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# Integrated Risk-Informed Condition Based Maintenance Capability and Automated Platform: Technical Report 1

July 2021

Changing the World's Energy Future

Nicholas Goss, Brad Diggans, Francis Lukaczyk, Peter Lahoda, Jacob Hanson, Harry Palas, Vivek Agarwal, Andrei V Gribok, Vaibhav Yadav, James A Smith, Nancy J Lybeck, Koushik Araseethota Manjunatha

Idaho National Laboratory

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# Integrated Risk-Informed Condition Based Maintenance Capability and Automated Platform: Technical Report 1

## Advanced Reactor Development Projects

June 2020


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# ABSTRACT

Due to continuing global energy market trends, driven heavily by the abundant preserves of natural gas, there is an immediate need to reduce costs associated with operation and maintenance (O&M) for the current domestic nuclear power industry and for future reactor developments. This is to ensure that nuclear power generation remains an economically competitive and viable option in the energy market. O&M costs include labor-intensive preventive maintenance (PM) programs, which involve manually-performed inspection, calibration, testing, and maintenance of plant assets at periodic frequency and time-based replacement of assets, irrespective of their condition. This has resulted in an expensive, labor-centric business model to achieve high capacity factors. Fortunately, there are technologies (advanced sensors, data analytics, and risk assessment methodologies) that can enable the transition from a labor-centric business model to a technology-centric business model. The technology-centric business model will result in a significant reduction of PM activities, laying the foundation for real-time condition assessment of plant assets, reducing overall labor and part costs. To enable this transition, PKMJ Technical Services LLC is partnering with the U.S. Department of Energy's Idaho National Laboratory (operated by the Battelle Energy Alliance, LLC) and the Public Services Enterprise Group (PSEG) Nuclear, LLC in the Integrated Risk-Informed Condition-Based Maintenance Capability and Automated Platform Project.

In this report, the configuration of a digital cloud platform using Microsoft Azure is discussed, data from the PSEG Salem Nuclear Generating Station Units 1 & 2 are imported into a digital cloud platform, and the data is used for an evaluation of several key areas: cost impact analysis, risk-informed model development, and preventive maintenance strategy optimization. First, the cost impact analysis reviews which plant assets are potential good candidates for condition-based monitoring. Next, INL utilized the data in their local environment to develop the risk-informed model; which provides estimates of failure rates and probability of failures of assets based upon their past performance. The developed model is performed on assets selected from the cost impact analysis. Lastly, engineers assess the preventive maintenance strategy for the selected assets at PSEG against maintenance strategies in the nuclear industry for similar assets to potentially identify acceptable justification for the extension of current maintenance frequencies.

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# EXECUTIVE SUMMARY

In support of the U.S Department of Energy (DOE) Office of Nuclear Energy's (NE's) priority for Advanced Nuclear Technology Development, PKMJ Technical Services, in partnership with Idaho National Laboratory and Public Service Enterprise Group (PSEG) Nuclear, LLC is leading this research to address challenges in the implementation of risk-informed, condition-based predictive maintenance (PdM). The research outcomes will be models and methods to enable deployment of a risk-informed PdM program at a nuclear power plant. Implementation of a risk-informed PdM program is one of the critical advancements required to ensure long-term safe and economical operation, automation, efficiency, and enhanced reliability of plant systems in nuclear power plants.

To achieve the project objective, three goals are defined. They are:

**Goal 1: Develop a risk-informed approach to optimize equipment maintenance frequency:** Perform research and development (R&D) activities to develop a new capability that will enable the optimization of preventive maintenance frequency for the circulating water system (CWS) based on a risk-informed approach. In this activity, historical plant process data for the CWS, preventive and corrective maintenance records, failure data, and already available expert opinions will be utilized to enhance the risk insights needed to prioritize and inform maintenance decision making.

**Goal 2: Develop a risk-informed condition-based maintenance approach:** Perform R&D activities using advancements in sensor technologies and advanced data analytics to develop and deploy digital monitoring and to develop an automated diagnosis and prognosis process that provides insight into plant equipment health condition within the CWS.

**Goal 3: Develop and demonstrate a digital, automated platform to centralize the implementation of monitoring technologies:** Perform R&D activities to integrate the capabilities developed in Goals 1 and 2 into a centralized automated platform to support the implementation of technologies for use by industry to the broadest extent to achieve the greatest returns on investment and economies of scale.

The outcomes presented in this report directly address Goal 1 and initial research performed to support Goals 2 and 3. These include

1. Initial results of a risk-informed approach to optimize equipment maintenance frequency;
2. Design and implementation of the PKMJ digital platform based on requirements that align with nuclear industry requirements. This will provide guidance to NPPs as they plan to develop or acquire their own digital platform;
3. Approaches for data extraction, cleansing, and enhancing necessary to transform the raw data received in order to properly stage the data for use in advanced analytics;
4. Cost impact analysis and selection of the equipment within the circulating water system;
5. Installation of wireless vibration sensors on the circulating water system at both the Units of the Salem NPP. Installation, best practices, and lessons learned are discussed;

6. Approach, assumptions, execution, and results of risk-informed models based on two-state and three-state Markov chain process; and
7. Preventive Maintenance Optimization (PMO) analysis, resulting recommendations, and potential savings.

The report highlights the extraction and transfer of existing sensor information as well as data from the newly installed wireless vibration sensors onto a Cloud Platform. This is one of the major efforts required by commercial nuclear power plants across the nuclear fleet to enable cloud-based analytics for online monitoring. This data, which was centralized in the PKMJ Digital Platform, was leveraged by the Cost Impact Analysis, Risk-Informed Model Development and PMO Analysis described in this report. This data will also support the R&D activities for the next phases of the project to support technology driven condition-based maintenance in a centralized, automated digital platform.

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# CONTENTS

# FIGURES

# TABLES

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# ACRONYMS

| | |
|---|---|
| AI | artificial intelligence |
| APR | advanced pattern recognition |
| ARM | Azure Resource Manager |
| CDF | core damage frequency |
| CHIP | component health indicator program |
| CPU | central processing unit |
| CRADA | Cooperative Research and Development Agreement |
| CW | circulating water |
| CWP | circulating water pump |
| CWS | circulating water system |
| DOE | Department of Energy |
| EOP | emergency operating procedure |
| EPRI | Electric Power Research Institute |
| FEG | functional equipment group |
| gpm | gallons per minute |
| HRA | human reliability analysis |
| IB | inboard-bearing |
| INL | Idaho National Laboratory |
| LER | licensee event record |
| LWR | light-water reactor |
| LWRS | Light-Water Reactor Sustainability |
| M&D | monitoring and diagnostic |
| MCMS | machine condition monitoring software |
| MP | maintenance plan |
| NPP | nuclear power plant |
| NRC | Nuclear Regulatory Commission |
| OB | outboard-bearing |
| O&M | operation and maintenance |
| PdM | predictive maintenance |
| PM | preventive maintenance |
| PRA | probabilistic risk assessment |
| PSEG | Public Service Enterprise Group |
| RBAC | Role-Based Access Control |

| | |
|---|---|
| R&D | research and development |
| rpm | revolutions per minute |
| SIEM | Security Information and Event Management |

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# Integrated Risk-Informed Condition-Based Maintenance Capability and Automated Platform

## 1. INTRODUCTION

The primary objective of this research is to address challenges in the implementation of risk-informed, condition-based predictive maintenance (PdM), which reduces operating costs while still maintaining the safety and reliability of commercial nuclear power plants (NPPs). To achieve the objective, risk models are being developed by taking advantage of advancements in data analytics, deep learning, machine learning, and artificial intelligence (AI). The project is also researching and developing an automated platform to support agile business processes to implement technology for use by the nuclear industry. The outcomes of the project will provide modeling tools and methods that will enable industry led innovation and technology deployment in the current fleet of U.S. NPPs to ensure the nuclear industry remains an economically competitive and viable option in the energy market.

This project is a collaborative research effort between PKMJ Technical Services LLC (PKMJ), Idaho National Laboratory (INL), and Public Service Enterprise Group (PSEG) Nuclear, LLC. This collaboration, led by PKMJ, is part of the industry Funding Opportunity Announcement Award under the Advanced Nuclear Technology Development FOA #DE-FOA-0001817. A pilot demonstration of developed models and methods will be undertaken by PSEG Nuclear LLC at their Salem and Hope Creek Nuclear Generating Stations. The pilot will focus on the circulating water system (CWS), which provides one of the largest economic benefits, among other plant systems.

To achieve the project objective, three goals are defined. They are:

**Goal 1: Develop a risk-informed approach to optimize equipment maintenance frequency**

Research and development (R&D) activities to develop a new capability that will enable the optimization of preventive maintenance frequency of CWS based on a risk-informed approach. In this activity, historical plant process data on CWS, preventive and corrective maintenance records, failure data, and expert opinions already available will be utilized to enhance the risk insights to prioritize and inform maintenance decision making.

**Goal 2: Develop a risk-informed condition-based maintenance approach**

R&D activities will be performed using advancements in sensor technologies and advanced data analytics to develop and deploy digital monitoring and to develop an automated diagnosis and prognosis of plant equipment health condition for CWS. Using the capability developed through Goal 1, these R&D activities will employ advanced monitoring and diagnostic and prognostic models to recommend condition-based maintenance activities on plant equipment. This will move maintenance activities away from frequency-based scheduled activities to activities that are performed when necessitated by conditions—informed by advanced monitoring, analytics, and models of the equipment itself—to reduce the amount and types of maintenance that are performed. This marks the transition to technology-enabled, condition-based, and risk-informed maintenance activities.

**Goal 3: Develop and demonstrate a digital, automated platform to centralize the implementation of monitoring technologies**

The move from scheduled to condition-based maintenance will represent a significant shift in both the methods and tools for plant monitoring and cost reduction. The greatest economies of scale are to be realized when these technologies are centralized—that is deployed in multiple plant settings or in a fleet of plants—to monitor a fleet of components or fleets of components. R&D activities will be performed to integrate the capabilities developed in Goals 1 and 2 into a centralized automated platform to support the implementation of technologies for use by industry to the broadest extent to achieve the greatest returns on investment and economies of scale. The platform will automate business processes like the automatic generation of work orders (WOs), inventory parts management, align work with the right skilled and trained field worker, and update the system with the feedback once the work package is complete. The platform will provide a schedule optimization tool to track and realign (if required) activities to ensure on-time completion. This is achieved through the development of applications that interface with one another on the platform, while pulling the required utility information from the central data-lake.

Outcomes of the R&D activities associated with Goal 1 are discussed in detail in this report. However, the R&D activities associated with Goal 1 are still active because it is linked to Goal 2 activities and vice versa. In addition, models developed as part of Goal 1 will be continuously updated as new information becomes available. Progress made to date in achieving Goals 2 and 3 are also included in this report.

## 1.1 Motivation/Background

Global energy market trends are driven heavily by the abundant reserves of natural gas. As such, there is an immediate need to reduce costs associated with operating and maintaining the current domestic fleet of nuclear plants (96 operating units). Operating in a market selling wholesale electricity for $22/MWh becomes unsustainable with current nuclear plant operation and maintenance (O&M) costs accounting for at least 66% of the total operating cost. Prices for producing nuclear energy start higher than market price of electricity, with the nuclear industry average operating cost at approximately $34/MWh and O&M costs of approximately $22/MWh. On average, annual O&M costs equate to approximately $145M per station.

Right now these O&M costs (including a labor-intensive preventive maintenance (PM) program) are a major contributor to total operating costs. They involve manually-performed inspection, calibration, testing, and maintenance of plant assets at periodic frequency, along with time-based replacement of assets, irrespective of condition. This has resulted in a costly, labor-centric business model. Fortunately, there are technologies (advanced sensor, data analytics, and risk assessment methodologies) that can enable the transition to a technology-centric business model. The technology-centric business model will result in the significant reduction of PM activities, driving down costs since labor is a rising cost and technology is a declining cost. This transition will also enable nuclear plants to maintain, and perhaps even achieve, higher capacity factors, while still significantly reducing O&M costs.

The challenges facing the industry are clearly understood by regulators, operators, and vendors alike. The Nuclear Energy Institute has issued several efficiency bulletins related to reducing the cost of maintenance. The PdM R&D plan [1] laid the foundation for the real-time condition assessment of plant assets. Successful execution of the R&D plan will result in the development of a deployable, risk-informed PdM maintenance program for plant use, thereby enhancing the safety, reliability, and economics of operation.

This report builds on the collaborative research performed under the Technology Enabled Risk-informed Maintenance Strategy (TERMS) project within the U.S. Light-Water Reactor Sustainability Program's Plant Modernization Pathway. The Statement of Work for the TERMS project was finalized in October 2018 and was updated in December 2018. The Cooperative Research and Development Agreement (CRADA) 18-CR-22 Mod 1, with the agreed upon statement of work, was fully executed on June 3, 2019. The statement of work focused on developing a deployable, risk-informed PdM strategy that would enable the existing fleet of light-water reactors to transition from a labor-centric business model to a technology-centric business model, as shown in Figure 1.


Figure 1. Transition from a PM program to a risk-informed PdM program.

## 1.2 Report Layout

This report is organized as follows:

- Section 2 presents the process of digital platform configuration.
- Section 3 describes the approach developed to perform PM cost impact analysis.
- Section 4 describes the research effort to develop a risk model by taking into consideration historical plant process data, preventive and corrective maintenance records, and expert opinion.
- Section 5 presents a PM optimization strategy based on nuclear industry data as well as cost and risk models.
- Section 0 summarizes the progress to date and outlines continuing activities needed to achieve project objectives.

# 2. DIGITAL PLATFORM CONFIGURATION

This section describes requirements that were considered during the implementation of the PKMJ Digital Platform and shares the discovered best practices that can be utilized by NPP, should they decide to develop or acquire their own digital platform. A digital platform is made up of multiple components that enhance a business' capabilities for large data volume processing, modeling, storage and access, advanced data analytics techniques (e.g., Machine Learning, Artificial Intelligence), data visualization, and reporting. PKMJ uses mixed discipline teams of data experts who apply cutting edge principles to rapidly explore data, unlock and test new ideas, and turn those ideas into services. These teams accelerate new ideas of predictive and data-led services in areas such as:

- optimization of plant processes
- mitigation / elimination of parts readiness challenges
- reduction of unnecessary plant maintenance
- work schedule stability and planned work survival rates

PKMJ previously performed an evaluation of several Platform and Cloud providers, considering several factors across overall capabilities, synergies with existing technology in use, ease of use/learning curve, and alignment to future vision/goals. This evaluation resulted in the selection of Microsoft Azure Cloud Services for the PKMJ Digital Platform.

While any Cloud Service Provider can be chosen to support a digital platform, this section covers the Microsoft Azure Cloud Service strategy configured by PKMJ for their Service Delivery Center and to be accessed by nuclear power customer Monitoring and Diagnostic (M&D) centers.

## 2.1 Management Structure and Governance Board

When implementing a cloud strategy, especially one used within the nuclear industry, it is critical to establish a governance board to ensure the proper management and maintenance of the cloud infrastructure and continued growth. Charters need to be developed to govern the different use cases of cloud services and handle architecture and use case changes.

Six key focus areas were identified, and as such, the responsibilities of the board include:

- Understanding business issues, such as regulatory requirements, cyber security or funding
- Establishing clear, measurable business and Information Technology (IT) goals for the cloud strategy
- Developing best practices and monitoring these processes
- Programming standards, proper design, reviewing, certifying, and monitoring applications from a technical perspective
- Maintaining standards/policies, and approving changes prior to implementation
- Controlling costs.

While the U.S. Nuclear Regulatory Commission (NRC) does not prescribe its own specific requirements for use of cloud computing, they do utilize guidance from other internationally recognized groups, such as the National Institute of Standards and Technology (NIST). From the smart electric power grid and electronic health records to atomic clocks, advanced nanomaterials, and computer chips, innumerable products and services rely in some way on technology, measurement, and standards provided by NIST [2]. They have several publications that provide guidance in the adoption of a cloud strategy, which can be used by any cloud computing stakeholders, including nuclear utilities.

NIST Special Publication (SP) 500-293, “US Government Cloud Computing Technology Roadmap Volumes I and II” was reviewed while configuring PKMJ’s Digital Platform [3]. As published in NIST SP 800-145 and reiterated in NIST SP 500-293, there were five common characteristics among all cloud computing services that were taken into consideration by PKMJ when establishing clear and measurable business and IT goals:

- On-demand self-service: A consumer can unilaterally provision computing capabilities, such as server time and network storage, as needed automatically without requiring human interaction with each service’s provider.

- Broad network access: Capabilities are available over the network and accessed through standard mechanisms that promote use by heterogeneous thin or thick client platforms (e.g., mobile phones, laptops, and personal digital assistants [PDAs]).

- Resource pooling: The provider’s computing resources are pooled to serve multiple consumers using a multitenant model, with different physical and virtual resources dynamically assigned and reassigned according to consumer demand. There is a sense of location independence in that the subscriber generally has no control or knowledge over the exact location of the provided resources but may be able to specify location at a higher level of abstraction (e.g., country, state, or data center). Examples of resources include storage, processing, memory, network bandwidth, and virtual machines.

- Rapid elasticity: Capabilities can be rapidly and elastically provisioned, in some cases automatically, to quickly scale in and out. To the consumer, the capabilities available for provisioning often appear to be unlimited and can be purchased in any quantity at any time.

- Measured Service: Cloud systems automatically control and optimize resource use by leveraging a metering capability at some level of abstraction appropriate to the type of service (e.g., storage, processing, bandwidth, and active user accounts). Resource usage can be monitored, controlled, and reported, providing transparency for both the provider and consumer of the utilized service.

During initial governance meetings, the following requirement/design principles and functional requirements were established:

Table 1. Requirement/design principles.

| Number | Objective |
|---|---|
| P-01 | Adopt a cloud-native approach to ensure that speed and supportability, cloud-native capabilities, and tools will be adopted where reasonably applicable in the context of the PKMJ environment. |
| P-02 | Dependencies on PKMJ's existing in-house environment will be minimized. |
| P-03 | Industry and open standards will be used as much as possible. |
| P-04 | All deployment, support, and maintenance activities should be automated. |
| P-05 | The design will adhere to PKMJ compliance rules (security, privacy, regulatory). |
| P-06 | Reference designs and proven practices will be used as much as possible (e.g., https://docs.microsoft.com/en-us/azure/architecture/) to help determine the PKMJ Nuclear Platform design. |
| P-07 | Production and nonproduction workloads shall be logically separated. |
| P-08 | Cloud-native services are preferred over shared services, which are preferred over dedicated services. |
| P-09 | Decisions shall be made based on a long-term focus. When choosing between short-term benefit at the expense of long-term gain, the long-term gain will be preferred. |
| P-10 | All services are to be hosted in United States cloud locations only; export controls regulation may require future regional requirements. |
| P-11 | The disaster recovery region must be in a completely different geographic location from the primary platform region. |
| P-12 | Comprehensive insight into the platform services being consumed for use transparency and cost management is required. |

Table 2 - Functional requirements.

| Number | Objective |
|---|---|
| FR-01 | Role-Based Access Control (RBAC) integrated with the existing in-house solution |
| FR-02 | Authorized user access using corporate login credentials on corporate-issued Information Technology (IT) assets |
| FR-03 | Ability to enable Single Sign-On |
| FR-04 | Support for DevOps style development environments, providing PKMJ developers with agile access to Platform as a Service (PaaS) services for application builds, tests, releases, and monitoring |
| FR-05 | Support for joint development activities with external parties who will require secure access to the PKMJ Nuclear Digital Platform |
| FR-06 | Authorized users are able to access a centralized, secure, and elastic functional data store |
| FR-07 | Dedicated private network fiber connection |
| FR-08 | Data Integration service to develop Extract-Transform-Load and Extract-Load-Transform processes with minimal coding or maintenance |
| FR-09 | Data must be encrypted in transit and at rest |
| FR-10 | Create and publish Application Programming Interface(s) (API) to developers, external parties, and employees securely and at scale |
| FR-11 | Ability to securely automate the access and use of data across private and public cloud environments |
| FR-12 | Cognitive search as a service to reduce complexity of data ingestion and index creation |
| FR-13 | Data/site recovery service with ability to test without impacting production environment(s) |
| FR-14 | Machine learning and enterprise-grade analytics engine as a service |

| | |
|---|---|
| FR-15 | Elastic repository for big data analytics workloads |
| FR-16 | Ability to host secure, scalable, and highly available externally-facing web applications |
| FR-17 | Web application firewall, distributed denial-of-service (DDoS) protection as well as Intrusion Detection & Prevention System (IDS/IPS) scanning and a reverse proxy |
| FR-18 | Supports Transmission Control Protocol/User Datagram Protocol (TCP/UDP), such as HTTP, HTTPS, and SMTP, and protocols used for real-time voice and video messaging applications |
| FR-19 | Autoscaling with increasing application traffic |
| FR-20 | Ability to control inbound and outbound network traffic as well as to protect private networks |
| FR-21 | Security management service for authorized users to manage all PaaS security options to align with security policies required by PKMJ and its customers (e.g., ISO 27001) |

The governance board consists of both business and IT stakeholders and meets on a regular basis to ensure standards and policies are maintained. They also are responsible for reviewing any proposed changes prior to implementation as technologies and standards evolve, keeping the platform up-to-date; and removing legacy and preventing new vulnerabilities.

## 2.2 Subscription Taxonomy

Microsoft has a comprehensive set of online documentation to help organizations begin their Azure cloud service transition. Guides are available on docs.microsoft.com, such as “Microsoft Cloud Adoption Framework for Azure” [4]. Azure provides four levels of management scope: management groups, subscriptions, resource groups, and resources. Figure 2 and the following bullet points describe the relationship of these levels [5].

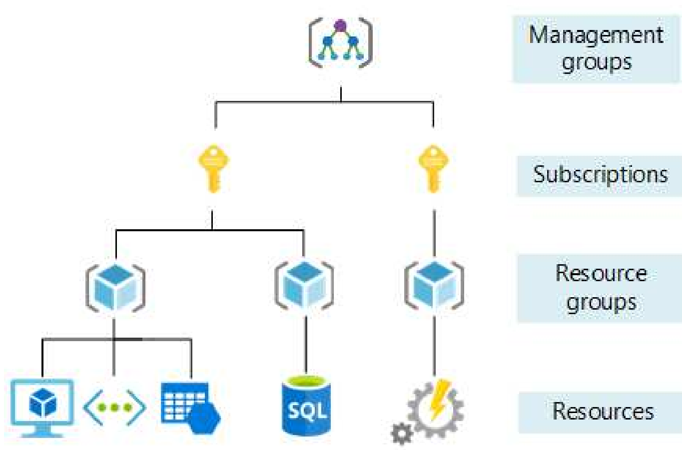


Figure 2. Azure’s four levels of management scope.

- Management groups: These groups are containers that help you manage access, policy, and compliance for multiple subscriptions. All subscriptions in a management group automatically inherit the conditions applied to the management group.

- Subscriptions: A subscription logically associates user accounts and the resources that were created by those user accounts. Each subscription has limits or quotas on the amount of resources you can create and use. Organizations can use subscriptions to manage the costs and resources that are created by users, teams, or projects.

- Resource groups: A resource group is a logical container into which Azure resources like web apps, databases, and storage accounts are deployed and managed.

- Resources: Resources are instances of services that you create, like virtual machines, storage, or SQL databases.

Starting at the top level of the Azure Cloud framework, PKMJ only required one management group for the digital platform. For subscription taxonomy, there are two fundamentally different models in terms of managing the Azure enrollment, either a single tenant with collaboration or a multitenancy environment that were reviewed.

The first can be described as a decentralized model, where full control is delegated to another group within an organization. In this model, it is common to see a subscription given to each functional group or department and they manage all aspects of the subscription. This model also assumes the business unit has trained IT staff that has well-documented and rigorous processes around security, governance, and operational management. The other common methodology uses a centralized strategy, where assets are provisioned by a shared services group and requestors are provided delegated access to manage certain aspects of the resource. It is important to note that the centralized model does not preclude the ability to provision a stand-alone subscription. If requirements arise where a business unit requires its own subscription, it can be accomplished under a centralized model. This scenario should be treated as an exception, and due diligence must be applied to ensure IT governance standards are enforced.

The best fit model for PKMJ was a centralized model that matches how on-premises resources are currently deployed. Plans were developed to allow a pipeline for developers to streamline from development to production through the proper use of custom Role-Based Access Control (RBAC) and policy controls. Subscriptions are separated to maintain cost centers throughout the organization.

### 2.3 Resources and Services

Several resources are supported with the PKMJ Digital Platform listed in Table 3 below. Each supported resource is provisioned through the Azure portal or migrated by Azure Automation Runbooks, leveraging Azure Resource Management (ARM) templates and PowerShell code. Alternatively, Ansible, Terraform, and/or Rancher can be used for infrastructure-as-code deployments. This ensures that resources are set up and configured in a consistent manner; however, it is important to pair these with Azure Resource Policies to make sure that changes cannot be made to resources outside of the defined guidelines.

Table 3. Azure resources and services.

| Name | Resource Provider | Description |
|---|---|---|
| Networking | Microsoft.Network | Includes resources such as Virtual Networks, Gateways, Subnets, Network Interfaces, Traffic Manager, Load Balancers, and Network Security Groups. |
| Shared Services | Microsoft.Automation<br>Microsoft.KeyVault<br>Microsoft.OperationsManagement<br>Microsoft.RecoveryServices<br>Microsoft.Scheduler<br><br>Microsoft.AzureActiveDirectory | There are several shared services required to manage and operate the cloud environment. These include Key Vault encryption and storage of credentials or certificates. Automation and Scheduler are required to run scheduled jobs or workflows. Finally, Recovery Services is required for automated backups. |
| Storage | Microsoft.Storage | Includes resources such as Storage Accounts and Managed Disks. |
| Virtual Machines | Microsoft.Compute | Includes resources such as Availability Sets, Virtual Machines, Images, and Scale Sets. |
| Data Warehousing | Microsoft.SQL<br>Microsoft.Databricks<br>Microsoft.Datafactory<br>Microsoft.AnalysisServices<br>Microsoft.DataLakeStore | Includes SQL Platform as a Service (PaaS) services as well as integration for data moves. Geared towards data analytics. |
| App Services | Microsoft.Web<br>Microsoft.Logic | App Service enables building and hosting of web applications, mobile back ends, and RESTful APIs in the programming language of choice without managing infrastructure.<br><br>Azure Logic Apps is a cloud service that helps users schedule, automate, and orchestrate tasks, business processes, and workflows when needed to integrate applications, data, systems, and services across an organization. |
| DevOps | Microsoft.Visualstudio | Collaborate on software development through source control, work tracking, and continuous integration and delivery, both on-premises and in the cloud.<br><br>Provides developer services to support teams to plan work, collaborate on code development, and build and deploy applications. Developers can work in the cloud using Azure DevOps Services or on-premises using Azure DevOps Server. Azure DevOps Server was formerly named Visual Studio Team Foundation Server. |

## 2.4 Region Usage/Backup and Recovery

As mentioned in Section 2.1, the disaster recovery region must be in a completely different geographic location from the primary platform region. The Eastern U.S. region is the primary location of resources deployed to Azure. This location relates to a Site-to-Site circuit to PKMJ through the connection of the on-premises firewall to a defined Network Security Group. An unmetered Express route provides the best method for connectivity to the environment, with protected traffic traversing an integral IPsec virtual private network. Based on proximity to the PKMJ office, the Eastern U.S. region was identified as the recommended primary location for all production resources required for the PKMJ Digital Platform. Disaster recovery is located in a separate U.S. region to ensure geographic separation while maintaining U.S. only locations.

Primary Azure virtual machines (VM) that allow for on-demand, scalable computing resources were deployed to the Eastern U.S. region. Backup and disaster recovery are handled by Recovery Services vaults and agents that run on the VM in Azure. Business rules are applied to each of these to determine Recovery Point Objective/Recovery Time Objective (RPO/RTO) as well as total retention. High availability is handled in two ways: availability and scale sets. Availability sets are multiple copies of the same workload, load balanced and running seamlessly in the background. This insulates from hardware level failure as well as Microsoft patching bringing a workload down during maintenance. Scale sets are an autoscaling mechanism for an image-based application that clones out more load balanced copies or automatically vertically scales the backend compute resource.

The Azure Backup vault is leveraged for all Windows/Linux systems utilizing Geo-Redundant Storage (GRS) replication to a paired datacenter. It should also be mentioned that many on-premises systems (Windows) can leverage this functionality with the use of the backup Agent but with limitations, such as not being application aware. Azure Backup vault is leveraged for individual Infrastructure-as-a-Service (IaaS) SQL databases with a fitting Full/Transactional log backup schedule and retention policy.

Azure Site Recovery is used for machine replication to the disaster recovery site for supported systems. This technology also supports replication of on-premises physical machines, virtual machines running in Hyper-V or VMWare, and Azure virtual machines.

Traffic manager is used to maintain connectivity between primary and secondary datacenters, using priority routing. In the event of a total site loss, the system will automatically be transferred to the new disaster recovery region.

## 2.5 Azure Portal & Platform Security

The ARM portal is available via the public internet and leverages Windows Accounts or Azure Active Directory (AAD) for authentication. Users can be granted access to various components leveraging a cascading security model. Starting at the subscription level, a single principal can be identified as the Owner & Service Administrator with multiple co-administrators. A best practice is to leverage a Service Account for these roles and to not use co-administrators. Instead of defining co-administrators, users should be assigned specific RBAC roles that leverage a least privilege configuration. To support this type of implementation, AAD Groups with appropriate members must be created to control access rights within Azure. Multifactor Authentication is required for all Owner and Contributor level accounts for access into the Azure portal.

Never have more than two owners per resource. Also, best practice is to only assign owners to a resource group or individual resource when necessary. The use case is for some level of autonomy, but there would still need to be enforced policy to limit the scope of autonomy. Groups should be defined as the specific roles and access levels, through the AAD Connect and services provided by AAD Federation Services. Azure Multifactor Authentication or an equivalent Multifactor Authentication can be used for multifactor authentication.

### RBAC Built-In Global Roles

Global roles in Azure can be applied at the Subscription, Resource Group, or Resource levels. Certain resource types have more granular roles available, but the following roles can be used universally in Azure:

Table 4. Azure global roles.

| Name | Description |
|---|---|
| Billing Reader | Allows read access to billing data |
| Contributor | Allows user to manage everything except access to resources |
| Owner | Allows user to manage everything, including access to resources |
| Reader | Allows user to view everything but not make any changes |
| Security Admin | Within Azure Security Center, users can view security policies, view security states, edit security policies, view alerts and recommendations, and dismiss alerts and recommendations |
| Security Reader | Within Azure Security Center, users can view recommendations and alerts, view security policies, and view security states but cannot make changes |
| User Access Administrator | Allows user to manage user access to Azure resources |

There are additional granular permissions available per resource that range from full control with the ability to add users to Azure Identity and Access Management to simply being able to read logs. A best practice is to have clearly defined RBAC policy that drives which level of access each team or business unit within an organization needs to properly administer their resources. Leverage least privileged access everywhere possible.

## 2.6 Data Storage

Azure Storage is Microsoft's cloud storage solution for data storage scenarios. Azure Storage offers a scalable object store for data objects, a file system service for the cloud, a messaging store for reliable messaging, and a NoSQL store. There are several variants of storage based on I/O operations per second available to the underlying disk or disk array presented in Azure. Data mobility is a big piece to any analytics strategy and leveraging active/inactive data stores or having a means to quickly mirror data is imperative. Requirements considered for the PKMJ Digital Platform include:

- Azure Storage accounts are provisioned as General Purpose v2 under the Standard performance tier. Premium storage is reserved for Managed Disks and only supports Locally Redundant Storage (LRS) replication.
- Secure Transfer (SSL) is required in all cases and Microsoft Managed Keys is used for encryption.
- Access to storage accounts leverage Virtual Network and Firewall rules for least privilege access. By default, the Allow Access to Trusted Microsoft Resources setting is disabled.
- Geo-Redundant Storage (GRS) replication will be the default option for storage accounts. LRS or Zone Redundant Storage is leveraged for noncritical data such as logs files or for exceptions granted for a specific request.

Azure SQL Databases and Oracle Databases are used for storage of relational data sets currently, but other linked services & datasets are available for future use within the PKMJ Digital Platform.

Linked Services & Datasets

A linked service connects data from a source to a destination (sink); it stands to reason that there would therefore be the same for a data set. Rather than having two separate lists, Table 5 below has a column for Linked services and datasets.

Table 5. Linked services and datasets.

| Type | Linked Service | Name | Linked Service | Dataset | Full |
|---|---|---|---|---|---|
| Azure | Azure Blob Storage | ABLB_ | LS_ABLB_ | DS_ABLB_ | LS_ABLB_Example |
| | Azure Data Lake Store | ADLS_ | LS_ADLS_ | DS_ADLS_ | LS_ADLS_Example |
| | Azure SQL Database | ASQL_ | LS_ASQL_ | DS_ASQL_ | LS_ASQL_Example |
| | Azure SQL Data Warehouse | ASDW_ | LS_ASDW_ | DS_ASDW_ | LS_ASDW_Example |
| | Azure Table Storage | ATBL_ | LS_ATBL_ | DS_ATBL_ | LS_ATBL_Example |
| | Azure DocumentDB | ADOC_ | LS_ADOC_ | DS_ADOC_ | LS_ADOC_Example |
| | Azure Search Index | ASER_ | LS_ASER_ | DS_ASER_ | LS_ASER_Example |
| Databases | SQL Server* | MSQL_ | LS_SQL_ | DS_SQL_ | LS_SQL_Example |
| | Oracle* | ORAC_ | LS_ORAC_ | DS_ORAC_ | LS_ORAC_Example |
| | MySQL* | MYSQ_ | LS_MYSQ_ | DS_MYSQ_ | LS_MYSQ_Example |
| | DB2* | DB2_ | LS_DB2_ | DS_DB2_ | LS_DB2_Example |
| | Teradata* | TDAT_ | LS_TDAT_ | DS_TDAT_ | LS_TDAT_Example |

| | | | | | |
|---|---|---|---|---|---|
| | PostgreSQL* | POST_ | LS_POST_ | DS_POST_ | LS_POST_Example |
| | Sybase* | SYBA_ | LS_SYBA_ | DS_SYBA_ | LS_SYBA_Example |
| | Cassandra* | CASS_ | LS_CASS_ | DS_CASS_ | LS_CASS_Example |
| | MongoDB* | MONG_ | LS_MONG_ | DS_MONG_ | LS_MONG_Example |
| | Amazon Redshift | ARED_ | LS_ARED_ | DS_ARED_ | LS_ARED_Example |
| File | File System* | FILE_ | LS_FILE_ | DS_FILE_ | LS_FILE_Example |
| | HDFS* | HDFS_ | LS_HDFS_ | DS_HDFS_ | LS_HDFS_Example |
| | Amazon S3 | AMS3_ | LS_AMS3_ | DS_AMS3_ | LS_AMS3_Example |
| | FTP | FTP_ | LS_FTP_ | DS_FTP_ | LS_FTP_Example |
| Others | Salesforce | SAFC_ | LS_SAFC_ | DS_SAFC_ | LS_SAFC_Example |
| | Generic ODBC* | ODBC_ | LS_ODBC_ | DS_ODBC_ | LS_ODBC_Example |
| | Generic OData | ODAT_ | LS_ODAT_ | DS_ODAT_ | LS_ODAT_Example |
| | Web Table (table from HTML) | WEBT_ | LS_WEBT_ | DS_WEBT_ | LS_WEBT_Example |

## 2.7 Machine Learning

Using the advanced analytics and machine learning tools available from Third Parties and Cloud Service Providers like Microsoft, nuclear utilities and their supporting vendors can gain greater control of and insight into utilities' operations. These insights can be used to find opportunities for increased efficiency and to mitigate / eliminate risks (e.g., forced outages, unexpected failures). The tools available from Microsoft Azure range from entire machine learning platforms (e.g., Databricks, Machine Learning Studio, Azure Machine Learning) to services that specialize in specific areas (e.g., Cognitive Search, Anomaly Detector). Based upon the programming languages and analytics frameworks familiar to PKMJ's Data Science and Analytics team, Databricks was chosen as the main PKMJ Digital Platform Advanced Analytics tool.

Azure Databricks, as shown in Figure 3, is an Apache Spark-based analytics platform optimized for the Microsoft Azure cloud services platform. Designed with the founders of Apache Spark, Databricks is integrated with Azure to provide one-click setup, streamlined workflows, and an interactive workspace that enables collaboration between data scientists, data engineers, and business analysts [6]. Azure Databricks allows PKMJ's Data Science and Analytics teams to develop analytics in Python, R, and SQL with flexibility to use multiple languages in a single analytic.

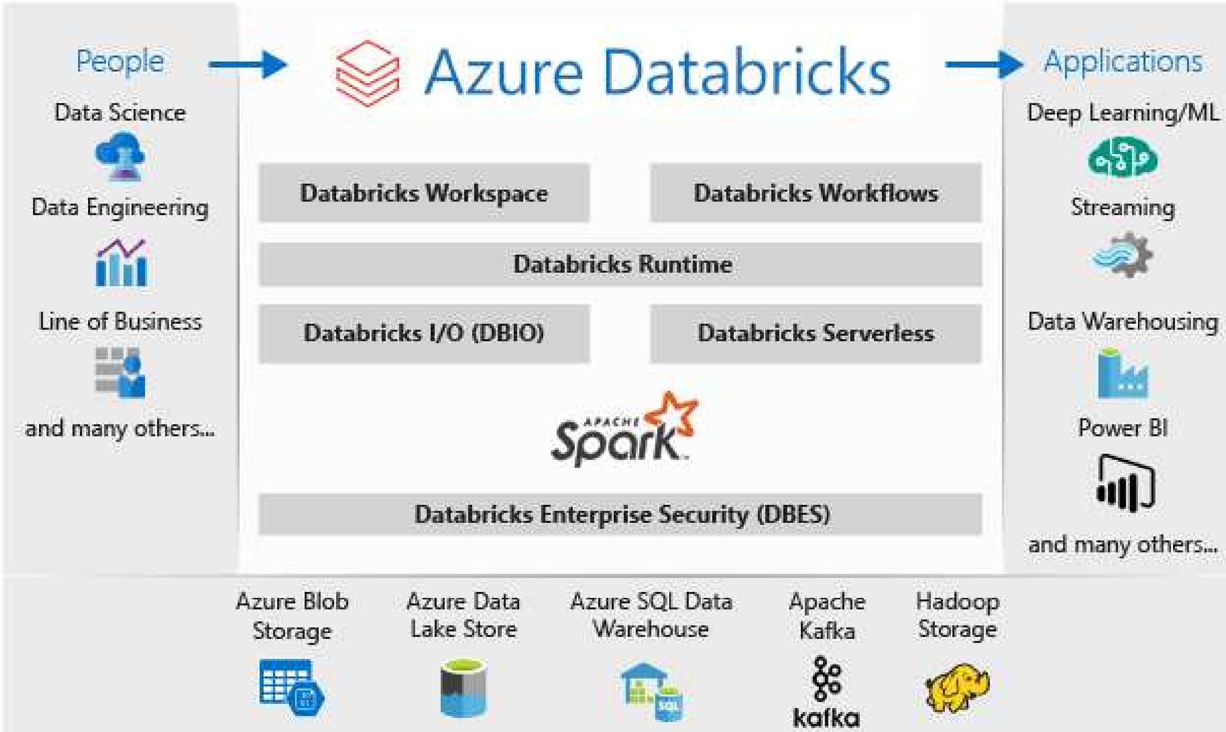


Figure 3. Azure Databricks overview.

### 2.8 Reporting and Visualizations

The Microsoft Azure Cloud is capable of integrating with any number of Third Party or Microsoft-based reporting and visualization tools. Microsoft's Power BI is an Azure service that is AAD integrated for authentication and access as well as security auditing. ThoughtSpot is an example of Third Party business-intelligence analytics software that can be used within the Azure environment. It enables users to view and analyze data through a search-based user interface [7]. Both Power BI and ThoughtSpot will be used as primary methods of data visualization and business-intelligence reporting within the PKMJ Digital Platform. This section focuses on Microsoft's Power BI tool.

There is a public access component that is inherent with using something over the open internet; however, there are ways to privatize and leverage a more secure connection mechanism to limit public internet-facing traffic. For example, leveraging Private Peering on ExpressRoute, all Power BI services can be routed over the peer point instead of the open internet.

Microsoft Cloud Services Verified with International, Regional, and Industry specific standards and terms:

- Strong Privacy and Security Commitments
- FedRAMP
- IRS 1075
- FFIEC
- HITRUST CSF Assurance Program Assessment

- CSA STAR SelfAssessment
- Australia IRAP
- FISC (Japan)
- SSAE 18 SOC 1 Report
- SSAE 18 SOC 2 Report
- ISO 27001
- ISO 27018
- EU Model Clauses (EUMC)
- HIPAA Business Associate Agreement
- No mining of customer data for advertising
- No voluntary disclosure of customer data to law enforcement agencies
- General Privacy and Security Terms of the Online Services Terms
- FERPA

Each Power BI deployment consists of two clusters—a Web Frontend cluster and a Backend cluster, which have Azure resources subject to Azure Governance and Security footprints. Power BI uses AAD for account authentication and management and is gated by a licensing requirement. Power BI also uses the Azure Traffic Manager to direct user traffic to the nearest datacenter, determined by the Domain Name System record of the client attempting to connect, for the authentication process and to download static content and files. This changes if a private peering point over ExpressRoute is leveraged but would require users to access through Unified Communications Networking. It is imperative to note that only Azure API Management and Gateway roles are accessible through the public internet. Azure API Management and Gateway provide authentication, authorization, DDoS protection, throttling, load balancing, routing, and other capabilities.

When a user imports an Excel workbook into the Power BI service, an in-memory Analysis Services tabular database is created, and the data is stored in-memory for up to one hour (or until memory pressure occurs on the system). The data is also sent to Azure Blob storage for retention. Metadata about a user's Power BI subscription, such as dashboards, reports, recent data sources, workspaces, organizational information, tenant information, and other metadata about the system is stored and updated in Azure SQL Database. All information stored in Azure SQL Database is fully encrypted using Azure SQL's Transparent Data Encryption technology. All data that is stored in Azure Blob storage is also encrypted.

All data requested and transmitted by Power BI is encrypted in transit using HTTPS to connect from the data source to the Power BI service. A secure connection is established with the data provider, and only once that connection is established will data traverse the network. There is not an option to tunnel this traffic over an IPSEC tunnel because of the Azure endpoints that need to be reached. With Power BI and ExpressRoute, an organization can create a private network connection to Power BI (or using an ISP's colocation facility), bypassing the internet to better secure sensitive Power BI data and connections.

## 2.9 Monitoring

Monitoring is used to gain an insight into how well a system is functioning. Monitoring is a crucial part of maintaining quality-of-service targets. Best practices for collecting monitoring data include:

- Ensuring that the system remains healthy
- Tracking the availability of the system and its component elements
- Maintaining performance to ensure that the throughput of the system does not degrade unexpectedly as the volume of work increases
- Guaranteeing that the system meets any service-level agreements established with customers
- Protecting the privacy and security of the system, users, and their data
- Tracking the operations that are performed for auditing or regulatory purposes
- Monitoring the day-to-day usage of the system and spotting trends that might lead to problems if they're not addressed
- Tracking issues that occur, from initial report through to analysis of possible causes, rectification, consequent software updates, and deployment
- Tracing operations and debugging software releases.

There are several monitoring options available in Azure. Log Analytics is a service that can be used for items that are not preconfigured in the Azure Monitor service and alerting sets, such as disk space and memory caps. The Azure Monitor service is used by the PKMJ Digital Platform to provide a common alerting framework. Azure Monitor provides several options to handle alerts including email, SMS, web hooks, and automation runbooks.

Signals - Example signals to monitor include: Up/Down, >90% CPU utilized over 2 hours and 100% >30 mins, Memory > 95% over 3 hours period, and disk free logical utilization under 5GB.

Email - Emails are the primary medium for alerts and are managed and maintained through the appropriate action group to the Infrastructure team distribution list.

Enterprise Security Information and Event Management (SIEM) - Azure Sentinel is a SIEM solution that provides an automated collection of security data, threat detection, and the ability to investigate and quickly respond to possible threats.

Network - Azure Network Watcher provides tools to monitor, diagnose, view metrics, and enable or disable logs for resources in an Azure virtual network and is enabled for each region being used within Azure.

Security Logs - When registering the Microsoft Security Resource Provider for a subscription and to start using Azure Security Center or Azure Sentinel, there are workspace design choices that will affect the logging experience. The best practices for an optimal Log Analytics workspace design are:

- Use as few Log Analytics workspaces as possible, consolidate into a “central” workspace.
- Avoid bandwidth costs by creating “regional” workspaces, so that the sending Azure resource is in the same Azure region as a workspace.
- Explore Log Analytics RBAC options like “resource centric” and “table level” RBAC before creating a workspace based on organization level RBAC requirements.
- Consider “Table Level” retention when different retention settings for different types of data are needed.
- Use ARM templates to deploy Virtual Machines, including the deployment and configuration of the Log Analytics VM extension. Ensure alignment with Azure Policy assignments to avoid conflicts.
- Use Azure Policy to enforce compliance for installing and configuring Log Analytics VM extension. Ensure alignment with the DevOps team if using ARM templates.

- Avoid multihoming, it can have undesired outcomes. Strive to resolve multihoming by applying proper RBAC.
- Be selective in installing Azure monitoring solutions to control ingestion costs.

## 2.10 Cost Management

Azure billing and consumption data must be available for analysis, monitoring, and accurate division of invoicing across different business units of an organization. Access to billing data is available in several ways, including summary information in the Azure portal, downloadable in a CSV format, and the Azure Billing APIs.

### Azure Portal Cost Information

Accessing cost details from the Azure portal is available and provides high level details regarding costs related to Azure resources that a user has been granted Billing Reader access to. This method will be used to give consumers quick access to summary details.

### 3rd Party Solutions

There are several 3rd party solutions available to analyze cloud billing and usage data. These include Cloudyn (now owned by Microsoft), RightScale, and CloudCheckr. These solutions provide advanced capabilities to analyze data in several ways, including tags. The capabilities come at a higher cost, which is generally a percentage (2.5–5%) of overall monthly cloud spend. Larger enterprises can generally see charges starting around $25K and can climb much higher. These solutions also do not provide the ability to access data via API.

### Azure Billing APIs

The Azure Billing APIs are available to Enterprise Agreement customers to retrieve data and integrate into existing systems and processes. These APIs provide the capabilities to meet the requirements outlined by the Billing and Administration team and will be the methodology to consume billing and consumption data.

### Applied Cloud Services (ACS) Offering

Cloud Analytics is an ACS Offering that uses a combination of database, API calls, and Power BI to provide a holistic view into the environment, as high as subscriptions and as detailed as down to tagging for individual resources. It provides a very detailed breakdown of individual cost expenditures by departments, resource, and resource owners. There is automated invoicing capability, and this is a self-contained per subscription option that satisfies data residency requirements.

### Azure Advisor

To maintain optimal functional levels and costs, Azure Advisor will need to be checked periodically by the cloud governance team. This allows for an analysis of the resource configuration and usage telemetry. It then recommends solutions to help improve the performance, security, and high availability of resources while looking for opportunities to reduce overall Azure spend. Any changes should be properly vetted and communicated with the resource owners prior to adjustments.

Reserved Instances

Azure offers Reserved Instances for Virtual Machine Sizes higher than "A"-tier machines. This functionality can drastically reduce the cost of Virtual Machines running within Azure. When doing an Infrastructure Assessment of on-premise infrastructure with Azure's tool, it will provide information on a pricing comparison for a Virtual Machine for Pay-As-You-Go models. It provides the monthly estimated cost for 1 year, 3 year, and no reserved instances. These instances can be interchangeable and scaled to other types of VMs in the same VM tier.

# 3. PREVENTIVE MAINTENANCE COST IMPACT ANALYSIS

The PKMJ Digital Platform described in Section 2 was utilized and configured for this effort to enable efficient data ingestion, cleansing, analytics, and visualizations. This section describes the initial data extraction and cleansing steps taken to prepare the data, the equipment targets provided by PSEG, the cost impact analysis performed, the final equipment selection process, and the additional data extracted for the selected equipment.

## 3.1 Data Extraction, Cleansing, and Enhancing

PKMJ worked with PSEG personnel to extract and transfer initial data from their Enterprise Data System into the PKMJ Digital Platform in support of the cost impact analysis. This information will also support the Risk-Informed Model and Preventive Maintenance Optimization (PMO) analytics within this report as well as the additional analytics and platform development efforts in Goals 2 and 3 of this overall project.

The PSEG Enterprise Data System houses both historical and scheduled corrective maintenance and preventive maintenance data, including the associated equipment and their required piece parts. This data lays the foundation for the Cost Impact Analysis, Preventive Maintenance Optimization, Machine Learning Work Order Failure Classifier, and Equipment Work Order history provided to INL. Component, Maintenance Plan, Work Order, and Stock data sets were ingested, analyzed, and validated between PSEG and PKMJ. Once data was validated for correctness, it was then cleaned and merged into a relational database to preserve data quality and integrity. At this point, the data feed was configured for automated ingestion into the database.

All data must go through various cleaning and enhancing stages to handle errors due to manually entered data, some of which can be handled during the merge into the database and some that need to be handled within analytics. The cleaning also involves the standardization of the particular field for ease of future analytics. Standardizing fields, such as Equipment Object Type or Work Order Type, becomes paramount to being able to gain insights from similar industry and even site equipment.

The following are examples of Data Cleaning and Standardization:

- Ingestion Cleaning: Upon ingestion, all fields are trimmed to eliminate spaces before and after the text as well as a removal of special characters like carriage returns and line feeds.

- Maintenance Plan (MP) Data Set Cleaning: MP status sometimes isn't up-to-date, so an analytic is generated to search through MP descriptions to eliminate potentially deactivated MPs that have an 'Active' status.

- Component Object Type Standardization: Object type standardization is essential for grouping similar items within the nuclear industry and sometimes, even within a fleet/site. An example would be that

Component Object Types of ‘mg’, ‘motors’, ‘motor’, ‘001’ can be grouped to ‘MOTOR,’ so all motors are relatable via one common identifier.

In addition to Data Cleansing, PKMJ utilizes analytics to enhance data provided to improve the ability to extract intelligence. One example of this would be the Work Order Failure Classifier enhancement. This enhancement analytic is based on a Convolutional Neural Network (CNN) that utilizes a Word2Vec component to convert words and their context, within work order descriptions, to numerical vectors. These numerical vectors are then used as an input into the multilayered CNN, so that the model may make predictions and ultimately learn how to categorize a Work Order as a “Failure,” “Degradation,” or “Other” based on work order descriptions, resulting in a valuable timeline of equipment operation history. In order to get a clearer picture of operational history, a Natural Language Process (NLP)-based classifier was developed and applied to work orders identified as failure or degradation.

NLP is a relatively new advanced machine learning technique and a rapidly growing field of study. NLP allows computers to understand human speech patterns in a way that allows analysis and predictions to be performed. Essentially, NLP unlocks the ability to process and analyze large amounts of natural language-based data (i.e. free text or string information)—like this document, history logs, and records, such as work order descriptions. By labeling a sample of data with an appropriate category, NLP models can actively learn from a small amount of data to predict the category of a much larger set of unlabeled data.

This effort aims to develop a model that can accurately determine if the work order description identifies equipment failure, degradation of that equipment, or neither. Our method to develop this model is outlined below, with Figure 4 outlining the workflow:

- Define categories
- Identify training data samples
- Label training data (SMEs)
- Train model
- Predict evaluation set and determine areas for improvement
- Label samples that potentially target areas for improvement
- Reevaluate as necessary and assess model performance

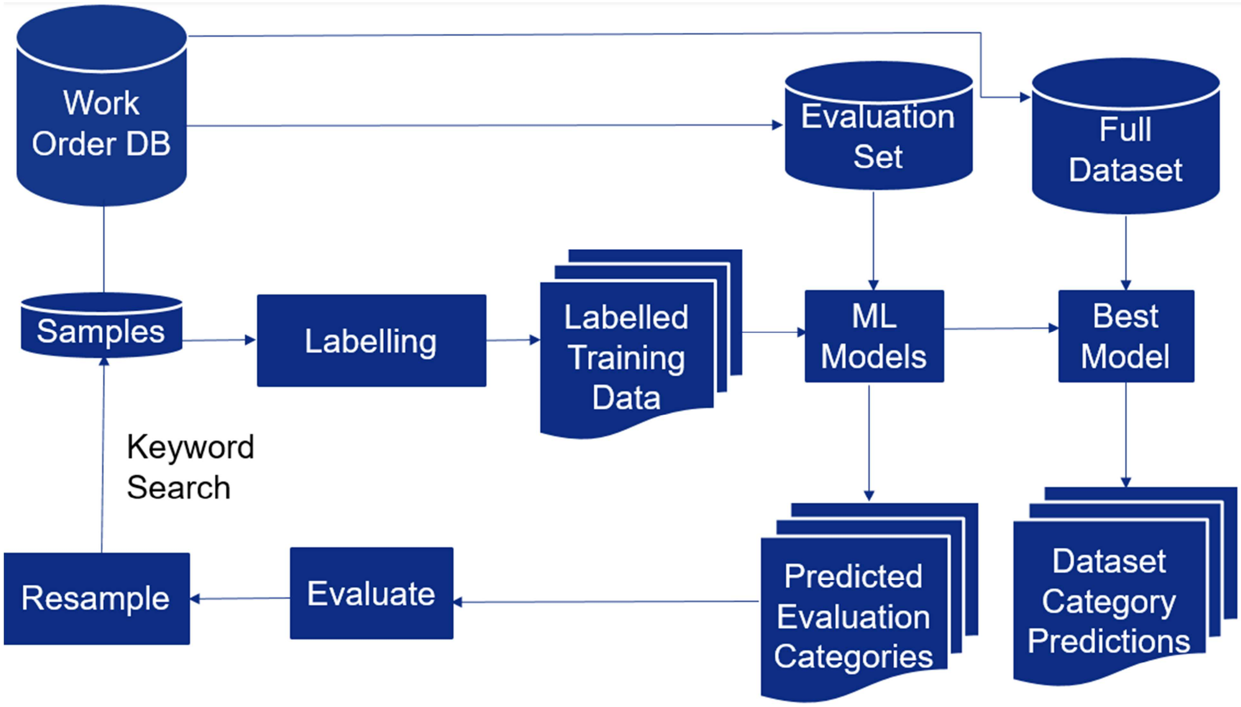


Figure 4. Work Order Classifier NLP work flow.

### 3.2 Equipment Targets

The first priority of PSEG is the safe and reliable operation of the plant; the station cannot support a pilot program that might jeopardize any direct plant operation outputs. When first determining what equipment/groups were good targets for a reduction in maintenance, PSEG station leadership was consulted to ensure there was alignment on and an understanding of the potential risks involved in changing maintenance strategies and the potential performance impact for the selected equipment. The challenge is keeping high equipment reliability while still reducing maintenance cost. PSEG provided a set of high and medium risk equipment as seen below to give us their view of station impact.

PSEG Equipment Targets

Would not recommend due to ***high*** risk:

- Main Turbine
- Main Power Transformers
- Main Generator
- Main Condenser
- Vacuum Pumps
- Reactor Coolant Pumps (RCPs)
- Steam Generator Feed Pumps
- Emergency Diesel Generators

Would be good candidates that are ***medium*** risk:

- Turbine Auxiliary Cooling Pumps (TAC)
- Chemical Volume Control System
- Component Cooling Pumps
- Service Water Pumps
- Condensate (CN) Pumps
- Circulating Water (CW) Pumps
- Stator Water System
- Electrohydraulic Control Pumps
- Feedwater Heaters (FWHs)
- Heater Drain Pumps (HDPs)
- Station Air Compressors (SACs)
- Rod Control System (RCS)
- Chillers
- Auxiliary Power Transformers
- Station Power Transformers
- Radiation Monitors
- Control Air Dryers

The high risk equipment were eliminated from consideration, because these represent equipment that would have a high cost of failure due to lost generation and would also have high replacement costs if an unexpected failure did occur. PSEG also provided a list of asset groupings by equipment type (e.g., Accumulators, Heat Exchangers, Screens, Tanks, Valves), along with their total maintenance cost values for review. After the initial equipment screenings, the asset groupings that showed the largest cost burden at PSEG were Vertical Pumps/Motors, Fans and Valves with large potential savings from extending major PMs, such as overhauls/replacements that account for the larger cost maintenance. While the asset groupings by equipment type did show some good sources of values, their review and extension of maintenance would be complicated due to the large cross-section of systems the groupings were in.

After narrowing down the potential assets list, using the criteria above, the first set of PMs selected were from the Service Water System pumps/motors. Key factors in the decision were: each Salem reactor unit has six pump/motor pairs, the pairs are all installed in an enclosed intake structure that allows for easy access to potentially install additional sensor equipment, and the locations of the pairs for both units are in similar operational environments, which allows for comparable data analyses. However, during a review of the preliminary requirements for installation of wireless sensors, it was determined by the PSEG Engineering Department that a detailed modification would be required due to the Technical Specification requirements and the safety-related classification of this equipment. Therefore, the PKMJ Data Science and Analytics team performed a cost impact analysis to select a different system and set of equipment for the pilot program.

### 3.3 Cost Impact Analysis

The cost impact analysis incorporates cost and risk data with an Asset Selection process, as both are used to select the initial target set of equipment. When selecting screening criteria for the analysis, the research team had to factor in what equipment could feasibly be monitored within the two year timeline of the federal award. In the end, six main screening criteria were used for removing equipment from the analysis:

Equipment type - To focus on rotating equipment (e.g., pumps, motors or fans), only the following object types were considered for the analysis:

- Air Compressor
- Bearing
- Chiller
- Compressor
- Control Rod Drive
- Coupling
- Engine
- Fan
- Gearbox
- Generator
- Governor
- Heating, Ventilation, and Air Conditioning (HVAC)
- Main Turbine
- Motor
- Pump
- Separator
- Turbine
- Turning Gear
- Vibrator

Safety Class - Safety-related equipment has a higher degree of risk and cost in adopting condition-based monitoring (e.g., potential licensing challenges based on an in-depth review of potential failure modes and impacts being required, sensors wouldn't support any accident analyses and the existence of the sensors (electromagnetic interference/radio frequency interference) or them falling (physical) off may inhibit some accident mitigation function).

Mitigating System Performance Index (MSPI) - There is less benefit in adopting online monitoring to Standby Safety Pumps and Motors in MSPI designated systems (e.g., Diesel Generator, Fuel Oil, Auxiliary Feedwater, Safety Injection, Residual Heat Removal, and Service Water).

Technical Specification - There is greater risk and additional cost involved to adopting sensors onto any Technical Specification designated equipment.

Single Point Vulnerabilities (SPVs) - Similar to Technical Specification, there is greater risk and additional cost involved to adopting sensors onto any SPV designated equipment.

PM Costs - Annualized PM Costs had to be greater than \$100k per system prior to Equipment Type screening, then greater than \$50k per system after Equipment Type screening.

### 3.4 Final Pilot Equipment Target Set Selection

The equipment target set list produced by the screening in Section 3.3 above was presented to PSEG as potential condition-based monitoring candidates for the pilot. After extensive deliberation, the pump/motor pairs within the Salem Nuclear Generating Station's circulating water system were chosen as the new targeted set of equipment for the pilot. The key factors in the determination were:

Location - The circulating water system has all the pump and motor sets located in their own buildings near the intake structures. This makes it convenient to use one wireless base station to collect all the wireless sensor information. Additionally, being outside of any radiation areas makes installation of wireless sensors and monitor equipment easier.

Sensor requirements - The team used EPRI 3002010577 "On-Line Monitoring Guide" to determine what type of wireless sensor would be needed to cover the failure mode of the PM that was going to be extended or be converted to condition-based maintenance. This guide does limit target sets towards Fans, Vertical Pumps/Motors, and Vibration Monitoring tasks; however, these components tend to have the higher cost maintenance strategies at nuclear sites.

Upcoming Schedule Maintenance - The circulating water system has a routine of major maintenance on a rotating basis of all the pumps and motors. PM extensions resulting from this pilot effort would give the station some immediate cost benefit but also will give a before and after look to help with defining failure pattern signatures.

Parts availability and redundancy - The circulating water system has 12 pump and motor pairs and a spare set that would be available for maintenance in the event of premature failure due to condition-based monitoring. Having 12 similar pairs will also help with identifying operational pattern signatures.

### 3.5 Additional Data Collection and Quality Check

After Asset Selection, PKMJ worked with PSEG personnel to extract and transfer additional data specifically for the CWS into the platform where it was then combined with the initial PSEG data (Component, Inventory, Work Order, Maintenance Plan, etc.) and industry information (Maintenance Strategies, Failure information, etc.). Below is additional information extracted related to the selected CWS equipment:

Modification Information

An important process to determine failure modes, preventive maintenance strategies, and frequency of corrective work of the Circulating Water pumps and motors is to evaluate any major modifications or replacements. As each pump or motor is overhauled or replaced, they return to 100% availability. A lot of the preventive maintenance and failure modes can restart to the initial estimates that are derived from industry and vendor data. A major modification can also change the time projections of this data. PSEG is on the Delaware River and close enough to the ocean to be susceptible to tides and brackish water. Prior to 2015, the brackish water was causing a more severe impact to the pump housing life due to the corrosion effects, resulting in short rebuild cycles of three years. In 2015, the station started implementation of a major modification to a more corrosion resistant metal in the pump casing. This has extended the time-based frequency of the pump change outs from 3 years to 6 years. Further extension will be discussed in Section 5.3.

Installed Sensor Data

PSEG utilizes a Monitoring and Diagnosis (M&D) center to monitor their entire generation system. For the nuclear units, that equipment has a fixed number of installed data points that include rotor temperatures, discharge pressures, breaker positions, and fluid temperatures related to the circulating water pumps. That data is sent to the M&D center via PSEG's OSI PI system. A spreadsheet of hourly data recorded from 2009 to 2019 was given to the pilot team to help track and trend possible performance issues with the pumps or motors and identify any type of failure mode information. The data required a lot of cleansing, as there was a lot of missing data that made certain time periods from 2009 to 2019 unusable for trending. A team visit was also made to the M&D center to gather information on the data they use from the circulating water system, some trends that they have established, and some of the past degradations that they have seen from the system and components.

Vibration Information

The current method of performing vibration monitoring of the circulating water system pumps and motors is to do quarterly manual vibration checks. This allows engineers to do some trending and predicting of the circulating water system; however, it only provides a snapshot of the equipment, and changes in the conditions have to be taken into consideration.

### 3.6 Vibration Sensor Installation

Vibration monitoring instrumentation contain accelerometers that sense changes in the amplitude and frequency of dynamic forces that can impair rotating equipment. Identifying degradation at its onset by analyzing vibration measurements allows personnel to identify issues, such as imbalance, looseness, misalignment, or bearing wear in assets prior to significant degradation and failure. This gives the plant more options and more time to respond, allowing for more effective resolutions.

Periodic vibration measurements are collected on a circulating water pump (CWP) motor. The collection of continuous vibration measurements, as part of the CWS process data, enhances the diagnosis and prognosis of CWP motor conditions. This aligns with the objective of achieving PdM on plant assets in commercial NPPs. To achieve the objective, the team decided to continuously monitor the CWP motors using wireless vibration sensor nodes from KCF Technologies. The installed models are Vibration Sensor Node (VSN), i.e., SD-VSN-3 [8]. The VSN-3 specification sheet is in Appendix A. Sixty VSN-3 sensor nodes have been installed across 12 CWP motors and associated CWP bypass valve of Salem NPP. Three wireless vibration sensor nodes are installed on each CWP motor and two sensors on the associated CWP bypass valve at the plant site. Each sensor node consists of two accelerometers sensitive to orthogonal in-plane motion and a temperature sensor. The sensor nodes can be mounted on to the plant asset either via a magnetic base in the node or a mounting plate attached using epoxy. PSEG uses magnetic mounting of the sensor nodes.

The KCF Technologies wireless sensing system and its components are shown in Figure 5 [8] [9]. A cloud configuration was installed at the Salem plant site to support the deployment of wireless sensor nodes on CW pumps and motors. The sensor node transmits X- and Y-direction vibration data along with temperature data to the base station over a cellular network which then transmits the data using the PSEG Wi-Fi network to the KCF cloud. The data stored in the cloud is accessed through KCF SMARTDiagnostics® (SD) machine condition monitoring software (MCMS). SMARTDiagnostics® provides an interface to visualize the data and the state of the equipment as well as the ability to export the data to a text file.

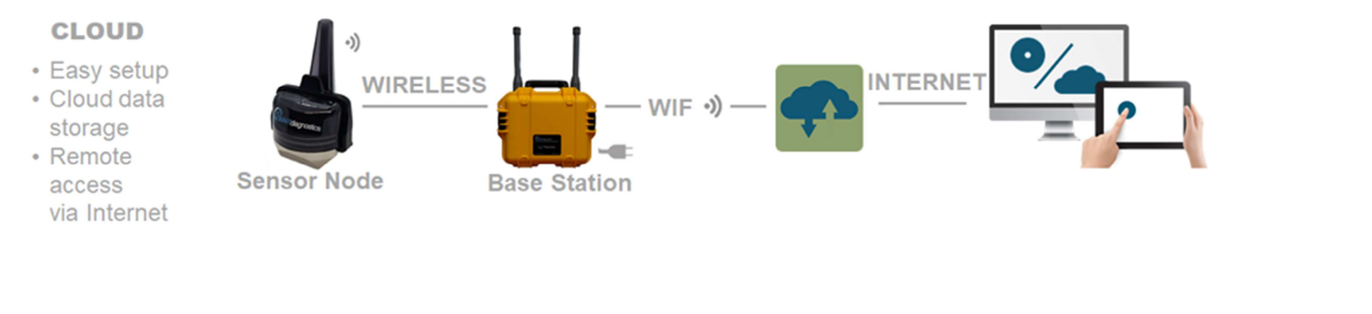


Figure 5. The KCF wireless sensing system and its components.

### 3.6.1 Wireless Transmission through the Base Station to the Cloud

The KCF Technologies' SMARTDiagnostics® wireless network has a proprietary protocol for communication between the sensor nodes and wireless base stations [9]. SMARTDiagnostics® uses the 2.4 GHz Industrial, Scientific, and Medical (ISM) Radio Frequency (RF) band for sensor node communication. The 2.4 GHz ISM RF band is able to effectively balance energy efficiency and transmission range within industrial facilities. Other bands, such as the 915 MHz ISM band, offer an insufficient data rate to transfer large data sets effectively. The 5.8 GHz band has a range that is too close for practical application in industrial conditions.

The SMARTDiagnostics® transceiver is comparable to the transceivers used by Bluetooth®. SMARTDiagnostics® uses a wireless protocol, named DARTwireless™, that differs from Bluetooth® in several respects. DARTwireless™ is designed for ultralow power, low bandwidth consumption, and communicating with hundreds of devices. A channel adaptation scheme is employed to determine the most effective channels to be used. Channel choice is determined by interference and internet workload balancing among multiple receivers. DARTwireless™ does not employ frequency hopping. RF traffic generated by SMARTdiagnostics® has the following general characteristics:

- Modulation – Gaussian Frequency Shift Keying (same as Bluetooth®)
- Over the air rate – 2 Mbps
- Channel half-power bandwidth – 2 MHz
- Peak RF power – 15 dBm
- Typical range – 800' line-of-site, 100–300' industrial indoor.

### 3.6.2 Vibration Data Types

Once the raw vibration data is safely stored in the cloud, the data is accessed through the KCF SMARTdiagnostics® MCMS, which provides an interface to visualize the data, evaluates the state of the equipment, and provides text output. The raw data consists of the asset's acceleration with time. From this time domain data, an acceleration frequency spectrum is calculated by executing a Fast Fourier Transformation routine. It is also possible to convert the acceleration data into velocity signals in both time and frequency domains. Acceleration generally highlights high-frequency vibration. Velocity tends to be more effective for evaluating vibrations throughout the entire frequency spectrum. Thus, four base data types are available to be processed for PdM:

- Acceleration time waveform (raw measured signal)
- Acceleration frequency spectrum (calculated)
- Velocity time waveform (calculated)
- Velocity frequency spectrum (calculated)

### 3.6.3 Wireless Vibration Sensor Node Installation on Circulating Water System at Salem Plant Site

The KCF SD-VSN-3 were installed on August 23, 2019. Each CWP motor system has five SD-VSN-3 mounted on the assets. Three VSNs have been installed on each CWP motor adjacent to vibration measurement locations labeled as inboard node, outboard node, and top node in Figure 6 Two VSNs have been installed on the associated pump valve. The concerns associated with electromagnetic interference, radio-frequency interference, and cyber-security were addressed as part of the installation and testing process of wireless VSNs.

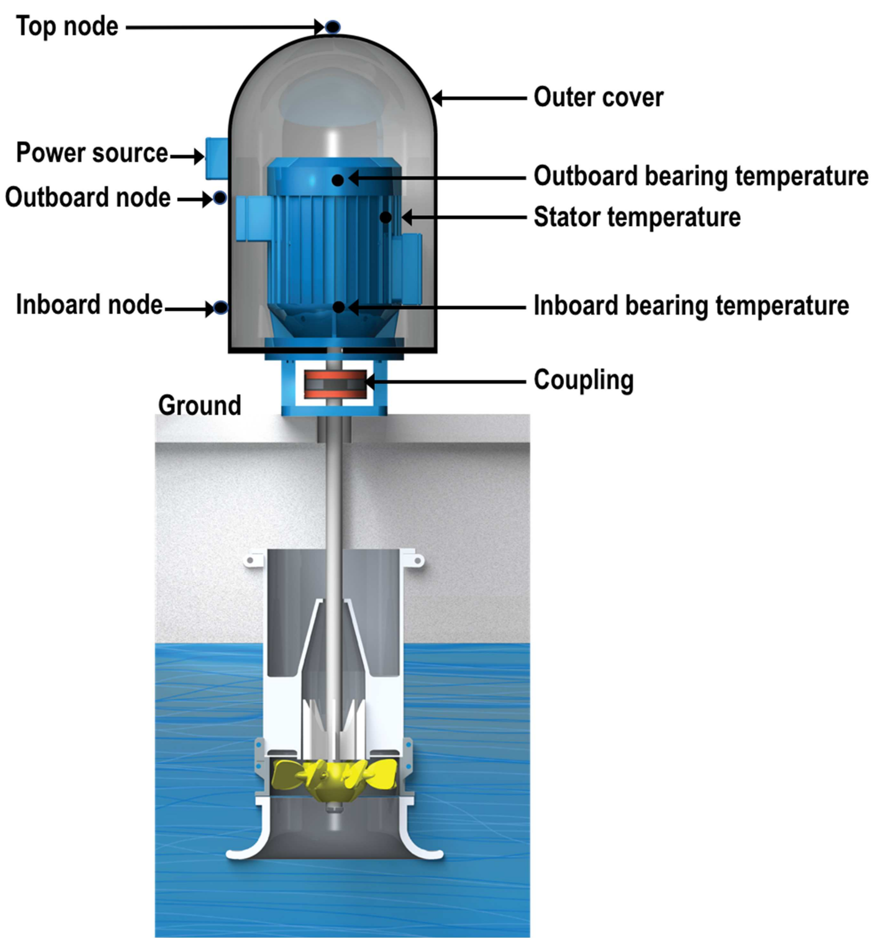


Figure 6. Mounting locations of the VSN nodes on the CWP motor.

Figure 7 shows the relative location of the VSNs on the side of the motor outer covering for the 12 CWP motors. The VSNs are placed as close as possible to the buttons that have been used for the PSEG historical data monitoring inboard and outboard vibrations. The historical vibration measurements are taken on these locations every three months. The VSN recorded vibration data will be compared with the historical vibration data to ensure they are capturing data and performing as expected. The top VSN captures both in-plane vibrations at the same time. The representative location of the top VSN for all CWP motors is shown in Figure 8.

The pump valve for a CWP motor can be seen in the upper left corner in Figure 9. The relative position of the pump valve with respect to the electric motor is shown as well as the location of the VSNs on the pump. This gives the relative position of the pump valve with respect to the electric motor. The relative positions are similar to the locations for all motors. Figure 9 shows the VSN locations on the pump valve.

It is anticipated that the regularly spaced data from the VSN will provide excellent coverage to capture the vibration signature of CW motors and pumps, enabling online monitoring and providing necessary data to develop models to support PdM. The CWPs are submerged, making it difficult to instrument the pumps directly. The pump valve is chosen as an indirect measure of the pump vibrations. The pump valve is the closest component that is readily accessible to the pump. The pump valve will contain vibrations directly related to the operation of the pump.

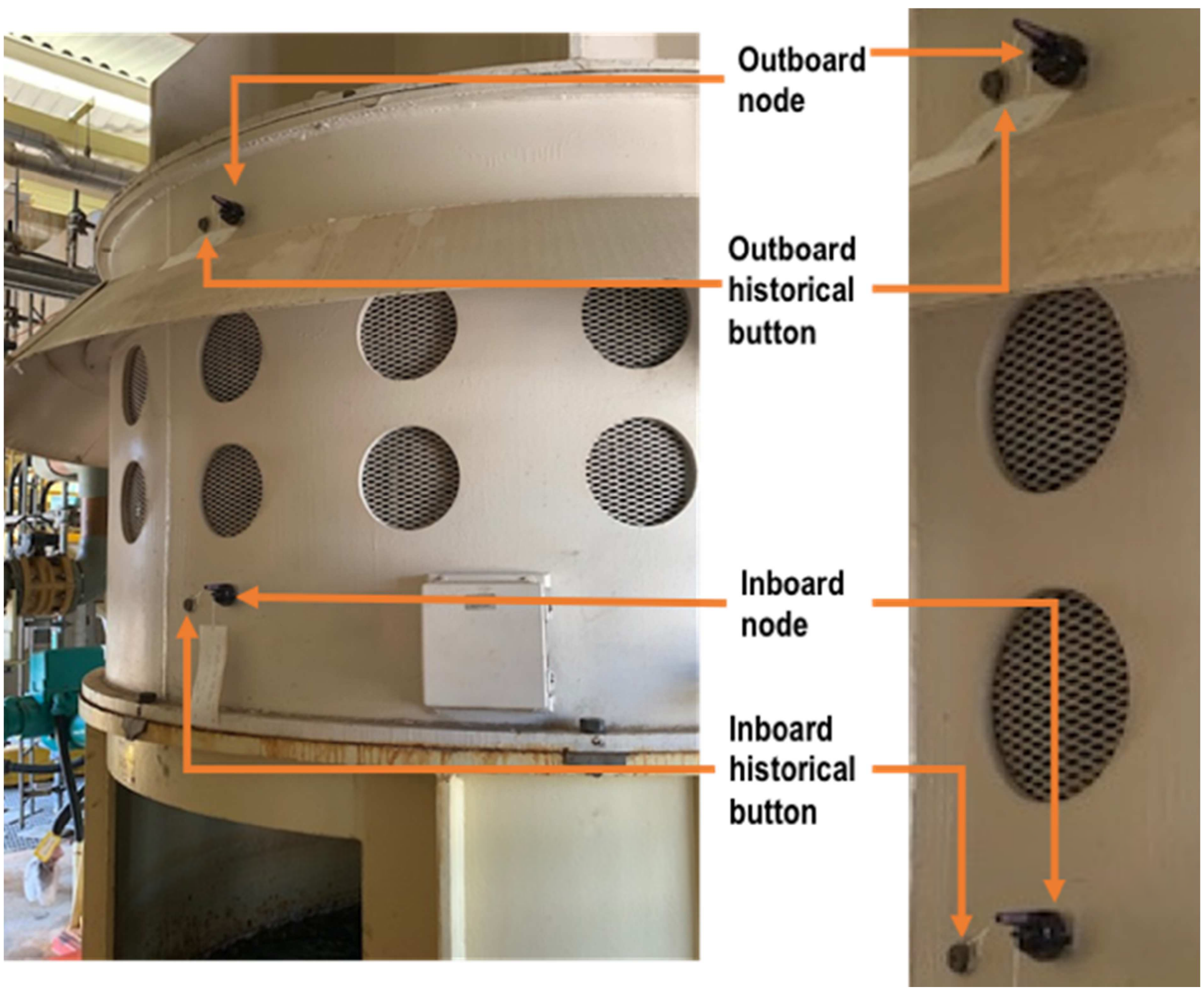


Figure 7. VSNs are in close proximity to the locations where historical vibration data has been taken for motor 23B.

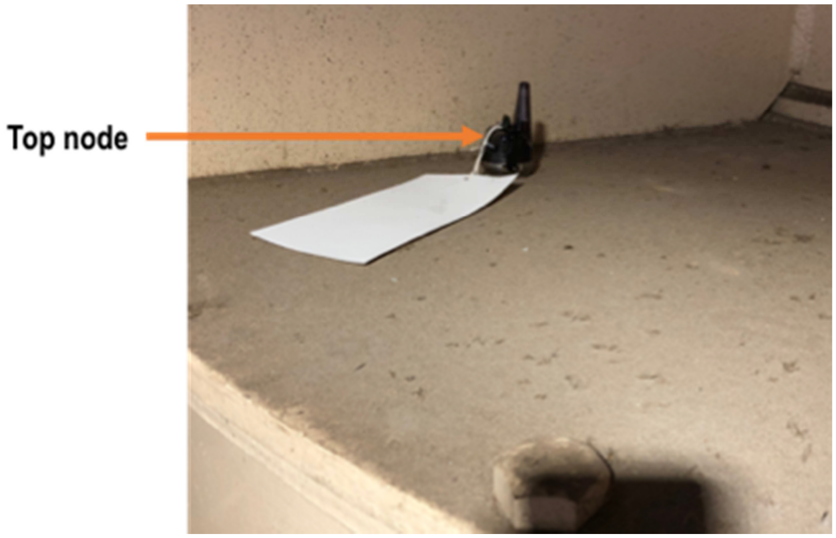


Figure 8. A VSN mounted on top of the CW motor cover in line with the historical buttons.

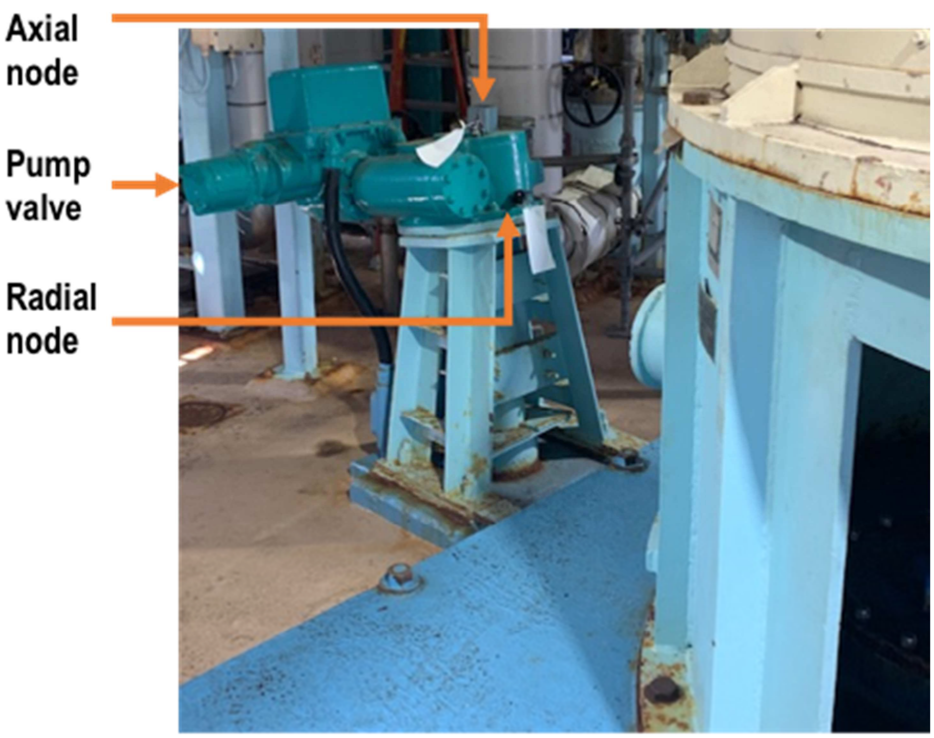


Figure 9. The relative position of pump valve 12A with respect to the motor cover is shown as well as the location of VSNs on the pump.

### 3.6.4 Installation Challenges

The process of hardware installation and system set up was very simple and quick. Installation of 60 wireless magnetic sensors, base station and repeater set-up all took approximately one hour of field time. For the KCF SMARTDiagnostics® system, the typical means of data transfer method is to transmit through cellular network with a national provider. KCF has already established contracts through national carriers which makes this method seamless to a customer they are providing for. However, the station notified the team that the cellular network option was not possible due to poor cellular reception around the CWS location. This required the team to use the PSEG wireless network for system operation. This method resulted in data transfer challenges that the team needed to troubleshoot.

### 3.6.5 Troubleshooting

There were several troubleshooting conference calls between PSEG, KCF and PKMJ to understand why the system would not allow data transfer. The problem was determined to be the PSEG corporate firewall. Further meetings were held with the PSEG Corporate IT team and the KCF software team, and a fix to the base station transmission was applied that corrected the issue. The system has had stable operation and the team has been able to use the data to identify trends.

### 3.6.6 Lessons Learned

Issues with the setup of the system derived from the switch to using the PSEG wireless network instead of a cellular network. The lesson learned was that a site IT member with knowledge of the corporate network / firewalls should have been committed to the team during the initial installation phase of the project. Engagement of the KCF software team and field experts was also a vital part of getting the system running after installation.

### 3.6.7 Wireless Vibration Sensor Node Data

The installed VSNs transmit data every hour to the KCF cloud via an API. The vibration data can be accessed and analyzed through web-based SMARTDiagnostics® software (https://sd.kcftech.com/login). The data can also be exported in a comma separated values format for further analysis and predictive model development. The screenshots of the SMARTDiagnostics® user interface and representative vibration signal transmitted by VSNs installed on a CWP motor are shown in Figure 39 and Figure 40 of Appendix B.

### 3.6.8 Installation Validation Strategy

The collection and interpretation of plant vibration data is a complex undertaking. PSEG has existing infrastructure and processes to successfully accomplish vibration monitoring. To take full advantage of PSEG's existing infrastructure and knowledge base, the wireless nodes should be installed in a manner that can be directly compared to the historical data from the existing vibration monitoring program. Using the historical vibration monitoring processes as the baseline will enable the validation as well as the justification of the wireless vibration data.

The following implementation conditions are being followed to maximize the effectiveness of the comparison with the historical baseline. The wireless vibration nodes should be

- Positioned next to the PSEG's vibration locations
- Taken at approximately the same time
- Monitored with similar data acquisition parameters.

The previous section discussing the sensor node locations on the CWP motor show that the wireless nodes are collocated near the PSEG measurement locations. Since the wireless nodes operate independent of the PSEG's vibration sensors, the two vibration monitoring processes can take data at the same time. The KCF data acquisition parameters can be selected to be functionally equivalent to the PSEG sensor settings, as discussed in the next section. Thus, the wireless vibration data can be effectively compared to PSEG's baseline data. This will ensure that the project has effectively installed the wireless sensors on the CWP motors and the data generated is high quality data. The goal of this initial phase of the sensor node installation is to ensure that the KCF VSN Nodes are properly installed; communicating data to the cloud data base and note any potential issues.

### 3.6.9 Setting Effective Data Acquisition Parameters

The setting of the data acquisition parameters should be based on the operating properties of the motors. If the vibration measurement system is properly specified, the data acquisition system should have little impact on the acquisition parameters. Based on the information provided by PSEG, the CWP motors have the following design characteristics: (1) The design running speed of the CWP motor is 294 revolutions per minute (RPM), i.e., 4.9 Hz; and (2) the CWP is a four-vane pass configuration and the diffuser has six stationary vanes. The resulting frequency spectrum obtained from a CWP, CWP motor, and diffuser will contain the following major harmonics:

- 4.9 Hz 4.9 Hz Fundamental harmonic
- 4.9 Hz* 4 19.6 Hz Harmonic caused by the pump vanes
- 4.9 Hz* 6 29.4 Hz Harmonic caused by the diffuser vanes
- 4.9 Hz*4*6 117.6 Hz Harmonic caused by the combination of the pump and diffuser vanes
- 120 Hz 120 Hz Vibration caused by the electric line frequency

There will also be minor harmonics and cross harmonics evenly spaced by multiples of 4.9 Hz. The major harmonics will be used as signatures to perform the initial comparison between the KCF and Emmerson data to ensure the wireless data is valid.

Historically, PSEG takes data with the following data acquisition parameters using an Emmerson CSI 2140. The parameters were selected based on the slow running speed (4.9 Hz) of the CWP motor. Emmerson has confirmed that their CSI 2140 has the appropriate antialiasing filters built-in for all the Fmax settings available in the CSI 2140.

- Sample rate 2048 Sa/s
- Fmax 180 Hz
- Lines of resolution 800
- Spectral resolution 0.225 Hz
- Sample duration 4.4 seconds

A comparable KCF acquisition setting is selected that is functionally equivalent to the historical data acquisition parameters that PSEG uses with the CSI 2140. KCF's available settings are given in the Accelerometer Sampling table within the Smart Diagnostics® Application Note: Vibration Sensor Performance [10]. The VSN setting that most closely mimics the historic CWP data acquisition parameters is the 512 Sampling Frequency (Sa/s) and a spectral resolution of 0.31 Hz for the data collected for 3.2 s duration. The number of data points per sample set is fixed at 1650, so the number of lines of resolution in a frequency spectrum is fixed at 825. The KCF VSN has an antialiasing filter at 4 kHz.

The slightly different data acquisition parameters from PSEG historical data should not affect VSN data quality or analysis. These KCF node settings are the agreed upon data acquisition parameters that will be used for taking the majority of the wireless vibration data.

Because rotating machinery are cyclic, frequency spectrums are an efficient method to identify the signatures displayed by the spectral plots generated by the rotating equipment. Because of the ease in identifying pump signatures in the frequency domain, most plots will be frequency spectrum plots. Time domain plots/processing are better suited to identifying and locating transients and baseline shifts. This subsection will focus on initial wireless vibration data analysis in the frequency domain to ensure that the data is of sufficient quality to compare with historical information.

In describing the data displayed in the frequency spectrum plots several terms will be used: Synchronous and Asynchronous. Synchronous harmonics are defined as proportional to running speed. Synchronous harmonics usually manifest narrow peaks in frequency spectrums. Asynchronous harmonics are independent of running speed and tend to manifest as broad peaks or humps in the frequency spectrums. Because there can be other cyclic processes in a plant, asynchronous harmonics can also be narrow peaks. The vibrations caused by the motor at twice the electrical line frequency at 120 Hz is a classic example of a narrow band asynchronous harmonic.

To effectively interpret the spectral content generated by the CWP motors using the KCF VSN sensor data, the discussion is presented in the following order.

1. Surveying CWP motor frequency content
2. Aliasing review
3. Initial discussion on the wireless data

To understand the frequency contents present in the wireless vibration data up to the antialiasing cutoff frequency of 4 kHz, the data acquisition parameters is collected at 4096 Hz. The resulting survey of the frequency spectrum confirms the presence of higher frequency components up to the 4,000 Hz bandwidth of the antialiasing filter, as stated in Appendix A. The presence of frequencies above 256 Hz presents a potential aliasing concern when the acquisition system is configured for the typical data rate of 512 Sa/s, if an antialiasing filter is not used at all Fmax settings.

Most vibration monitoring vendors consider their antialiasing filters proprietary information and do not readily provide details. To be cautious, the project plans to run several simple experiments at PSEG to understand Emmerson's and KCF's antialiasing filters and how they are implemented. A short review on aliasing will be given to remind the reader the importance of understanding aliasing effects.

Surveying CWP Motor Frequency Content

To gain a better understanding of the frequency content produced by the CWP system, the data rate for the VSN was changed to be 8192 Sa/s. This will give a more complete view of the spectral components generated from the CW pump system. The impact of narrowing the frequency content to 256 Hz will be better evaluated. The VSN takes acceleration data. To obtain velocity and displacement signals, the acceleration data must be processed. Figure 10 shows the frequency spectrum of a Salem Motor Inboard Vertical (MIB-Y) sensor, and there is significant frequency content just beyond 4,000 Hz. A similar observation is observed in Figure 11, which shows the Salem Motor Out Board Vertical (MOB-Y) signal.

Both Figure 10 and Figure 11 indicate that the higher frequencies (> 500 Hz) dominate the acceleration spectrum. The lower frequency harmonics generated by the motor are hidden by the higher frequency amplitudes in these graphs. To flatten the higher frequencies and accentuate the lower frequencies, vibration analysts generally work with velocity plots. The velocity signals can be derived from the acceleration by weighting each spectral component by $1/(2\pi f)$.

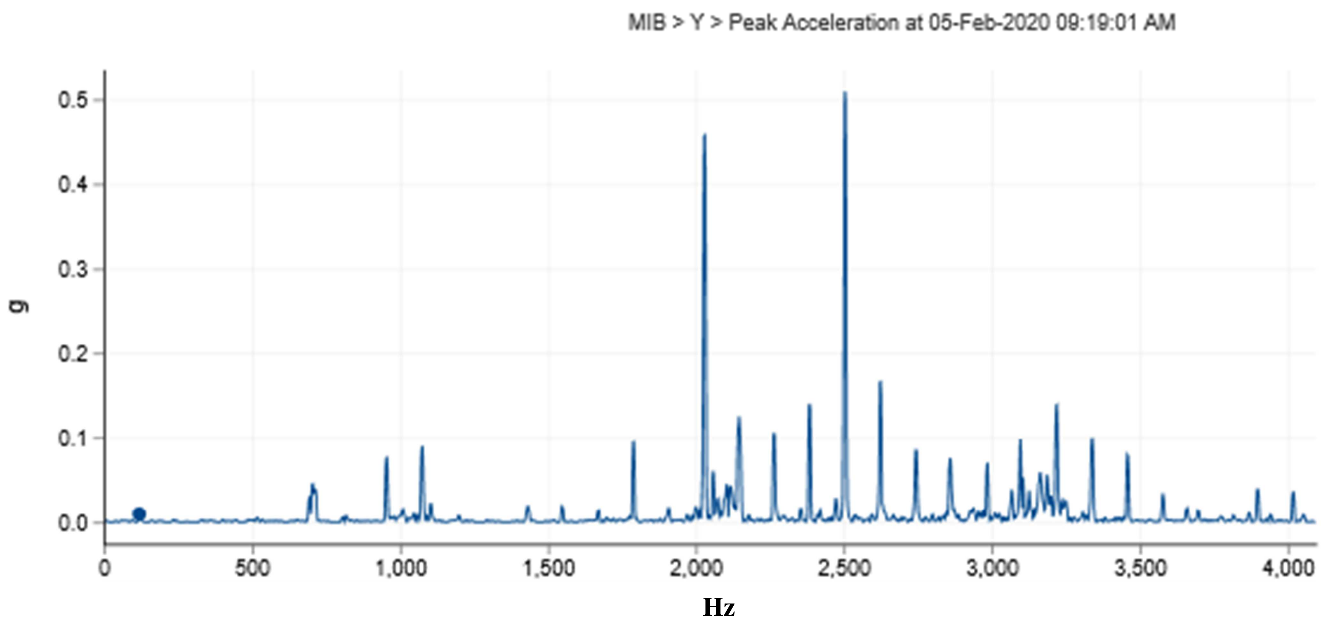


Figure 10. The acceleration data displayed is representative of the vertical Inboard motor acceleration for the Salem 21A Motor.

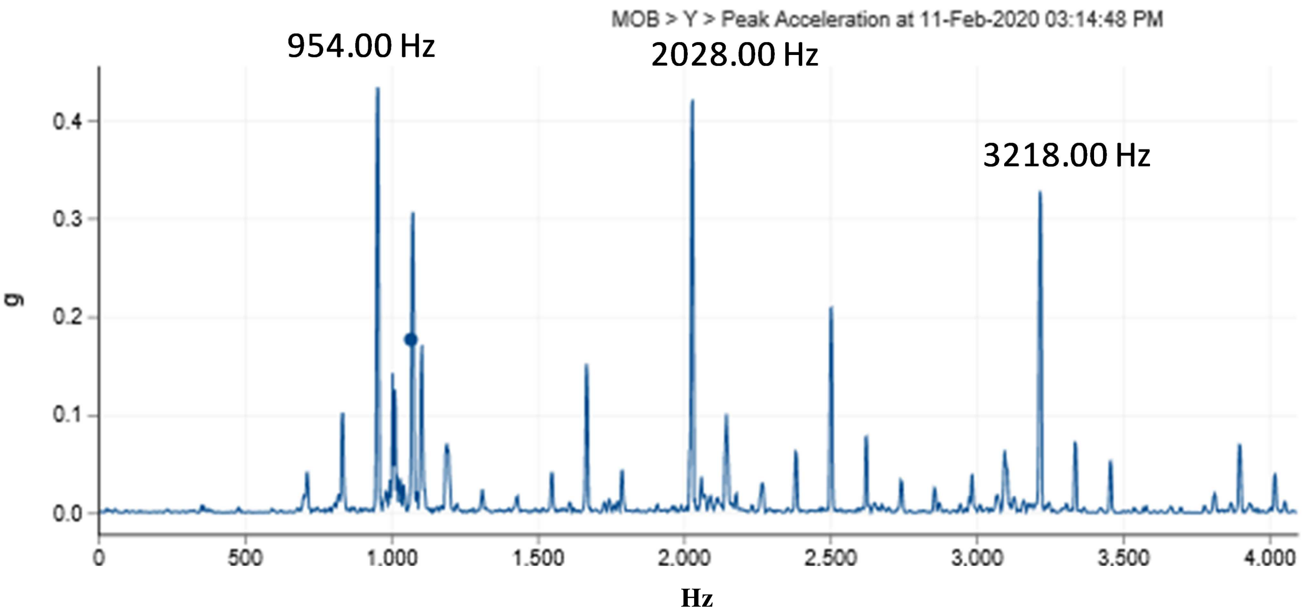


Figure 11. The acceleration data displayed is representative of the vertical outboard motor acceleration for the Salem 21A Motor.

Aliasing Review

As mentioned previously, the KCF sensors are normally set to operate at a data acquisition rate of 512 Sa/s, i.e., with the bandwidth of 256 Hz. Figure 12 shows representative acceleration data taken using the normal sensor settings. This limited bandwidth accentuates the harmonics generated by the motor/pump with plenty of resolution to resolve each peak. The spectrum is typical of rotating machinery.

The importance of making sure that we fully understand the operational effects of the antialiasing filters is illustrated with the following example. The frequencies labeled in Figure 12 come from the three largest labeled harmonics in Figure 11. The selected frequencies in Figure 11 are well above the 256 Hz bandwidth displayed in Figure 12. If an antialiasing filter has a cutoff frequency of greater than 256 Hz, there would be concern that the higher frequency harmonics will be aliased into the 256 Hz spectral window. The selected frequencies in Figure 11 were "folded" down into the 256 Hz bandwidth shown in Figure 12 [11]. The locations where the aliased frequency components should fall are indicated by AHz units. It can be seen that the aliased components can land next to or on top of harmonics resulting from the motor/pump.

The concern with aliased signals is that they confound the interpretation of the frequency spectrum. The higher frequency components may not be related to the pump/motor vibrations or are not representative of the vibrations at the lower frequencies. Aliased frequencies can cause misdiagnosis and undue concerns. Aliased frequencies are also hard to track down the generating source, since the troubleshooter will be looking for sources that generate vibrations in the incorrect frequency range. The project team is working with KCF Technologies in resolving the antialiasing concern by performing additional testing. Initial results from additional testing is providing evidence that could ensure that antialiasing is not a major concern. Figure 13 is representative of the spectrum variation between different accelerometers, sensitivity directions, and locations. The x-sensitivity of the sensor node appears to be more aligned with the 120 Hz motion caused by the motor/pump. This type of variation between Figure 12 and Figure 13 is normal.

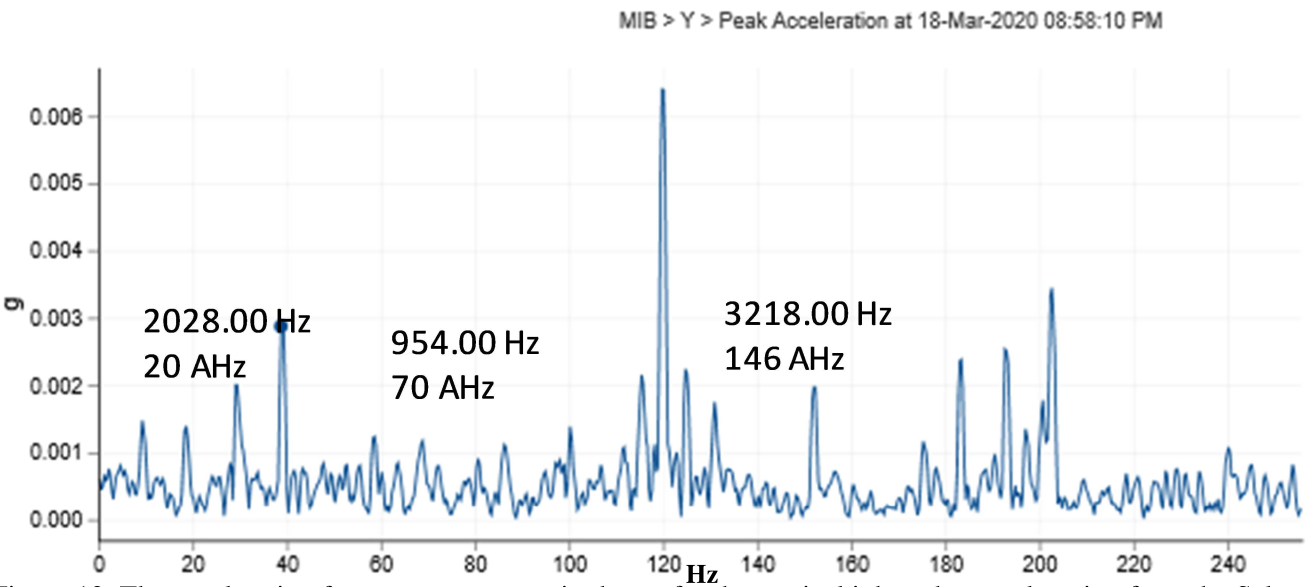


Figure 12. The acceleration frequency spectrum is shown for the vertical inboard motor location from the Salem 21A Motor.

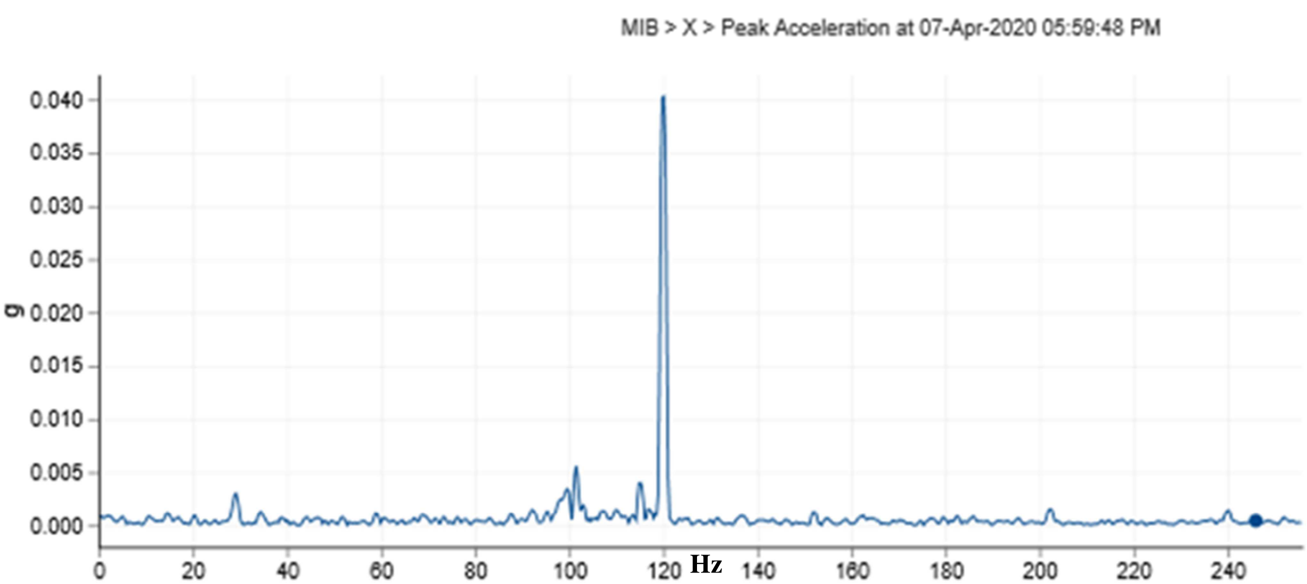


Figure 13. The acceleration frequency spectrum is shown for the horizontal inboard motor location from the Salem 21A Motor.

Once the data has been digitized, it is impossible to conclusively prove or disprove aliasing within the data collected. Thus, it is critical to ensure that there is an effective antialiasing filter prior to the digitizer and that the filter is working properly. There are a significant number of higher frequency harmonics, as shown in Figure 10 and Figure 11. Thus far, the data appears to be properly digitized as one would expect to see more harmonics in the resulting 256 Hz frequency spectrum if the high-frequency harmonics were aliased. An antialiasing test was performed by KCF that suggests frequencies greater than 256 Hz are filtered out. In lieu of having antialiasing specifications from KCF and Emmerson, a test using PSEG's standard vibration measurement equipment has been planned to be performed at PSEG. The results from this experiment will provide additional clarity on the operation of the antialiasing filters for both Emerson and KCF sensors.

### 3.6.10 Initial Discussion on The Wireless Data

Since the aliasing review results indicate that the antialiasing filters are working as expected, the focus of this subsection is to perform initial data analysis on the KCF sensor vibration data. This cursory analysis will confirm that sensors are working as expected and give the reader an idea of the natural variation between vibration measurements.

Even though velocity data is more useful for asset diagnosis for motors/pumps at slower running speeds, the data presented in this subsection will be acceleration data. It is best to confirm the quality of the raw acceleration data prior to introducing processing techniques. The VSN data presented in this section is taken at 512 Sa/S for 1,650 points. The frequency spectrum will be displayed with a bandwidth 256 Hz and at a resolution of 0.31 Hz.

Figure 12 is an example of a frequency spectrum with a bandwidth of 256 Hz showing the harmonics generated by the motor/pump. There are several harmonics close to the expected frequencies listed in a previous subsection. There are also a few harmonics that are not a multiple of the running frequencies. The distinct harmonics shown in Figure 12 are not common in the VSN data looked at thus far but are not abnormal. Most of the frequency plots have fewer and closer spaced harmonics as shown in Figure 14. Because of the dynamic nature of vibrations, there can be significant temporal and spatial variations reported by sensors. The dynamic nature of vibration measurements provides the motivation to install wireless sensors that will take data at regular intervals.

<u>Data from a CWP Motor</u>

The outer motor cover is an integral part of the motor. The placement of the VSNs on the outer cover is designed to provide acceptable diagnostic information on the motor and pump while being easily accessible. Since the pump is directly coupled to the motor shaft, the resulting vibrations will be generated by the interaction between the motor and pump. The vibrations within the motor cover can originate from two locations and can interact with each other, creating complicated responses. The electrical motor and shaft are connected to the outer cover via two structural plates. The attachment locations on the cover connecting to the plates act as vibration sources. The two vibration sources can then interact and cause constructive and destructive interference. The interference can complicate the vibrational response. One plate contains the outboard-bearing and is connected to the cover at that level. The other plate contains the inboard-bearing and is connected to the cover at that level. The placements of the three sensor nodes placed on the outer cover is shown in Figure 6.

Historic plant data contains measurements in three directions (X, Y, Z) while the VSN node data has only two directions (X, Y). The third VSN node affixed to the top of the motor cover provides motion in the radial (Z) direction in the reference frame of the other two nodes. The node on the top of the motor cover provides complimentary radial motion and redundant tangential motion information.

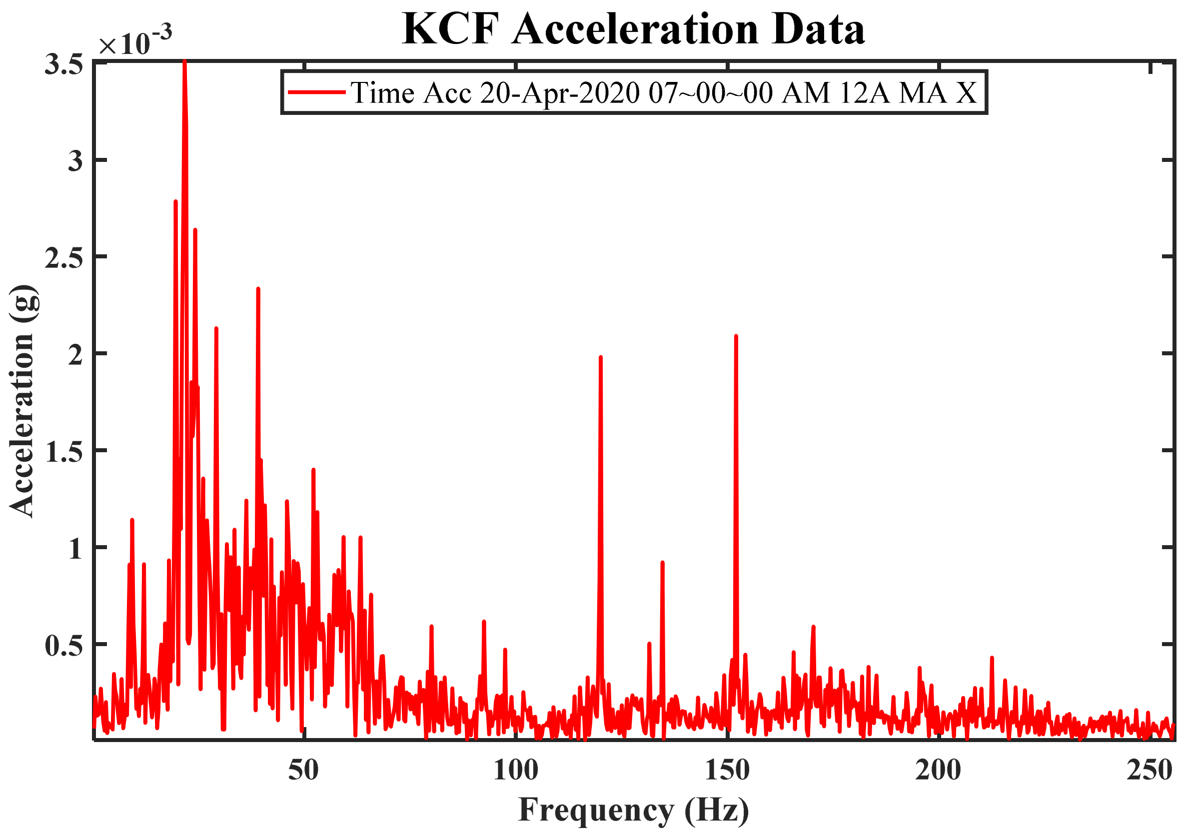


Figure 14. Frequency spectrum obtained from the motor axial node with X-sensitivity for motor 12A.

The data obtained from the inboard and outboard positions are shown in Figure 15 and Figure 16. The dominant signal in almost all of the plots is the 120 Hz motion induced by the line frequency. The harmonics in the MOB data (X & Y) tend to be larger in amplitude. This may simply be from the MOB VSN being closer to the motor end plate, which is the support structure for the motor. The MIB-X vibrations are significantly smaller than the MOB vibration levels shown in the plots. The sensor locations contain similar information, such as the harmonics at 120 Hz and 150 Hz. This is important as the similarities can indicate that a transducer is malfunctioning if there are deviations in the data. The X-direction data suggest that MOB has more asynchronous information at the lower frequencies around 20 Hz. MIB has more frequency content for frequencies greater than 75 Hz. There are frequency components that change amplitude between repeated sets. The harmonics near 50 and 150 Hz appear to be asynchronous and have an unknown source. The Y-direction plot, Figure 16, contains similar information as in Figure 15. The 120 Hz line frequency is generally prominent along with the 150 Hz harmonic but in some traces they have reduced amplitude. The 50 Hz harmonic appears to be absent. MOB-Y still has larger asynchronous activity than MIB-Y. These noted variations show the complex nature of vibrational motion and are typical.

The placement of the VSN (MA) on the top of the outer cover base plate was to obtain axial vibration information of the motor. The X-sensitivity from the MA VSN is the radial component, and the Y-sensitivity is the tangential component that should be equivalent to MIB-X and MOB-X. From Figure 17 and Figure 18, it is interesting to note that the 120 Hz motor motion is mostly in the tangential direction (Y) within the base plate, as the vibration amplitude is significantly lower for Motor Axial radial sensitivity (MA-X). The MA data contains duplicate and complimentary information and is a good indication that the sensors are taking reliable data. The signal from MA-X more closely matches the signals from MOB-X and MOB-Y. The asynchronous low frequency (≈ 20 Hz) signatures look similar.

This may be due to the location of the MOB VSN being very close to the motor base plate on which the MA VSN is mounted (Figure 7). Please note that there is still complimentary information amongst the VSN sensors.

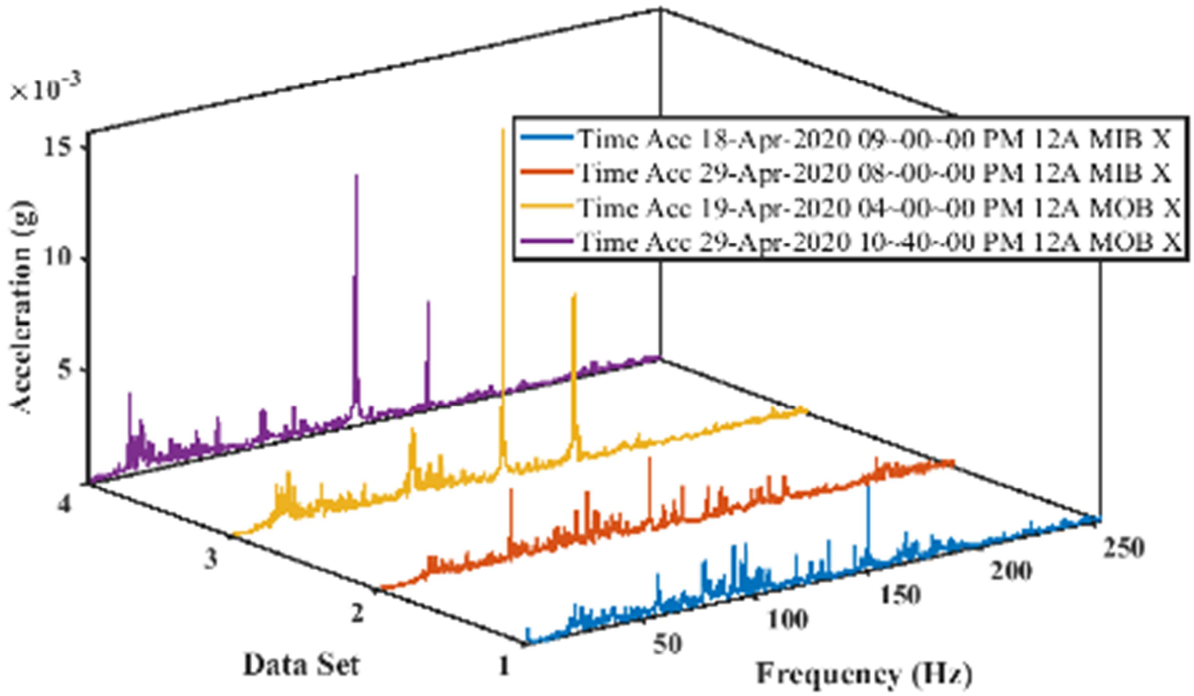


Figure 15. The results from the VSN accelerometers in the X-direction at the Inboard and outboard locations are shown.

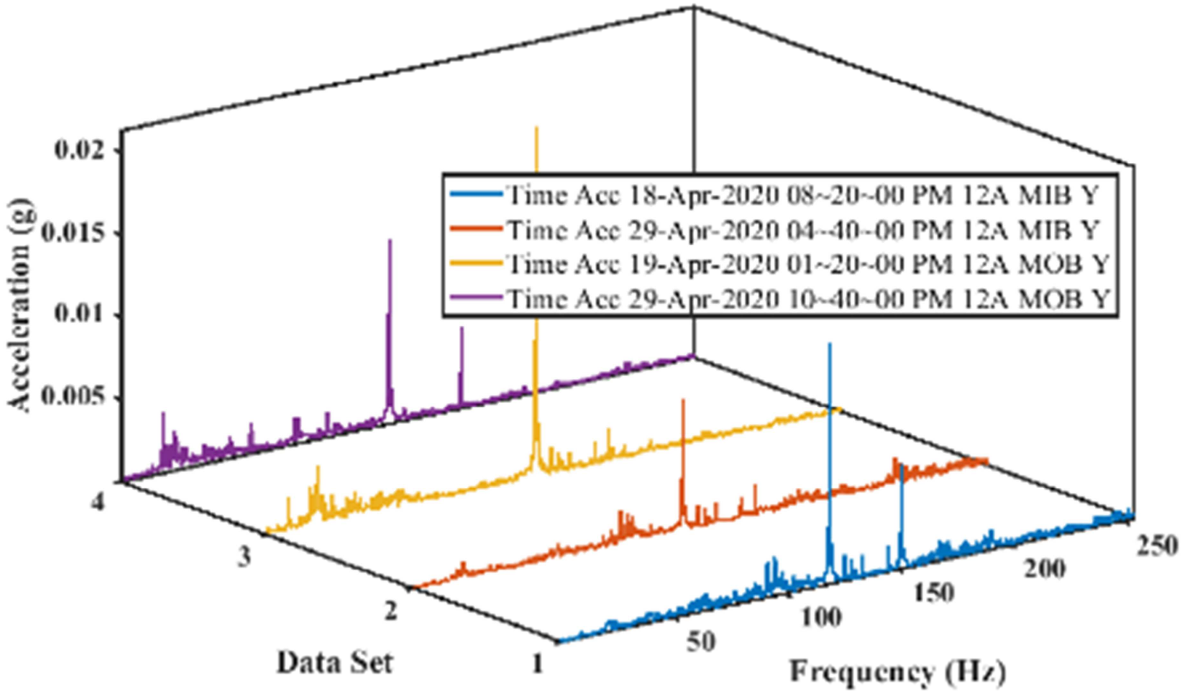


Figure 16. The results from the VSN accelerometers in the Y-direction at the Inboard and outboard locations are shown.

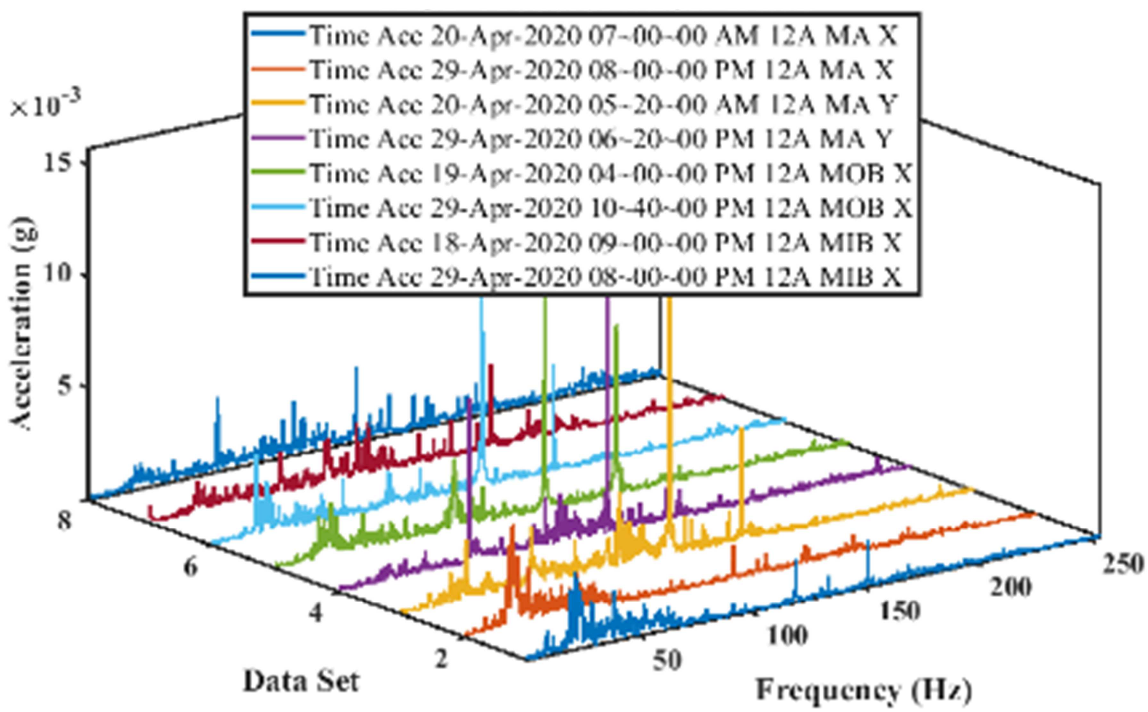


Figure 17. Comparing the MA data with the MIB-X and MOB-X data to confirm if additional information is present.

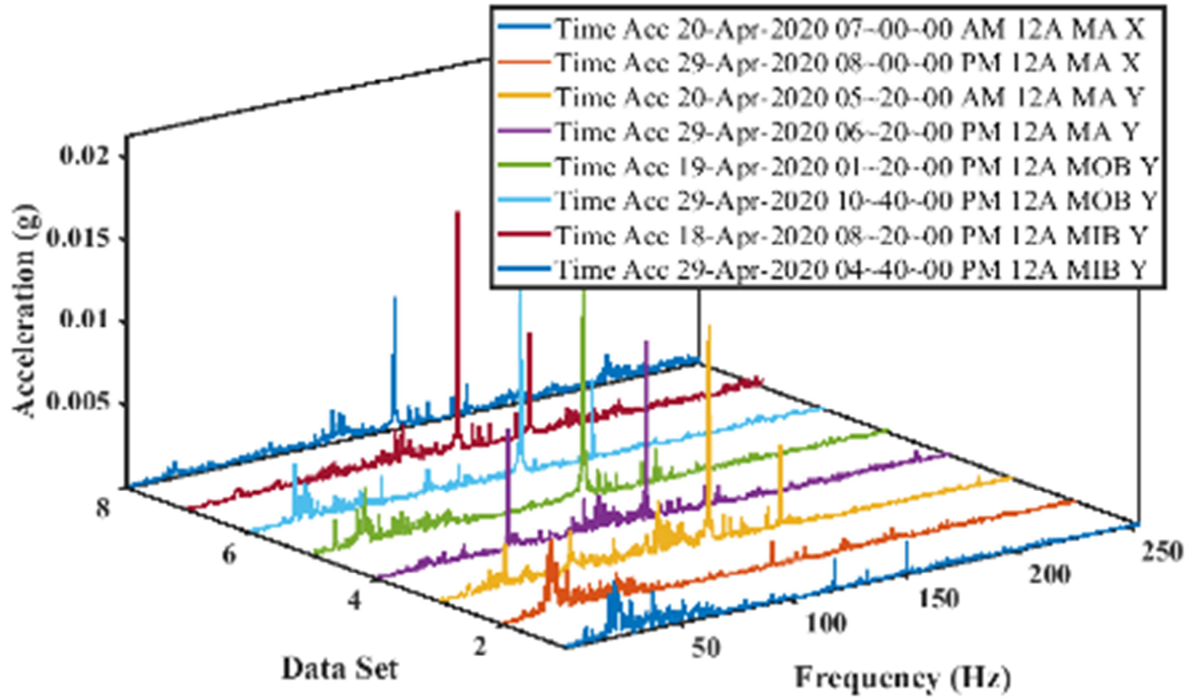


Figure 18. Comparing the MA data with the MIB-Y and MOB-Y data to confirm if additional information is present.

Data from the Pump Valve 12A

Currently, there is no effective way to obtain vibrations directly from a CWP due to it being underwater. To obtain CWP vibration data that is minimally confounded by the motor, sensors were placed on the CWP valve, as shown in Figure 9. The axial and radial placement of the transducers is designed to cover all three axes of motion. The Y-sensitivity of VA VSN should match the tangential sensitivity provided by the VR-X. The X-sensitivity of the VA VSN provides the radial component the valve motion.

The resulting data from the two orthogonally mounted sensors are plotted in Figure 19 and Figure 20. The first thing that one notices is that the 120 Hz motor motion is missing or greatly reduced from the plots. The major harmonics appear to be asynchronous, as they are not at close multiples of the running speed. Thus, the objective of reducing the influence of the motor on the designated pump data has been met. Both graphs of the valve data show asymmetric harmonics. It is unknown at this point how the frequency content gets generated in the valve graphs. As seen in the graphs, there is a significant amount of variation between the data sets. The majority of the variation most likely comes from the beating of two vibrational harmonics that are close in frequency and is shown in Figure 21. It is assumed that the interfering vibration is transmitted through the foundation from another nearby motor/pump system.

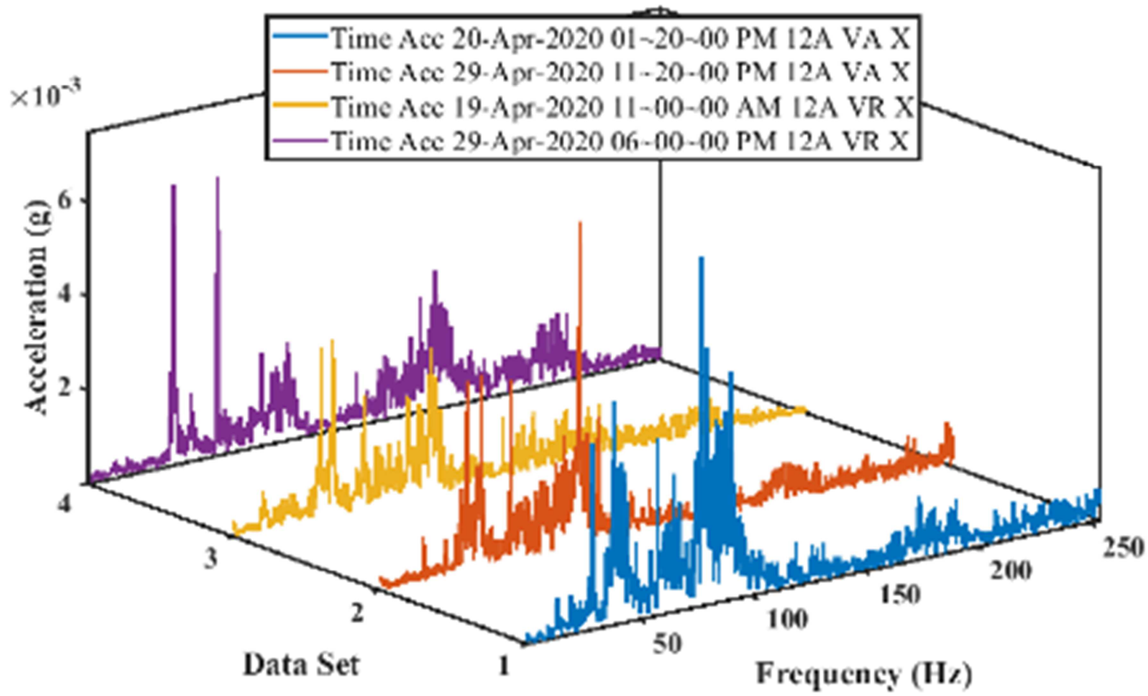


Figure 19. Acceleration data from two orthogonally mounted VSN sensors on the 12A CW pump valve is displayed for the X-sensitivities of the VSN.

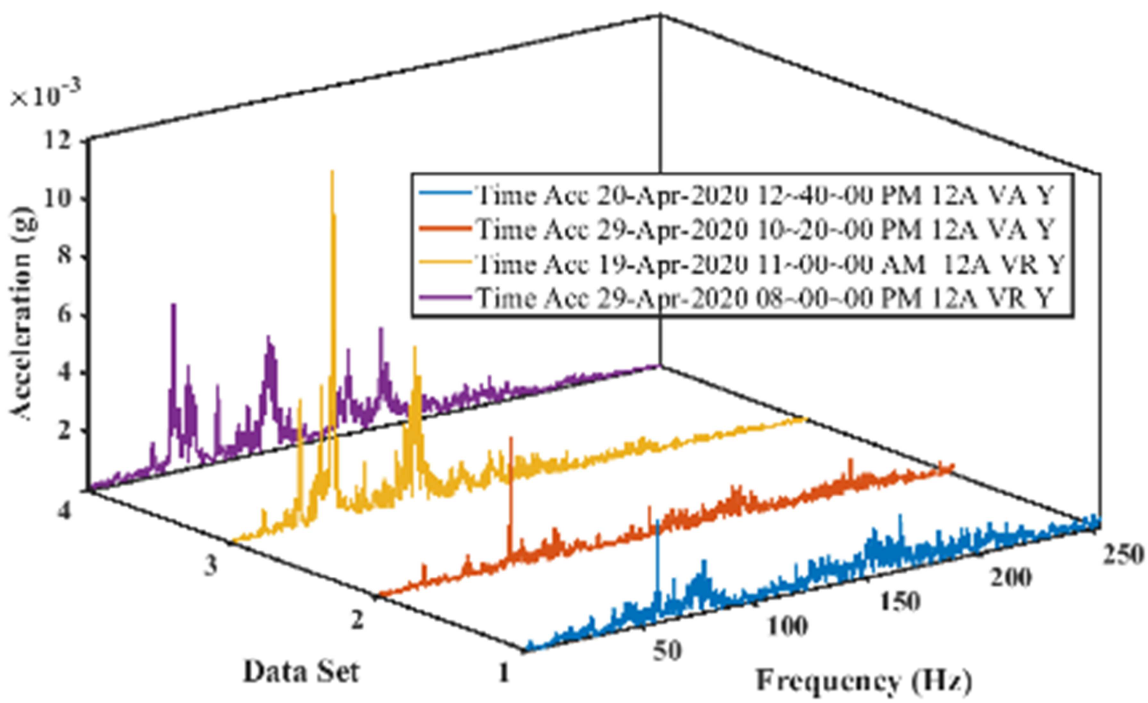

Figure 20. Acceleration data from two orthogonally mounted VSN sensors on the 12A CW pump valve is displayed for the Y-sensitivities of the VSN.

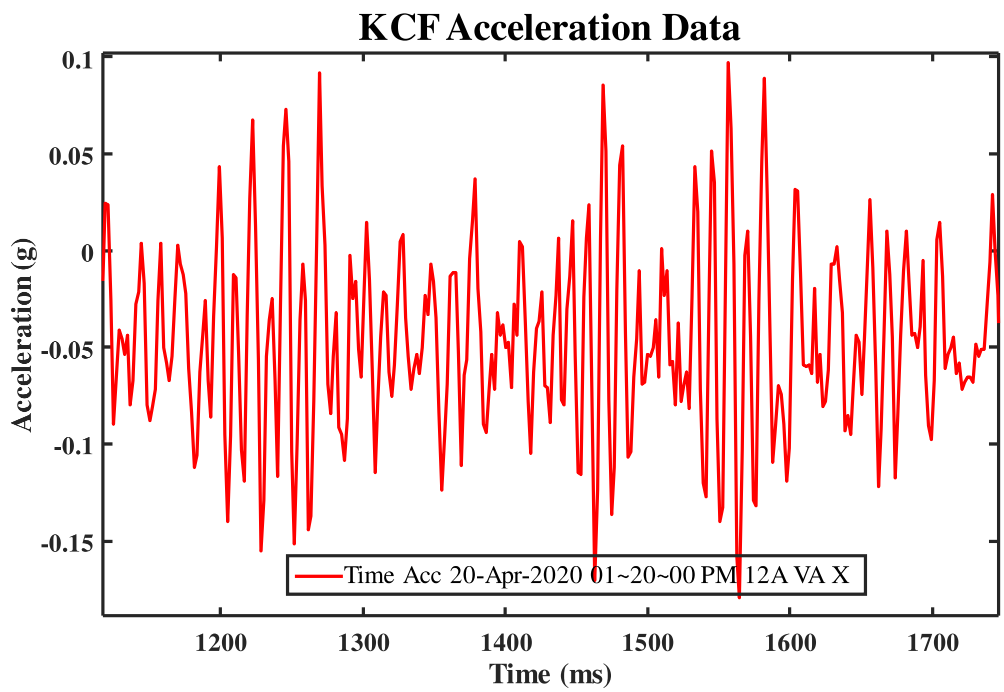


Figure 21. This time domain plot of VSN X-sensitivity acceleration data for CW Pump Valve 12A shows definite signs of beating between two close frequencies.

### 3.6.11 Historical Vibration Data

A representative sample of the historic data is shown in Figure 22 through Figure 24. Because the project is unable to make a direct comparison between the Emmerson and KCF data at this time, a general comparison between the two systems will be made. The salient characteristics to note are the frequency harmonics related to the motor running speed as given in the "Setting Effective Data Acquisition Parameters" subsection. In general, both vibration measurement systems display similar results showing the following typical spectra content:

- 4.9 Hz Fundamental harmonic
- 19.6 Hz Harmonic caused by the pump vanes
- 29.4 Hz Harmonic caused by the diffuser vanes
- 117.6 Hz Harmonic caused by the combination of the pump and diffuser vanes
- 120 Hz Vibration caused by the electric line frequency

Due to the dynamic nature and complexity of vibrational motion, there will be discrepancies between the Emmerson and KCF data plots, but there should always be a few common frequency peaks confirming that the sensors are producing similar data. The dynamic nature of vibration signals is why it is important to take vibration data at regular intervals. The installation of wireless sensor technology enables the regular collection of data.

The Salem plant site collects triaxial vibration data (Axial, Vertical, and Horizontal direction) using CSI Data collector and RBMWare software (Emerson Products) on all the CWP motors every 3 months at known locations (inboard and outboard) on the CWP motor casing. The triaxial vibration data (acceleration) is collected for 4.1 seconds. A sample axial outboard vibration signal and its frequency spectrum collected at the outboard location of the CWP motor 11A is shown in Figure 22. Similarly, horizontal and vertical vibration signals and their frequency plots collected at the outboard location of the CWP motor 11A are shown in Figure 23 and Figure 24, respectively. Vibration signals and frequency spectrums, corresponding to inboard locations on other CWP motors for both units are also collected, but not shown.

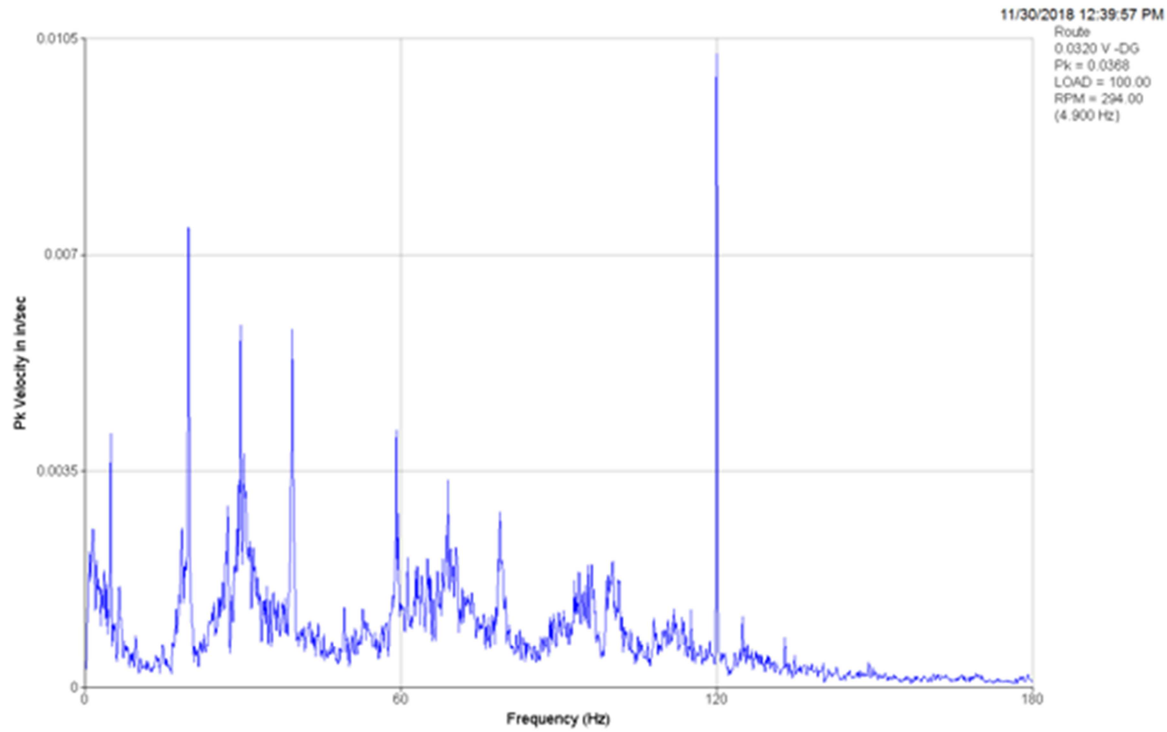

Figure 22. A sample outboard axial frequency spectrum generated by CWP motor 11A on November 20, 2018.

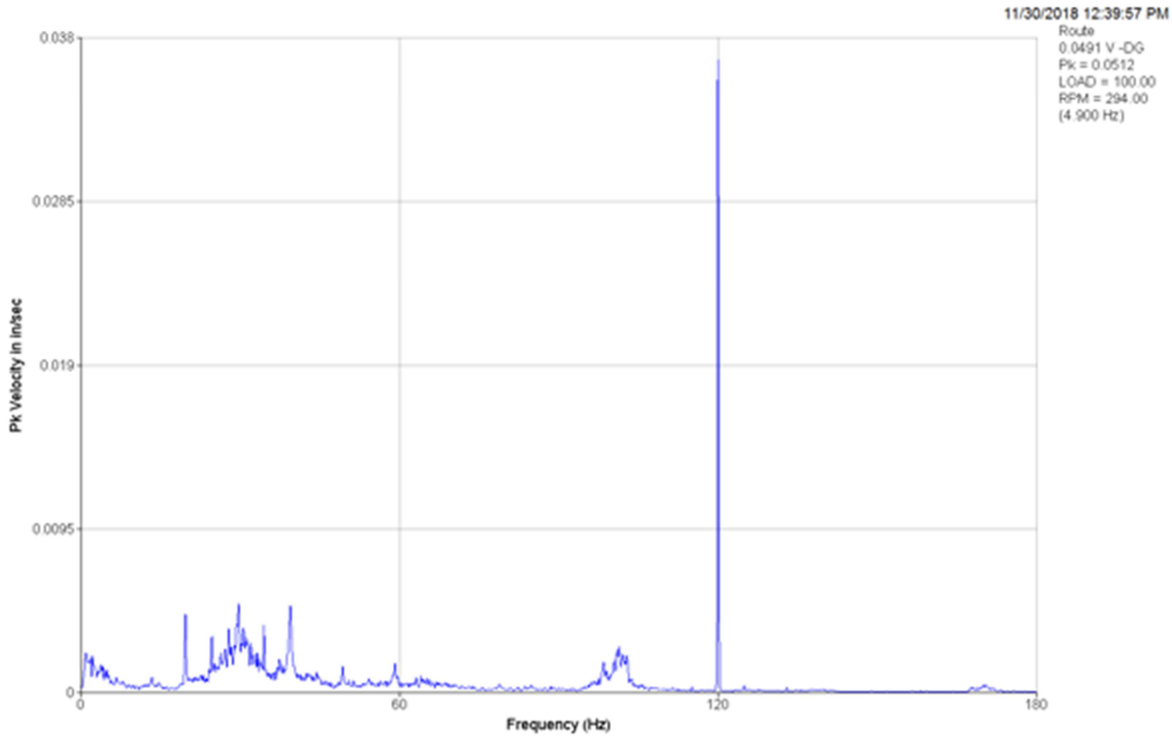


Figure 23. A sample outboard horizontal frequency collected from CWP motor 11A on November 30, 2018.

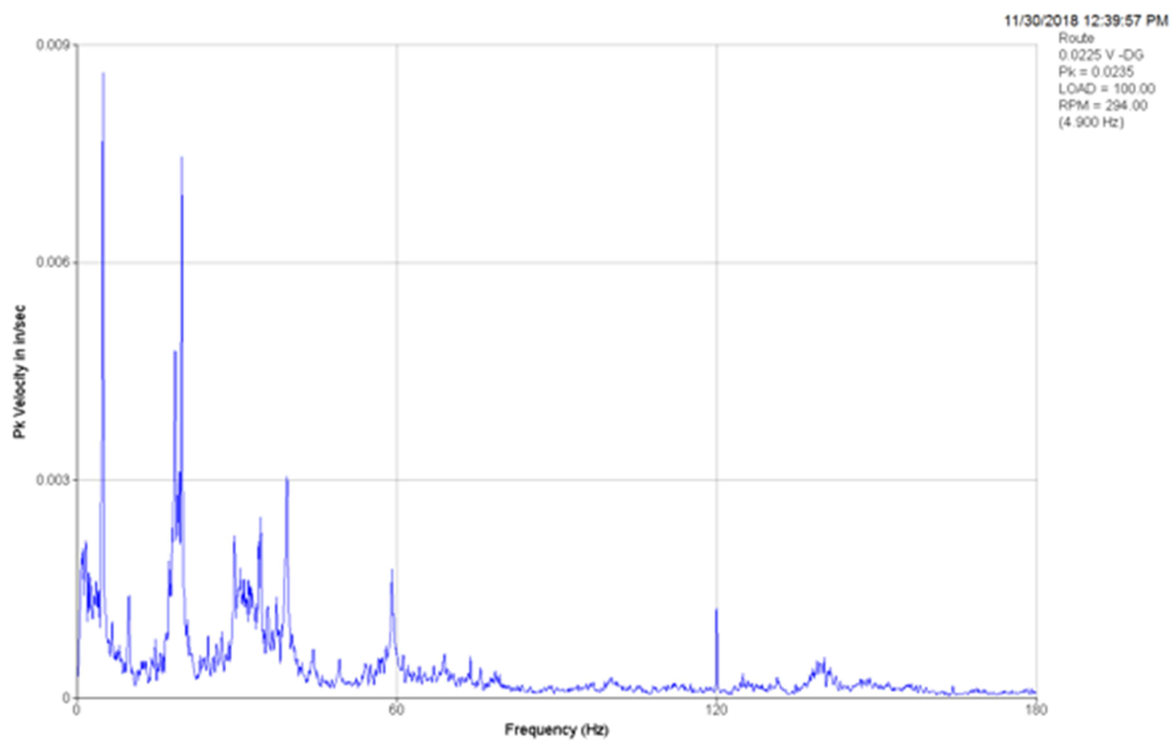


Figure 24. A sample outboard vertical frequency collected at CWP motor 11A on November 30, 2018.

## 4. RISK-INFORMED MODEL DEVELOPMENT

### 4.1 Markov Chain Models

Markov chains are one of the major modeling tools used in reliability and availability research [12] [13] [14]. The reasons for their success are the ease of use, wide applicability, and low computational burden. The Markov chain model postulates that most engineering systems can be described by two components: states and transitions. Typical assumptions are that the states are discrete, and their number is finite, or at least countable. The system must be in exactly one state at any given time and can make transitions from one state to another at random times. If the transition between states is possible only at fixed-unit time intervals, the Markov model is called a Discrete Time Markov Chain; however, if inter-state transitions are permitted at any real-valued time interval, the model is called a Continuous Time Markov Chain (CTMC) [15]. In this report, we shall be dealing with CTMC. This is due to the fact that we are interested in an optimization of corrective and preventive maintenance for a given asset, and the intervals between maintenance and its duration can span any real-time interval. The time between transitions, i.e. the time that the system remains in a given state, is called the state holding time. The most important assumption in Markov modeling is the assumption of the memoryless nature of the system's dynamics. This assumption postulates that the probability of future states depends only on the current state and does not depend on previous states [16] [17]. In other words, the system does not "remember" how it arrived in current state. Schematically, this Markovian property is illustrated in Figure 25.

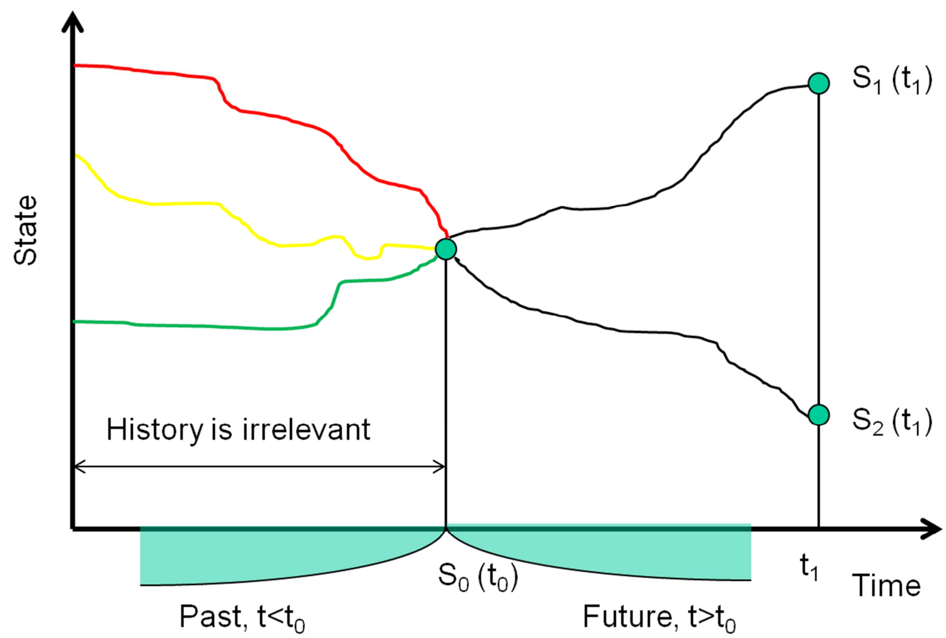


Figure 25. Schematic diagram of the Markovian property.

Currently, at time t_0, the system is in state S_0 (t_0). From this state, the system can find itself at time t_1 either in state S_1 or S_2. The probability that the system will end up in either one of those states depends only on S_0 and does not depend on how the system arrived at S_0—either through red, yellow or green trajectories. In other words, the system's behavior in the future depends only on its current state and not on how or when the system arrived in the current state. This is not to say that in the Markov model the future is completely independent of the past; the future does depend on the past in these models but only through the present. Making the Markovian assumption greatly simplifies the calculations at the expense of making concessions to the model's accuracy. It is interesting to note though that practically any process can be made Markovian if all its history is included in the current state through additional parameters.

In reliability studies, the states normally reflect the functionality of the system, i.e. if the system is operational or not. If an asset represents a system, the simplest possible CTMC for the asset will be the one shown in Figure 26. The system can only be in two states: operational or maintenance. Furthermore, the maintenance state includes both corrective and preventive maintenance.

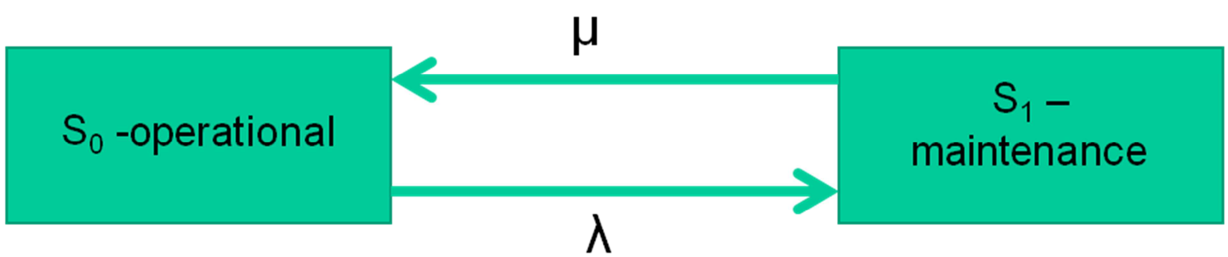


Figure 26. Transition diagram for a two-state model.

The system's dynamics are described by two transition rates $\lambda$ and $\mu$, which govern the length of time that elapses before the system moves from one state to another. The reciprocal of those two rates are average holding times for the two states. In other words, the reciprocal of $\lambda$ is the mean time between failures or the average time the systems holds in the operational state and the reciprocal of $\mu$ is the mean maintenance time or the average time it takes to maintain the system. We are interested in calculating probabilities of two states—$p_0$ (operational) and $p_1$ (maintenance) given transition rates $\lambda$ and $\mu$ [17].

Mathematically, the dynamics of CTMC are described by the system of differential equations that mnemonically can be written as:

$$\begin{aligned} &\mathit{Change\ in\ probability\ for\ state\ i} \\ &\qquad = \sum \mathit{incoming\ probabilities\ from\ all\ other\ states} \\ &\qquad - \sum \mathit{outgoing\ probabilities\ to\ all\ other\ states} \end{aligned}$$

This mnemonic rule is simplified and the rigorous formulation for the system depicted in Figure 26 will be as follows:

$$\frac{d\boldsymbol{p_0}}{d\boldsymbol{t}} = \boldsymbol{\mu p_1} - \boldsymbol{\lambda p_0} \tag{1}$$

$$\frac{d\boldsymbol{p_1}}{d\boldsymbol{t}} = \boldsymbol{\lambda p_0} - \boldsymbol{\mu p_1} \tag{2}$$

$$\boldsymbol{p_0(0) = 1, p_0(t) + p_1(t) = 1} \tag{3}$$

Equation (3) represents the initial conditions and normalization requirements [18] [19] [20]. The initial condition normally assumes that at time $t = 0$ the system is in operational state and, since, by definition at any given time, the system must be in one of the two states, the sum of probabilities should be equal to one. Equations (1-3) also assume that the two parameters, $\lambda$ and $\mu$, are available either from historical data, manufacturer's specifications, or theoretical considerations. An illustrational example of a solution for system (1) is shown in Figure 27 for $\lambda = 5$/year, $\mu = 10$/year, and $p_0(0) = 1$. After the transition period, the system settles into a steady state where the probability of being operational is $p_0$= 0.6667 and the probability of being maintained is $p_1$= 0.3333. In the steady state, the system does transfer from state to state; however, the probabilities of changing states are no longer dependent on time. The time constant $\tau = 1/(\lambda + \mu) = 1/15$ for this system is about 24 days, and the system settles into a steady state in $3\tau$ time interval.

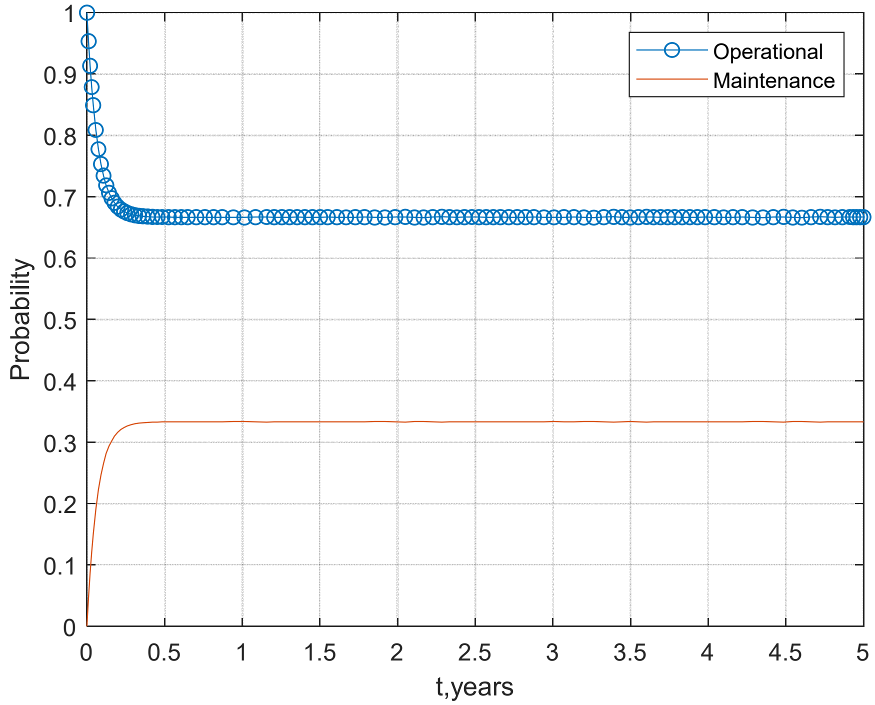

Figure 27. Solution of the system of differential equations for λ=5, μ=10, and p_0 (0)=1.

The steady-state probabilities have a very important practical interpretation as the average relative percentage of time that the system spends in a particular state. For the example above, the system on average would spend around 67% of the time being operational and 33% of the time being in service. While the equations (1-3) can be solved numerically, if we only need steady-state probabilities, the solution to (1) can be obtained analytically, utilizing the fact that in steady-state probabilities do not change and hence the left-hand side of two differential equations in (1) and (2) can be set to zero:

$$\mathbf{0 = \mu p_1 - \lambda p_0} \tag{4}$$
$$\mathbf{0 = \lambda p_0 - \mu p_1} \tag{5}$$
$$\mathbf{p_0(0) = 1, p_0(t) + p_1(t) = 1} \tag{6}$$

Using the normalization requirement and one of the two equations, the steady-state solutions can be expressed as:

$$\boldsymbol{p_0 = \frac{\mu}{\mu + \lambda}; p_1 = \frac{\lambda}{\mu + \lambda}} \quad (7)$$

An important parameter of a Markov model is the ratio $\rho = \lambda/\mu$ that is called the normalized rate and measures the "pressure" that is exerted on the system by a given failure rate $\lambda$ under the maintenance rate $\mu$. The higher value of ρ implies that the system is trying to cope with a high failure rate and long maintenance times. As previously mentioned, the steady-state probabilities can be interpreted as the relative percentage of time the system spends in a corresponding state. Under this assumption, if the hourly rates for the system being operational and being in repair are available, the profit can be calculated as:

$$\boldsymbol{Profit = Revenue - Expenses = Hourly\ rate\ \cdot p_0 - Expense\ hourly\ rate \cdot p_1} \quad (8)$$

The time trajectory of the two-state process can be presented as shown in Figure 28.

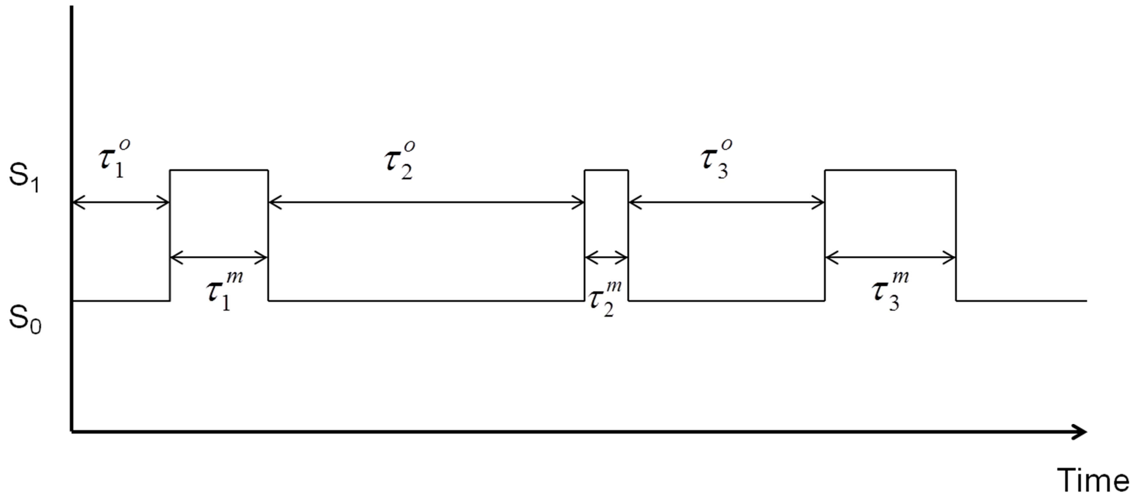


Figure 28. Time evolution of the two-state system.

It is assumed that the system starts in an operational state and, as time progresses, it transitions between two states at random moments of time and spends random intervals of time in either state. As seen from Figure 28, the system started at time zero in operational state, $S_0$, and after spending random time, $\tau_1^0$, transitions to the state of maintenance, $S_1$. After spending random time, $\tau_1^m$, in $S_1$, the system returned back to the operation state, $S_0$, at time $\tau_1^o + \tau_1^m$, and the cycle repeats as the process is renewed. Here, cycle can be understood as the transition from $S_0$ to $S_1$ and back to $S_0$. The time $\tau_1^o + \tau_1^m$ is the cycle time period (random variable). If historical data about asset's maintenance and operations are available, parameters, such as mean time between failures (MTBF) and mean maintenance time (MMT), can be estimated as follows:

$$\boldsymbol{MTBF = \frac{1}{N}\sum_{i=1}^{N} \tau_i^0\,; \lambda = \frac{1}{MTBF} - failure\ rate, \frac{1}{t}} \quad (9)$$

$$\boldsymbol{MMT = \frac{1}{N}\sum_{i=1}^{N} \tau_i^m\,; \mu = \frac{1}{MMT} - maintenance\ rate, \frac{1}{t}} \quad (10)$$

where, $N$ is the number of samples in historical data and $t$ is time.

The time intervals $\tau_i^o$ and $\tau_i^m$ are described by exponential distributions with corresponding parameters $\lambda$ and $\mu$. Exponential and Poisson distributions play special roles in Markov chain modeling and are discussed in the following section.

### 4.2 Poisson and Exponential Distributions

Poisson distribution is a discrete probability distribution, which is frequently used in reliability research to describe the failures of operating or standby components. It is also to model numbers of random events occurring within a given period of time $\tau = [t_i, t_{i+1}]$. Its probability mass function (PMF) is given by

$$f(x=m|\lambda,\tau)=\frac{(\lambda\cdot\tau)^m}{m!}\cdot e^{-\lambda\cdot\tau} \quad (11)$$

where $m$ is the number of events observed in time interval $\tau$ if the average number of events per unit of time is $\lambda$. For the purpose of Markov modeling, Poisson distribution is used to quantify the number of events in a time interval, for example, the number of failures in an hour. Figure 29 shows two PMFs for Poisson distribution with the same $\lambda = 5$ but two different $\tau = 1$ and $\tau = 2$. As can be seen, the PMFs depend on the length of time interval $\tau$; however, as can be demonstrated, they do not depend on the location of the time interval along the time axis, i.e., $t_i$. This property of Poisson process is called stationarity and is a frequent assumption in Markov modeling. Two other assumptions that are made about the Poisson process used in Markov chain modeling are the assumption of zero probability for two events to occur at the same time moment and the nonoverlapping time intervals are independent. Poisson distribution has just one parameter, $\lambda$, which is called the rate parameter as it quantifies an average number of events per unit of time. For Poisson distribution, its first two moments, mathematical expectation and variance, are equal to its parameter $\lambda$. Poisson distribution is intimately connected to exponential distribution as demonstrated in Figure 30.

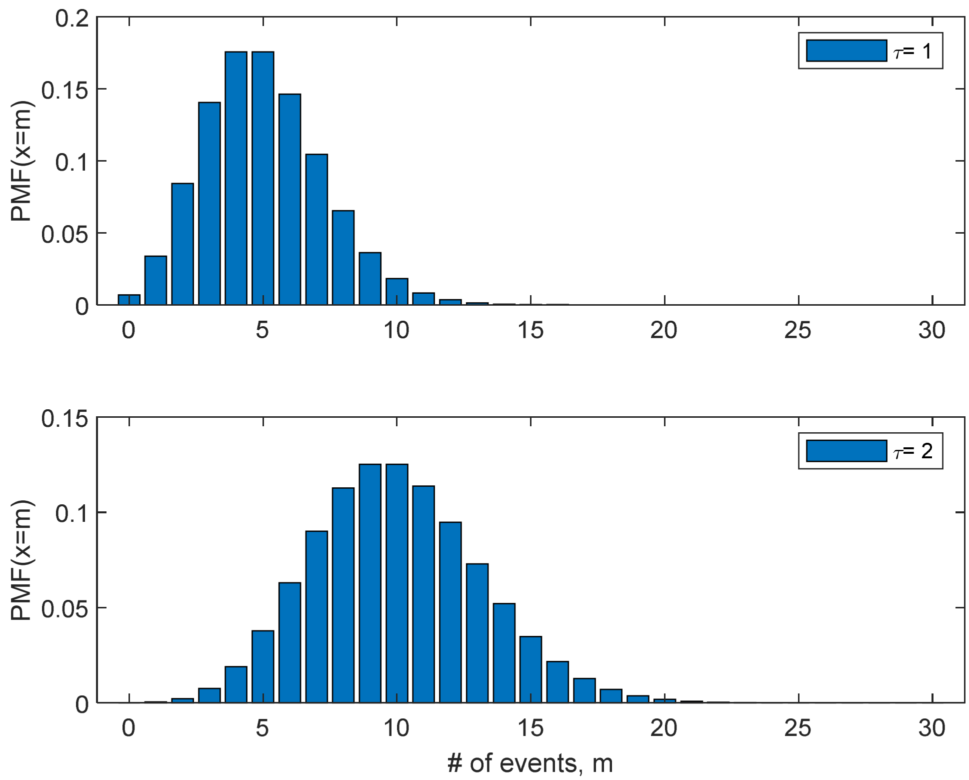


Figure 29. PMF for Poisson distribution, having the same rate parameter λ=5 but different time intervals.

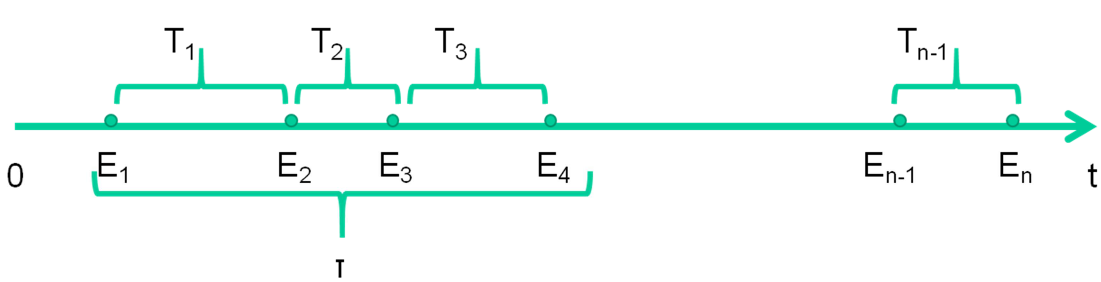


Figure 30. Representation of Poisson events and exponential time intervals distribution.

In Figure 30, the Poisson-distributed events $E_1, \cdots, E_n$ arrive at random times, and Poisson distribution quantifies the number of these events in a given time interval $\tau$. It can be shown that if the number of events have Poisson distribution with parameter $\lambda$ then the time intervals $T_1, T_2, \ldots, T_{n-1}$ have an exponential distribution with the same parameter given by

$$\varphi(t) = \lambda e^{-\lambda t}, t > 0 \quad (12)$$

The exponential distribution for $\lambda = 5$ is shown in Figure 31. Notice that in contrast to the Poisson distribution, the exponential distribution is a continuous distribution as it describes the probability density function (PDF) of a continuous variable-time.

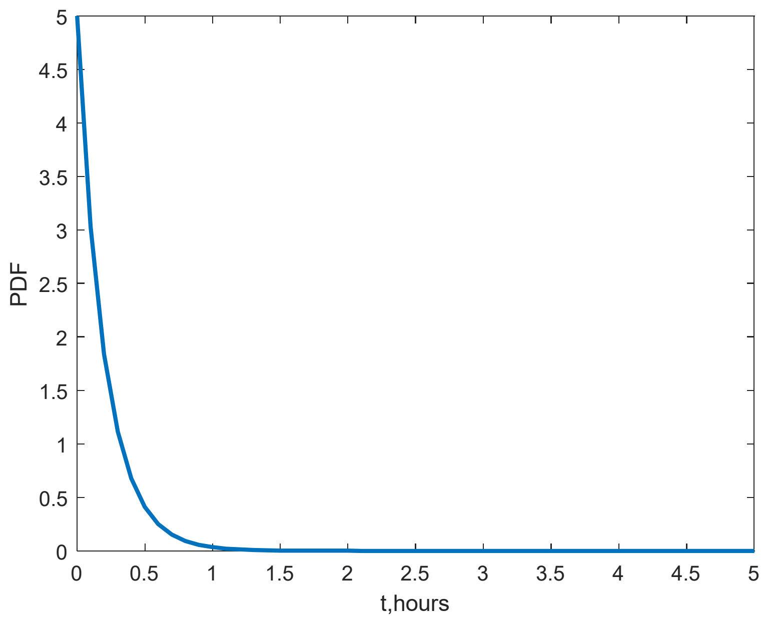


Figure 31. PDF of exponential distribution for λ=5.

The exponential distribution is the only continuous distribution with the property of being "memoryless", which makes it very suitable for Markov's chain modeling. This property implies that at any time instant, the distribution resets itself and can be described by the same distribution regardless of how much time has already elapsed. More rigorously, let $x$ be an exponentially distributed variable with parameter $\lambda$. Suppose we know that $T > t$, we would like to know what is the probability that $T > t + s$. In other words, if we have already waited for an event to happen for $t$ hours, what is the probability that we will wait for $s$ more hours? Using the definition of conditional probability, we can write

$$\boldsymbol{P(T > s + t \mid T > t) = \frac{P(T > s + t, T > t)}{P(T > t)} = \frac{P(T > s + t)}{P(T > t)}} \quad (13)$$

For the last equality, we used the fact that $T > s + t$ and $T > t$ are redundant, as the first event implies the second. Further, using cumulative distribution function for exponential distribution, we obtain

$$P(T > s+t \mid T > t) = \frac{P(T > s+t)}{P(T > t)} = \frac{e^{-\lambda(s+t)}}{e^{\lambda t}} = e^{-\lambda s} \quad (14)$$

The result shows that the conditional probability on the left does not depend on $t$. The probability of an exponential random variable exceeding the value $(s+t)$ given $t$ is the same as the variable originally exceeding that value $s$, regardless of $t$. This property of the exponential distribution is used in Markov chain modeling to assure that the model disregards the system's history and relies only on the current state.

In summary, to define a two-state Markov chain model, we need just two parameters $\lambda$ and $\mu$. These two parameters identify two exponential distributions governing the time between maintenance and maintenance duration.

### 4.3 Three-State Markov Chain Model

The two-state model presented in the previous sections may be too simplified or restrictive, as quite often the maintenance is divided into two categories: corrective and preventive. The corrective maintenance (CM), sometimes referred to as repair, happens when a component fails during operation or during standby. In this situation, performing maintenance is a necessity 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. Certain PMs are performed online, for example, periodic vibration measurements to assess the health of the component. For CM, the component is taken out of service. While time intervals between CM events are random, PM is performed more on a scheduled basis and time intervals are more regular with some variance. The transition diagram for the three-state model is shown in Figure 32.

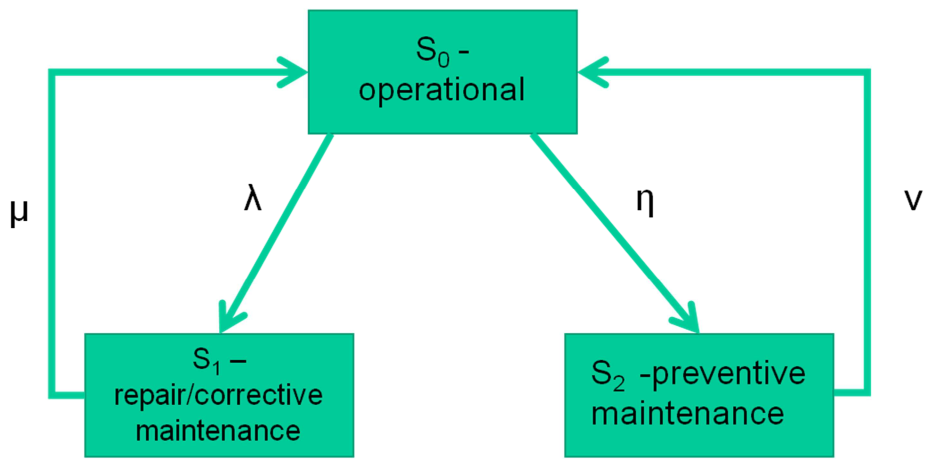


Figure 32. Transition diagram for a three-state model.

The three-state model is completely defined by four parameters: $\lambda$-failure rate, $\mu$-corrective maintenance rate, $\eta$-preventive maintenance scheduling rate, and $\nu$-preventive maintenance rate. Using the mnemonic rule introduced in previous sections, the system of differential equations, governing the evolution of the three-state system, can be written as follows:

$$\frac{dp_0}{dt} = \mu p_1 - \lambda p_0 + \nu p_2 - \eta p_0 \quad (15)$$

$$\frac{dp_1}{dt} = \lambda p_0 - \mu p_1 \quad (16)$$

$$\frac{dp_2}{dt} = \eta p_0 - \nu p_2 \quad (17)$$

$$p_0(0) = 1, p_0(t) + p_1(t) + p_2(t) = 1 \quad (18)$$

Using the normalization requirement and two of the three equations, the steady-state probabilities can be written as:

$$p_1 = \frac{1}{1 + \frac{\mu}{\lambda} + \frac{\mu \cdot \eta}{\lambda \cdot \nu}}; p_0 = \frac{\mu}{\lambda} p_1; p_2 = \frac{\eta}{\nu} p_1 \quad (19)$$

Figure 33 shows the time evolution of probabilities for the three-state model using the following parameters: $\lambda = 2.2831 \times 10^{-4}$, $\mu = 0.0417$, $\eta = 1.5432 \times 10^{-4}$, and $\nu = 0.0208$. Similar to the two-state model, after the transition period, the model settles into the steady state when probabilities are no longer functions of time.

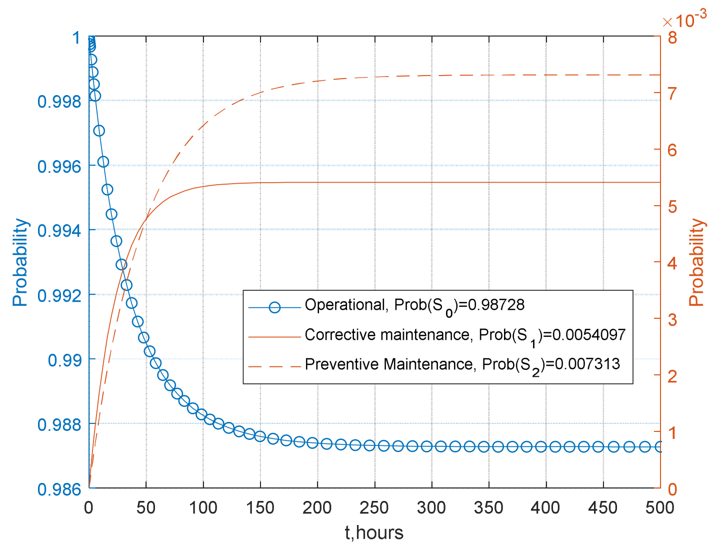


Figure 33. Solution of the system of differential equations for the three-state model.

A time trajectory for a three-state model is presented in Figure 34, where $\tau_i^0$ is the $i$-th random time duration when system is in the operational state; $\tau_i^m$ is the $i$-th random time duration when the system is in preventive maintenance state; $\tau_i^r$ is the $i$-th random time duration when the system is in the corrective maintenance state; and $\tau_i^s$ is the $i$-th time between preventive maintenances.

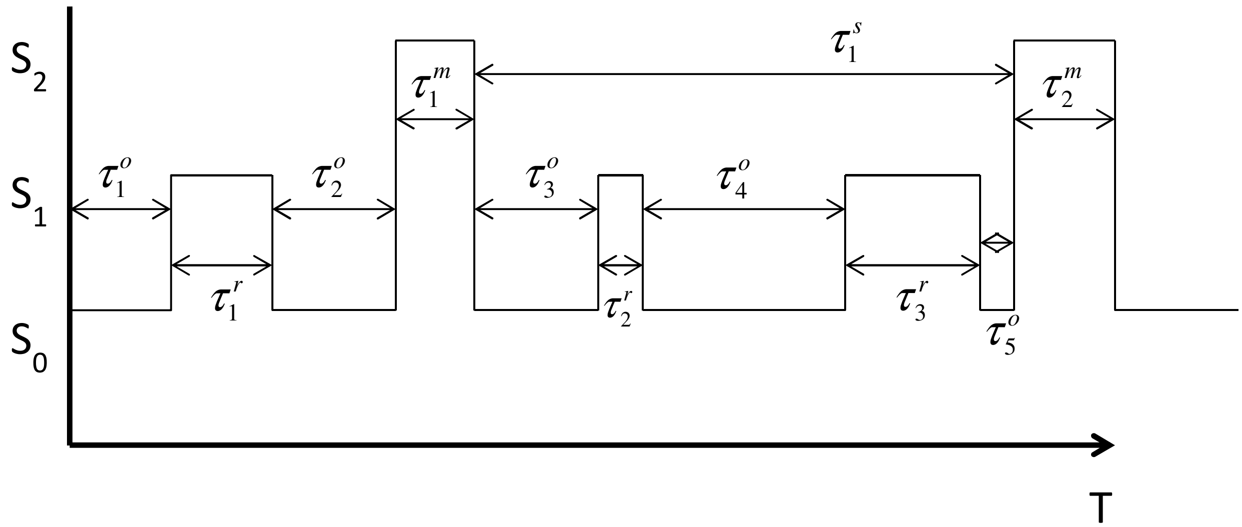


Figure 34. A realization of time evolution dynamics of a three-state system.

$$\boldsymbol{MTBF = \frac{1}{5}\sum_{i=1}^{5} \tau_i^o\, ; \lambda = \frac{1}{MTBF} - failure\ rate, \frac{1}{t}} \quad (20)$$

$$\boldsymbol{MCMT = \frac{1}{3}\sum_{i=1}^{3} \tau_i^r\, ; \mu = \frac{1}{MTBF} - \ corrective\ maintenance\ rate, \frac{1}{t}} \quad (21)$$

$$\boldsymbol{MPMT = \frac{1}{2}\sum_{i=1}^{2} \tau_i^m\, ; \nu = \frac{1}{MPMT} - \ preventive\ maintenance\ rate, \frac{1}{t}} \quad (22)$$

$$\boldsymbol{MTSM = \sum_{i=1}^{1} \tau_i^s\, ; \eta = \frac{1}{MTSM} - \ preventive\ maintenance\ scheduling\ rate, \frac{1}{t}} \quad (23)$$

If samples of the time durations are available from the historical records of a component's operation, the parameters of the three-state model (MTBF; mean corrective maintenance time, denoted as MCMT; mean preventive maintenance time, denoted as MPMT; and 4) mean time between successive preventive maintenance, denoted as MTSM) can be estimated. For the simple schematic of component’s operation shown in Figure 34, these parameters are computed using equations (20) to (23)

The profit optimization cost function for the three-state model can be expressed as

$$\boldsymbol{Profit = Revenue - Corrective\ Maintenance\ Cost}$$
$$\boldsymbol{- Preventive\ Maintenance\ Cost} \ (24)$$

or using the states' probabilities and hourly rates as:

$$\boldsymbol{Profit = Hourly\ rate \cdot p_0 - Corrective\ maintenance\ hourly\ rate \cdot p_1}$$
$$\boldsymbol{- Preventive\ maintenance\ hourly\ rate \cdot p_2} \ (25)$$

The following section presents the numerical implementation of the three- and two-state Markov models, utilizing the maintenance data from the CWS at the two units of Salem NPP.

### 4.4 Salem Circulating Water System PM and CM Data

Estimating the parameters of the three-state model requires the following information for Salem CWS components: number of CM each year, duration of each CM, number of PM each year, and duration of each PM. This information was extracted from Salem NPP's CWS maintenance data, which comprises a log of maintenance work orders performed on the CWPs and corresponding CWP motors across both the units. Recall, each Unit of Salem NPP has six CWPs and CWP motors.

For the three-state model parameter estimation, the maintenance work orders performed from 2009 through 2019 were considered. During this time, a total of 303 CM and 419 PM activities were performed across the 12 CWPs and CWP motors. Of the PM activities, 37 correspond to quarterly manual vibration measurement across CWP motors. The manual vibration measurement is performed while motors are in operation, i.e., online; therefore, PMs corresponding to vibration measurement are not considered in this analysis.

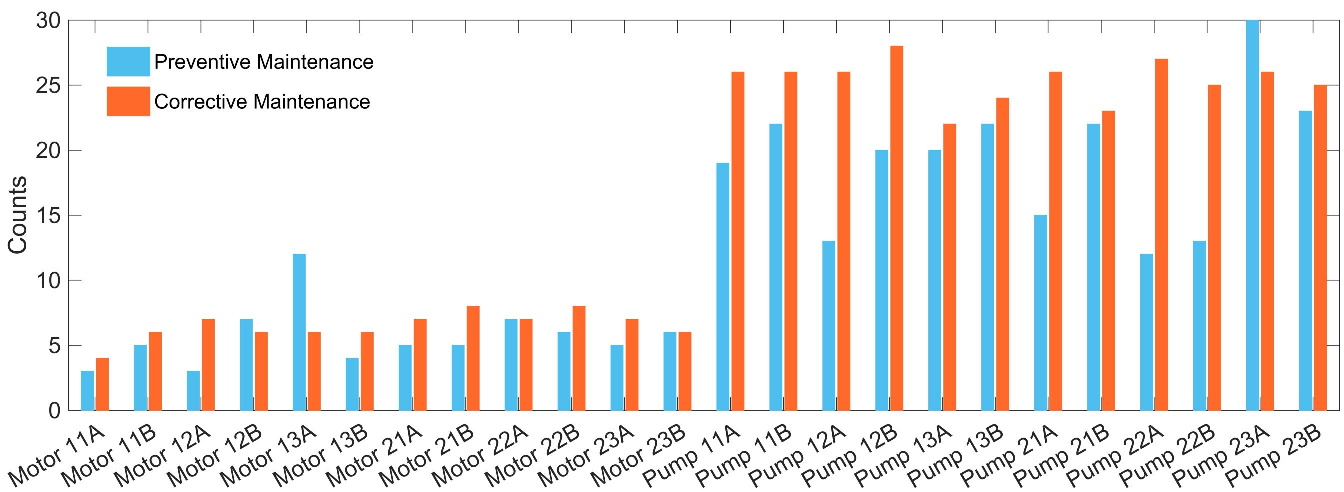

Figure 35. CM and PM counts from 2009 to 2019 for CWPs and CWP motors.

The counts of CM and PM for each CWP and CWP motor are illustrated in Figure 35, indicating a remarkably higher number of CM and PM activities for CWPs compared to CWP motors. Motors and pumps labeled 11A through 13B belong to Salem Unit 1 and those labeled 21A through 23B belong to Unit 2. The number of CM and PM required for parameter estimation were obtained directly from the maintenance log data. The start and end time of each maintenance activity has been historically logged manually and, in most cases, may not reflect the true start and end time of the activity. Therefore, the durations for PM activities were obtained based on the opinion of subject matter experts at Salem. Since there is a fixed set of PM activities performed on CWS pumps and motors, an average duration of downtime associated with each activity can easily be assigned as shown in Table 6.

Table 6. List of PM activities, their periodicity, and duration for CWS at Salem NPP.

| PM Activity | Periodicity (Months) | Average Downtime Duration (Hours) |
|---|---|---|
| Underwater Inspection - 9M | 9 | 12 |
| Bay and Piping Inspection | 18 | 0 |
| Rhodamine Flow Test* | 12 | 12 |
| Pump Change Out | 72 | 96 |
| Motor Inspection | 36 | 14 |
| Motor Replacement | 72 | 72 |
| Sensor Calibration | 48 | 0 |
| Tan-Delta Test | 72 | 14 |
| Underwater Inspection - 18M | 18 | 0 |

*Discontinued since 2014.

From the parameter estimation perspective, since the Bay and Piping Inspection activity (Table 6) is performed every refueling outage, i.e., every 18 months, and does not require CWP motor downtime specifically for this activity, the average downtime duration is considered to be zero hours. The average downtime duration associated with the Sensor Calibration activity is zero hours because it is performed online. The periodicity of underwater inspection was changed from every 9 months to every 18 months in 2016. Therefore, the underwater inspections prior to 2016 have a nonzero duration. After 2016, the underwater inspection is performed every refueling outage, therefore the average downtime duration is considered as zero hours.

Compared to PM activities, it is not a straight-forward exercise to group CM activities and estimate an average downtime duration. In order to obtain the average downtime duration due to CM activities, information from the PI server on CWP motor ON and OFF (also referred to as breaker status) and CMs from the maintenance log were used together. From the maintenance log, an estimated date of CM activities was first determined and then compared with the breaker status, during the estimated date to obtain the approximation of average downtime duration of the CWP motor that was used in this analysis.

Parameter Estimation

For the discrete random events occurring within given period of time $\tau$, recall that Equation (11) gives the PMF as $f(x = m|\lambda, \tau) = (\lambda \cdot \tau)^m / m! \cdot e^{-\lambda \cdot \tau}$, where $\lambda$ is the rate parameter. For the three-state model, the following events are random events: an occurrence of a CM activity, an occurrence of a PM activity, the time duration the CWP motor is operational after CM, and the time duration the CWP motor is operational after PM. For these four random events following the Poisson distribution, the corresponding rate parameters are described by the gamma distribution, whose PDF is given in Equation (26);

$$\boldsymbol{f(x; \alpha, \beta) = \frac{\beta^{\alpha} x^{\alpha-1} e^{-\beta\lambda}}{\Gamma(\alpha)}, x > 0, \alpha, \beta > 0} \quad (26)$$

where $\Gamma(\alpha)$ is the gamma function, $\alpha$ is the shape parameter, and $\beta$ is the rate parameter (also referred to as the inverse of the scaling parameter in the literature), and $x$ in this work can be any one of the four rates: $\lambda$-failure rate, $\mu$-corrective maintenance rate, $\eta$-preventive maintenance scheduling rate, and $\nu$-preventive maintenance rate. The gamma distribution has traditionally been used for defining the distribution of failure rates of mechanical systems. In the nuclear industry, the gamma distribution is used for defining the failure rates associated with various failure modes of mechanical components such as valves, motors, and pumps in the probabilistic risk assessment models.

Determining the distribution of the failure rate $x$ for a component entails finding the values of the parameters $\alpha$ and $\beta$. Bayesian inference is a powerful technique that has been commonly used for estimating the gamma distribution. Based on the industry-wide License Event Reports, event notifications, and equipment reliability data reported by NPPs, the U.S. NRC uses Bayesian inference for an annual update in the failure rate distribution of several safety components [21]. This work applies Bayesian inference [22] [23] for the CWPs and CWP motors based on the work order data provided by the Salem NPP from 2009 to 2019.

Using Bayesian inference for estimating the distribution of a quantity of interest entails finding the *posterior* distribution given by Bayes' theorem as:

$$\boldsymbol{posterior} \sim \boldsymbol{prior} \times \boldsymbol{likelihood} \quad (27)$$

where $prior$ is the distribution based on past belief and $likelihood$ is the distribution of the observed data. In this work, $likelihood$ is based on the observed random events following a Poisson distribution given by Equation (11), and $prior$ is the past belief that $\lambda$ follows a gamma distribution $f(x; \alpha_0, \beta_0)$. Here, $\alpha_0$ and $\beta_0$ are the shape and rate parameters, respectively, of the prior distribution. The likelihood distribution in Equation (11) gives Poisson PMF of random events such that $m$ random events are observed in time period $\tau$. For $\tau$ = 1 year, if components are operational for $L$ hours in a period of one year, the $posterior$ is a gamma distribution given by:

$$\boldsymbol{f(x; \alpha, \beta) = Gamma(\alpha_0 + m_x, \beta_0 + L_x)}. \quad (28)$$

The data obtained from Salem NPP comprises of observed events corresponding to CM and PM. Table 7 lists the values of $m_x$ and $L_x$ by year corresponding to the four parameters $\lambda$, $\mu$, $\eta$, and $\nu$ extracted from the CWS maintenance data of the Salem NPP.

Table 7. Duration and number of CM and PM events, and the run hours corresponding to the six CWPs and CWP motors of the CWS for each unit of the Salem NPP.

| Year | CM events ($m_\lambda$ and $m_\mu$) | | PM events ($m_\eta$ and $m_\nu$) | | Run hours ($L_\lambda$ and $L_\eta$) | | CM duration hours ($L_\mu$) | | PM duration hours ($L_\nu$) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Unit 1 | Unit 2 | Unit 1 | Unit 2 | Unit 1 | Unit 2 | Unit 1 | Unit 2 | Unit 1 | Unit 2 |
| 2009 | 14 | 17 | 2 | 0 | 49870 | 50190 | 425 | 1493 | 108 | 0 |
| 2010 | 15 | 7 | 3 | 3 | 49451 | 50210 | 208 | 588 | 24 | 36 |
| 2011 | 23 | 23 | 5 | 4 | 49282 | 49014 | 555 | 2852 | 110 | 38 |
| 2012 | 31 | 49 | 5 | 2 | 50612 | 49873 | 1081 | 2911 | 36 | 24 |
| 2013 | 20 | 11 | 3 | 7 | 49684 | 50731 | 1903 | 1024 | 38 | 218 |
| 2014 | 12 | 16 | 2 | 3 | 49992 | 50054 | 1185 | 1766 | 26 | 38 |
| 2015 | 10 | 13 | 2 | 3 | 51311 | 50368 | 333 | 1799 | 108 | 12 |
| 2016 | 8 | 3 | 3 | 3 | 49803 | 51108 | 197 | 121 | 12 | 12 |
| 2017 | 7 | 9 | 3 | 1 | 51002 | 50820 | 250 | 238 | 86 | 14 |
| 2018 | 8 | 4 | 1 | 2 | 50922 | 50436 | 205 | 262 | 0 | 0 |
| 2019 | 9 | 9 | 0 | 5 | 51449 | 52154 | 2102 | 116 | 0 | 182 |

Plugging the values of $m_x$ and $L_x$ into Equation (28) gives an annual estimate of the gamma distribution for each of the four parameters $\lambda$, $\mu$, $\eta$, and $\nu$ (replacing $x$). Note that estimating the posterior in Equation (28) requires the prior distribution $f(x; \alpha_0, \beta_0)$, i.e., knowing the values of $\alpha_0$ and $\beta_0$. Careful consideration must be given in choosing the correct $prior$, as the choice of $prior$ significantly impacts the posterior estimates. The method of Maximum Likelihood Estimate is used in this work for prior selection and is described in APPENDIX C

Prior Selection and Unit 2 Results. The data presented corresponding to years 2009–2011 was utilized in the process of prior selection, therefore the estimates of the four parameters $\lambda$, $\mu$, $\eta$, and $\nu$ are for 2012–2019. Table 8 shows the Markov chain parameters estimated for the Salem CWS. For a parameter following a Gamma $(\alpha, \beta)$ distribution, the corresponding annual parameter estimate is given by $\alpha/\beta$. The values listed in Table 8 are for the 12 CWPs across the two units of the Salem NPP. The table also shows average parameter values for each parameter and each unit. The average values are obtained by averaging parameters for eight years (2012–2019). These values are used in the optimization scenarios presented in the following section.

Table 8. Estimates of three-state model parameter for the two units of Salem NPP.

| | $\boldsymbol{\lambda}$ | | $\boldsymbol{\mu}$ | | $\boldsymbol{\eta}$ | | $\boldsymbol{\nu}$ | |
|---|---|---|---|---|---|---|---|---|
| Year | Unit 1 $(10^{-4})$ | Unit 2 $(10^{-4})$ | Unit 1 $(10^{-2})$ | Unit 2 $(10^{-2})$ | Unit 1 $(10^{-5})$ | Unit 2 $(10^{-5})$ | Unit 1 $(10^{-2})$ | Unit 2 $(10^{-2})$ |
| 2012 | 5.04 | 7.27 | 2.54 | 1.72 | 7.76 | 5.85 | 10.4 | 7.20 |
| 2013 | 4.66 | 5.32 | 1.74 | 1.57 | 7.34 | 7.82 | 9.51 | 4.00 |
| 2014 | 4.04 | 4.74 | 1.56 | 1.38 | 6.69 | 7.46 | 9.15 | 4.48 |
| 2015 | 3.58 | 4.28 | 1.65 | 1.24 | 6.22 | 7.21 | 5.84 | 5.24 |
| 2016 | 3.23 | 3.61 | 1.74 | 1.25 | 6.19 | 7.02 | 6.76 | 5.95 |
| 2017 | 2.95 | 3.33 | 1.79 | 1.33 | 6.15 | 6.39 | 5.92 | 6.00 |
| 2018 | 2.77 | 3.00 | 1.87 | 1.33 | 5.69 | 6.12 | 6.22 | 6.58 |
| 2019 | 2.65 | 2.85 | 1.48 | 1.42 | 5.11 | 6.48 | 6.22 | 5.26 |
| Average | 3.61 | 4.30 | 1.80 | 1.41 | 6.39 | 6.79 | 7.51 | 5.59 |

### 4.4.1 Sensitivity Analysis and Maintenance Scenarios

For the profit calculations, the following dollar values were used: $34 was used as the revenue hourly rate, and, for both CM and PM, the hourly rates were assumed to be $100 that included labor and parts' cost. In addition, for both types of maintenance, it was assumed that the unit is either offline or de-rated, and an additional cost of $34 was added, bringing the hourly maintenance cost to $134. Note, all cost calculations are performed per MWh and are chosen to demonstrate the sensitivity analysis. Analysis of Table 8 reveals that the smallest parameter for both units is $\eta$-the preventive maintenance scheduling rate with a mean time between preventive maintenance, $1/\eta = 15{,}649$ hours for Unit 1 and 14,728 hours for Unit 2. These mean times are significantly higher than mean times between failures, which are about 2,770 hours for Unit 1 and about 2,325 hours for Unit 2. For the modeling purposes, this means the system initially in operational state $S_0$ is much more likely to transition to state $S_1$ than to state $S_2$. This observation implies that the parameters $\lambda$ and $\mu$, which govern the dynamics of state $S_1$, are more important for the overall performance of the system than parameters $\eta$ and $\nu$.

To validate the above results, we performed a sensitivity analysis for the three-state model; the results for Unit 1 are presented in Table 9. For the sensitivity analysis, we first executed our model using average parameters from Table 8. The performance variables for those parameters are shown in the Baseline column in Table 9. Since the three-state model has four parameters, four different scenarios are considered where one of the four parameters is changed by an order of magnitude, while all others are kept equal to the Baseline. The parameters that were changed are highlighted in bold for each Scenario. The direction of the change in the parameters was such as to drive the Profit cost function up (see Equation 8). For example, the failure rate was reduced, while the corrective maintenance rate was increased.

Table 9. Three-state model's parameter sensitivity analysis for Unit 1 of the Salem NPP.

| | **Baseline** | **Scenario 1** | **Scenario 2** | **Scenario 3** | **Scenario 4** |
|---|---|---|---|---|---|
| Failure rate-λ, per hour | 3.61E-04 | 3.61E-04 | **3.61E-05** | 3.61E-04 | 3.61E-04 |
| Corrective maintenance rate-μ, per hour | 1.80E-02 | 1.80E-02 | 1.80E-02 | **1.80E-01** | 1.80E-02 |
| Preventive maintenance rate-ν, per hour | 7.50E-02 | 7.50E-02 | 7.50E-02 | 7.50E-02 | **7.50E-01** |
| Maintenance scheduling rate-η, per hour | 6.39E-05 | **6.39E-06** | 6.39E-05 | 6.39E-05 | 6.39E-05 |
| Revenue, $/hour | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 |
| Corrective maintenance cost, $ per hour | 1.00E+02 | 1.00E+02 | 1.00E+02 | 1.00E+02 | 1.00E+02 |
| Scheduled maintenance cost, $ per hour | 1.00E+02 | 1.00E+02 | 1.00E+02 | 1.00E+02 | 1.00E+02 |
| *Profit, $ per hour* | *3.06E+01* | *3.07E+01* | *3.35E+01* | *3.35E+01* | *3.07E+01* |
| P(Operational) | 9.80E-01 | 9.80E-01 | 9.97E-01 | 9.97E-01 | 9.80E-01 |
| P(CM) | 1.96E-02 | 1.97E-02 | 2.00E-03 | 2.00E-03 | 1.97E-02 |
| P(PM) | 8.35E-04 | 8.35E-05 | 8.50E-04 | 8.50E-04 | 8.35E-05 |
| Days operational | 3.58E+02 | 3.58E+02 | 3.64E+02 | 3.64E+02 | 3.58E+02 |
| Days maintenance | 7.47E+00 | 7.21E+00 | 1.04E+00 | 1.04E+00 | 7.21E+00 |
| MTBF, hours | 2.77E+03 | 2.77E+03 | 2.77E+04 | 2.77E+03 | 2.77E+03 |
| MCMT, hours | 5.56E+01 | 5.56E+01 | 5.56E+01 | 5.56E+00 | 5.56E+01 |
| MPMT, hours | 1.33E+01 | 1.33E+01 | 1.33E+01 | 1.33E+01 | 1.33E+00 |
| MPMST, hours | 1.56E+04 | 1.56E+05 | 1.56E+04 | 1.56E+04 | 1.56E+04 |

We are interested in the sensitivity of the cost function-Profit to those changes. As can be seen from the Profit row in Table 9, in italic, the hourly profit for the baseline operation is $30.60; changing either $\eta$ or $\nu$ can only improve it to $30.70. On the other hand, changing either $\lambda$ or $\mu$ brings the hourly profit to $33.50, which is very close to the maximum value of $34.00 achievable with this model. This confirms our observation that adjusting either $\lambda$ or $\mu$ is more important than $\eta$ or $\nu$. This can also be deduced from the parameter values themselves, as $\lambda = 3.61\text{E-}04$ and $\eta = 6.39\text{E-}05$ with $\lambda/\eta = 5.5$, which means that the system is more than five time more likely to transition to the CM state than to the PM state. Table 10 presents the results of the analysis of the three-state model's sensitivity to CM and PM costs. Similar to Table 9, the Baseline column represents the baseline scenario with all the parameters set to baseline values. The changed values are shown in bold for the other four columns. In Scenario 5, the CM cost has been reduced to half of the baseline value, and we can see that there is a marked increase in hourly profit. On the other hand, for Scenario 6, where the PM cost has been reduced to half of the baseline value, there is hardly any change in profit. This is because the model/system spends too little time in PM to make a noticeable impact on the bottom-line. Scenarios 7 and 8 were investigated to study the situation when a higher CM and PM rate will be performed at higher hourly costs. In Scenario 7, the CM rate has been reduced to half the baseline at the expense of doubling its hourly cost. As we can see, this caused a substantial reduction in profit. In Scenario 8, similar changes in the PM rate caused a significantly smaller decrease in profit. A conclusion can be made that scenarios with costlier but quicker maintenance are not economically viable.

Table 10. Three-state model's costs sensitivity analysis for Unit 1.

| | **Baseline** | **Scenario 5** | **Scenario 6** | **Scenario 7** | **Scenario 8** |
|---|---|---|---|---|---|
| Failure rate-λ, per hour | 3.61E-04 | 3.61E-04 | 3.61E-04 | 3.61E-04 | 3.61E-04 |
| Corrective maintenance rate-μ, per hour | 1.80E-02 | 1.80E-02 | 1.80E-02 | **9.00E-03** | 1.80E-02 |
| Preventive maintenance rate-ν, per hour | 7.50E-02 | 7.50E-02 | 7.50E-02 | 7.50E-02 | **3.75E-02** |
| Maintenance scheduling rate-η, per hour | 6.39E-05 | 6.39E-05 | 6.39E-05 | 6.39E-05 | 6.39E-05 |
| Revenue, $/hour | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 |
| Corrective maintenance cost, $ per hour | 1.00E+02 | **5.00E+01** | 1.00E+02 | **2.00E+02** | 1.00E+02 |
| Preventive maintenance cost, $ per hour | 1.00E+02 | 1.00E+02 | **5.00E+01** | 1.00E+02 | **2.00E+02** |
| *Profit, $ per hour* | *3.06E+01* | *3.15E+01* | *3.06E+01* | *2.35E+01* | *3.03E+01* |
| P(Operational) | 9.80E-01 | 9.80E-01 | 9.80E-01 | 9.61E-01 | 9.79E-01 |
| P(CM) | 1.96E-02 | 1.96E-02 | 1.96E-02 | 3.85E-02 | 1.96E-02 |
| P(PM) | 8.35E-04 | 8.35E-04 | 8.35E-04 | 8.18E-04 | 1.67E-03 |
| Days operational | 3.58E+02 | 3.58E+02 | 3.58E+02 | 3.51E+02 | 3.57E+02 |
| Days maintenance | 7.47E+00 | 7.47E+00 | 7.47E+00 | 1.44E+01 | 7.77E+00 |
| MTBF, hours | 2.77E+03 | 2.77E+03 | 2.77E+03 | 2.77E+03 | 2.77E+03 |
| MCMT, hours | 5.56E+01 | 5.56E+01 | 5.56E+01 | 1.11E+02 | 5.56E+01 |
| MPMT, hours | 1.33E+01 | 1.33E+01 | 1.33E+01 | 1.33E+01 | 2.67E+01 |
| MPMST, hours | 1.56E+04 | 1.56E+04 | 1.56E+04 | 1.56E+04 | 1.56E+04 |

The initial analysis of the three-state model demonstrates that the state of preventive maintenance is a relatively rarely visited state and its influence on overall performance of the system is minimal. On the other hand, the state of corrective maintenance is highly influential and significantly affects system's performance. This brings forward the idea of merging the two maintenance states together and performing an analysis of a simpler two-state model. The two-state model has only two parameters: $\lambda$-failure rate and $\mu$-maintenance rate. Table 11 presents the estimates of these two parameters and the average values over the eight-year period from 2012 to 2019. As can be seen from Figure 26 and Figure 32, the failure rate for the two-state model can be considered a the superposition of failure rate and preventive maintenance scheduling rate and the maintenance rate is the superposition of corrective and preventive maintenance rates. The results of sensitivity studies for the two-state model for Unit 1 are shown in
Table 12.

Table 11. Estimates of the two-state model parameter for the two units of Salem NPP.

| Year | $\lambda$ Unit 1 $(10^{-4})$ | $\lambda$ Unit 2 $(10^{-4})$ | $\mu$ Unit 1 $(10^{-2})$ | $\mu$ Unit 2 $(10^{-2})$ |
|---|---|---|---|---|
| 2012 | 6.00 | 7.98 | 2.96 | 1.79 |
| 2013 | 5.47 | 6.23 | 1.95 | 1.69 |
| 2014 | 4.72 | 5.55 | 1.75 | 1.51 |
| 2015 | 4.19 | 5.03 | 1.83 | 1.37 |
| 2016 | 3.84 | 4.33 | 1.97 | 1.42 |
| 2017 | 3.55 | 3.96 | 2.03 | 1.50 |
| 2018 | 3.31 | 3.60 | 2.11 | 1.52 |
| 2019 | 3.12 | 3.49 | 1.66 | 1.63 |
| Average | 4.28 | 5.02 | 2.03 | 1.55 |

Table 12. Two-state model sensitivity results for Unit 1.

| | **Baseline** | **Scenario 9** | **Scenario 10** | **Scenario 11** | **Scenario 12** |
|---|---|---|---|---|---|
| Failure rate-λ, per hour | 4.25E-04 | **2.12E-04** | 4.25E-04 | 4.25E-04 | 4.25E-04 |
| Maintenance rate-μ, per hour | 2.03E-02 | 2.03E-02 | **4.06E-02** | **4.06E-02** | **1.02E-02** |
| Revenue, $ per hour | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 |
| Maintenance cost, $ per hour | 1.00E+02 | 1.00E+02 | 1.00E+02 | **2.00E+02** | **5.00E+01** |
| *Profit, $ per hour* | 3.06E+01 | 3.23E+01 | 3.23E+01 | 3.12E+01 | 2.93E+01 |
| P(Operational) | 9.79E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.60E-01 |
| P(Maintenance) | 2.05E-02 | 1.04E-02 | 1.04E-02 | 1.04E-02 | 4.02E-02 |
| Days operational | 3.58E+02 | 3.61E+02 | 3.61E+02 | 3.61E+02 | 3.50E+02 |
| Days maintenance | 7.48E+00 | 3.78E+00 | 3.78E+00 | 3.78E+00 | 1.47E+01 |
| MTBF, hours | 2.35E+03 | 4.71E+03 | 2.35E+03 | 2.35E+03 | 2.35E+03 |
| MMT, hours | 4.93E+01 | 4.93E+01 | 2.46E+01 | 2.46E+01 | 9.85E+01 |

In Scenario 9, the failure rate-$\lambda$ has been halved, doubling the time between failures. It can be seen that this had a moderate effect on profit as the two-state model baseline scenario already has a profit close to the maximum possible for this model, $34.00 an hour. As the two-state model has only two parameters, their effect is reciprocal, as shown in Scenario 10 where $\mu$ has been doubled to keep $\lambda$ equal to the baseline value, thus providing an identical increase in profit. However, changes in the maintenance rate normally would incur some expenses if the rate goes up or savings, if we are willing to put up with slower maintenance. This situation is illustrated in Scenarios 11 and 12. In Scenario 11, the twofold increase comes at the expense of doubling the hourly maintenance cost. As can be seen from Table 11, this leads to a moderate increase in profit, suggesting that even doubling the expenses, provided that the maintenance is also doubled, is a beneficial and economically viable strategy. Scenario 12 presents the reverse situation where a longer maintenance is performed at lower hourly cost. As seen in

Table 12, this leads to a decrease in profit in comparison to the baseline operation.

In summary, an analysis of the three-state reveals that, under current conditions and using available data, the maintenance schedule for the CWS is close to optimal and the bottom-line cannot be significantly influenced by changing PM intervals or the time spent on PM. This is due to the fact that the CWS spends most of its time either operating or in CM. According to the three-state model, the economic benefits can be obtained by either reducing the failure rate or increasing the CM rate. As far as the cost of different activities is concerned, the three-state model shows that reducing the CM rate and increasing its cost would produce the smallest benefits, as expected, providing all other rates remain unchanged. The most beneficial strategy would be a reduction in corrective hourly cost, providing all rates remain the same. Reduction in the PM rate at the expense of a higher cost is detrimental to economic performance. The two-state model, in general, confirms these conclusions, as it points to the reduction in failure rate and increase in maintenance rate as two drivers for economic profitability. It also suggests that an increase in maintenance rate at the expense of higher costs is beneficial, while a reduction in maintenance rate and cheaper costs leads to economic losses in comparison to the baseline operations. Note that the numerical results discussed are obtained for Unit 1, however, the conclusion holds for Unit 2 as well, for which the numerical results are presented in APPENDIX C

Prior Selection and Unit 2 Results.

# 5. PREVENTIVE MAINTENANCE OPTIMIZATION (PMO)

NPPs follow an established MP to ensure safe and reliable plant operation. These established maintenance plans are part of a PM strategy and are defined for all equipment and systems at a plant site. The PM strategy is a combination of time-based and condition-based maintenance tasks. For the time-based maintenance tasks, workers from Electrical, Mechanical, and Instrumentation and Controls Maintenance perform these tasks at a defined interval, usually without taking into consideration the condition of the equipment and system. NPPs also perform additional maintenance actions, such as periodic surveillance, inspection, and testing. Due to the high cost and labor-intensive nature of these strategies, many NPPs have performed optimization of these intervals through PM Optimization (PMO).

The initial basis for the time-based interval was established using a combination of vendor recommendations, site operating experience, and an Industry PM Basis Database (EPRI PMBD), which was developed using Industry Subject Matter Experts and failure data for component types (e.g., air operated valves, motor operated valves, etc.). Once established, the intervals are continuously adjusted using the maintenance feedback process from the field. This process relies on multiple iterations of execution of the maintenance task in order to develop a trend to support optimization of the maintenance interval. Due to this feedback process, the process for optimizing the maintenance intervals is slow and NPPs continue to sink costs into their PM program on tasks that are performed too frequently. In order to accelerate this process, a PM Optimization process that leverages data analytics, using similar industry maintenance strategies, can be used in order to develop new baselines for optimized time intervals to accelerate the optimization of the NPP’s maintenance strategies.

## 5.1 General Description of Preventive Maintenance Strategy of Salem Circulating Water System

Following the model of the generalized PM strategy outlined above, the following sections outline the PM strategy for the CWS Pump and Motor as well as scheduled maintenance on additional CWS equipment that influence the overall PM strategy. A portion of the condition-based maintenance strategy for the CWS Pumps and Motors is determined using process data from both the CWS and Main Condenser System to collectively determine refurbishment and replacement frequencies.

Salem Circulating Water Pump Motor Preventive Maintenance Basis

The current maintenance strategy for the CWS Pump Motor is identified in Table 13 below.

Table 13. Salem CWP Motor Maintenance Strategy.

| | Task Title | Vendor Recommended Frequency | Current MP Frequency | MP Description |
|---|---|---|---|---|
| **Condition Monitoring Tasks** | Vibration analysis | 3 months | 3 months | Collect vibration data using triaxial accelerometer every 3 month |
| | Oil analysis | 6 months | 6 months | Extract an oil sample and examine for all CWP motors |
| | Monitor Stator RTD’s | Continuous | Continuous | Continuously monitored by operator |
| | Monitor Bearing (inboard and outboard) Temperature | Continuous | Continuous | Continuously monitored by operator |
| | Inspect/Electrical Testing | 36 months | 36 months | Inspect CWP motor and perform testing |
| **Time Directed Task** | Refurbish Motor | 6 years | 6 years | Perform change out of CWP motor |

Salem Circulating Water Pump Preventive Maintenance Basis

As per Salem plant site records, no evaluation or documentation was found supporting the current PM strategy of the CWP. The performance centered maintenance template for the CWS vertical pumps does not provide a frequency recommendation, and refurbishment is performed “as required.” The pump vendor recommends “complete overhauls of the pump be done at a frequency dependent upon the hours of operation for the pump, the severity of the conditions of service, the materials used in the pump construction, and the care the pump receives during operation.” Therefore, the Salem plant site developed a PM strategy to address and eliminate issues. The same measurement parameters are collected for all CWPs to support the PM strategy, as summarized in Table 14.

Table 14. Salem CWP Maintenance Strategy.

| | Task Title | Vendor Recommended Frequency | Current MP Frequency | MP Description |
|---|---|---|---|---|
| **Condition Monitoring Tasks** | Vibration analysis | 3 months | 3 months | Collect vibration data using triaxial accelerometer every 3 month[1] |
| | Performance trending | 1 year | Deleted | Perform flow measure as per Rhodamine dye test[2] |
| **Time Directed Tasks** | External visual inspection | 9 months | 18 months | Perform underwater inspection by divers |
| | Refurbishment[3] | 3 years | 6 years | Perform change out of CWP |

Functional Equipment Groups

To maximize the availability of the system and the efficiency for the execution of the PM strategy (including corrective maintenance), different subsystems of the CWS are grouped into functional equipment groups (FEGs) by their maintenance isolation boundaries. Each unit has 12 FEGs with maintenance performed on each FEG every 9 months (an illustration of FEG is shown below in Figure 36 [24]). The duration of each scheduled maintenance item (preventive or corrective or both) depends on the type of activities to be performed. There are instances when multiple FEGs scheduled maintenance activities are combined to reduce power de-rate and achieve efficiency. In order to maximize the return on investment for a PMO assessment, the maintenance strategies of the equipment within the FEG must also be reviewed in order to not lose the efficiencies gained from doing work on multiple pieces of equipment within a FEG.

[1] At present, no direct vibration data is collected on CWPs. Indirect vibration measurements to evaluate CWP performance are collected near the motor-pump coupling.

[2] The Rhodamine dye test is no longer performed due to high uncertainty and inaccuracy in flow estimation. The last Rhodamine dye test was performed in 2014.

[3] The refurbishment interval was increased from 3 years to 6 years based on the upgrade performed to the CWP material.

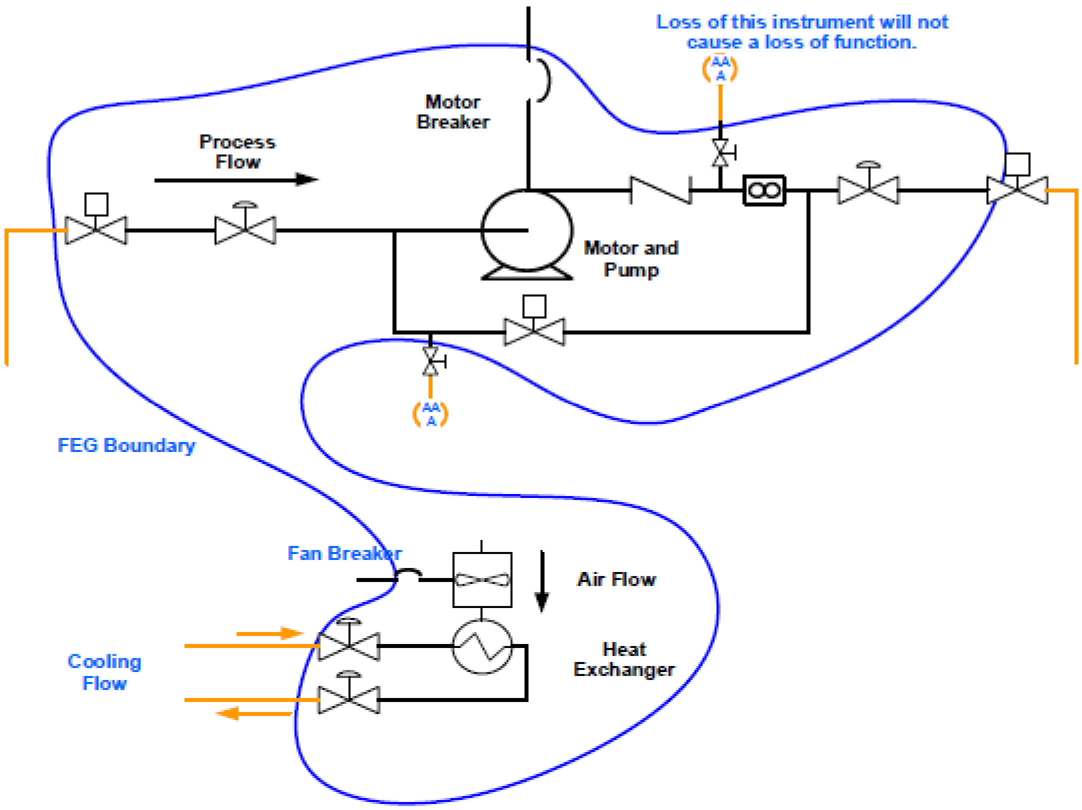


Figure 36. Example diagram of a Functional Equipment Group.

### 5.2 Preventive Maintenance Plans in Scope of Assessment

Since the goal of PMO is to optimize resources (labor and material cost) to do the right tasks at the right time, the main driver for this effort was the upcoming time-based refurbishments of the major equipment in the CWS system. Table 15 references Motor/Pump Refurbishment Timelines. Additionally, in order to provide a new baseline for the upcoming refurbishment PMs, all similar industry maintenance strategies were evaluated, including the other Pump/Motor refurbishments at Salem.

Table 15. Historical CWP motor refurbishment timeline.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Unit 1 | **CWP** | 11A | 11B | 12A | 12B | 13A | 13B |
| | **Pump** | 9/11/2024 | 1/7/2022 | 12/11/2023 | 7/26/2022 | 10/2/2024 | 12/21/2022 |
| | **Motor** | 9/30/2023 | 1/25/2025 | 2/28/2023 | 7/29/2022 | 10/06/2024 | 10/11/2025 |
| Unit 2 | **CWP** | 21A | 21B | 22A | 22B | 23A | 23B |
| | **Pump** | 10/5/2025 | 12/17/2023 | 5/25/2023 | 10/10/2022 | 5/21/2021 | 16/28/2024 |
| | **Motor** | 10/5/2025 | 6/16/2022 | 1/6/2026 | 01/03/2025 | 01/22/2025 | 1/1/2024 |

In order to leverage the benefits of FEG, all other time-based activities associated with equipment within the FEG were included in the scope to ensure alignment and provide additional resource optimization. Table 16 below lists all of the PMs in the Scope for PMO.

Table 16. PMs in the Scope for PM Optimization.

| Equipment | Task Title | Current Frequency | Count of PMS |
|---|---|---|---|
| Pump | Refurbishment | 6 years | 12 |
| | External Visual Inspection | 18/24 months | 12 |
| Motor | Vibration Analysis | 3 months | 2 |
| | Oil Analysis | 6 months | 2 |
| | Inspect/Electrical Testing | 3 years | 12 |
| | Replace Motor | 6 years | 12 |
| Motor Cable | VLF TAN-Delta Testing | 6 years | 12 |
| Protective Relays | Inspect/Calibrate | 6 years | 12 |
| Pressure Switch | Calibration | 4 years | 12 |

The following PMs were not included in the scope:

- PM To Clean Inspect Fish Sample Tube – These PMs enable the counting of fish in the circulating water intake, therefore they were not reviewed, since it was a New Jersey Pollutant Discharge Elimination System environmental requirement and has no impact on the reliability of the CWS system
- PM To Calibrate CWS Bearing Lube Water Flow Meter – This PM was removed from scope because it is already performed on condition

### 5.3 PMO Recommendations

The PM plans in the scope of assessment were then compared to industry PM strategies for similar equipment in the industry CWS. The industry average PM frequency intervals are compared against PSEG frequency intervals to see if there is a basis for PM frequency extension. As shown in Figure 37, if a nuclear utility is performing PM work at a greater frequency than the industry average, they are most likely doing excessive PM work (i.e. high cost) and have room to decrease their frequencies. In the reverse scenario, if a nuclear utility is performing PM work at a lower frequency than the industry average, they are most likely not doing enough PM work (i.e. high cost from equipment failure) and should increase their frequencies. A qualitative analysis of the maintenance feedback from both PM and CM history was then performed, along with site and industry operating experience, to further determine if PM frequency extension can be justified. Industry PM Intervals for CWS applications were used as basis to extend PSEG PMs, based on living Industry PM Programs being adjusted based on their internal maintenance feedback process. This process assumes similar operational context across the industry (duty cycle and environment) for CWS applications. Applicable industry information was narrowed down when potential stressors are known that would influence failures, such as the impact of Brackish Water.

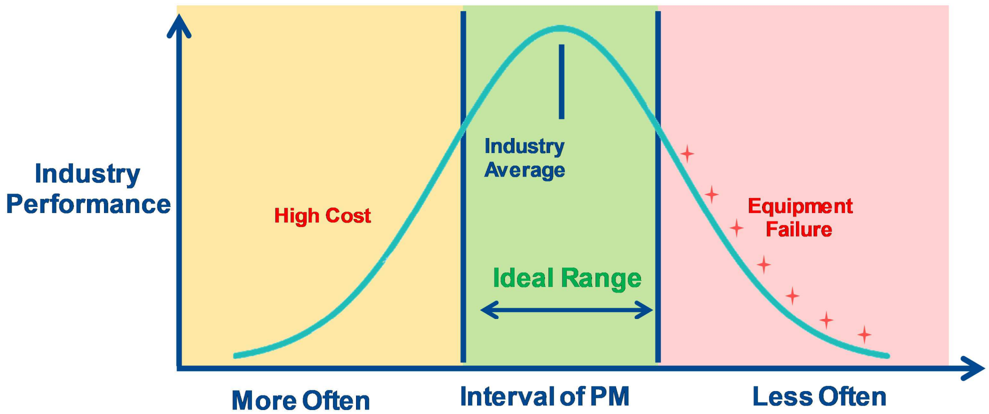

Figure 37. Overview of Ideal PM Frequency Interval.

Table 17 below shows the results of the CWS PM frequency comparison between PSEG and the industry average. Based upon this comparison and the qualitative analysis, recommendations to either keep the current frequency or perform PM work less frequent are derived. Justifications for each recommendation are given below the table and detail the qualitative history of Salem Unit 1 (11A, 11B, 12A, 12B, 13A, 13B) and Unit 2 (21A, 21B, 22A, 22B, 23A, 23B) pump / motor pairs.

Table 17. PMO Recommended Frequency Results.

| Equipment | Task Title | Current Frequency | Industry Average | Recommendation | Recommended Frequency |
|---|---|---|---|---|---|
| Pump | Refurbishment | 6 years | 14 years | Less Frequent | 9 years |
| | External Visual Inspection | 18/24 months | 2.8 years | Keep | 18 months |
| Motor | Vibration Analysis | 3 months | 5.5 months | Less Frequent | 6 months |
| | Oil Analysis | 6 months | 8 months | Keep | 6 months |
| | Inspect/Electrical Testing | 3 years | 3 years | Keep | 3 years |
| | Replace Motor | 6 years | 10.7 years | Less Frequent | 9 years |
| Motor Cable | VLF TAN-Delta Testing | 6 years | 7 years | Keep | 6 years |
| Protective Relays | Inspect/Calibrate | 6 years | 4 years | Keep | 6 years |
| Pressure Switch | Calibration | 4 years | 4.2 years | Keep | 4 years |

**Pump – Refurbishment (6 years)**

**Recommendation – Less Frequent (9 years)**

**Justification** – The subject PMs perform a replacement of the installed CW pump with a spare and sending the removed CW pump to be overhauled and repaired. Other preventive maintenance activities performed on the CW pump include an underwater inspection performed at a frequency of 18 months, a pressure switch calibration performed at a frequency of 4 years, and a CW bay and piping inspection performed at a frequency of every 6 outages (9 years). All 12 CW pump and motor units at Salem 1 and Salem 2 are also subject to vibration data collection and analysis at a frequency of 3 months. The Circulating Water pumps are 84" vertical wet pit pumps designed specifically for condenser circulating water service and are driven by 3-phase, 2000 HP, 292 RPM, 4160 V induction motors. The motors are vertical, high thrust, solid shaft motor through a rigid coupling. The CWS of each Salem unit consists of six axial flow Circulating Water Pumps/Motors (or Circulators).

A review of PM and CM history over the last 10 years was performed on the CW Pumps. There have been 28 PM work orders associated with the replacement of the 12 CW pumps at Salem. A review of the last replacement of each of the pumps showed an average replacement frequency of approximately 4.6 years due to many of the replacement PM WOs being scheduled and consolidated with other work being performed. Although the majority of the WOs did not detail unsatisfactory findings regarding the condition of the pump, there were at least five WOs that detailed degraded pump condition and/or other unsatisfactory findings. These WO findings include:

- below rated pump flow at 11B in 2011
- detached bellmouth with a broken flange and cracked impeller at 12B in 2010
- chatter in the wear ring and deficient gap/clearance between the impeller and diffuser blade at 13B in 2011
- corrosion and loose bolting along with required bellmouth replacement and out of tolerance alignment at 21B in 2011
- an unsatisfactory inspection at 23A in 2010.

Although relevant, these findings do not document catastrophic failure or a total loss of function of the pump. Additionally, all of the pumps associated with these findings have gone through at least one additional PM work order, since the degraded conditions were noted. There have been 223 CM work orders associated with the 12 CW pumps at Salem. The majority of CM work orders were initiated due to general corrosion/wear, packing leaks, clogged/leaking tubes/lines, casing replacement, spare pump inspection, and other tasks not considered to be emergent. The CM history of the CW Pumps over the past 10 years has been positive overall, revealing 16 WOs which detail degraded condition in pump performance with four WOs at 11A, one WO at 12A, two WOs at 12B, one WO at 21A, two WOs at 23A, and one WO at 23B. However, all of the WOs above predate the material changes which took place in 2019, 2017, 2016, 2013, 2015, and 2018 respectively.

Three WOs at 11B include one detailing sealing issues in 2011, one detailing a vibration issue in 2012 (both predating the material change in 2016), and then one detailing a vibration issue again in 2020. An underwater inspection was performed on pump 11B; however, no degraded condition in pump performance or pump failure was noted and proper operation was verified. One WO at 13A details the discovery of pump wear after an underwater inspection, due to indications that the pump had dropped its bellmouth and lower than expected running Amps. Although the bellmouth was subsequently replaced, there was no failure in pump operation. One WO at 13B details the refurbishment of the spare pump in 2017/2018, revealing severe pump damage. However, refurbishment on the 13B pump took place in 2011 and 2012, and this pump was thus in service prior to the material change in 2016.

Additionally, pump 21A was the first to undergo the material change in 2013 and was recently replaced in 2019, after almost 6 years in service with no degraded condition in pump performance noted and no CM during that time period that noted degraded condition in pump performance.

An industry search for PM activities with similar scopes related to CW Pump overhaul/rebuild was performed on non-safety related and noncritical equipment. The search resulted in 65 results across (12) sites, with an average frequency of 5,344 days (approximately 14 years). An additional industry search was performed for CW Pump changeout/refurbishment to focus on industry sites situated near saltwater to determine the effect this environment has on the PM. The search resulted in 18 results across 4 sites, with an average frequency of almost 7 years and with two sites performing a pump overhaul at 8 years. However, Salem has acted to mitigate the corrosion and erosion challenges posed by salt and brackish water in the CW System by implementing a design change package to replace the aluminum bronze wet end parts of the CW Pumps with AL6XN wet end parts. The implementation of this design change precipitated a frequency extension for the CW Pumps changeout PM to a frequency of 6 years, with the goal extending to a 9-year or ultimately a 12-year frequency.

The EPRI template for vertical pumps recommends a refurbishment frequency of as required/on condition (AR) for Non-Critical, Hi-Duty, Severe Service (NHS) components.

Based on the overall positive PM and CM work history of the CW pumps over the past 10 years, an EPRI template refurbishment frequency recommendation of AR, an average industry frequency of approximately 14 years for PM scopes related to CW pump overhaul/rebuild, the implementation of a material change to mitigate the challenges posed by a saltwater environment on the CW System, the existence of vibration monitoring and analysis, and in order to align with the CW pump motor refurbishment frequency extension recommendation, the recommendation is to extend the frequency of the PM from 6 years to 9 years.

**Pump – External Visual Inspection (18 months)**

**Recommendation – Keep (18 months)**

**Justification** – The subject PMs perform an underwater inspection of the (12) CW Pumps at Salem. Other preventive maintenance activities performed on the CW pump include a pump change out at a current frequency of 6 years, a pressure switch calibration performed at a frequency of 4 years, and a CW bay and piping inspection performed at a frequency of every 6 outages (9 years). A review of the last PM performed on each of the 12 CW Pumps and CM history of the CW Pumps over the last 10 years was performed. The last PM WO for each of the 12 CW Pumps was completed between 2018 and 2019, with overall positive findings. All bolts between the upper discharge elbow and transition piece were replaced on pump 11A in 2019. During the underwater inspection at 12B in 2019, the 12CW109 bottom cover cap bolts failed, and the cover was retrieved from floor, fish lip replacement was completed, and the stuffing box was cleaned. The upper fish lips were replaced at pump 21A in 2018. The lower fish lip was replaced at 22B in 2018. In 2018, the diver reported the 23A CW Pump bellmouth bolts were loose and pieces of the bellmouth came off when the bolts were retightened and the upper fish lip was replaced. The most recent PM WOs for the other seven CW Pumps 11B, 12A, 13A, 13B, 21B, 22A, and 23B were completed with no deficiencies noted.

There have been 223 CM work orders associated with the 12 CW pumps at Salem. The majority of CM work orders were initiated due to general corrosion/wear, packing leaks, clogged/leaking tubes/lines, casing replacement, spare pump inspection, and other tasks not considered to be emergent. There are at least 16 WOs that do detail degraded condition of performance of the pump, including four WOs at 11A, three WOs at 11B, one WO at 12A, two WOs at 12B, one WO each at 13A/13B/21A, two WOs at 23A, and one WO at 23B. The four WOs at 11A include two detailing a crack in the pump casing in 2010 (same issue) and two detailing vibration issues in 2013, with one resulting in a pump replacement. The three WOs at 11B include one detailing sealing issues in 2011 and two detailing vibration issues in 2012 (also casing degradation and bellmouth detachment) and then again in 2020. The one WO at 12A detailed bellmouth detachment and casing replacement in 2015. The two WOs at 12B detail a vibration issue and subsequent inspection of the removed pump, which revealed excessive shaft bearing sleeve wear and as well as wear on the suction guide barrel in 2013. The one WO at 13A details the pump inspection and subsequent discovery of excessive wear and pump replacement in 2017. The one WO at 13B details the refurbishment of the spare pump in 2017/2018, revealing severe pump damage. The one WO at 21A details the replacement of the bellmouth and guide barrel in 2013. The two WOs at 23A detail vibration and subsequent pump repair in 2010 as well as bellmouth detachment and guide barrel damage and subsequent pump replacement in 2011. The one WO at 23B details replacement of the pump due to the impeller touching the casing in 2011.

An industry search for PM activities with similar scopes related to CW Pump inspection was performed. The search resulted in 183 results across 18 sites, with an average frequency of 1,032 days (approximately 2.8 years).

The EPRI template for vertical pumps does not have a specific task for underwater inspections; however, the recommended frequency for operator rounds is one day while the recommended frequency for technical walkdown is one year for NHS components.

Although the PM and CM work history of the CW Pumps is overall positive and the industry average frequency for similar inspection PM is approximately 2.8 years, there have been several instances in which the PM at the current frequency identified unsatisfactory conditions as well as several instances of unsatisfactory findings in the CM history, which support keeping the current underwater inspection frequency. Additionally, keeping the current frequency for the underwater inspection PM will help mitigate the risk associated with the proposed frequency extension of CW Pump and Motor replacement PMs from 6 years to 9 years. The recommendation is to keep the PM at the current frequency.

**Motor – Vibration Analysis (3 months)**

**Recommendation – Less Frequent (6 months)**

**Alternate Recommendation – Delete and Change To Continuous Online Monitoring after Pilot**

**Justification** – The subject PMs perform vibration monitoring of the installed CW pump and motors at Salem 1 and Salem 2. Other preventive maintenance activities performed on the CW pump include an underwater inspection performed at a frequency of 18 months, a pressure switch calibration performed at a frequency of four years, and a CW bay and piping inspection performed at a frequency of every six outages (nine years). Other preventive maintenance activities performed on the CW pump motors include tan-delta testing performed at a frequency of six years, motor testing and inspection performed at a frequency of 3 years, and pump motor lube sampling performed at a frequency of six months.

A review of PM and CM history over the last ten years was performed on the CW Pumps and motors. There have been 79 PM work orders for vibration data of the rotating equipment associated with this PM performed at Salem. None of these WOs detailed any degraded function or condition regarding vibration data for the 12 CW pumps and motors or any other unsatisfactory findings specific to the CW pumps and motors. One WO in 2013 detailed that 13B travelling screen had high vibes of 0.788, which resulted in a notification on 6/1/2013. There have been 26 WOs since this occurrence. There have been 223 CM work orders associated with the 12 CW pumps at Salem. The majority of CM work orders were initiated due to general corrosion/wear, packing leaks, clogged/leaking tubes/lines, casing replacement, spare pump inspection, and other tasks not considered to be emergent. There are at least 16 WOs that do detail a degraded condition of performance of the pump, including four WOs at 11A, three WOs at 11B, one WO at 12A, two WOs at 12B, one WO each at 13A/13B/21A, two WOs at 23A, and one WO at 23B. The four WOs at 11A include two detailing a crack in the pump casing in 2010 (same issue) and two detailing vibration issues in 2013, with one resulting in pump replacement. The three WOs at 11B include one detailing sealing issues in 2011 and two detailing vibration issues in 2012 (also casing degradation and bellmouth detachment) and then again in 2020. The one WO at 12A detailed bellmouth detachment and casing replacement in 2015. The two WOs at 12B detail a vibration issue and subsequent inspection of the removed pump, which revealed excessive shaft bearing sleeve wear as well as wear on the suction guide barrel in 2013. The one WO at 13A details pump inspection and subsequent discovery of excessive wear and pump replacement in 2017. The one WO at 13B details the refurbishment of the spare pump in 2017/2018, revealing severe pump damage. The one WO at 21A details the replacement of the bellmouth and guide barrel in 2013. The two WOs at 23A detail vibration and subsequent pump repair in 2010 as well as bellmouth detachment and guide barrel damage and subsequent pump replacement in 2011. The one WO at 23B details replacement of the pump due to the impeller touching the casing in 2011.

There have been 60 CM work orders associated with the 12 CW motors at Salem, the majority of which were written due to routine testing, inspection, installation, cleaning/housekeeping issues as well as minor rework, which did not note any significant degradation of condition or loss of functional performance. Three of the WOs detailed oil issues including high viscosity, discoloration, and water content; however, the oil was changed, and no loss of motor function was noted. Five of the WOs detailed clogging of the air intake/screen due to salt buildup or other obstruction, which subsequently needed cleaning. There were four CM work orders that documented a possible degradation in performance. One WO noted high vibration at 13A in 2010, which was attributed to method of alignment. Another WO noted vibration at 12A in 2017 with no documented failure, with the motor being subsequently replaced. Another WO noted where the winding was observed to be packed with salt and was replaced with no specific failure noted, with the motor being subsequently replaced at 12B in 2010. Another WO noted a bad motor at 22B in 2011, which required motor replacement. However, this occurrence took place after maintenance was performed and the pump was being placed back in service. Successful replacement of the 22B motor occurred again in 2018, during the regular scheduled PM for replacement.

An industry search for PM activities with similar scopes related to CW Pump motor was performed. The search resulted in 227 results across 18 sites, with an average frequency of 167 days (approximately 5.5 months).

The EPRI template for vertical motors recommends a vibration monitoring frequency of six months for NHS components.

Based on overall positive PM and CM work history of the CW pumps and motors over the past 10 years, an EPRI template vibration monitoring frequency recommendation of six months, and an average industry frequency of 5.5 months, an extension of the current vibration monitoring of the CW pumps and motors (other associated equipment included in PM should be evaluated separately) from a frequency of three months to six months is warranted. The recommendation is to extend the frequency of the PM from three months to six months. Alternatively, it is recommended that this time-based activity be retired ultimately and replaced with a condition-based activity of online vibration monitoring of the CW pumps and motors.

**Motor – Oil Analysis (six months)**

**Recommendation – Keep (six months)**

**Justification** – The subject PMs perform oil analysis of the installed CW pump motor. A review of PM and CM history over the last 10 years was performed on the CW motors. There have been 40 PM work orders associated with the lube sampling of the 12 CW motors at Salem, the majority of which did not note any significant degradation or other unsatisfactory findings related to the lube sampling. Of the 40 WOs, only four noted findings that could be considered unsatisfactory, including in September of 2011 when it was noted that the sample taken at the lower position of motor 1CWE4 contained water, in August of 2011 when it was noted that the sample taken at the lower position of motor of 2CWE1 contained water, in March of 2011 when it was noted that particles were found in most of the S2 samples, and in August of 2010 when it was noted that samples from CW Pump Motors 21A, 23A, 22B, and 23B were dark in color. Since these 2011 occurrences, there have been 17 PM WOs performed at both Salem 1 and Salem 2, which did not note lube degradation or other unsatisfactory findings.

There have been 60 CM work orders associated with the 12 CW motors at Salem, the majority of which were written due to routine testing, inspection, installation, cleaning/housekeeping issues as well as minor rework, which did not note any significant degradation of condition or loss of functional performance. Three of the WOs detailed oil issues including high viscosity, discoloration, and water content; however, the oil was changed, and no loss of motor function was noted. Five of the WOs detailed clogging of the air intake/screen due to salt buildup or other obstruction, which subsequently needed cleaning. There were four CM work orders that documented a possible degradation in performance. One WO noted high vibration at 13A in 2010, which was attributed to method of alignment. Another WO noted vibration at 12A in 2017 with no documented failure, with the motor being subsequently replaced. Another WO noted where the winding was observed to be packed with salt and was replaced with no specific failure noted, with the motor being subsequently replaced at 12B in 2010. Another WO noted a bad motor at 22B in 2011, which required motor replacement. However, this occurrence took place after maintenance was performed and the pump was being placed back in service. Successful replacement of the 22B motor occurred again in 2018, during the regular scheduled PM for replacement.

An industry search for PM activities with similar scopes related to CW Pump Motor oil analysis was performed. The search resulted in 35 results across six sites with an average frequency of 240 days (approximately eight months).

The EPRI template for vertical motors recommends an oil analysis frequency of one year for NHS components.

Although the overall PM and CM work history of the CW pump motors over the past 10 years has been positive and the EPRI template oil analysis frequency recommendation is 1 year, the average industry frequency of approximately eight months for PM scopes related to CW pump motor oil analysis does not support a frequency extension, which would be worthwhile and which would also align with the frequencies of other PM activities. Additionally, maintaining the current lube analysis frequency mitigates the risk associated with the recommend extension of the motor replacement PM extension from six years to nine years. The recommendation is to keep the frequency of the PM at the current frequency of six months.

**Motor – Inspect/Electrical Testing (three years)**

**Recommendation – Keep (three years)**

**Justification** – The subject PMs perform testing, oil change, and inspection at the 12 CW pump motors at Salem 1 and Salem 2. A review of PM and CM history over the last 10 years was performed on the CW motors. There have been 37 PM work orders associated with the testing/oil change/inspection of the 12 CW motors at Salem, the majority of which did not note any significant degradation or loss of function related to the motors. Of the 37 WOs, only two noted any type of unsatisfactory findings. In 2017, at 21A rust/corrosion and ventilation blockage due to buildup was noted. In 2012 at 21B, the PI was found to be lower than the acceptant criteria, and a notification was created, with the test being performed again SAT. This PM has been performed SAT at least once at each of the motors since these occurrences.

There have been 60 CM work orders associated with the 12 CW motors at Salem, the majority of which were written due to routine testing, inspection, installation, cleaning/housekeeping issues as well as minor rework, which did not note any significant degradation of condition or loss of functional performance. Three of the WOs detailed oil issues including high viscosity, discoloration, and water content; however, the oil was changed, and no loss of motor function was noted. Five of the WOs detailed clogging of the air intake/screen due to salt buildup or other obstruction, which subsequently needed cleaning. There were four CM work orders that documented a possible degradation in performance. One WO noted high vibration at 13A in 2010, which was attributed to method of alignment. Another WO noted vibration at 12A in 2017 with no documented failure, with the motor being subsequently replaced. Another WO noted where the winding was observed to be packed with salt and was replaced with no specific failure noted, with the motor being subsequently replaced at 12B in 2010. Another WO noted a bad motor at 22B in 2011, which required motor replacement. However, this occurrence took place after maintenance was performed and the pump was being placed back in service. Successful replacement of the 22B motor occurred again in 2018, during the regular scheduled PM for replacement.

An industry search for PM activities with similar scopes related to CW Pump Motor testing/oil change/inspection was performed. The search resulted in 45 results across 11 sites with an average frequency of 1,620 days (approximately 4.4 years).

The EPRI template for vertical motors recommends an offline electrical testing frequency of two years and an online testing frequency of three years for NHS components.

Although the overall PM and CM work history of the CW pump motors over the past 10 years has been positive, the EPRI template offline and online electrical testing frequency recommendation is two years and three years, respectively, and the average industry frequency of approximately 4.4 years for PM scopes related to CW pump motor testing/oil change/inspection does not support a frequency extension, which would be worthwhile and which would also align with the frequencies of other PM activities. Additionally, maintaining the current testing/oil change/inspection frequency mitigates risk associated with the recommend extension of the motor replacement PM extension from six years to nine years. The recommendation is to keep the frequency of the PM at the current frequency of three years.

**Motor – Replace Motor (six years)**

**Recommendation – Less Frequent (nine years)**

**Justification** – The subject PMs perform a replacement of the installed CW pump motor with a spare. A review of PM and CM history over the last 10 years was performed on the CW motors. There have been 23 PM work orders associated with the replacement of the 12 CW motors at Salem, the majority of which did not note any significant degradation or loss of function related to the motors. The most recent PM work orders for each of the 12 CW motors are either the first or second occurrence (six years since last occurrence) of the PM at the current six year frequency. The most recent PM work orders for 11A and 12B appear to be the first at the 6Y frequency, with the next most recent PM work orders having been completed in 2008 and 2007, respectively. Two of the 23 PM work orders documented motor failure and were completed under CM work orders. The first occurred on the 21B motor at the end of 2008 when it was noted that water was running from around the motor; however, this motor had been replaced earlier that year, likely due to damage from vent obstruction. The 21B PM has been completed SAT twice since this occurrence. The second occurred on the 22B motor in 2011 when a breaker tripped after the pump was placed in service and smoke/noise from the motor was noticed; however, this was following maintenance being performed and the 22B PM has been completed SAT once since this occurrence.

There have been 60 CM work orders associated with the 12 CW motors at Salem, the majority of which were written due to routine testing, inspection, installation, cleaning/housekeeping issues as well as minor rework, which did not note any significant degradation of condition or loss of functional performance. Three of the WOs detailed oil issues including high viscosity, discoloration, and water content; however, the oil was changed, and no loss of motor function was noted. Five of the WOs detailed clogging of the air intake/screen due to salt buildup or other obstruction, which subsequently needed cleaning. There were four CM work orders that documented a possible degradation in performance. One WO noted high vibration at 13A in 2010, which was attributed to method of alignment. Another WO noted vibration at 12A in 2017 with no documented failure, with the motor being subsequently replaced. Another WO noted where the winding was observed to be packed with salt and was replaced with no specific failure noted, with the motor being subsequently replaced at 12B in 2010. Another WO noted a bad motor at 22B in 2011, which required motor replacement. However, this occurrence took place after maintenance was performed and the pump was being placed back in service. Successful replacement of the 22B motor occurred again in 2018, during the regular scheduled PM for replacement.

An industry search for PM activities with similar scopes related to CW Pump Motor overhaul/rebuild/replacement was performed for non-safety related and noncritical equipment. The search resulted in 69 results across eight sites with an average frequency of 3,930 days (approximately 10.7 years).

The EPRI template for vertical motors recommends a refurbishment frequency of 10Y for NHS components.

Based on overall positive PM and CM work history of the CW pump motors over the past 10 years, an EPRI template refurbishment frequency recommendation of 10 years, an average industry frequency of approximately 10.7 years for PM scopes related to CW pump motor overhaul/rebuild/replacement, and alignment with the CW pump refurbishment frequency extension recommendation, the recommendation is to extend the frequency of the PM from six years to nine years.

**Motor Cable – VLF TAN-Delta Testing (six years)**

**Recommendation – Keep (six years)**

**Justification** – The subject PMs perform VLF tan-delta testing on motor cables at the 12 CW pump motors at Salem 1 and Salem 2. A review of PM and CM history of the last 10 years was performed on the CW motors. There have been 16 PM work orders associated with the VLF tan-delta testing of the 12 CW motors at Salem. All of the 16 PM work orders were completed, and none of the WOs noted any deficiency or degraded function or condition.

There have been 60 CM work orders associated with the 12 CW motors at Salem, the majority of which were written due to routine testing, inspection, installation, cleaning/housekeeping issues as well as minor rework, which did not note any significant degradation of condition or loss of functional performance. Three of the WOs detailed oil issues including high viscosity, discoloration, and water content; however, the oil was changed, and no loss of motor function was noted. Five of the WOs detailed clogging of the air intake/screen due to salt buildup or other obstruction, which subsequently needed cleaning. There were four CM work orders that documented a possible degradation in performance. One WO noted high vibration at 13A in 2010, which was attributed to method of alignment. Another WO noted vibration at 12A in 2017 with no documented failure, with the motor being subsequently replaced. Another WO noted where the winding was observed to be packed with salt and was replaced with no specific failure noted, with the motor being subsequently replaced at 12B in 2010. Another WO noted a bad motor at 22B in 2011, which required motor replacement. However, this occurrence took place after maintenance was performed and the pump was being placed back in service. Successful replacement of the 22B motor occurred again in 2018, during the regular scheduled PM for replacement.

An industry search for PM activities with similar scopes related to CW Pump Motor tan-delta testing was performed. The search resulted in 24 results across five sites, with an average frequency of 2,547 days (approximately seven years).

The EPRI template for vertical motors does not specify any recommendations specifically related to VLF tan-delta testing. The EPRI template for vertical motors recommends an offline electrical testing frequency of two years (online testing frequency of three years) for NHS components. Additionally, the EPRI templates for circuit breakers and cables recommend testing frequencies of AR for noncritical components.

Although the overall PM and CM work history of the CW pump motors over the past 10 years has been positive, the average industry frequency of approximately seven years for PM scopes related to CW pump motor tan-delta testing does not support a frequency extension, which would be worthwhile and which would also align with the frequencies of other PM activities. Additionally, maintaining the current tan-delta testing frequency mitigates the risk associated with the recommend extension of the motor replacement PM extension from six years to nine years. The recommendation is to keep the frequency of the PM at the current frequency of six years.

**Protective Relays – Inspect/Calibrate (six years)**

**Recommendation – Keep (six years)**

**Justification** – The subject PMs perform inspection and calibration of the 4KV breaker protective relays and current transformers. The current transformers are 600/5 ratio transformers and are supported in their operation by an auxiliary trip monitoring relay, an indicating overload relay, a spring charger failure auxiliary relay, and Phase A/C/neutral overcurrent relays.

A review of PM and CM history of the last 10 years was performed on the 12 CW pump motors at Salem 1 and Salem 2. There have been 27 PM work orders associated with the inspection and calibration of the CW pump motor relays at Salem. All WOs were completed SAT with no degraded function or condition noted except one WO at 21B in 2012. The WO details a failure of the Phase C overload relay during testing and subsequent replacement in 2012. Since this occurrence, the PM has been performed once in 2015 (SAT) with no degraded function or condition noted. There have been no CM WOs performed on the associated equipment within the past 10 years.

An industry search for PM activities with similar scopes related to CW Pump Motor relay inspection and calibration was performed. The search resulted in 83 results across seven sites with an average frequency of 1435 days (approximately four years). Additionally, an industry search for PM activities associated with General Electric Type IAC overcurrent relays was performed for noncritical equipment. The search resulted in 6,819 results across seven sites, with an average frequency of 2,107 days (approximately 5.8 years).

The EPRI template for Protective - Electromechanical Relays recommends a calibration and testing frequency of eight years for Non-Critical, Lo-Duty, Mild Service components.

Although overall PM and CM work history over the past 10 years has been positive and the EPRI template recommended frequency for relay calibration is eight years, the average industry frequency is approximately four years for similar PM activities and approximately 5.8 years for PM activities associated with General Electric Type IAC overcurrent relays. A frequency extension which would be worthwhile and would also align with the frequencies of other PM activities is not supported at this time. The recommendation is to keep the frequency of the PM at the current frequency of six years.

**Pressure Switch – Calibration (four years)**

**Recommendation – Keep (four years)**

**Justification** – The subject PMs perform calibration of CW pump pressure switches. The pressure switches make up part of the permissive circuitry for the associated circulator.

A review of PM and CM history of the last 10 years was performed on the CW switches. There have been 27 PM work orders associated with the calibration of the switches for the 12 CW pump/motors at Salem. Of the 27 WOs, 15 detailed switches being out of calibration and/or requiring replacement of one or more of the switches due to degraded function. The eight WOs detailing a switch replacement include 12A in 2010 (two WOs completed since, with one detailing out of calibration in 2014), 12B in 2019 and 2015, 13B in 2017 and 2012, 21A in 2016, 22A in 2014 (one WO completed since in 2018, which did not detail out of calibration), and 23B in 2011. There have been 10 CM work order associated with the switches for the 12 CW pump/motors at Salem. Of the 10 WOs, three detailed issues with the function of an associated switch, including a replacement in 2012 after a recent calibration in 2011 at 11A, a replacement in 2017 after a recent replacement in 2017 at 12B, and a failed switch and subsequent replacement in 2019 at 12B. There was also a fourth WO detailing the replacement of an associated switch at 23A in 2018 due to a crack in the cover glass.

An industry search for PM activities with similar scopes related to CW Pump pressure switch calibration was performed. The search resulted in 41 results across eight sites with an average frequency of 1,548 days (approximately 4.2 years).

The EPRI template for a pressure switch recommends a calibration frequency of four years for NHS components.

Based on the PM and CM work history over the past 10 years showing several instances of equipment being out of calibration and requiring replacement, the EPRI template pressure switch calibration frequency recommendation of four years, and the average industry frequency of approximately 4.2 years, a frequency extension that would be worthwhile and would also align with the frequencies of other PM activities is not supported at this time. The recommendation is to keep the frequency of the PM at the current frequency of four years.

The recommendations provided above will provide PSEG with the basis to extend the interval of the PMs; however, since there are changes to all 12 Pump/Motor PMs, the actual scheduled maintenance for PMs performed within the window will need to be rebaselined in order to level resource requirements. This could include utilizing grace on PM tasks and/also performing work prior to the PM due date. If implemented at the site, these changes could potentially result in a net savings of approximately $4.37M over the next six years. This value was calculated using an assumed standard rate of $75/man hour, approximated material costs and is shown in Table 18 below. The net position was calculated by identifying the work scope (i.e. man hours and parts) to be removed from each calendar year based on original due date as potential savings, adding the work scope added to each calendar year based on new due date after extending frequency as additional cost, and removing the man hours needed for the Vibration Monitoring as additional savings.

Table 18. Potential six year net position if PM extensions are implemented at Salem.

| | | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | |
|---|---|---|---|---|---|---|---|---|
| Removed | Man Hours | 490 | 2,809 | 1,997 | 1,983 | 1,911 | 281 | |
| | Material | $400,000 | $2,600,000 | $1,100,000 | $1,500,000 | $2,300,000 | $75,000 | |
| Added | Man Hours | 0 | 0 | 0 | 490 | 2,809 | 1,997 | |
| | Material | | | | $400,000 | $2,600,000 | $1,100,000 | |
| Vibration | Man Hours | 408 | 408 | 408 | 408 | 408 | 408 | |
| Net | Man Hours | 898 | 3,217 | 2,405 | 1,901 | -490 | -1,308 | |
| | Man Hours Cost | $67,350 | $241,275 | $180,375 | $142,575 | $(36,750) | $(98,100) | |
| | Material | $400,000 | $2,600,000 | $1,100,000 | $1,100,000 | $(300,000) | $(1,025,000) | |
| | **Total** | **$467,350** | **$2,841,275** | **$1,280,375** | **$1,242,575** | **$(336,750)** | **$(1,123,100)** | **$4,371,725** |

All recommendations are provided to PSEG as a Preventive Maintenance Change Request (PCR), which is the formal vehicle to adjust PM Frequencies at PSEG. The PCRs are then reviewed and approved via ER-AA-210-1005 - Rev. 0 Predefine Change Processing.

# 6. SUMMARY AND PATH FORWARD

This report presented the R&D performed by PKMJ in collaboration with INL and PSEG to develop a risk-informed approach to optimized equipment maintenance frequencies for the CWS at Hope Creek and Salem. In support of the R&D, historical plant process data on CWS, preventive and corrective maintenance records, failure data, and expert opinions already available were utilized to enhance the risk insights to prioritize and inform maintenance decision making.

The PKMJ Digital Platform was utilized and configured for the project to enable efficient data ingestion, cleansing, analytics, and visualizations. PKMJ worked with PSEG personnel to extract and transfer Sensor data from the PSEG PI Data Historian into the platform where it was then combined with additional PSEG data (Component, Inventory, Work Order, Maintenance Plan, etc.) and industry information (Maintenance Strategies, Failure information, etc.). Additional sensor information was then integrated into the platform via the sensor provider's cloud solution. Data cleansing and simple analytics were then performed on the data to properly stage the data for use in advanced analytics.

PKMJ and INL were able to use the cleansed data to perform advanced analytics for a cost impact analysis, a Risk-Informed Model, and a PMO. The report discussed the approach, methodology, and results of each of the advanced analytics.

The cost impact analysis was performed to identify the best candidates for the Risk-Informed Condition-Based Monitoring based on several factors, including equipment type, safety classification, criticality, and costs. It was then further refined by looking at accessibility/location, upcoming maintenance, parts availability, and ease of maintenance. Recognizing that additional monitoring equipment was going to be needed, the team used EPRI 3002010577 "On-Line Monitoring Guide" to determine what type of wireless sensor would be needed to cover the failure mode of the PM that was going to be extended or be converted to condition-based maintenance. The use of a vibration probe to have continuous monitoring of the equipment can detect many of the failure modes that the PMs are being used to keep maintain reliability of the equipment. The additional sensors would also be a nonintrusive addition to any equipment. Output of the analysis was compared to PSEG provided targets, resulting in the Asset Selection of the 12 CWS pump and motor pairs.

The Risk-Informed Model was developed by reviewing multiple Markov chains models, as they are one of the major modeling tools used in reliability and availability research. In summary, an analysis of the three-state model revealed that the greatest economic benefits can be obtained by either reducing the failure rate or reducing the corrective maintenance duration (and increasing its cost), provided all other parameters remain unchanged. The two-state model, in general, confirms these conclusions, as it points to the same two drivers for economic profitability.

The PMO Analysis was performed on the CWS pump and motor pairs to identify any opportunities to extend maintenance frequencies of existing scheduled work based on the Risk-Informed Model and industry insights related to actual failures vs frequencies on similar equipment. Overall, 88 PMs were reviewed and evaluated for potential extensions. For the pump change out and motor refurbishment PMs, the recommendation was to extend from a six year to a nine year frequency. If implemented at the site, these changes could potentially result in a net savings of approximately $4.37M over the next six years.

The path forward for this research project in collaboration with PSEG and Idaho National Labs is to perform R&D activities using advancements in sensor technologies and advanced data analytics to develop and deploy digital monitoring and automated diagnosis and prognosis of plant equipment health condition for CWS and to integrate the advanced analytics and monitoring capabilities developed into a centralized automated platform in support of the nuclear industry to achieve the greatest returns on investment and economies of scale.

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# APPENDIX A

# KCF Technologies Wireless Vibration Sensors: Technical Specifications

The primary axis of measurement is perpendicular to the mounting surface. The SMARTDiagnostics® vibration sensor collects data at a fixed rate of either 1,650 data points per sample set, with 825 spectral lines, or 4,096 data points per sample, with 2,048 spectral lines. However, the frequency resolution of a sample set can be adjusted. SMARTDiagnostics® vibration sensors use a MEMS transducer instead of a piezoelectric transducer. This allows the sensor to factor in the sensor orientation, but any small errors in the acceleration static signal will lead to a drift of the velocity signal. A high-pass filter is used to remove this error. The table below shows the possible sampling conditions, with 1,650 data points and 825 spectral lines.

Table 19. Accelerometer sampling frequencies and relevant features.

| Sampling Frequency (Hz) | Sample Duration (s) | Spectral Resolution (Hz) | Frequency Cutoff (Hz) |
|---|---|---|---|
| 8192 | 0.2 | 5.0 | 19.9 |
| 4096 | 0.4 | 2.5 | 9.9 |
| 2048 | 0.8 | 1.24 | 5.0 |
| 1024 | 1.6 | 0.62 | 2.5 |
| 512 | 3.2 | 0.31 | 1.2 |
| 256 | 6.4 | 0.16 | 0.6 |
| 128 | 13 | 0.08 | 0.3 |
| 64 | 26 | 0.04 | 0.16 |

The SMARTDiagnostics® network consists of nodes, repeaters, base stations, and a data server. Base stations serve as data collection points for the nodes. If a node is out of range of the base station, it will connect to a repeater and that repeater will connect to the base station. All data gathered by the base stations is sent to the data server. Local network connections, such as ethernet or Wi-Fi, as well as a cellular network can be used to connect the base stations to the network. The table below shows the hardware specifications for a typical SMARTDiagnostics® network.

Table 20. Hardware specifications for KCF Technologies wireless sensor network.

| | |
|---|---|
| Node | 800-ft range in an open area, 200-ft range in typical industrial environment. Uses magnetic or stud mounts. |
| Repeater | Recommended 50 nodes per repeater or base station depending on data acquisition interval. Environmental enclosure. Typically powered by 120V AC but can be powered by 24V DC. 2400-ft range in open area, 600-ft range in typical industrial environment. |
| Base Station | Up to four repeaters per base station. Environmental enclosure. Typically powered by 120V AC but can be powered by 24V DC. Uses Wi-Fi connection, ethernet, or cellular. |

The base stations send the information they collect to a data server. The table below contains the necessary specifications for that server.

Table 21. Hardware specifications for KCF Technologies wireless sensor network.

| | |
|---|---|
| Operating system | Windows 2008 R2 or above |
| Hard Drive Space | 103 TB direct-attached |
| RAM | Minimum 8 GB |
| Processor | 10 core 2.2 GHz |

The SMARTDiagnostics® network utilizes the DARTwireless protocol. The table below outlines the specifications of this protocol.

Table 22. DARTwireless specifications.

| | |
|---|---|
| Modulation | Gaussian Frequency Shift Keying |
| Data Rate | 2 Mpbs |
| Frequency Channels | 2429, 2436, 2443, 2450, and 2457 MHz |
| Channel Half-Power Bandwidth | 2 MHz |
| RF Channel Bandwidth Consumed | 0.8–5.7% |
| Peak RF Power | 15 dBm |
| Range | 800 ft for line-of-site, 100–300 ft for typical industrial environment |

There is no limit on the number of sensor nodes per channel, but the starting point is usually 50 nodes per channel or 250 nodes per collection server. Assuming a data acquisition/transmission interval of 10 minutes, this network size limit assures a 98% throughput. However, decreasing the sampling interval also decreases the throughput. Using a sampling interval of 1 minute brings the throughput down to 95% and a sampling interval of 12 seconds further brings the throughput down to 70%.

Table 23. Vibration sensor node specifications.

| | |
|---|---|
| Mechanical | |
| Dimensions | 2.06 in. Max width × 3.21 in. height (52.3 mm x 81.5 mm) |
| Weight | 6.6 oz (188g) |
| Enclosure Material | 303 Stainless Steel and Radel R 5800 |
| Environmental | |
| Storage Temp | -40 to 238°F (-40 to 120°C) |
| Min. Operating Temp | -4°F (-20°C) |
| Max Operating Temp | 230°F (110°C) surface @ 72°F (22°C) ambient<br>212°F (100°C) surface @ 105°F (40°C) ambient<br>167°F (75°C) surface @ 167°F (75°C) ambient |
| IP Rating | IP68, Dust-tight and water-tight |
| Impact Resistance | Survives 5-ft drop onto concrete surface |
| Hazardous Certification | Class I, Division 2, Groups A-D, T5 (model SD-VSN-3N) |
| Wireless Radio | |
| Radio | KCF DART wireless 2.4 GHz ISM band, FCC ID #Z515D2 |

| | |
|---|---|
| Range | 800 ft line-of-sight |
| Antenna | Internal dipole antenna |
| Power | |
| Power source | 3V Lithium Manganese Dioxide |
| Battery Life | Full spectrum acquisitions every:<br>60 minutes–8 years<br>15 minutes–6 years<br>2.5 minutes–2 years |
| Accelerometer | |
| Range | +/- 19 g typical, +/- 16g nominal |
| Resolution | 0.866 mg nominal w/ individual NIST-traceable calibration |
| Noise Floor | 1.496 mg RMS @ 64 Hz / 12.01 mg RMS @ 8192 Hz |
| Transverse Sensitivity | 10% Typical |
| Frequency Response | +/- 5% 0–2700 Hz, +/- 3 dB 2700–4000 Hz |
| Samples per Acquisition | 4096 (standard) or 1650 (battery saver) |
| Spectral Lines | 2048 (standard) or 825 (battery saver) |
| Antialiasing Filter | 4000 Hz low-pass cut off, 3rd order Sallen-Key |
| Sampling Frequency | 64–8192 Hz configurable |
| Temperature Sensor | |
| Range | -4 to 167°F (-20 to 75°C) |
| Resolution | +/- 1°F (+/- 0.5°C) |

Table 24. Base station specifications.

| | |
|---|---|
| Mechanical | |
| Dimensions | 11.8 × 9.8 × 7.7 in (300 × 250 × 200 mm) without cables or antennas |
| Weight | 9.8 lb (4.4 kg) |
| Environmental | |
| Storage Temperature | -40 to 176°F (-40 to 80°C) |
| Operating Temperature | 32 to 140°F (0 to 60°C) |
| Case | Pelican Storm iM2075 Case |
| IP Rating | IP 65 |
| Software and Connectivity | |
| Software | BalenaOS (Linux) |
| Network Communications | Ethernet (IEEE 802.3)<br>Wi-Fi (IEEE 802.11)<br>Cellular |
| Ethernet (IEEE 802.3) | 1 PRN included. Add up to 4 optional Repeaters for additional PRNs. |
| Power | |
| Power Source | 110–240 VAC 50/60 Hz |

| | |
|---|---|
| Power Consumption | ≤ 60 Watts |
| Wiring | Standard Three-blade AC power cable SJ00W rated, 7ft |
| Data Reliability | |
| Offline Data Caching During Network Outage | Stores up to 285,000 vibration data samples<br>Automatic retransmission of cache when communication is restored |

Table 25. Repeater specifications.

| | |
|---|---|
| Mechanical | |
| Dimensions | 11.8 × 9.8 × 4.7 in (300 × 250 × 120 mm) without cables or antennas |
| Weight | 3 lb (1.4 kg) |
| Environmental | |
| Storage Temperature | -40 to 176°F (-40 to 80°C) |
| Operating Temperature | 32 to 140°F (0 to 60°C) |
| Case | Pelican Storm iM2050 Case |
| IP Rating | IP 65 |
| Hazardous Certification | Class I, Division 2, Groups A-D, T4 (model SD-RN Only) |
| Software and Connectivity | |
| Network Communications | Self-contained 2.4 GHz wireless to Base Station Up to 4 Repeaters per Base Station |
| RF Range | 2400 ft (730 m) line-of-sight (site survey recommended for installation) |
| PRN Connectivity | 1 PRN included; add additional Repeaters for additional PRNs |
| Power | |
| Power Source | 24 VDC or 110-240 VAC 50/60 Hz |
| Power Consumption | ≤ 10 Watts |
| Wiring | SD-R: Standard three-blade AC Power cable SJOOW rated, 7 feet long<br>SD-RN: Hazardous-Location NEMA 5-15 three-blade connector OR conduit per Class 1 Division 2 Standards |

Table 26. Accelerometer Sampling.

| Accelerometer Sampling | | |
|---|---|---|
| Sampling Frequency (Hz) | Sample Duration (s) | Spectral Resolution (Hz) |
| 8192 | 0.2 | 5.0 |
| 4096 | 0.4 | 2.5 |
| 2048 | 0.8 | 1.24 |
| 1024 | 1.6 | 0.62 |
| 512 | 3.2 | 0.31 |
| 256 | 6.4 | 0.16 |
| 128 | 13 | 0.08 |
| 64 | 26 | 0.04 |

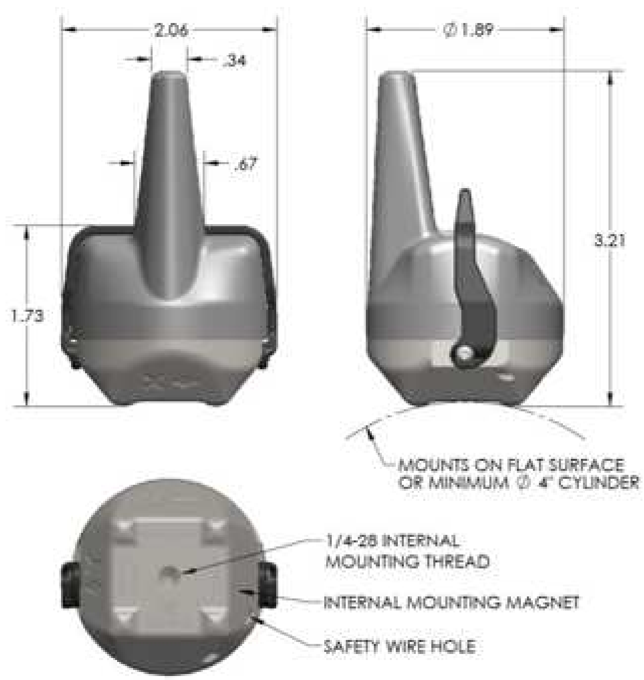


Figure 38. SD-VSN-3 sensor node dimensions.

# APPENDIX B

# SMARTDiagnostics® Software to Visualize KCF Wireless Vibration Sensor Node Data

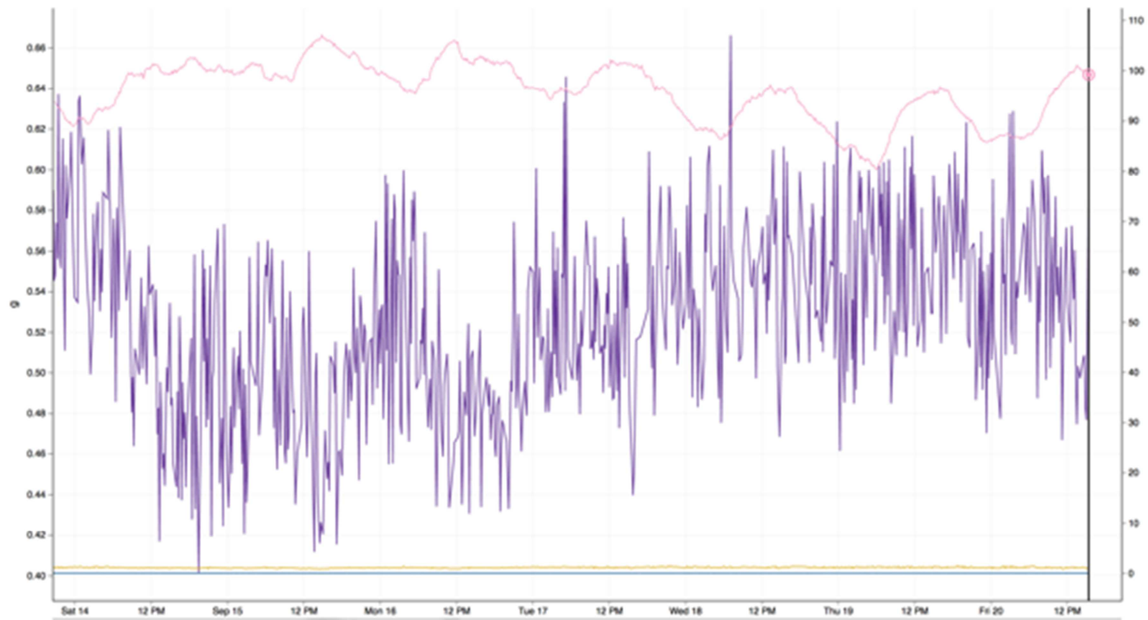


Figure 39. Horizontal inboard vibration signal received on September 13, 2019 from the VSN installed on CWP motor 11A.

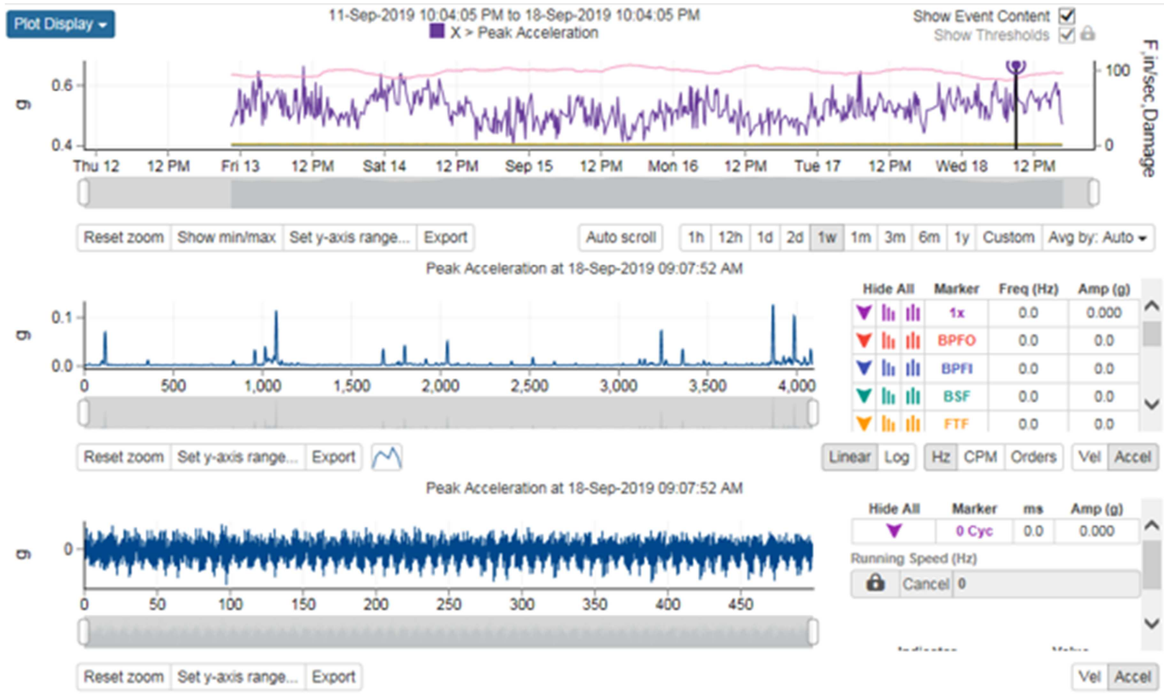


Figure 40. Horizontal inboard vibration signal received during the week of September 11, 2019 from the VSN installed on CWP 11A motor along with the Peak Acceleration indicator values for September 18, 2019.

# APPENDIX C

# Prior Selection and Unit 2 Results

Prior Selection

In Bayesian inference for parameter estimation (Equation (28)), the prior distribution of $\lambda$ ~ Gamma ($\alpha_0, \beta_0$) has a significant impact on the posterior estimation. Prior is our past belief about the distribution of $\lambda$ and can either be a noninformative or an informative prior. Noninformative priors are commonly used when we lack prior knowledge or understanding of the behavior of the parameters. Commonly used noninformative priors are uniform, Jeffrey's noninformative, reference priors etc. Because the gamma distribution of failure rate $\lambda$ is commonly used in the nuclear industry to define failure rates and the availability of CWS pump failure data, we used these two sources of prior knowledge for calculating and comparing informative priors.

The NRC developed the Reliability and Availability Data System (RADS) that contains the voluntary data and other data available to the NRC. RADS is used to meet NRC's need for reliability data for Probabilistic Risk Assessment (PRA) and risk-informed applications and provides NRC staff and industry a source of unit-specific and generic component-level data on reliability (demand failure probability, standby-stress failure rate, and rate of failure to operate) and train or component-level data on availability (planned unavailability and unplanned unavailability) [21]. RADS uses the industry-wide failure data that is voluntarily reported by the U.S. NPPs in their Safety System Performance Indicator system and the Equipment Performance and Information Exchange (EPIX) system and provides the current estimate of $\lambda$ ~ Gamma ($\alpha_0, \beta_0$) distribution. For the prior estimation, we searched in RADS for the 2009 update of failure rate of Motor Driven Pump Fail to Run (MDP-FR) failure mode, because the maintenance data from Salem is for CWS-MDP and has been available since 2009.

The second approach for prior estimation is to use the available maintenance data from Salem CWS. Table 7 presents the duration and number of CM and PM events and the run hours corresponding to the six pumps and motors in the CWS of Unit 1 and 2 of Salem NPP. A subset of this data in Table 7, from 2009 to 2011, was used for calculating prior using three techniques: Maximum Likelihood Estimate (MLE), Method of Moments (MM), and Constrained Noninformative. Details about these methods of prior estimation are available elsewhere [23] [25] [26] [27] [28].

Figure 41 shows the Probability Density Functions (PDFs) of the $\lambda$ ~ Gamma ($\alpha_0, \beta_0$) distribution for the four priors. To compare the performance of the four priors in providing the posterior with best prediction, define a root mean square error (RMSE) in prediction as:

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\lambda_{est}^{i} - \lambda_{data}^{i}\right)^2} \quad (29)$$

where N is the number of years over which the prediction is made that in this work is eight years (2012–2019), $\lambda_{est}^{i}$ is the estimate of $\lambda$ for the $i^{\text{th}}$ year obtained from using a specific prior, and $\lambda_{data}^{i}$ is the value of $\lambda$ in just the year $i$ obtained from the data. The lower the value of RMSE, the better the performance of the prior in predicting the future $\lambda$. The RMSE values for the four priors were obtained as: MLE = 6.169e-05, MM = 6.169e-05, CNI = 6.169e-05, and RADS = 2.666e-04. MLE is chosen as the prior in this work based on a desirable PDF curve in Figure 41 and lowest RMSE value.

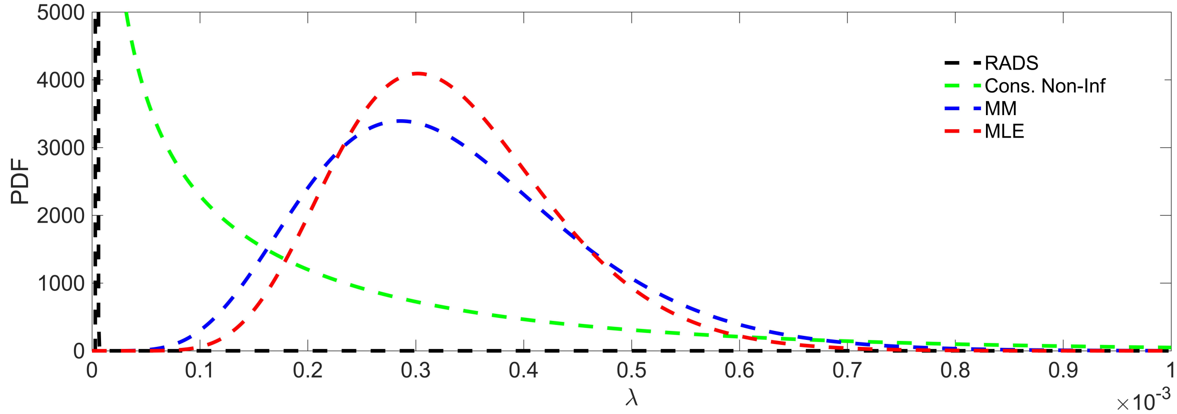

Figure 41. Probability density function curves of λ ~ Gamma (α_0,β_0) distributions for the different priors.

Results for Unit 2

Table 27. Three-state model's parameter sensitivity analysis for Unit 2.

| | **Baseline** | **Scenario 13** | **Scenario 14** | **Scenario 15** | **Scenario 16** |
|---|---|---|---|---|---|
| Failure rate-λ, per hour | 4.30E-04 | 4.30E-04 | **4.30E-05** | 4.30E-04 | 4.30E-04 |
| Corrective maintenance rate-μ, per hour | 1.41E-02 | 1.41E-02 | 1.41E-02 | **1.41E-01** | 1.41E-02 |
| Preventive maintenance rate-ν, per hour | 5.59E-02 | 5.59E-02 | 5.59E-02 | 5.59E-02 | **5.59E-01** |
| Maintenance scheduling rate-η, per hour | 6.79E-05 | 6.79E-06 | **6.79E-05** | 6.79E-05 | 6.79E-05 |
| Revenue, $/hour | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 |
| Corrective maintenance cost, $ per hour | 1.00E+02 | 1.00E+02 | 1.00E+02 | 1.00E+02 | 1.00E+02 |
| Scheduled maintenance cost, $ per hour | 1.00E+02 | 1.00E+02 | 1.00E+02 | 1.00E+02 | 1.00E+02 |
| *Profit, $ per hour* | *2.88E+01* | *2.90E+01* | *3.33E+01* | *3.33E+01* | *2.90E+01* |
| P(Operational) | 9.69E-01 | 9.70E-01 | 9.96E-01 | 9.96E-01 | 9.70E-01 |
| P(CM) | 2.96E-02 | 2.96E-02 | 3.04E-03 | 3.04E-03 | 2.96E-02 |
| P(PM) | 1.18E-03 | 1.18E-04 | 1.21E-03 | 1.21E-03 | 1.18E-04 |
| Days operational | 3.54E+02 | 3.54E+02 | 3.63E+02 | 3.63E+02 | 3.54E+02 |
| Days maintenance | 1.12E+01 | 1.08E+01 | 1.55E+00 | 1.55E+00 | 1.08E+01 |
| MTBF, hours | 2.33E+03 | 2.33E+03 | 2.33E+04 | 2.33E+03 | 2.33E+03 |
| MCMT, hours | 7.09E+01 | 7.09E+01 | 7.09E+01 | 7.09E+00 | 7.09E+01 |
| MPMT, hours | 1.79E+01 | 1.79E+01 | 1.79E+01 | 1.79E+01 | 1.79E+00 |
| MPMST, hours | 1.47E+04 | 1.47E+05 | 1.47E+04 | 1.47E+04 | 1.47E+04 |

Table 28. Three-state model's costs sensitivity analysis for Unit 2.

| | Baseline | Scenario 17 | Scenario 18 | Scenario 19 | Scenario 20 |
|---|---|---|---|---|---|
| Failure rate-λ, per hour | 4.30E-04 | 4.30E-04 | 4.30E-04 | 4.30E-04 | 4.30E-04 |
| Corrective maintenance rate-μ, per hour | 1.41E-02 | 1.41E-02 | 1.41E-02 | **7.05E-03** | 1.41E-02 |
| Preventive maintenance rate-ν, per hour | 5.59E-02 | 5.59E-02 | 5.59E-02 | 5.59E-02 | **2.80E-02** |
| Maintenance scheduling rate-η, per hour | 6.79E-05 | 6.79E-05 | 6.79E-05 | 6.79E-05 | 6.79E-05 |
| Revenue, $/hour | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 |
| Corrective maintenance cost, $ per hour | 1.00E+02 | **5.00E+01** | 1.00E+02 | **2.00E+02** | 1.00E+02 |
| Preventive maintenance cost, $ per hour | 1.00E+02 | 1.00E+02 | **5.00E+01** | 1.00E+02 | **2.00E+02** |
| *Profit, $ per hour* | *2.88E+01* | *3.03E+01* | *2.89E+01* | *1.84E+01* | *2.84E+01* |
| P(Operational) | 9.69E-01 | 9.69E-01 | 9.69E-01 | 9.41E-01 | 9.68E-01 |
| P(CM) | 2.96E-02 | 2.96E-02 | 2.96E-02 | 5.74E-02 | 2.95E-02 |
| P(PM) | 1.18E-03 | 1.18E-03 | 1.18E-03 | 1.14E-03 | 2.35E-03 |
| Days operational | 3.54E+02 | 3.54E+02 | 3.54E+02 | 3.44E+02 | 3.53E+02 |
| Days maintenance | 1.12E+01 | 1.12E+01 | 1.12E+01 | 2.14E+01 | 1.16E+01 |
| MTBF, hours | 2.33E+03 | 2.33E+03 | 2.33E+03 | 2.33E+03 | 2.33E+03 |
| MCMT, hours | 7.09E+01 | 7.09E+01 | 7.09E+01 | 1.42E+02 | 7.09E+01 |
| MPMT, hours | 1.79E+01 | 1.79E+01 | 1.79E+01 | 1.79E+01 | 3.58E+01 |
| MPMST, hours | 1.47E+04 | 1.47E+04 | 1.47E+04 | 1.47E+04 | 1.47E+04 |

Table 29. Two-state model sensitivity results for Unit 2.

| | Baseline | Scenario 21 | Scenario 22 | Scenario 23 | Scenario 24 |
|---|---|---|---|---|---|
| Failure rate-λ, per hour | 5.02E-04 | **2.51E-04** | 5.02E-04 | 5.02E-04 | 5.02E-04 |
| Maintenance rate-μ, per hour | 1.55E-02 | 1.55E-02 | **3.10E-02** | **3.10E-02** | **7.75E-03** |
| Revenue, $/hour | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 | 3.40E+01 |
| Maintenance cost, $ per hour | 1.00E+02 | 1.00E+02 | 1.00E+02 | **2.00E+02** | **5.00E+01** |
| *Profit, $ per hour* | 2.87E+01 | 3.13E+01 | 3.13E+01 | 2.97E+01 | 2.68E+01 |
| P(Operational) | 9.69E-01 | 9.84E-01 | 9.84E-01 | 9.84E-01 | 9.39E-01 |
| P(Maintenance) | 3.14E-02 | 1.59E-02 | 1.59E-02 | 1.59E-02 | 6.08E-02 |
| Days operational | 3.54E+02 | 3.59E+02 | 3.59E+02 | 3.59E+02 | 3.43E+02 |
| Days maintenance | 1.15E+01 | 5.82E+00 | 5.82E+00 | 5.82E+00 | 2.22E+01 |
| MTBF, hours | 1.99E+03 | 3.98E+03 | 1.99E+03 | 1.99E+03 | 1.99E+03 |
| MMT, hours | 6.45E+01 | 6.45E+01 | 3.23E+01 | 3.23E+01 | 1.29E+02 |