintenance Capability and Automated Platform: Technical Report 1 (PKM-DOC-20-0013)*, PKMJ Tech. Services, LLC, Idaho Nat. Lab., Public Service Enterprise Group (PSEG) Nuclear, LLC, Falls, ID, USA, 2020.

[9] V. Agarwal, K. A. Manjunatha, J. A. Smith, A. V. Gribok, V. Yadav, H. Palas, M. Yarlett, N. Goss, S. Yurkovich, B. Diggans, N. J. Lybeck, M. Pennington, and N. Zwiryk, "Machine learning and economic models to enable risk-informed condition based maintenance of a nuclear plant asset," Idaho Nat. Lab. (INL), Idaho Falls, ID, USA, Tech. Rep. INL/EXT-21-61984-Rev000, 2021. [Online]. Available: https://www.osti.gov/biblio/1770866

[10] *Integrated Risk-Informed Condition Based Maintenance Capability and Automated Platform: Technical Report 3 (PKM-DOC-21-0007)*, PKMJ Tech. Services, LLC, Idaho Nat. Lab., Public Service Enterprise Group (PSEG) Nuclear, LLC, Falls, ID, USA, 2021.

[11] E. Kee, A. Sun, A. Richards, J. Liming, J. Salter, and R. Grantom, "Using risk-informed asset management for feedwater system preventative maintenance optimization," *J. Nucl. Sci. Technol.*, vol. 41, no. 3, pp. 347–353, Mar. 2004.

[12] M. Xiliang and X. Yongkui, "Study on maintenance strategy optimization of nuclear power plants after the implementation of maintenance rule," in *Proc. Int. Conf. Nucl. Eng.*, vol. 86489, 2022, Art. no. V013T13A046.

[13] NRC. *Industry Average Parameter Estimates*. Accessed: Aug. 1, 2022. [Online]. Available: https://nrcoe.inl.gov/AvgPerf/

[14] M. Muhammad, M. A. Abd Majid, and N. A. Ibrahim, "A case study of reliability assessment for centrifugal pumps in a petrochemical plant," in *Engineering Asset Lifecycle Management*. Berlin, Germany: Springer, 2010, pp. 398–404.

[15] W. Kahle and C. E. Love, "Modeling the influence of maintenance actions," in *Mathematical and Statistical Methods in Reliability*. Singapore: World Scientific, 2003, pp. 387–399.

[16] M. Tanwar, R. N. Rai, and N. Bolia, "Imperfect repair modeling using Kijima type generalized renewal process," *Rel. Eng. Syst. Saf.*, vol. 124, pp. 24–31, Apr. 2014.

[17] M. Soleimani, M. Pourgol-Mohammad, A. Rostami, and A. Ghanbari, "Design for reliability of complex system: Case study of horizontal drilling equipment with limited failure data," *J. Quality Rel. Eng.*, vol. 2014, pp. 1–13, Nov. 2014.

[18] R. E. Barlow and F. Proschan, *Statistical Theory of Reliability and Life Testing: Probability Models*, vol. 1. New York, NY, USA: Holt, Rinehart and Winston, 1975.

[19] V. V. Krivtsov, "Practical extensions to NHPP application in repairable system reliability analysis," *Rel. Eng. Syst. Saf.*, vol. 92, no. 5, pp. 560–562, May 2007. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S095183200600113X

[20] W. Thompson, *Point Process Models With Applications to Safety and Reliability*. Berlin, Germany: Springer, 2012.

[21] D. R. Cox and P. A. Lewis, *The Statistical Analysis of Series of Events*. Berlin, Germany: Springer, 1966.

[22] L. H. Crow, "Reliability analysis for complex repairable systems," *Rel. Biometry*, vol. 13, no. 6, pp. 379–410, 1974.

[23] M. Kaminskiy and V. Krivtsov, "G1-renewal process as repairable system model," *Rel., Theory Appl.*, vol. 5, no. 3, pp. 7–14, 2010.

[24] M. Kijima and U. Sumita, "A useful generalization of renewal theory: Counting processes governed by non-negative Markovian increments," *J. Appl. Probab.*, vol. 23, no. 1, pp. 71–88, Mar. 1986.

[25] Y. Fu and J. Wang, "Optimum periodic maintenance policy of repairable multi-component system with component reallocation and system overhaul," *Rel. Eng. Syst. Saf.*, vol. 219, Mar. 2022, Art. no. 108224.

[26] L. Doyen, R. Drouilhet, and L. Brenière, "A generic framework for generalized virtual age models," *IEEE Trans. Rel.*, vol. 69, no. 2, pp. 816–832, Jun. 2020.

[27] L. Brenière, L. Doyen, and C. Bérenguer, "Optimization of preventive replacements dates and covariate inspections for repairable systems in varying environments," *Eur. J. Oper. Res.*, vol. 308, no. 3, pp. 1126–1141, Aug. 2023.

[28] A. Deep, S. Zhou, and D. Veeramani, "A data-driven recurrent event model for system degradation with imperfect maintenance actions," *IISE Trans.*, vol. 54, no. 3, pp. 271–285, 2022.

[29] Z. Wang and R. Pan, "Point and interval estimators of reliability indices for repairable systems using the Weibull generalized renewal process," *IEEE Access*, vol. 9, pp. 6981–6989, 2021.

[30] W. Si, Q. Yang, L. Monplaisir, and Y. Chen, "Reliability analysis of repairable systems with incomplete failure time data," *IEEE Trans. Rel.*, vol. 67, no. 3, pp. 1043–1059, Sep. 2018.

[31] R. Guo, H. Asher, and E. Love, "Generalized models of repairable systems: A survey via stochastic processes formalism," *ORiON*, vol. 16, no. 2, pp. 87–128, Jan. 2014.

[32] T. Koutsellis, Z. P. Mourelatos, and Z. Hu, "Numerical estimation of expected number of failures for repairable systems using a generalized renewal process model," *ASCE-ASME J. Risk Uncertainty Eng. Syst., B, Mech. Eng.*, vol. 5, no. 2, Jun. 2019, Art. no. 020904.

[33] J. R. Norris, *Markov Chains*, vol. 2. Cambridge, U.K.: Cambridge Univ. Press, 1998.

[34] H. Guo, A. Mettas, and A. Monteforte, "Reliability evaluation and application for systems with different phases," in *Proc. Annu. Rel. Maintainability Symp.*, 2008, pp. 1–7.

[35] R. J. Cook and J. F. Lawless, *The Statistical Analysis of Recurrent Events*. Berlin, Germany: Springer, 2007.

[36] W. B. Nelson, *Recurrent Events Data Analysis for Product Repairs, Disease Recurrences, and Other Applications*. Philadelphia, PA, USA: SIAM, 2003.

[37] E. Seneta, *Non-Negative Matrices and Markov Chains*. Berlin, Germany: Springer, 2006.
[38] G. Bolch, S. Greiner, H. De Meer, and K. S. Trivedi, *Queueing Networks and Markov Chains: Modeling and Performance Evaluation With Computer Science Applications*. Hoboken, NJ, USA: Wiley, 2006.
[39] J. González-Domínguez, G. Sánchez-Barroso, and J. García-Sanz-Calcedo, "Scheduling of preventive maintenance in healthcare buildings using Markov chain," *Appl. Sci.*, vol. 10, no. 15, p. 5263, Jul. 2020.
[40] A. Mettas, "Different analysis procedures for computing the reliability of repairable systems," *J. KONBiN*, vol. 25, no. 1, pp. 129–144, 2013.
[41] A. Mettas and W. Zhao, "Modeling and analysis of repairable systems with general repair," in *Proc. Annu. Rel. Maintainability Symp.*, 2005, pp. 176–182.
[42] H. Pham and H. Wang, "Imperfect maintenance," *Eur. J. Oper. Res.*, vol. 94, no. 3, pp. 425–438, 1996.
[43] M. Kijima, "Some results for repairable systems with general repair," *J. Appl. Probab.*, vol. 26, no. 1, pp. 89–102, Mar. 1989.
[44] B. Veber, M. Nagode, and M. Fajdiga, "Generalized renewal process for repairable systems based on finite Weibull mixture," *Rel. Eng. Syst. Saf.*, vol. 93, no. 10, pp. 1461–1472, Oct. 2008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0951832007002499
[45] M. S. Finkelstein, "The concealed age of distribution functions and the problem of general repair," *J. Stat. Planning Inference*, vol. 65, no. 2, pp. 315–321, Dec. 1997.

**RYAN M. SPANGLER** received the B.S. degree in mechanical engineering from the University of Pittsburgh, Pittsburgh, PA, USA, in 2018, where he is currently pursuing the Ph.D. degree in mechanical engineering.

His Ph.D. research focuses on operations and maintenance decision-making for low-volume and high-value systems in nuclear power plants using deep reinforcement learning. He is currently with the Idaho National Laboratory, Department of Instrumentation, Controls, and Data Science, as an Applied Nuclear Data Scientist. His research interests include risk-informed decision-making, prognostics and health management, predictive maintenance, machine-learning, artificial intelligence, and control systems. In these domains, he is exploring techniques to reduce operating costs, enhance decision-making, and facilitate the integration of machine-learning and artificial intelligence in the nuclear power industry.

Mr. Spangler was awarded the Research Assistant of the Year Award, in 2023, from the Department of Mechanical Engineering and Material Science, University of Pittsburgh. He holds the position of the Student Representative Chair of the Human Factors and Instrumentation and Controls Division of the American Nuclear Society. Additionally, he has served as the Vice President for the American Nuclear Society's University of Pittsburgh Section.

**VIVEK AGARWAL** received the B.E. degree in electrical engineering from the University of Madras, Chennai, India, in 2001, the M.S. degree in electrical engineering from the University of Tennessee, Knoxville, TN, USA, in 2005, and the Ph.D. degree in nuclear engineering from Purdue University, West Lafayette, IN, USA, in 2011.

He is currently a Senior Research Scientist with the Idaho National Laboratory, Department of Instrumentation, Controls, and Data Science. He has authored 30 journal articles, about 70 peer-reviewed conference articles, and coauthored a book chapter on diagnosis and prognosis in nuclear power. He has a U.S. patent and has had several software copyrights issued. His current research interests include interdisciplinary, ranging from prognostics health management, wireless sensor networks, instrumentation and controls, mathematical modeling, computer vision, signal/image processing, and nuclear engineering.

Dr. Agarwal was awarded the 2015 Presidential Early Career Awards for Scientists and Engineers, the 2019 American Nuclear Society Ted Quinn Early Career Award, and the 2016 Laboratory Director Early Career Achievement Award. He is also the Publication Chair of the American Nuclear Society's Human Factors and Instrumentation and Controls Division and a Secretary of the American Society of Mechanical Engineer's Nondestructive Prognostics and Diagnostics Division. He is on the editorial board of the *Journal of Pattern Recognition Research*.

**DANIEL G. COLE** (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in mechanical engineering from Virginia Tech, in 1991, 1992, and 1998, respectively. He is currently an Associate Professor with the Department of Mechanical Engineering and Materials Science, Swanson School of Engineering, University of Pittsburgh. His research interests include advanced control-theoretic techniques to improve operation, maintenance, and control of nuclear power plants. This work has focused on methods of condition monitoring of plant components and he has used AI and machine-learning for decision-making and asset management of the low-volume and high-value systems in nuclear power plants. This work on nuclear power has led his research to the security of our critical infrastructure—In particular our networked industrial control systems. In these efforts, he is investigating how to choose strategies to protect our infrastructure, determine avenues of attack, detect and mitigate threats, and secure cyber-physical systems. In this highly interdisciplinary field, he is working to create opportunities for industry-university collaborations with pitt and area stakeholders.