Scalable Risk-Informed Predictive Maintenance Strategy for Operating Nuclear Power Plants

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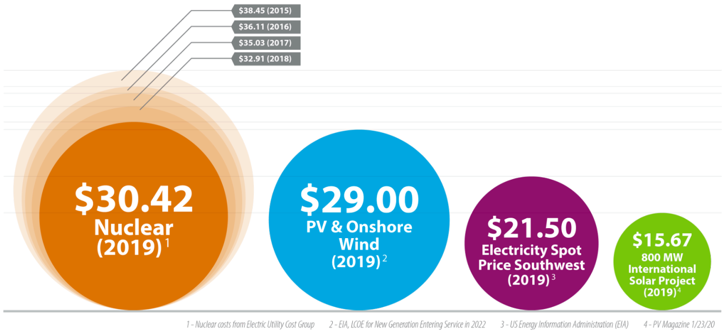
Abstract: Over the years, the nuclear fleet has relied on labor-intensive, time-consuming preventive maintenance programs, driving up operation and maintenance costs to achieve high capacity factors. The primary objective of the research presented in this paper is to develop scalable technologies deployable across plant assets and the nuclear fleet in order to achieve a risk-informed predictive maintenance (PdM) strategy at commercial nuclear power plants (NPPs). We developed a well-constructed risk-informed PdM approach for an identified plant asset in this research, taking advantage of advancements in data analytics, machine learning, artificial intelligence, risk models, and visualization. The demonstration and deployment of these technologies would allow commercial NPPs to reliably transition from the current labor-intensive preventive maintenance program to a technology-driven PdM program, eliminating unnecessary operation and maintenance costs. The research and development approach presented in the paper is being developed as part of a collaborative research effort between Idaho National Laboratory and Public Service Enterprise Group Nuclear LLC. This paper presents a scalable risk-informed predictive maintenance framework with a brief discussion on scalable predictive modeling approach using the federate-transfer learning approach. The paper describes component to plant-level risk modeling based on a three-state Markov chain and its integration with circulating water system health information using the proportional hazard modeling approach. The state probabilities obtained are used to estimate the profit as part of the economic model. The paper also outlines the development of a user-centric visualization application to ensure the right information is available to the right person, in the right format, and at the right time. The research outcomes presented in this paper lay the foundation and provide a much-needed technical basis to start focusing on additional needs, such as the explainability and trustworthiness of machine-learning- and artificial-intelligence-based technologies as part of future research.

1. INTRODUCTION

Sustaining the value of the United States (U.S.) nuclear power fleet can be achieved through cost-effective, reliable operation, managing obsolescence, and diversifying revenue. Many of the currently operating plants in the U.S. are in their first period of extended operations (i.e., 40-60 years), and several of them have already received or have applied for subsequent license renewal (60-80 years). The current fleet's long-term safe and economical operation can be achieved by developing, demonstrating, and deploying technologies; ensuring the reliable operation, effective maintenance, and monitoring of vital structures, systems, and components; and presenting viable economics in competing energy market.

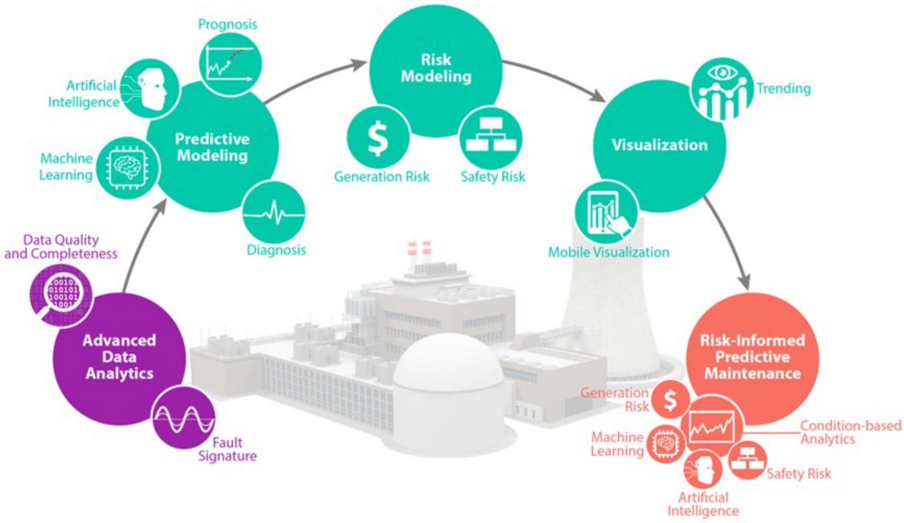
Most of the operating costs of the current fleet are due to high operation and maintenance (O&M) costs. There is an immediate need to reduce the O&M costs associated with the current domestic fleet of nuclear power plants (NPPs). Operating in a market selling wholesale electricity for $22/MWh becomes unsustainable with current (as of 2019) total average operating costs for the entire fleet at $30.42/MWh (Figure 1). Prices for producing energy with nuclear plants have reduced since 2015 (Figure 1) but remain high compared to other energy sources. In addition, the global energy market trends are heavily driven by the abundant reserves of natural gas and declining costs of renewable energy systems.

Figure 1. Total average operating costs ($/MWhr) for different energy sources.



Nuclear O&M costs involve manually performed preventive maintenance (PM) activities, such as the inspection, calibration, testing, and maintenance of plant assets at periodic frequencies, along with the time-based replacement of assets, irrespective of condition. This has resulted in a costly, *labor-centric business model.* Fortunately, technologies exist (advanced sensor, data analytics, and risk assessment methodologies) that enable the transition to a *technology-centric business model* that will significantly reduce PM activities. Part of the transition is to a technology-driven predictive maintenance (PdM) program (see Figure 2), thus eliminating unnecessary O&M costs.

Figure 2. A risk-informed PdM strategy.



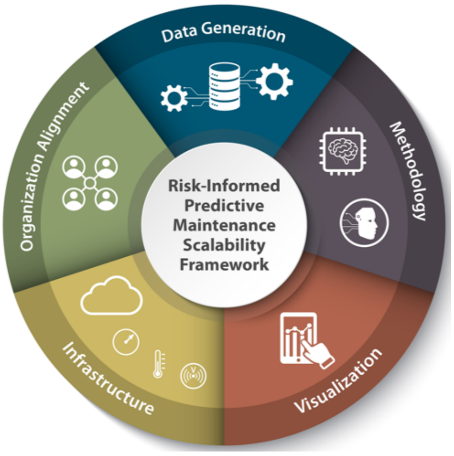
The risk-informed PdM strategy (Figure 2) [1] includes advanced data analytics, predictive analytics, risk modeling economic modeling, and visualization. The framework to scale the risk-informed PdM strategy (Figure 3) [2], presented in this paper was developed and demonstrated on a circulating-water system (CWS) at the Public Service Enterprise Group Nuclear LLC (PSEG) owned NPPs. Specifically, this paper focuses on methodology and visualization elements of the framework. The CWS, an important non-safety-related system, is omnipresent across the fleet of existing light-water reactors (LWRs). Traditionally, most PdM approaches in the nuclear industry are developed at the component level [3–6]. These approaches [3–6] are not holistic and present challenges when scaled to the system or plant level. Furthermore, they prevent NPP sites from reaping the maximum benefits in terms of automation, optimization of labor and material resources, cost savings, etc. The research approach presented in this paper addresses these limitations.

In this paper, Section 2 presents the framework to scale the risk-informed PdM strategy. Section 3 briefly describes the CWS and data collected. The scalable predictive model developed using CWS data is based on a federated-transfer learning (FTL) approach. Section 4 talks about risk and economic models. Section 5 briefly discusses the user-centric visualization schema for decision-making. Finally, conclusions and path forward are presented in Section 6.

2. FRAMEWORK TO SCALE RISK-INFORMED PREDICTIVE MAINTENANCE STRATEGY

Optimization and automation of maintenance activities can be accomplished by transitioning to a risk-informed PdM strategy [1] and is an essential part of the industry's strategy for modernizing and sustaining the existing fleet of operating LWRs. The implementation of technologies to ensure scalability across plant systems and the nuclear fleet is critical to the deployment of a risk-informed PdM strategy at commercial NPPs [2]. There are many ways to define and understand scalability but for our purposes, *scalability is expanding the capabilities of a target entity to meet current and future application-specific requirements*. Here entity refers to the elements of the suggested framework in Figure 3: data generation and governance, methodologies, visualization, infrastructure, and organization alignment. The following subsections take a deeper look at these elements (except organizational alignment). All framework elements must be reliable, acceptable, maintainable, and secure. In addition, each element should be flexible, modular, a certain level of redundant, and simple.

Figure 3. A framework to scale risk-informed PdM strategy.



2.1. Data Generation and Governance

Data is the engine of any PdM program. As mentioned in Reference [6], PSEG's two plants sites, Salem and Hope Creek NPPs collects a wide range of data on the CWS, including data from recently installed wireless vibration sensor nodes. In addition to the volume of data, the collection and storage of heterogeneous data, each having its own unique data structure, presents a challenge. Therefore, there must be a technology in place to collect, process, prepare and structure the massive amounts of data that will be stored in the organization's ecosystem. Once the technology is in place, it is important to develop and implement data governance for managing the data through its lifecycle. The data governance must incorporate data security, network security policies, access limitations to prevent unauthorized users, and ongoing processes to detect vulnerabilities. The technology supporting data generation must follow a standard. This is one of the ways to ensure its universal acceptance across plant systems and the nuclear fleet.

2.2. Methodologies

Once data is streaming in from plant assets, machine learning (ML) and artificial intelligence (AI) can be applied in real time to learn data patterns and develop predictive models. There are many ML and AI algorithms, and it is important to select the right algorithms to perform diagnosis (early detection of degradation) and prognosis (prediction of the future state of the plant asset based on the diagnosis and operating conditions). ML and AI algorithm selection depends on the application and data types. For example, the ML and AI algorithms used to develop predictive analytics for the CWS in PSEG-owned plants might not be directly applicable to their service water or feedwater and condensate systems. It is important to address this issue to ensure the scalability of developed methodologies. A database of ML and AI algorithms will enable plant sites to choose an algorithm based on the application, data type, and performance metric of interest (e.g., accuracy, execution time, or ease of implementation). On a similar note, the development of risk models (with a focus on either safety or generation) depends on the classification of the plant asset (safety versus non-safety), failure mode, and significance of its contribution to the top event (as determined from cut sets in a probabilistic risk assessment). To ensure correctness, the risk assessment tool must be comprehensive and capable of incorporating dynamic information related to the plant asset age and degradation.

2.3. Visualization

The risk-informed PdM outcomes allow plant operators to make effective decisions. Visualization tools will enable plant operators and monitoring and diagnostic center experts to make informed decisions quickly and efficiently. In the nuclear industry, visualization has historically been restricted to standard static conventional methods (e.g., tables, histograms, timelines, Venn diagrams, frequency spectrum, power spectral density). There is a growing emphasis on presenting information through interactive visualizations in a readily digestible format. There is no existing standard or style guide for the visualization of risk-informed predictive analytics in the nuclear industry. Therefore, it is necessary to develop interactive visualization techniques and lay the groundwork to standardize information visualization techniques to benefit plant operators. The developed interactive visualizations and standards must be consistent across different platforms (i.e., monitor displays to handheld displays) to ensure a smooth user experience.

2.4. Infrastructure

Given the technologies to collect, process, and store data are in place to support development of predictive analytics and visualization, it is important for plant owners to ensure they have a platform in place to integrate them. For example, to avoid delays, the outcomes of predictive analytics should be integrated with enterprise resource planning to ensure work orders and work packages are issued automatically, the needed parts are secured in timely manner, and plant personnel responsible for execution of the work package are informed automatically. The chosen platform must be agile and open. To ensure this is the case, a detailed requirements document must be developed, including functional requirements, external interfaces (people, system hardware, and additional software), nonfunctional requirements (speed, availability, security, communication protocol), and use cases for all new user interfaces. To ensure the platform works seamlessly across plant systems, a secure and safe communication infrastructure must exist. The platform must be dynamically supported and able to promptly incorporate software and technological advancements.

2.5. Organization Alignment

The transition from an established PM program to a new risk-informed PdM program triggers culture change, one of the most challenging hurdles to overcome. For a smooth transition, organizations must communicate early and clearly their intentions throughout the organization for honest feedback.

3. PREDICTIVE MODELING USING FEDERATED-TRANSFER LEARNING APPROACH

In this section, we present a brief description of predictive modeling using an FTL approach. For details, refer to Reference [7]. The FTL approach allows predictive models to be scalable across plant assets and the fleet. The data from the CWS is used to develop the FTL-based predictive models.

3.1. Circulating-Water System

To develop initial scalable methods and models, we selected the CWS at two NPPs as the identified plant asset. The CWS is an important non-safety-related system. As the heat sink for the main steam turbine and associated auxiliaries, the CWSs at PSEG-owned plants maximize steam power cycle efficiency [8]. A CWS consists of [8]:

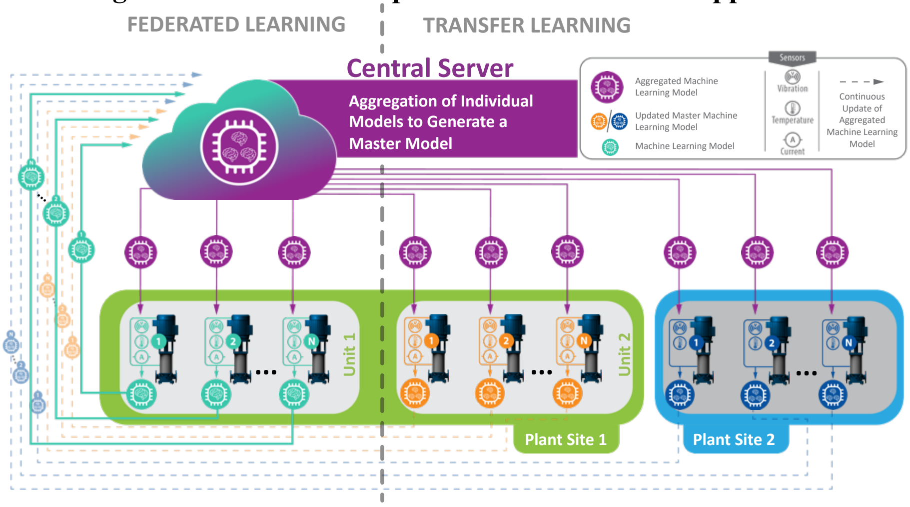
- Vertical, motor-driven circulating pumps (e.g., "circulators"), each with an associated fixed trash rack and traveling screen at the pump intake to filter out debris and marine life
- Main condenser (tube side only)
- Condenser waterbox air removal system
- Circulating-water sampling system
- Screen wash system
- Necessary piping, valves, instrumentation, and controls to support system operation.

Data collected from the plant system contain metadata related to plant processes, maintenance logs, operator logs, and condenser information. Typical plant process data relevant to the CWS include gross load, river inlet and outlet temperatures and motor-related information, such as on-off duration and status, motor current, and temperature measurements at the motor stator and bearings. Condenser data include condenser backpressure, exhaust temperature, exhaust hood temperature, condensate hotwell temperature, and vacuum pump status. Additional data sets include river level, inlet, and outlet, operator actions, discharge header pressure, and ambient air temperature.

3.2. Federated-Transfer Learning

This section describes a learning approach to scale ML models developed at a component level to the system level, and even to the plant-level, that can be leveraged across the fleet of LWRs. Here we discuss two approaches, federated learning (FL) [9] and transfer learning (TL) [10], that focus on: (1) developing an individual component-level model using component-specific available data sources, (2) consolidating the knowledge gained from individual component models for a given plant asset into a master model, (3) using the master model for diagnostic and prognostic estimations of the entire system, and (4) applying (i.e., transferring) the master model for diagnostic and prognostic estimations of a similar plant system at either the same or different plant site. The FTL approach is schematically shown in Figure 4.

Figure 4. A schematic representation of the FTL approach.



FL, a collaborative learning method where many clients (e.g., circulating water pumps [CWPs] as seen in Figure 4) collaboratively train a model under the orchestration of a central controller without exchanging a user's original data. FL enables focused data collection and minimization by reducing systematic privacy risks and costs resulting from traditional, centralized ML. The FL process is typically driven by a model engineer developing an AI model for a particular application. A typical FL workflow and training process is:

- **Problem identification:** The model engineer identifies the problem that can be solved with FL.
- **Asset instrumentation:** Clients are instrumented to store their local data for training.
- **Federated model training:** Multiple federated tasks are started to train different model variations with different hyperparameters.
- **Aggregation:** The central controller aggregates model updates from all the clients.
- **Model evaluation and update:** After the tasks are sufficiently trained, the models are analyzed and good candidates are selected by the central controller or server. Analysis may include metrics computed on standard dataset in the central controller. Aggregating can also be done by taking the average of hyperparameters. For example, taking the average of bias and weights of multiple neural networks at each layer, or combining support vectors (SVs) of multiple support vector machine models and redistributing them to each client to retrain their model using SVs.
- **Deployment:** Once the models are selected, a hybrid model is selected and sent back to the clients for the deployment.

Training and building a complete AI model could be cumbersome under circumstances such as limited access to data, limited computational capacity, and lack of time to train a sophisticated AI model. Hence, to enhance model training and performance, TL is a mechanism where an already trained model solves either a classification or regression task in another or related domain, with or without further model training. In some cases, the model needs additional training to optimize the hyperparameters, and this can be done using a small amount of training data from the task it is transferred to. The main advantages of this approach are that the training time is reduced significantly, and the approach requires very little or no training data. Transferring a trained model means sharing hyperparameters, such as the bias and weights of different layers in neural networks, SVs in support vector machine models. The details on the application of the FTL approach to PSEG-owned plants CWS are presented in Reference [7].

4. RISK AND ECONOMIC MODELING

This section presents details on the risk, proportional hazard, and economic models. The three states of the Markov chain risk model are based on scale (i.e., component, state, or plant level). The proportional hazard model is used to integrate prognostic model outputs with the Markov chain risk model via the state transition rate parameter, λ. The integration informs the estimation of each state probability, which then can estimate the profit based on the CWS state of health.

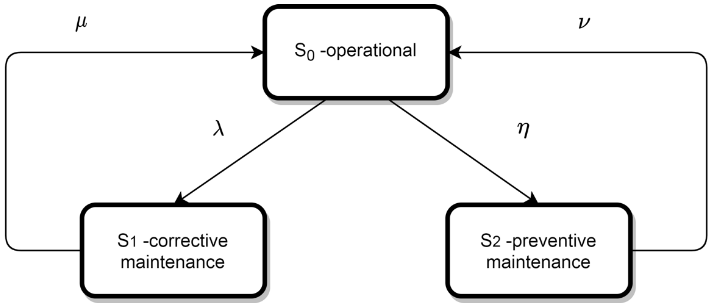
4.1. Component-Level Three-State Markov Model

The component-level three-state Markov chain model of a CWS motor and pump (M&P) set assumes that most maintenance performed on the set (or any plant asset) is divided into two categories: corrective and preventive. Corrective maintenance (CM), sometimes referred to as repairs, occurs when a component randomly fails during operation or standby. In such situations, CM is necessary for returning the component to an operational state. On the other hand, PM is normally performed when a component is operational but requires some service. Often, PM is performed when the component is online; however, PM may require power derating (i.e., the power generation is between zero and the maximum value) the unit. In addition, PM is mostly performed at fixed time frequencies (with some variance due to operating schedules). A transition diagram of the three-state model is shown in Figure 5. The three-state model is completely defined by four parameters: λ represents the failure and degradation rate, μ represents the CM rate, η represents the PM scheduling rate, and ν represents the PM rate and its initial conditions.

4.2. Plant-Level Three-State Markov Model

Generally, a plant's CWS has more than one M&P set. If a plant or unit has even a single CWP

Figure 5. Transition diagram for the component-level three-state model.



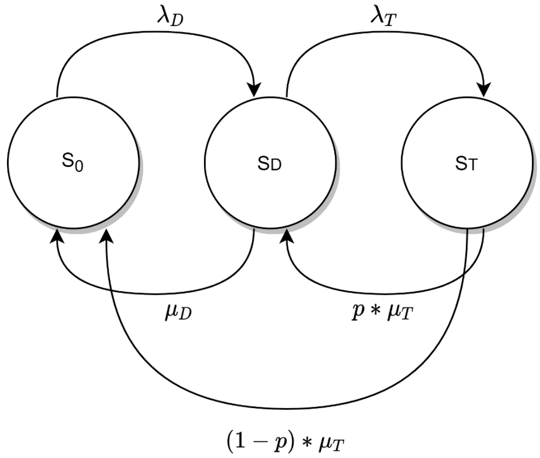
unavailable, its power generation is impacted (i.e., derated); if a plant or unit has a certain number of CWPs unavailable at a given time, it could lead to a trip (i.e., the power generation falls to zero). This generalization of the Markov chain model for the plant and unit level is obtained by considering a three-state Markov model in which each node represents the state of the whole plant and unit under different conditions, as shown in Figure 6. In this model (Figure 6), S_0 is the fully operational state in which all plant systems are available and running, with no loss of power generation. S_D is the derated state in which some loss in power generation occurs due to the unavailability of one or more plant systems (including CWS M&P sets). S_D is the trip state in which the plant and unit generation goes to zero. λ_D is the compound rate of transferring from the operational state to a derated state. λ_T is the hourly rate of transferring from a derated state to the trip state. Each downtime rate (λ_D or λ_T) is compound, meaning that it includes a superposition of transition rates from several plant subsystems. μ_D and μ_T are maintenance rates that reflect how quickly the plant can recover from a derated or tripped state, respectively. The maintenance rates μ_D and μ_T are identical, can be represented as μ without any loss of information, and do not depend on the plant's state. Note that, for the model in Figure 6, an additional rate covering the direct transition from S_T to S_0 is introduced to account for the possibility of different maintenance scenarios at different utilities. The parameter p is the probability of the utility choosing to go online in a derated state as soon as some plant systems become partially available, while $1-p$ is the probability that the utility will wait to go online until the utility is in a fully operational state in which all plant systems are available. Both recovery scenarios are possible, and this model provides additional scalability to specific utility maintenance practices. While the transition from S_T to S_0 delays the recovery until fully operational, it provides a safety margin in case a plant system goes down again. Due to the additional edge connecting S_T and S_0, this mixed-scenario model is not a birth-death model, and no analytical solution is available for steady-state probabilities.

4.3. Parameter Estimation

For the plant-level Markov model, this section estimates the parameters λ_D, λ_T, μ_T, and μ_D. The parameters for the component-level Markov model were estimated using the work order data, along with some information from the CWS plant process data (i.e., CWP status and gross load). For details on the component-level Markov model parameter estimation, see Reference [6]. In this research, the parameters of the plant-level Markov model were estimated solely from the CWS process data. It is important to note here that derates and trips of the plant or unit as a result of other plant systems are not used in the parameter estimation. However, it is a straightforward extension of the presented parameter estimation approach.

The CWP status, the time instances in which a CWP is unavailable, the number of unavailable CWPs, and the duration of unavailability are all used for parameter estimation. The number of unavailable CWPs is used to estimate the transition rate from the operational state, S_0, to the derate state, S_D, and and from the derate state, S_D, to the trip state, S_T. The duration of unavailability is used to estimate maintenance rates and also in the profit calculation. The steps involved in extracting transition and maintenance rates for the plant-level Markov model for both the Salem and Hope Creek NPPs—using their respective CWS information—are presented as follows:

Figure 6. Transition diagram for the component-level three-state model.



1. From the CWS plant process data on both the Salem and Hope Creek NPPs, the CWP status and gross load data are extracted after filtering out the instances in which the gross load equals zero. A gross load of zero indicates that the plant or unit has either tripped or is in an outage. A non-zero gross load indicates that either the plant or unit is in a derated or fully operational state.
2. From the filtered data, the number of CWPs that were down at each time instance is calculated.
3. For derate cases, the instances when CWPs were unavailable are determined (along with their duration) and used to estimate λ_D and μ_D. For each Salem unit, the number of unavailable CWPs ranges from one to three, and for the Hope Creek NPP, it ranges from one to two.

$$\lambda_D = \frac{1}{P} \sum_{K_D} \frac{Count(CWPs\ down == K_D)}{Total\ CWP\ run\ hour} \tag{1}$$

$$\mu_D = \frac{1}{P} \sum_{K_D} \frac{Duration(CWPs\ down == K_D)}{Total\ CWP\ run\ hour} \tag{2}$$

4. Also, the trip parameter, λ_T, is calculated as:

$$\lambda_T = \frac{1}{P} \frac{Count(CWPs\ down == K_T)}{Total\ CWP\ run\ hour} \tag{3}$$

In Equations (1–3), P is the total number of CWPs in a plant and unit. For each Salem unit, $P = 6$ and $K_D = \{1,2,3\}$ for the derated state. For $K_T = 4$, the Salem unit is in a trip state. For the Hope Creek NPP, $P = 4$ and $K_D = \{1,2\}$ for the derated state. For $K_T = 3$, the Hope Creek plant is in a trip state.

To estimate μ, we assumed a minimum of a 5% drop in the gross load compared to its maximum value when the plant is fully operational. Thus, accounting for both CWS and other system maintenances, μ is calculated as follows, using the gross load:

$$\mu = \frac{Duration(0 < Gross\ load < 95\% * \max(Gross\ load))}{Total\ operational\ duration\ of\ plant} \tag{4}$$

For the plant-level Markov model, the following system of differential equations are solved with the normalization condition,

$$\frac{dp_{S_D}}{dt} = \lambda_d \cdot p_{S_0} + (\mu_T \cdot p) \cdot p_{S_T} - \mu_D \cdot p_{S_D} - \lambda_T \cdot p_{S_D}$$
$$\frac{dp_{S_0}}{dt} = \mu_D \cdot p_{S_D} + (\mu_T \cdot (1-p)) \cdot p_{S_T} - \lambda_D \cdot p_{S_0}$$

$$\frac{dp_{S_T}}{dt} = \lambda_T \cdot p_{S_D} - (\mu_T \cdot p) \cdot p_{S_T} - (\mu_T \cdot (1-p)) \cdot p_{S_T} \quad (5)$$

$$p_{S_0}(t) + p_{S_D}(t) + p_{S_T}(t) = 1$$

The solution of Equation (5) results in steady-state probabilities:

$$p_{S_0} = \frac{1}{1+\frac{\lambda_D}{\mu_D}+\frac{\lambda_D \cdot \lambda_T}{\mu_D \cdot \mu_T}}; p_{S_D} = \frac{\lambda_D}{\mu_D} \cdot p_{S_0}; p_{S_T} = \frac{\lambda_D}{\mu_D} \cdot p_{S_D} \quad (6)$$

where p_{S_0}, p_{S_D}, and p_{S_T} are probabilities of the corresponding states, S_0, S_D, and S_T, respectively. The calculated values of λ_D, λ_T, and μ for the Salem and Hope Creek NPPs are shown in Table 1. By substituting the values in Table 1 in Equation (6), will provide the steady-state probabilities, also presented in Table 1.

Table 1. Estimated transition rates and steady-state probabilities for Salem Units 1 and 2 and the Hope Creek Plant.

Parameter	λ_D	λ_T	μ	p_{S_O}	p_{S_D}	p_{S_T}
Salem Unit 1	0.002767	7.30E-06	0.0439	0.940737	0.059257	5.27E-06
Salem Unit 2	0.00149	2.39E-05	0.0355	0.959764	0.040222	1.36E-05
Hope Creek	0.000283	0.000141	0.0910	0.9969021	0.003095	2.52E-06

4.4. Economic Model

Given the stationary transition rates and probabilities of different states (interpreted as a percentage of time spent in a given state), the hourly profit is estimated for different p values by using the plant-level model (Figure 6) for a 1,200 MWe unit. The hourly profit is calculated via the following formulation:

$$Hourly\ Profit = Hourly\ Revenue\ at\ Full\ Power \cdot p_{S_0} - [(LR + FR_1 + MC)T_1 + (LR + FR_2 + MC)T_2 + \mathbb{I} \cdot (LR + FR_3 + MC)T_3] \cdot p_{S_D} - (LR + Hourly\ Revenue\ at\ Full\ Power + MC) \cdot p_{S_T} \quad (15)$$

where FR_1, FR_2, and FR_3 represent the hourly foregone revenue whenever 1–3 CWPs are unavailable, respectively. LR is the hourly labor rate (industry average value is used), and MC is the hourly cost of materials (a representative cost value is used). T_1, T_2, and T_3 are the proportions of time in which 1–3 CWPs are unavailable, respectively, out of the total number of run hours at the time of hourly profit estimation. The indicator $\mathbb{I} = 0$ is for the Hope Creek NPP, and $\mathbb{I} = 1$ is for the Salem NPP. The hourly profit equation reflects the fact that the derated state is compound with possibly 1–3 CWPs unavailable. The T_1, T_2, and T_3 values are obtained from operational data for both the Salem and Hope Creek NPPs. The results of applying the Markov chain model, along with the corresponding benefits to the Salem and Hope Creek NPPs, are shown in Table 2 for different p values. The tripped state is also compound; however, the loss in the tripped state is assumed identical, as the plant is offline regardless of how many CWS M&P sets are down. Additionally, the cost of maintenance in this case is small compared to the hourly foregone revenue.

Analysis of Table 2 reveals that the highest hourly profit for all three units is achieved for $p = 0$ (in other words, going from the tripped state directly to the fully operational state is the most economical strategy). The Hope Creek NPP has the highest hourly profit, due to featuring the lowest transition rate to the derated state, λ_D, and also due to having the highest maintenance rate, μ. For the currently used model, we assumed that $\mu = \mu_D = \mu_T$—namely, that the maintenance rates are the same when transitioning from tripped or derated states. Also, due to lower downtime rates and higher maintenance rates, the Hope Creek NPP has the highest probability of being in a fully operational state for all three values of the parameter p.

Table 2. Stable probabilities of different states and hourly profit values for Markov chain models of different units for different p values.

	$p=0$			$p=0.5$			$p=1$		
	Salem Unit 1	Salem Unit 2	Hope Creek	Salem Unit 1	Salem Unit 2	Hope Creek	Salem Unit 1	Salem Unit 2	Hope Creek
Profit, $/hour	115,619	128,702	154,231	115,616	128,694	154,230	115,612	128,685	154,228

4.5. Proportional Hazard Model

The Markov chain model, however, can be generalized to time-dependent transition rates—for example, to account for equipment degradation. Equipment degradation is normally detected via a degradation variable (e.g., temperature, vibration, strain, or a combination thereof). Having obtained the degradation variable, a time-dependent transition rate, λ(t), can be represented through a proportional hazard model [11]:

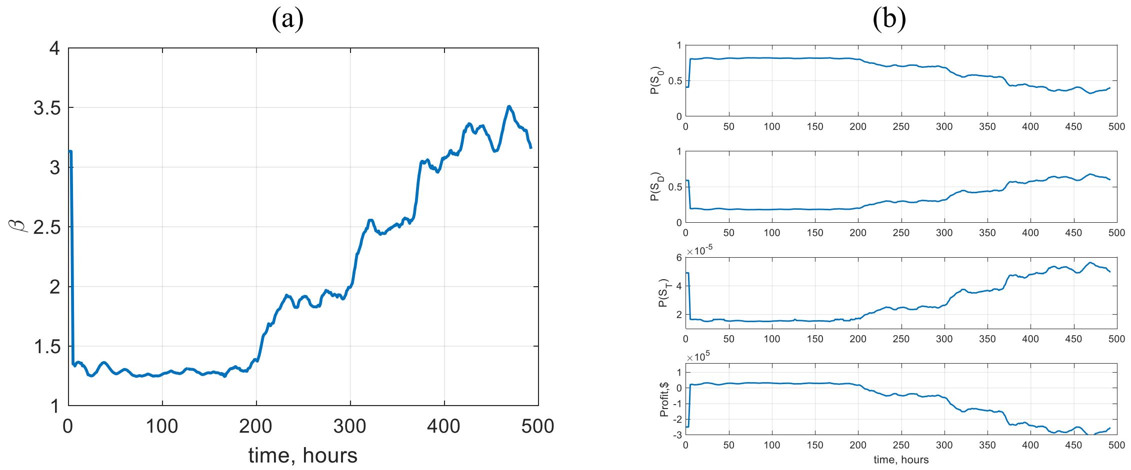
$$\lambda(t|\beta) = \lambda_0 \cdot e^{\beta(t)} \tag{18}$$

where λ_0 is the stationary downtime rate in the absence of any degradation and β is the degradation variable that reflects the deterioration of a piece of equipment. The approach details are summarized in Reference [2]. In this report, the Salem Unit 1 CWP diffuser degradation determined via the vibration data is used to demonstrate how degradation information is captured using the proportional hazard model. For details on the CWP diffuser degradation and the computation of the degradation variable, β, see Reference [8]. The time evolution of the degradation variable for the CWP diffuser is shown in Figure 7a. As seen in Figure 7a, after a time stamp of 200 hours, the degradation variable starts to increase, reflecting the deteriorating condition of the CWP. For this report, the proportional hazard model was only used for parameter λ_D. The time evolution of state probabilities and hourly profit for the proportional hazard model is shown in Figure 7b. As seen in Figure 7b, the probability of being fully operational, p_{S_0}, starts to decrease at a time stamp of around 200 hours. At the same time, the probabilities of two other states (i.e., the derated state, P_{S_D}, and the tripped state, P_{S_T}) starts to increase, reflecting the degradation of a CWS M&P set. The bottom panel in Figure 7b shows the changes in expected hourly profit for the unit, revealing that, under this degradation scenario, the unit quickly starts losing money unless the degradation process is reversed or fixed. It should be emphasized that, while an economic analysis of the system performance is beneficial for foreseeing economic losses and gains, it can only be meaningfully applied in the case of long-term operations (e.g., the duration of the fuel cycle).

5. USER-CENTRIC VISUALIZATION

To develop the scalable visualization strategy, the research focused on developing a dashboard to display ML outputs and their surrounding context, with links to databases containing synthesized and raw data on the analyzed components and systems. The overall design and evaluation process occurred over two main phases. The first phase entailed an operating experience review and user needs assessment, both of which were conducted in an interview format. The operating experience review captured existing practices and identified issues pertaining to the system and tools used by the analyst to diagnose anomalies to give a maintenance recommendation. The user needs assessment focused on capturing their ability to detect anomalies and report them to the relevant decision makers with advanced analytics. The information garnered from these two activities was critical to achieving the goal of user-centered scalability [12], as it fostered an understanding of how the participants processed information and made decisions. The second phase focused on evaluation of a dashboard human-machine interface (HMI) prototype, which displayed data of a single CWP over a specific six-week period. The choice to limit the initial prototype to data from a single component over a narrow slice of time was meant to ensure that the designed visualization and ML model proof of principle was acceptable for users and that any immediate issues could be flagged prior to increasing the scale and scope of the visualization

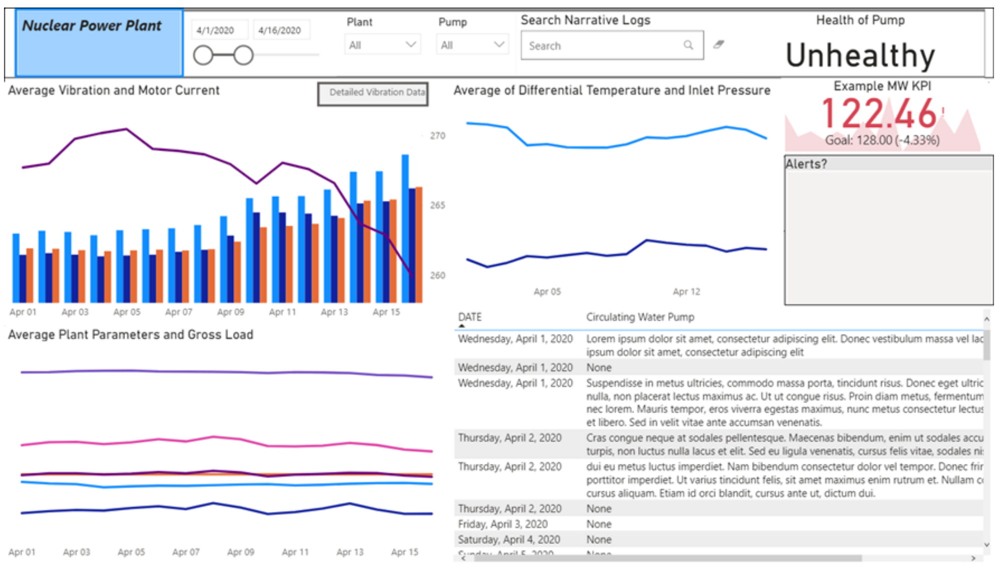
Figure 7. (a) Time dynamics of degradation variable β for Salem Unit 1. (b) Markov model probabilities of state and profit for the proportional hazard model for Salem Unit 1.



and ML model. The following research activities were performed to support the visualization strategy development:

1) Operating experience review—Capture the current concept of operations for monitoring and maintenance and identify issues regarding historic operations
2) User needs assessment—Capture user needs for the envisioned risk-informed PdM HMI system.
3) Prototype HMI development—Implement a prototype HMI (see Figure 8) based on a specific use-case scenario by integrating plant-provided data with actual risk-informed PdM algorithm analysis
4) Prototype HMI evaluation—Examine the usability, effectiveness, and scalability of the prototype HMI, employing representative users from the collaborating utility to help refine the design.

Figure 8. An HMI prototype.



6. CONCLUSION AND PATH FORWARD

The scientific framework and research accomplishments summarized in this paper stem at a high-level from developing innovative scalable technological solutions that signify advancements in (1) online asset monitoring, (2) data analytics, (3) risk assessment methodologies, and (4) user-centered design strategies. These advancements are leading the transformation of the nuclear industry to adopt risk-informed PdM strategies. This adoption would drive automation, efficiency gains, enhanced reliability of plant systems, and substantial cost savings via dramatic reduction or elimination of unnecessary time-consuming, labor-intensive maintenance activities, helping nuclear power to achieve economic competitiveness in the energy market. Transferring the scalable technologies to the nuclear industry would allow them to achieve the greatest return on investment based on economies of scale. The scalable risk-informed PdM research lays the foundation for future efforts on the explainability and trustworthiness of ML and AI-based technologies. These important, challenging aspects need to be addressed prior to adoption by the nuclear industry.

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