TURBINE GENERATOR PERFORMANCE DASHBOARD FOR PREDICTIVE MAINTENANCE STRATEGIES

by

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To my friends and family

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

AC –	Alternating Current
Btu –	British Thermal Unit
DC –	Direct Current
GPM –	Gallons per Minute
Hg –	Inch of Mercury
HR –	Heat Rate
IoT –	Internet of Things
KPPH –	Kilo Pounds per Hour
KW –	Kilowatt
kWh –	Kilowatt hour
lb. –	Pound
MW –	Megawatt
PdM –	Predictive Maintenance
PSI –	Pounds per Square Inch
RPM –	Rotations per Minute
TG1 –	Turbine Generator 1

GLOSSARY

Amplitude – “The maximum displacement or distance moved by a point on a vibrating body or wave measured from its equilibrium position” (Britannica, The Editors of Encyclopedia (n.d.))

British Thermal Unit (Btu) – “The quantity of heat required to raise the temperature of one pound of water one degree Fahrenheit at a specified temperature” (Merriam-Webster (n.d.))

Disruptive innovation – A service, product, or innovation which increases accessibility and affordability to a wider population, competing against and displacing proven rivals (Christensen, Raynor, & McDonald, 2015)

Frequency – “The number of waves that pass a fixed point in unit time; also, the number of cycles or vibrations undergone during one unit of time by a body in periodic motion” (Britannica, The Editors of Encyclopedia (n.d.))

Industry 4.0 – “The fourth revolution in manufacturing adopting automation for “smart and autonomous systems fueled by data and machine learning” (Marr, 2019)

Internet of Things (IOT) – “The networking capability that allows information to be sent to and received from objects and devices (such as fixtures and kitchen appliances) using the Internet” (Merriam-Webster (n.d.))

Metric – “A standard of measurement” (Merriam-Webster (n.d.))

Resonance – “A vibration of large amplitude in a mechanical or electrical system caused by a relatively small periodic stimulus of the same or nearly the same period as the natural vibration period of the system” (Merriam-Webster (n.d.))

Turbine generator (TG) – “an electric generator driven by a steam, gas, or hydraulic turbine” (Merriam-Webster. (n.d.))

Watt – “the absolute meter-kilogram-second unit of power equal to the work done at the rate of one joule per second or to the power produced by a current of one ampere across a potential difference of one volt: $^{1}/_{746}$ horsepower” (Merriam-Webster. (n.d.))

ABSTRACT

Equipment health is the root of productivity and profitability in a company; through the use of machine learning and advancements in computing power, a maintenance strategy known as *Predictive Maintenance* (PdM) has emerged. The predictive maintenance approach utilizes performance and condition data to forecast necessary machine repairs. Predicting maintenance needs reduces the likelihood of operational errors, aids in the avoidance of production failures, and allows for preplanned outages. The PdM strategy is based on machine-specific data, which proves to be a valuable tool. The machine data provides quantitative proof of operation patterns and production while offering machine health insights that may otherwise go unnoticed.

Purdue University's Wade Utility Plant is responsible for providing reliable utility services for the campus community. The Wade Utility Plant has invested in an equipment monitoring system for a thirty-megawatt turbine generator. The equipment monitoring system records operational and performance data as the turbine generator supplies campus with electricity and high-pressure steam. Unplanned and surprise maintenance needs in the turbine generator hinder utility production and lessen the dependability of the system.

The work of this study leverages the turbine generator data the Wade Utility Plant records and stores, to justify equipment care and provide early error detection at an in-house level. The research collects and aggregates operational, monitoring and performance-based data for the turbine generator in Microsoft Excel, creating a dashboard which visually displays and statistically monitors variables for discrepancies. The dashboard records ninety days of data, tracked hourly, determining averages, extrema, and alerting the user as data approaches recommended warning levels. Microsoft Excel offers a low-cost and accessible platform for data collection and analysis providing an adaptable and comprehensible collection of data from a turbine generator. The dashboard offers visual trends, simple statistics, and status updates using 90 days of user selected data. This dashboard offers the ability to forecast maintenance needs, plan work outages, and adjust operations while continuing to provide reliable services that meet Purdue University's utility demands.

CHAPTER 1. INTRODUCTION

Chapter One described the problem, purpose, and research questions posed while creating a dashboard using Microsoft's Excel, specific to the maintenance and monitoring needs of a turbine generator. This chapter described the research's scope and significance, through the lens early error detection and the benefits of predictive maintenance strategies. Finally, Chapter One detailed the assumptions, limitations, and delimitations encountered.

1.1 Problem Statement

Equipment maintenance plays a critical role in the reliability and efficiency of a facility's production as the U.S. Census Bureau estimates that manufacturers spent $240 million on maintenance and repair in 2018 (*Annual Survey of Manufacturers: Summary Statistics for Industry Groups and Industries in the U.S.: 2018*., 2018). Machine health is the root of optimal production. Malfunctions, unplanned shutdowns, and inadequate funding lead to catastrophic production failures (Douglas, 2018) while wasting time, money, and labor hours. The world has undergone three industrial revolutions, each powered by disruptive innovation. The steam engine, the assembly line, and the high-speed computer not only transformed work and production efficiency but forever altered the work process (Munirathinam, 2019). Founded in the Industrial Internet of Things ("IoT"), Industry 4.0, builds on computer technology, focusing on machine learning and interconnectivity. The Industrial IoT links physical systems and cyber data, resulting in what is referred to as "big data." The key benefits of big data lie in its volume, velocity, and variety. The quantity, speed of accessibility, and the assortment of variables available offer a wealth of company-specific knowledge as they reveal patterns, trends, and faults (Munirathinam, 2019). Big data insights can also forecast production disturbances, finding discrepancies in data while in minute stages. Big data predictions allow for planned maintenance needs, lessening the likelihood of catastrophic disruptions and justifying machine care.

The availability and reliability of equipment is largely dependent on the quality of maintenance the system receives. When correcting failures, maintenance is nearly always in reactive mode, as companies focus on "what can we do" to repair failures as opposed to "what should we do" means of prevention (DeGrendel, 2018). Predictive maintenance is a condition-based strategy. Machine-specific data can alert personnel to impending faults, allowing time to plan and execute maintenance repairs before errors impact production (Douglas, 2018).

The Wade Utility Plant is responsible for providing reliable energy and utility services to Purdue University's campus. The first step in reliable services is ensuring the health of equipment. The Wade Utility Plant has condition-based data readily available for Turbine Generator One (TG1) but does not have predictive analytics, as these software packages are costly to install and maintain. The problem addressed in this study is how to leverage existing big data to forecast maintenance needs in a cost-effective and accessible manner.

1.2 Purpose

The Wade Utility Plant collects a multitude of data for the utility plant through OSIsoft's PI System, consulting historic data for operational purposes. However, Wade does not monitor nor analyze equipment data with the intention of maintenance predictions. Aggregating and navigating large volumes of data, while looking for useful insights, can be challenging and costly. The purpose of this study is to design and create a platform for Wade Utility Plant's TG1, monitoring conditional and operational data for early error detection. This dashboard promotes the ideals of predictive maintenance (PdM), offering an analytic platform that is accessible, comprehensible, and adaptive.

1.3 Significance

Initial startups of PdM programs are expensive, though forecasting maintenance offers a competitive advantage. A Deloitte report finds that PdM programs offer a 5-10% cost savings in both operations and maintenance (Coleman et al., 2017) and the Department of Energy finds implementing a PdM program has the potential to save 30-40% based on reliance and material conditions when compared to reactive maintenance programs (Sullivan et al., 2010). The significance of this study show that big data and maintenance predictions are achievable at an in-house level. The dashboard provides data-centric and justifiable proof of TG integrity, while maintenance forecasts strengthen production reliability and financial planning logistics.

1.4 Research Questions

The problem addressed in this study was how to leverage a turbine generator's big data to forecast maintenance needs cost-effectively and accessibly. The purpose of this study was to design and create a platform for Wade Utility Plant's TG1, monitoring conditional and operational data for early fault detection.

1. *What are the variables and critical metrics needed to justify quality maintenance in a turbine generator?*

2. *What is an accessible, comprehensive, and adaptive way to leverage big data for the intention of predictive maintenance in a turbine generator?*

1.5 Scope

The work in this study utilizes big data collected from a turbine generator, creating an operational and performance dashboard, which alerts to up-coming maintenance needs. The dashboard's purpose is to provide a simplified summary of monitoring, operational, and performance data in an accessible and low-cost fashion. The intent is to navigate big data to create a dashboard that is user-friendly yet comprehensive, justifying TG health and service dependability. The scope of this study investigates the key metrics needed to justify the maintenance needs of a turbine generator. Data from vibration, temperatures, flow rates, pressures, velocities, electrical power production, and heat rate is trended and analyzed in the dashboard.

1.6 Limitations

The data collected from PI historian was assumed accurate, based on the Wade Utility Plant's operating standards. Data used to create the dashboard is historical and real-time, collected from PI Data Archive input into Microsoft Office's Excel. The scope of this research has no input on system or sensor calibrations, instrument precision, sensitivities, or monitoring equipment accuracy. Variable conversion and signal processing for data acquisition and transmission are unknown. Discrepancies in transmission, collection, and operating strategies may cause the dashboard to display errors, as the dashboard may not have access to a complete set of data for the chosen variables. Data has the potential to be inaccurate or missing from the dashboard due to programing and rounding errors, in sensors, calibrations, transmission, and display. While the dashboard is adaptable and sizable, the memory, analytic functions, and computing capabilities are limited to the capabilities available in Microsoft Excel.

1.7 Delimitations

The scope of this research study contains specific operation and performances monitoring metrics available for TG1. These boundaries are set forth under the research and recommendations of existing industry maintenance techniques, operational reporting for turbine generators, and by actual operation and reporting needs at the Wade Utility Plant. Metrics recorded in this research are machine specific and made available through OSIsoft's PI. The discrepancies and errors reported by the dashboard prove noteworthy as the data is sourced from historic and real-time operation and production. Justifying TG1's health using quantifiable data aids proper performance and provides alerts to impending maintenance needs.

The computing and representation of available data for the dashboard is programmed and presented using Microsoft's Excel. Employees who have access to PI system database and Excel will have the ability to access the dashboard. Employees at the Wade Utility Plant have varying levels of statistical knowledge. The analytics of the dashboard are kept simple and straightforward to provide inclusivity and comprehensibility across varying departments.

1.8 Chapter One Summary

Chapter One summarized the problem of leveraging big data for useful maintenance insights. The chapter described the purpose and significance of this research, as the dashboard can justify TG1 reliability, while alerting to data discrepancies. Finally, the chapter detailed the scope, limitations and delimitations encountered while designing and building a predictive maintenance minded dashboard for Purdue University's Wade Utility Plant. Chapter Two presents the literature review, investigating industry recognized maintenance programs, maintenance program importance, the principles of equipment testing and the recommended turbine generator maintenance practices.

CHAPTER 2: REVIEW OF LITERATURE

Chapter Two provided an overview of industry-recognized maintenance programs, machine maintenance testing procedures and data collection, maintenance program missions, and professional suggestions for the successful transmission and incorporation of predictive maintenance programs and techniques. Finally, the review of literature concludes by detailing the the functions, operations, and integral component of a steam turbine generator, as well as reviewing industry-suggested maintenance practices to ensure care of a turbine generator.

2.1 Background

A widespread issue in machine maintenance programs is ineffective management, as a lack of quantifiable machine data exists to justify systems and equipment repairs. With rapidly changing technology and increased competition, it is beneficial to a company to ensure that vital equipment is maintained appropriately (Gilabert et al. 2017). Ineffective maintenance strategies have grave impacts, as improper or unnecessary work results in the loss of time, money, and potential production (Mobley, 2002). Maintenance programs use statistical and time-based trends, ("runtime"), or failures to establish a baseline for proper operating performance. Industry 4.0 and automated processing have made great strides in data availability, allowing constant collection for individual components, machines, systems, and processes (Mobley, 2002; Passlick et al., 2020).

2.2 Industry Recognized Maintenance Programs

Ensuring vital equipment is appropriately maintained, is to a company's benefit, in order to protect infrastructure, and remain competitive. A well-organized and robust strategy for maintenance can help identify failures and be useful in time-based replacement for passing inspections, extending warranties, and ultimately ensuring the function and safety of components (Gilabert et al. 2017). There, are five commonly recognized maintenance schedules in the industry: corrective maintenance, predetermined maintenance, condition-based maintenance, preventive maintenance, and predictive maintenance.

Corrective maintenance restores a broken component to working order, and it is reactive, meaning it happens after an active fault occurs (Swanson, 2001). Corrective maintenance plans break down into four corrective action patterns; *immediate*, *deferred, planned*, and *unplanned* (*Corrective maintenance comparisons*, n.d.). In immediate corrective maintenance, actions to restore the component take place as soon as possible (Bengtsson & Lundström, 2018). Deferred corrective maintenance allows for delays, meaning after an issue has occurred, repairs may not be deemed critical and allow for prioritization (Bengtsson & Lundström, 2018). Planned corrective maintenance occurs when a piece of equipment is deliberately run to failure (Stenström et al., 2015). Finally, unplanned corrective maintenance occurs when errors are unavoidable, meaning a piece breaks unexpectedly and must be fixed quickly (Christiansen, 2019). Corrective maintenance requires organization, as it is retroactive and presents planning challenges. Company communication is vital; problem identification and reporting must be efficient, and maintenance personnel needs access to detailed problem reports, previous repair history, and equipment manufacturer specifications (Wang, Deng, Wu, Wang, & Xiong, 2014). Attention to past maintenance, correct part replacement, and proper organization will help safeguard that a repair occurs correctly (Wang, Deng, Wu, Wang, & Xiong, 2014).

Condition-based maintenance programs rely on data collection, assessment, and maintenance actions specific to a machine's needs. This strategy is deployed in intervals of time and operation or can be done in a continuous fashion. Condition monitoring, in physical and operational assessments, uses maintenance-testing techniques to determine needed maintenance repairs (Condition Based Maintenance & Monitoring (CBM Maintenance,) n.d.). When applied correctly, condition-based maintenance is a resource-consuming and expensive maintenance approach, but discrepancies and faults are discovered early, minimizing unplanned downtime (Jardine, Lin, Banjevic, 2005).

Predetermined maintenance is scheduled based on fixed intervals, regardless of equipment's needs or operation. Predetermined maintenance plans are baselined from manufacturers' specifications or suggestions, frequently found through the statistical analysis of run time; an example of this would be "mean time to failure" found in reliability testing (Malik, 1979; Bengtsson & Lundström, 2018). Creating a company maintenance schedule with this data can hypothesize when general repairs, part replacement, or overhaul may be necessary (Au-Yong, Shah Ali, & Ahmad, 2016). The predetermined maintenance approach is machine-specific, but testing conditions in a lab may vary from the stresses a machine experiences in the field (Malik, 1979). As this program lacks company-specific operational use patterns, maintenance repairs waste time, money, and resources fixing a component that may not need repair (Bengtsson & Lundström, 2018).

Preventative maintenance keeps a record of the machine's operation, and its past maintenance history to manage scheduled outages and repair (Arno, Dowling, & Schuerger, 2015). Preventative maintenance is a proactive strategy, though it involves extensive planning, both long and short-term (Arno, Dowling, & Schuerger, 2015). Preventative maintenance follows two paths, time-based, and usage based. Time-based preventative maintenance occurs on a scheduled interval (Shang et. al, 2018). In contrast, usage-based preventative maintenance will be specific to the machine's workings or production at specified limit (Shang et. al, 2018). Parameters must be adjusted to fit a company's needs and based on criticality. This strategy is time-intensive; if faults go unnoticed, unreported, or under-serviced, assets will fail (Trout, 2008). The reactive maintenance in these situations is costly and may affect a system (Arno, Dowling, & Schuerger, 2015).

Predictive maintenance utilizes computerized learning to analyze machine health by monitoring data, creating trends, and identifying patterns in machine data (Sagnier, 2019). Predictive programs alert to deviations in data, giving advanced warning to a machine’s future maintenance needs (Selcuk, 2016; Persigehl, Gellermann, Thumm, & Stoiber, 2020). This program is possible through Industry 4.0's big data analysis, as continuous monitoring facilitates better management and control of machine wear (Passlick et al., 2020). While implementing this technology is time-intensive and has high up-front costs; it allows for real-time planning catered to a machine's needs, eliminating excess or redundant maintenance work. Predictive maintenance practices, because they are based in machine-specific data, offer quantifiable proof of equipment condition, and give advanced warning for future needs (Persigehl, Gellermann, Thumm, & Stoiber, 2020).

2.3 Maintenance Program Impacts

Maintenance management is essential to proper function and productivity. Not only does machine care affect the reliability and quality of functions, but it also allows for competitiveness and profitability in the marketplace (Swanson, 2001). A maintenance program's objectives are to ensure the safety and dependability of components and systems while also facilitating proper outage planning and financial planning (Stenström et al., 2015). Previously, middle, and corporate level management viewed maintenance as a "necessary evil" with focused efforts on product quality, production costs, and ultimately profitability (Mobley, 2002). Predicated data, such as a company's expected output, manufacturers' recommendations, and failure rates were previously the center of maintenance scheduling, though the integration of computing powered instrumentation in machining operations has changed this mindset (Mobley, 2002). This instrumentation provides the means to explore operations, showing real-time machine-specific data, leading to predictive maintenance strategies (Persigehl, Gellermann, Thumm, & Stoiber, 2020).

Abnormalities in performance reduce productivity, lessen reliability, produce unforeseen expenses, and threaten safety (Mobley, 2002). A well-organized predictive strategy is more profound than just a computerized data collection system, as predictive technologies fill the critical void of unknown performance (Swanson, 2001). However, switching from or between maintenance strategies is challenging, as the perceptions of data analysis must be broken down and explained as an instrument for optimizing success (Bengtsson & Lundström, 2018). To corporate-level management, machine runtimes, failure data, and machine histories just data (Mobley, 2002). With little maintenance knowledge, management may not see the insights this data holds. Data collection and analysis are the founding principles, but correct usage and implementation produce results (Bengtsson & Lundström, 2018). Maximizing the efforts of predictive maintenance tools involves management strategy, provided support, and continued maintenance actions.

2.3.1 Maintenance Mission

Predictive maintenance technologies change the ideals behind maintenance programs. The focus of maintenance is no longer centered on "fixing" a system that is broken, but rather changes focus on "prevention and mediation" of losses caused by operational errors (Mobley, 2002).

Pertinent data must be available to ensure proper care and baseline future work. The maintenance must be specific for the system, done efficiently, and most importantly, be correct. A company must have spare part planning available and work with vendors for suitable replacements, as well as with outside companies for efficient repair turnarounds (Silaipillayarputhur, 2016). This may also mean optimizing available resources, such as planning for systems to run alternatively or creating backup operations when a system needs maintenance. Sustained up-keep on new practices and techniques or relative maintenance technologies is beneficial (Bengtsson & Lundström, 2018). Finally, having a trained, well-versed maintenance staff to fix found issues is key (Levitt, 2011). Cross-training, continued training, and refresher training courses should be made adequately available and required for technicians at hand. Growth in a predictive maintenance strategy will mean reviewing existing maintenance practices, reliability studies, safety programs, and training for dependable use of existing equipment (Silaipillayarputhur, 2016; Bengtsson & Lundström, 2018). When management, personnel, funding, and maintenance come together in an organized and motivated manner, a maintenance program's benefits emerge (Levitt, 2011).

2.4 Machine Maintenance Testing Methods

Machine maintenance testing is the foundation for robust maintenance programs. Machine maintenance verifies assets' health using scheduled monitoring, issue investigation, and problem resolution (QA Platforms, 2019). Machine testing is versatile, being scaled and performed to fit maintenance needs. Testing routines may encompass entire systems, individual pieces of equipment, or specific components. Testing can be invasive, meaning a system shuts down to run machine diagnostics, or noninvasive, as a system maintains its operation during an inspection (QA Platforms, 2019).

2.4.1 Vibration Analysis

Vibration analysis measures a rotating component's vibration signatures, looking at the amplitude and frequency of a specified period's waveforms (Petherus, Nirbito, & Nurhantoko, 2019). This data is analyzed with computer algorithms, and trained vibration experts can pinpoint issues on specific components (Reimche et. al., 2003; Soliman, 2021).

Vibration testing is often applied to monitor gears, bearing impellers, or motors, granting insight into wear conditions, or degradation that may go unnoticed (Soliman, 2021). Vibration formulas use rotations per minute and the count of bearing balls or rollers, gear teeth, pump cylinders, or turbine blades (Vibration Analysis n.d.). One example of vibrational diagnostic testing is the identification of vibration peaks produced during operational running speeds. These integer vibrational peaks may signify imbalance, misalignment issues, or looseness. In contrast, non-integer peaks found in higher intervals of this speed suggest bearing wear issues (Vibration Analysis n.d.). Aside from misalignment and imbalance, vibration monitoring can find bending, eccentricity (off-set from center,) looseness, resonance, and wear, though analyzing these readings may not always be so straightforward (Reimche et. al., 2003). When using vibration monitoring in predictive maintenance practices, the key to proactively detecting potential issues is creating a robust baseline system of operational measurements used in comparisons (Trout, 2019). Establishing this baseline occurs through regular testing, trending, and tracking of equipment in operation. It may be done by equipment walk-throughs of vibration technicians or with fixed analyzer equipment that collects readings continuously (Trout, 2019). Vibration monitoring is both proactive and retroactive, employed to find and diagnose problems for preventative and corrective practice (Reimche et. al., 2003). Today, with the continuous real-time collection, data aggregation, and predictive analytics, this form of testing is transforming proactive strategies. By trending frequency patterns, small deviations in the waveform can be monitored and tracked, predicting impending operation failures well in advance (Reimche et. al., 2003).

2.4.2 Oil Analysis

Oil analysis tests both physical and chemical properties of lubrication conditions and indicates a machine's health. In this analysis, lubricants are tested for degradation and contamination, such as acidity, particle count, water content, and viscosity (Fitch, 2013). Samples' findings can also indicate specific machine-wear issues through concentration, size, color, and shape of debris found (Fitch, 2013). Sample findings can also include identification of abrasion, sealing wear, corrosion, and cavitation (Soliman, 2020) Oil sampling can occur when a component is running, as it is noninvasive.

When creating a maintenance plan involving lubrication monitoring, it is essential to keep sampling collection places and procedures identical, such as the location, operating conditions, and environment, and to avoid external contamination (Fitch, 2013). The samples' reports get tracked and recorded in predictive strategies (Soliman, 2020). In conjunction with other testing techniques and maintenance records, wear patterns and degradation may show associations and insights into a machine's malfunctions or needs (Soliman, 2020).

2.5 Turbine Generator

A steam turbine generator converts the fluid energy of steam into mechanical energy, where, in conjunction with an alternating current (AC) generator, it gets converted into electrical energy. Fluid energy breaks down into three forms: speed (kinetic), pressure, and temperature, all of which significantly impact a steam turbine's design (Steam Turbine Basic Parts, 2018).

The mechanical aspects simplify into four parts the casing, the shaft, the rotors, and the stators. The shaft runs lengthwise and has rotors attached, which are fin-shaped blades blasted by steam (Landis F., Budenholzer R., 2017). The rotors' airfoil design creates a pressure difference, inducing a lift force that propels the blades, allowing for rotation of the shaft. As these blades absorb the fluid energy, it is turned into mechanical energy as the shaft rotates (Maheshwari & Singh, 2019). Within this system, as the fluid energy is converted, speed, pressure, and temperature decrease. The steam's velocity powers the system's rotations, and to optimize the rotation of the shaft, velocity must be maintained to produce enough lift force throughout the system. To increase the velocity of this steam after its rotor impact, there are stationary stators attached to the casing of the machine (Landis F., Budenholzer R., 2017). They are also aerodynamically designed, taking the steam off the rotors, and essentially act as nozzles. Flow area decreases as steam rushes through the stators, creating an increase in velocity (Maheshwari & Singh, 2019). This repetition of the design of the rotors and stators repetition throughout the turbine's casing optimally mediates the steam flow rate (Steam Turbine Basic Parts, 2018).

As steam flows through a turbine, energy balance states that as the steam's kinetic energy increases, the steam's pressure and temperature will decrease, so the system energy remains constant (Landis F., Budenholzer R., 2017). This concept is the fundamental basis in the design of the turbine. As the system's pressure reduces drastically, the volume will increase, and accommodate for this, and so must the flow area. This effect gives the turbine its shape, as each series of rotors and stators increases to adjust for this, growing larger and longer towards the outlet, thereby mediating the flow speed (Landis F., Budenholzer R., 2017). Steam turbines design also breaks into stages such as high pressure, intermediate and low pressure allowing for steam extraction for use in auxiliary equipment and systems.

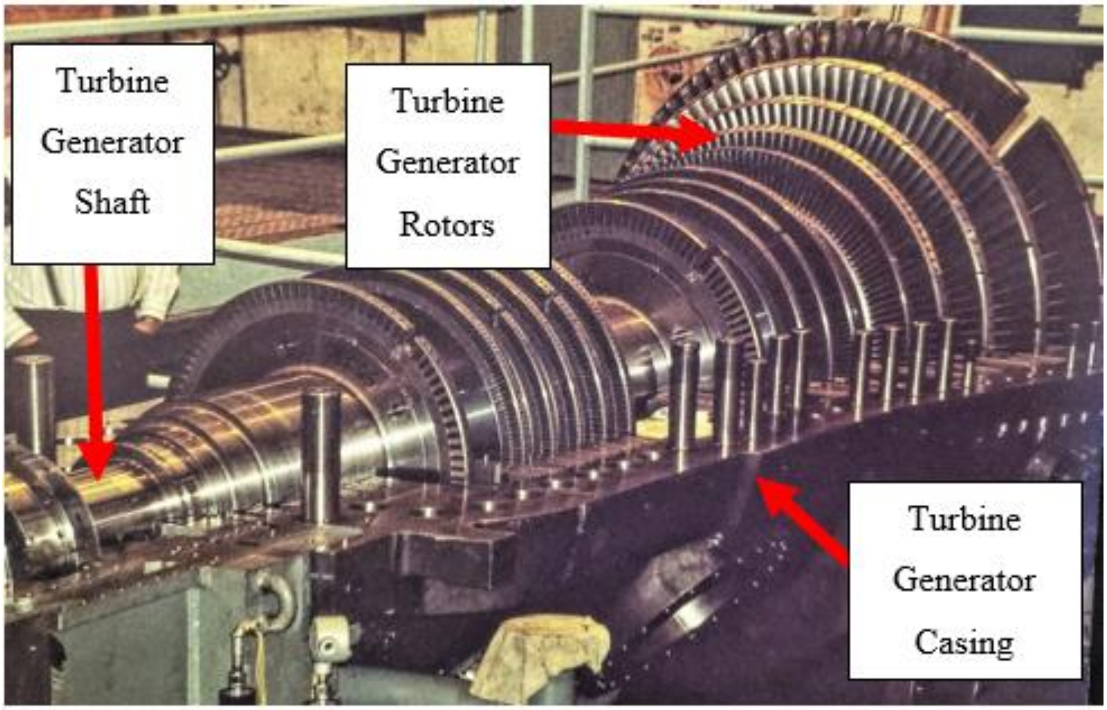

Figure 2.1 TG1 Installation (Wade Utility Plant, n.d.)

The turbine generator creates electricity using an alternating current (AC) generator. The shaft's mechanical energy is converted into electrical energy through electromagnetic induction. This conversion is based on Faraday's law of induction (Electricity explained, The science of electricity, 2020). Inside the AC generator, a magnetic conductor attached to the turbine shaft spins inside a series of cylindrically wound wire coil. This action produces an electromagnetic field and creates a flow of electrons, thus inducing a voltage (Electricity explained, The science of electricity, 2020). Electromagnetism occurs between the atomic nuclei and the orbiting electrons, creating the force which holds the atom together. Similarly, electric charges can attract or repel, as do magnetic poles, with north and south seeking poles, creating a magnetic field (Electricity explained Magnets and Electricity, 2020). The strength of the current in the coils is proportional to the rate of change through the magnetic field; thus, the faster the conductor spins, the more electricity produced (Electricity explained, The science of electricity, 2020).

The turbine, being a high-pressure steam vessel, needs strong support to alleviate extraneous forces. The three common types of bearings found within turbines are fluid-film, radial and thrust bearings. Fluid-film (oil) bearings have a stationary outer ring, supporting an inner ring which holds the turbine generator's shaft. A film of lubricant separates the rings, enabling rotary motion during operation (Bigret, 2001). Radial bearings are sets of rollers or balls encased between an inner ring, where the turbine shaft sits, and the outer ring braces and is attached to the supports (Pennacchi, 2017). When a turbine is at a standstill, the weight of the rotors can bend the shaft. Thus, radial bearings offer support in both axial and radial loads (Steam Turbine Basic Parts, 2018). Thrust bearings hold the shaft in the axial direction and offer support through the various stages and pressure drops in the system (Pennacchi, 2017). Thrust bearings alleviate the steam's constant pushing pressure, keeping the rotors steady (Steam Turbine Basic Parts, 2018).

Seals are also an essential efficiency and safety component in turbines, reducing leakage between the system's moving and stationary parts (Blažević, Mrzljak, Anđelić, & Car, 2019). Shaft seals and gland seals prevent steam leaks and unwanted air entrances from areas where the shaft enters or exists the casing (Steam Turbine Basic Parts, 2018; Blažević, Mrzljak, Anđelić, & Car, 2019). Common types include carbon rings and labyrinth seals. Layers of carbon rings and garter springs make the carbon ring seal. As the shaft rotates, pressure creates a seal with close tolerance ranges, preventing leaks (Steam Turbine Basic Parts, 2018). Labyrinth seals are non-contact, using a passageway of various chambers and the shaft rotation to create a pressurized seal in which fluid cannot escape (Steam Turbine Basic Parts, 2018). The spring-loaded labyrinth seals are most commonly made of brass or stainless steel (Steam Turbine Basic Parts, 2018). Blade seals prevent leaking between the shaft and the stators and significantly impact the turbine's efficiency.

2.5.1 Turbine Generator Maintenance

Proper maintenance sustains proper performance. Turbines are multifaceted, and to maintain proper function need rigorous maintenance programs to ensure long-term performance. Daily maintenance monitoring tracks a system's performance, including steam flow rate, speed, loading, voltage, current, and power output (Akers, Dickinson, & Skooglund, 1968; Steam Turbine Generator Maintenance Programs, 2016). These elements allow for remote adjustment performed by trained operators. On-site daily maintenance includes lubrication and oil monitoring, bearing temperatures, bearing vibrations levels, seals conditions, inlet steam pressures, outlet steam pressures, and temperatures, visual and auditory walkthrough, steam leak checks, and chemistry checks of the boiler feed-water (Fenton, Gott, & Maughan, 1992; Steam Turbine Generator Maintenance Programs, 2016). Monthly maintenance includes valve trip checks, air and oil filter replacements, draining or replacement of bearing lubrication, and ventilation or air intake checks.

Annual inspections include in-depth inspections of bearing housings, pipes, filters, drains, and valves (Steam Turbine Generator Maintenance Programs, 2016). Maintenance checks will encompass mechanical and electrical conditions and testing of all instrumentation and calibrations (Akers, Dickinson, & Skooglund, 1968). Annual inspections encompass steam leaks, proper valve positioning, conduit, wiring, and insulation. Proper turbine generator maintenance includes tracking planned starts and stops, unplanned outages, and operating errors experienced within the year (Fenton, Gott, & Maughan, 1992). Proper annual maintenance offers critical information when planning both minor and significant system over-hauls (Steam Turbine Generator Maintenance Programs, 2016).

2.6 Chapter Two Summary

Chapter Two described industry-recognized maintenance programs, including corrective, predetermined, condition-based, preventative, and predictive maintenance. Chapter Two also described maintenance testing techniques, the importance of managerial support, and professional suggestions for the successful incorporation of predictive maintenance. Finally, the literature review also detailed the integral components and turbine generator as well as industry-suggested maintenance routines to ensure equipment integrity. Chapter Three will discuss the methodology for this research study.

CHAPTER 3: RESEARCH METHODOLOGY

Chapter Three Methodology contained the elements, variables, and decisions used in developing a predictive maintenance dashboard for a turbine generator. The dashboard utilizes historical and real-time data from OSIsoft's PI System (PI System: Operational Intelligence – Data Infrastructure, n.d.). The predictive dashboard tracked standard operating parameters, maintenance data and calculates performance metrics. The research methodology presented in Chapter Three included the equation used for calculating heat rate, the procedures used in developing a predictive maintenance dashboard, and an explanation for the dashboard's implementation into standard maintenance practices.

3.1 Heat Rate Computation

The predictive maintenance dashboard's central purpose is to aggregate monitoring, operational, and performance data points, displaying critical metrics used to quantify the maintenance requirements of TG1. Real-time and historical data used include bearing vibration monitoring, bearing temperature monitoring, oil sampling, operational temperatures and pressures, heat rate, and production. Heat Rate is a critical metric when evaluating a turbine generator's operational efficiency, as it is the total amount of energy required to produce one kilowatt-hour. Equation 1 defines the heat rate (HR) as a function of heat input (Btu) over Kilowatt output (kWh). The lower the heat rate of a turbine, the higher the efficiency.

$$Heat\ Rate = \frac{Heat\ Input}{kW\ Ouput}\left[\frac{Btu}{kWh}\right]$$

(Eq.1)

Heat input is determined by performing a heat balance around TG1 and the cooling towers which feed water to the system. Equation 2 defines the Heat Input Rate ($\dot{Q}_{in}$) as the Work Rate of TG1 $\left(\dot{W}_{turbine}\right)$ added to the Heat $\dot{Q}_{out}$ dissipated by the system.

$$\dot{Q}_{in} = \dot{W}_{turbine} + \dot{Q}_{out}$$

(Eq. 2)

Initial heat input occurs as TG1 receives inlet steam pressure of 650-pounds. First level extraction occurs as 125-pound steam is extracted from TG1. 125-pound steam is sent to campus for heating needs, excess is returned to the system at 15-pounds, and the system is subject to heat lost in condensate. Here, heat balance is defined by Equation 3.

$$\Delta \dot{Q}_{Steam} = \dot{W}_{turbine} + \dot{Q}_{condensate}$$

(Eq. 3)

Heat balance ($\dot{Q}$) is found using mass flow ($\dot{m}$) and enthalpy (h), also known as internal energy plus the product of pressure and volume (Hurley & Shamieh, 2020). The heat balance for TG1 found in Equation 4 is found by the input of 650 psi steam (provided by boilers,) the extraction of 125 psi steam (for campus use,) and the input of 15 psi steam returning from campus The total is equal to the work done by the turbine, and the heat loss in condensate returning from campus.

$$\dot{m}_{650}h_{650} - \dot{m}_{125}h_{125} + \dot{m}_{15}h_{15} = \dot{W}_{turbine} + \dot{m}_{cond}h_{cond}$$

(Eq.4)

Manipulating equation 4, to solve for the work rate of TG1 ($\dot{W}_{turbine}$) produces equation 5.

$$\dot{m}_{650}h_{650} - \dot{m}_{125}h_{125} + \dot{m}_{15}h_{15} - \dot{m}_{cond}h_{cond} = \dot{W}_{turbine}$$

(Eq. 5)

Figure 3.1 is a pictorial representation of the heat balance of TG1 at the Wade Utility plant. The figure shows the input of 650 psi and 15 psi steam, as well as cooling tower water inputs. The outputs displayed are the 125 psi steam and the condensate.

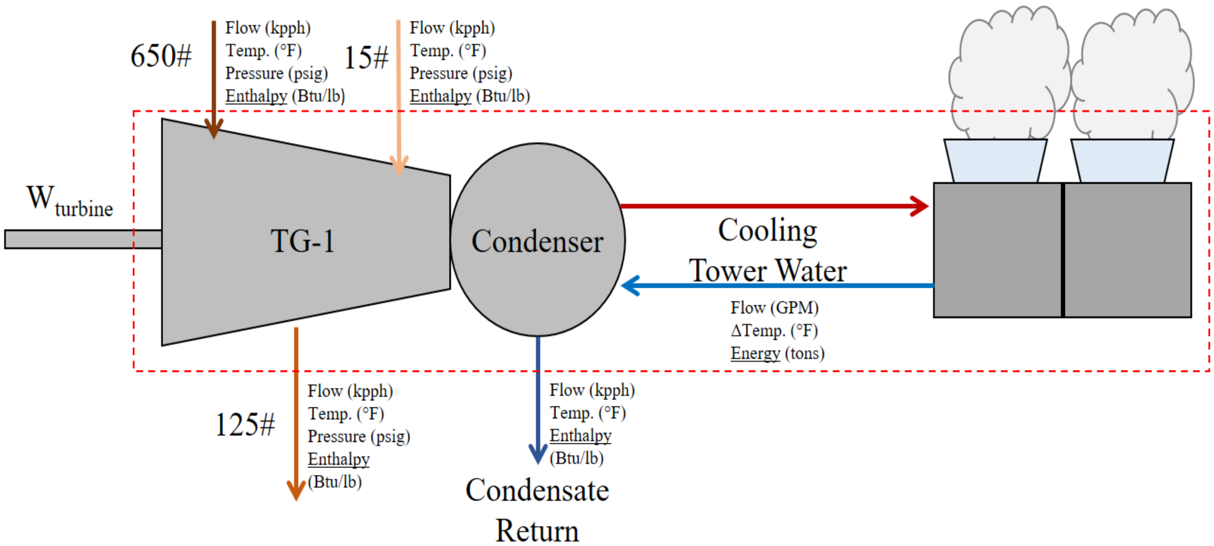

Figure 3.1. TG1 Heat Balance (Ramaraj, 2018)

3.2 Turbine Generator Dashboard Data

The predictive maintenance dashboard is a tool that trends, analyzes, and displays utility performance metrics for TG1. The dashboard collects and connects data points from outside sources, displaying the data in a central location using graphs, tables, and charts. The data accounts for monitoring data, operational data, and performance data. Monitoring Data is data specific to machine health monitoring and contains component-specific data. Included are bearing vibrations, bearing temperatures, stator temperatures, seal temperatures, seal pressures, and lubrication data. Turbine operators do not control these data points, and deviations from expected conditions indicate the need for maintenance. Operational data is data specific to production processes. These include hot well level, valve throttle, water tower flow, steam temperature, and steam pressures. Operators can control these data points, though the data points should not experience fluctuation unless the system is purposely altered. Variations in this data can be accounted for based on operators logs, and equipment runtime schedules. Deviations in operational data points outside of intentional adjustment show operation issues could need potential maintenance. Performance Data is data that is calculated or is the output of the system. This data includes steam velocity, TG1 heat rate, TG1 megawatt production, and stator over speed. Operators control these variables, and changes should be expected based on the demand for steam or electricity need on campus.

Table 3.1 provides a list of variables recorded for TG1. The table includes the categories of monitoring, operational, and performance, the variable type and the unit of measurement. The chosen variables and performance metrics are significant as they affect turbine performance, efficiency, and are direct indicators for future maintenance. For example, comparing a specific day's Axial1 vibration readings to the next day's values may show what appears to be negligible difference on a microscopic scale. As the dashboard trends Axial1 vibrations over a month of consistent use, the deviation from normal operating conditions grows. On the macroscopic scale, it is evident that a problem is developing. The dashboard displays operational data, enabling early error detection, allowing time to plan for maintenance, and avoiding unexpected outages.

Table 3.1: Predictive Maintenance Dashboard Variables

Category	Type	Unit
Monitoring	Bearing Vibration	mils
	Bearing Temperature	°F
	Stator Temperature	°F
	Seal Temperature	°F
	Seal Pressure	psi
Operational	Hot Well Level	in Hg
	Valve Throttle	%
	Tower Water Flow	gpm
	Steam Temperature	°F
	Steam Pressure	psi
	Steam Velocity	kpph
	Stator Over Speed	RPM
Performance	TG1 Heat Rate	btu/kw
	Megawatt Production	MW

3.3 Turbine Generator Dashboard Development

The TG1 data is built into a dashboard using Microsoft's Excel, a platform available to all employees at Wade Utility Plant. The real-time dashboard capabilities will be compatible on the machines of all employees who have access the PI Database. Employees who do not have access to the PI Database can specify the time frame of data he or she would like to view and download a copy of the data to review on machines where PI Database is not accessible. The intent of developing the dashboard in Excel is managing big data at an in-house level. The company's understanding of predictive maintenance data and immediate actions involves more than just engineering departments and maintenance technicians. Forecasting maintenance procedures from big data requires management and financial planning departments. The graphing and trending aspect of this research depicts information pictorially, breaking data down piece by piece for those who may not be familiar with the workings or maintenance needs of TG1. Excel provides a platform for accessibility and easier understanding across multiple departments. This is a vital first step for quantifiable predictive maintenance program results.

3.3.1 The Use of Microsoft Excel

The maintenance dashboard comprises four major areas of data: vibrations, temperatures, operational data, and performance sampling. For organization, ease of use, and computation purposes, the Excel workbook is comprised of six sheets in total. The first sheet is the main page of the workbook and displays the predictive dashboard. The first sheet has the analysis and trending that depicts the operational trends and alerts to discrepancies. The subsequent five sheets are the supporting data for the dashboard, organized into bearing vibrations, bearing temperatures, stator data, steam data, and operational data points. The data is pulled from the PI historian database using "tag" names as assigned in the PI system.

3.3.2 OSIsoft's PI System

The data from PI database server are assigned output names and may have alarm levels (if applicable). The variables in this research project are assigned output names for user traceability and trackability throughout the workbook. This is necessary should a person need to find a data point within the supporting data sheets as opposed to visually on the dashboard. The variables of bearing vibrations and temperatures, seal temperatures and pressures, and rotor speed have associated alarm units. The alarm levels come from TG1 manufacturer specifications. Alarm levels are static points of data programmed into the trends and are not pulled from the PI server. The alarm levels act as alerts as deviations occur.

Data pulled from the PI server is recorded once an hour as an average and is pulled in 90 day stretches. The workbook is programmed to pull the previous 2,160 hours of data for each variable when the user specifies a start date. The data retrieval is done using time and date functions compatible with PI database. The workbook also has an override for time and date starting and ending points. The user may enter an "ending date and time." The workbook will automatically pull the data hourly between the two specified dates. This allows for user customization and is important for tracing errors or deviations. Variables with alarm points are trended as scatter plots and have warning points given lines. Each variable is also listed in a chart, calculating the daily mean, weekly mean, 30 day mean, 90 day mean, as well as the maximum and minimums for the day and the 30 day data pulls. The data which has specialized alarm levels also contains a status alert. If daily data is outside of specified limits, the dashboard gives a warning to the user.

3.4 Chapter Three Summary

Chapter Three provided an overview of the heat rate computation for TG1, and the design concepts for the ideals of a predictive maintenance dashboard for a turbine generator. Chapter Three covered the reasoning for creating on an accessible platform, as well as the elements, variables, and decisions used in developing a predictive maintenance. Chapter Four discusses the results of creating the dashboard, further discussing data collection, analysis, and accessibility.

CHAPTER 4: RESULTS

Chapter four described the results of the TG1 dashboard for predictive maintenance. The dashboard is built in Microsoft's Excel and sources data points from OSIsoft's PI Data Historian. The workbook consists of a dashboard page, which serves as the user interface for data selection. The following worksheets provide the sourced data. The dashboard displays data visually and uses simple statistics to alert Wade personnel to errors and discrepancies in operational patterns. As employees have access to and are familiar with Excel, the workbook offers simple navigation and customization to fit the Wad Utility Plant's needs.

4.1 Dashboard Overview

The optimal up-keep of TG1 is vital for energy and utility generation. The planning, forecasting, and purchasing involved for energy and utility production involves employees with a wide range of skill sets, backgrounds, and educations. This dashboard promotes predictive maintenance ideals, leveraging big data analysis to forecast maintenance needs through early error detection. The data from TG1 is gathered and arranged to create a dashboard using Microsoft Excel. Commercial forecasting and analytic software is expensive to both install and maintain. Limited licensing, software training, and difficulty in user comprehension means big data insights go unseen and misunderstood. This research creates a platform to leverage big data from a turbine generator, building a dashboard in Excel. Communication and interconnectivity between OSIsoft's PI Data Historian and Microsoft Excel provide an in-house, and accessible path for employees to navigate and analyze TG1 data. The maintenance dashboard is low-cost, as the project is built with preexisting programs purchased by The Wade plant, and outside predictive software and machine learning are not used.

The dashboard is built in an Excel workbook, containing six data sheets. The first page of the workbook is the dashboard, which acts as the user control and interface for data navigation. The dashboard aggregates and displays the trending and statistical analysis of TG1 data. The following five pages of the workbook collect data from OSIsoft's PI Data Historian using assigned "tag" names for each variable. The data is collected and stored in arrays, input from the data historian in the form of data strings. The strings are converted into data values, which are displayed visually in plots, and statistically analyzed over a single day, week, 30 day and 90 day period. The dashboard is accessible to all employees at the Wade Utility Plant, provided the employee has access to Microsoft Excel and the PI Data Historian. The workbook is unlocked, meaning the user may adapt and make changes to both the dashboard and the supporting data sheets as needs changes.

4.2 Predictive Dashboard Analysis

As previously mentioned in *Chapter One: Introduction*, the Wade Utility Plant has already invested in equipment monitoring instrumentation and data storage. This research study creates a platform to navigate big data from a turbine generator, creating a dashboard for the Wade Utility Plant employees. Early error detection is integral in predictive maintenance strategies, giving employees time to detect and plan for maintenance outages, as discrepancies and faults are found before unforeseen disruptions in production occur. The first page of the workbook is the dashboard, which acts as the user interface. As seen in Figure 4.1, the user enters a start date, in the highlighted yellow Excel cell. The dashboard provides written instructions prompting the user to enter the date as month, day, year, and the time as hour, minute, second (mm/dd/yyyy hh:mm:ss). The date function gives the user the ability to enter the current day's date, or a previous date for past historical trending. Once the user enters a start date, Excel will count back 90 previous days using the function EDATE, taking the stating date and automatically subtracting 90 days. Figure 4.1 provides an example with the starting dates as June 1, 2021, at 00:00:00. Excel back-dates 90 days, outputting an ending date of March 3, 2021, at 00:00:00. Using the start and end date, each variable is pulled as an hourly average. The following five workbook pages use the starting and ending dates as a reference to source operational data for TG1, outputting hourly data for each variable,

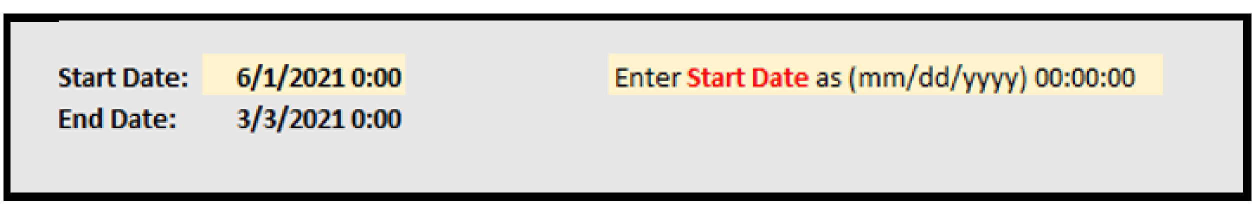

Figure 4.1. Date Control for Dashboard

4.2.1 Data Collection

The workbook collects four primary areas of data: vibrations, temperatures, operational data, and performance data. For organization, ease of use, and computation purposes, the Excel workbook consists of six pages, the first page being the dashboard, and the five following pages providing sourcing and analyzing data for display. The first page is titled *Dashboard*, with the following worksheets labeled *Vibration Data*, *Bearing Temperature Data*, *Stator Data*, *Steam Data*, and *Operational & Performance Data.* Table 4.1 details the variables tracked in the workbook. Each variable has a description, and output name, an associated alarm if applicable, and a unit of measurement. The measurement description gives the variable type and states what variable is being recorded. The output name lists the shortened variable description with locations detailed. Output names are included for user traceability and trackability throughout the workbook. The alarm level is included if specified by operation specifications. Variables that have associated warning levels include bearing vibrations, bearing temperatures, stator temperatures, steam seal pressures, and rotor speed.

Table 4.1. TG1 Variables

Measurement Description	Output Name	Alarm	Unit
Bearing Vibration	Brng1X	4	mils
Bearing Vibration	Brng1Y	4	mils
Bearing Vibration	Brng2X	4	mils
Bearing Vibration	Brng2Y	4	mils
Bearing Vibration	Brng3X	4	mils
Bearing Vibration	Brng3Y	4	mils
Bearing Vibration	Brng4X	4	mils
Bearing Vibration	Brng4Y	4	mils
Bearing Vibration	Axial1	-22	mils
Bearing Vibration	Axial2	-29	mils
Bearing Temperature	Brng1T1	225	°F
Bearing Temperature	Brng1T2	225	°F
Bearing Temperature	Brng2T1	225	°F
Bearing Temperature	Brng2T2	225	°F
Bearing Temperature	Brng3TA	225	°F
Bearing Temperature	Brng3TB	225	°F
Bearing Temperature	Brng3TC	225	°F
Bearing Temperature	Brng3TD	225	°F

Table 4.1 continued

Bearing Temperature	Brng4TA	225	°F
Bearing Temperature	Brng4TB	225	°F
Bearing Temperature	Brng4TC	225	°F
Bearing Temperature	Brng4TD	225	°F
Stator Temperature	GS1	275	°F
Stator Temperature	GS2	275	°F
Stator Temperature	GS3	275	°F
Stator Temperature	GS4	275	°F
Stator Temperature	GS5	275	°F
Stator Temperature	GS6	275	°F
650 Steam Velocity	650kpph	N/A	kpph
650 Steam Temperature	650T	N/A	°F
650 Steam Pressure	650PSI	N/A	psi
125 Steam Velocity	125kpph	N/A	kpph
125 Steam Temperature	125T	N/A	°F
650 Steam Pressure	125PSI	N/A	psi
15 Steam Velocity	15kpph	N/A	kpph
15 Steam Temperature	15T	N/A	°F
Steam Seal Temperature	StmSTemp	N/A	°F
Hot Well Level	HWL	N/A	in Hg
Chilled Water Valve	GCWV	N/A	%
Condensate Valve	CV	N/A	%
Condensate Pump Flow	CPF	N/A	gpm
Steam Seal Pressure	StmSPres	1.5-7.0	psi
Tower Water Flow	TWF	N/A	gpm
MW Production	TG1_MW	N/A	MW
Heat Rate	TG1_HR	N/A	btu/kw
Rotor Speed	OvrSpd	3680	RPM

Each listed data point has a specific tag name associated with OSIsoft's PI Data Historian, and produces data reliably, as specified by section *3.3.1 The Use of Excel.* An example of a PI tag name is *"g1-bb1x,"* referring to turbine generator one (*g1*,) bearing one (*bb1*,) and vibration in the X direction (*x*), perpendicular to the rotor's axis of rotation. Each tag is programmed into a data array, which is produced by Excel when downloading from the data historian. Figure 4.2 provides an example of the data array used for bearing vibrational data for Bearing One. The image Figure 4.2 describes the variable, *Bearing 1 Vibration X direction,* the tag name associated with

The variable in PI, *gi-bbx1x,* and the name assigned to the variable in the workbook, *Bearing1X*. While each variable in the workbook has an associated tag in relation to PI Data historian, proper names and variables descriptions are not always provided. The names and descriptions described within the workbook are taken from PI or created with the intention of traceability, and user comprehension.

Description:	**Bearing 1 Vibration X direction**
Tag Name:	g1-bb1x
Name	Bearing1X
31-May-21 23:00:00	0
31-May-21 22:00:00	0
31-May-21 21:00:00	0
31-May-21 20:00:00	0
31-May-21 19:00:00	0
31-May-21 18:00:00	0

Figure 4.2 Bearing Vibration Data Array

The PI data enters the arrays as strings, taken as an hourly average, and is displayed alongside the date and hour from which it is recorded. As discussed in Section 4.2**,** the date on which the data is collected is time sourced from a user input. The Wade Utility Plant installed recording instrumentation in 2015, thus the user can trace issues or errors back up to six years.

4.3 Data Analysis

Microsoft Excel 365 is a software that offers the ability to collect, document, and analyze data for TG1, and offers a low-cost platform to create the TG1 dashboard. Excel is also an optimal choice for this research project, as the program is also used to answer and catalog operational, engineering, and financial data for the utility plant.

Predicting maintenance needs is a competitive strategy. Operational and performance errors caught early allow time to plan maintenance outages around production needs and demand. Operators and engineers, as well as managers and financial planning staff must work together to effectively understand and allocate time, and resources to service TG1. As the dashboard is available to a range of employees, understanding and navigating TG1's data is essential. As the employees have a wide array of skills and statistical understanding, the dashboard primarily focusses on graphically representing the data. Data plots offer an effective balance of form and function, removing noise while effectively highlighting patterns and outliers with a quick glance. The dashboard incorporates scatter plots, which use Cartesian coordinates and line plots to display data for the 90-day interval.

Figure 4.3 is an example of data visualization, showing the Axial 1 and Axial 2 vibration data. Axial 1 data from TG1 is displayed as green data markers, with a visual warning line at -22 mils, left of bearing origin. Axial 2 data is displayed as blue data markers with a visual warning at -29 mils as dictated by vibration alarm specifications. The physical sensing equipment attached TG1 collects data via direct current (DC) voltage. The voltage gaps produced in the turbine's shaft are converted to mils, describing the displacement of vibration in references to software offsets in the data acquisition software. According to Tom Spettel, previous auditor for Bentley Nevada, common practice for system vibrations read by a sensing probe show positive axial vibrations as the shaft shifts closer to the probe, and readings report negative axial vibrations as the shaft moves away from the sensing probe (T. Spettel, personal communication, October 21, 2021).

The scatter plot in Figure 4.3 displays both axial vibrations, while keeping the data and variable warnings in separate colors. The scatter markers show visual variability within the data range while warning lines remain constant, allowing for quick identification. For example, Axial 1's standard operating vibration patterns during the 90 days sit within the range of -12 to -9 mils. The user can see that the data sits well above the -22 mils warning. Axial 2 data shows more variability during its vibrations, falling in the -14 to -21 range. This variable also its well above its -29 mils warning and does not alert to serious shaft vibration. Users can see both bearings follow similar vibrational patterns as they rise and fall during operation. The trend also visualizes an operational shut-down and start-up as vibrational data spikes on March 16, 2021, during shut down. During the shut-down, both Axial 1 and Axial 2 show a significant decrease. As the turbine generator is brought back online, around, April 3, 2021, we see a decrease and then reasonably steady vibration values.

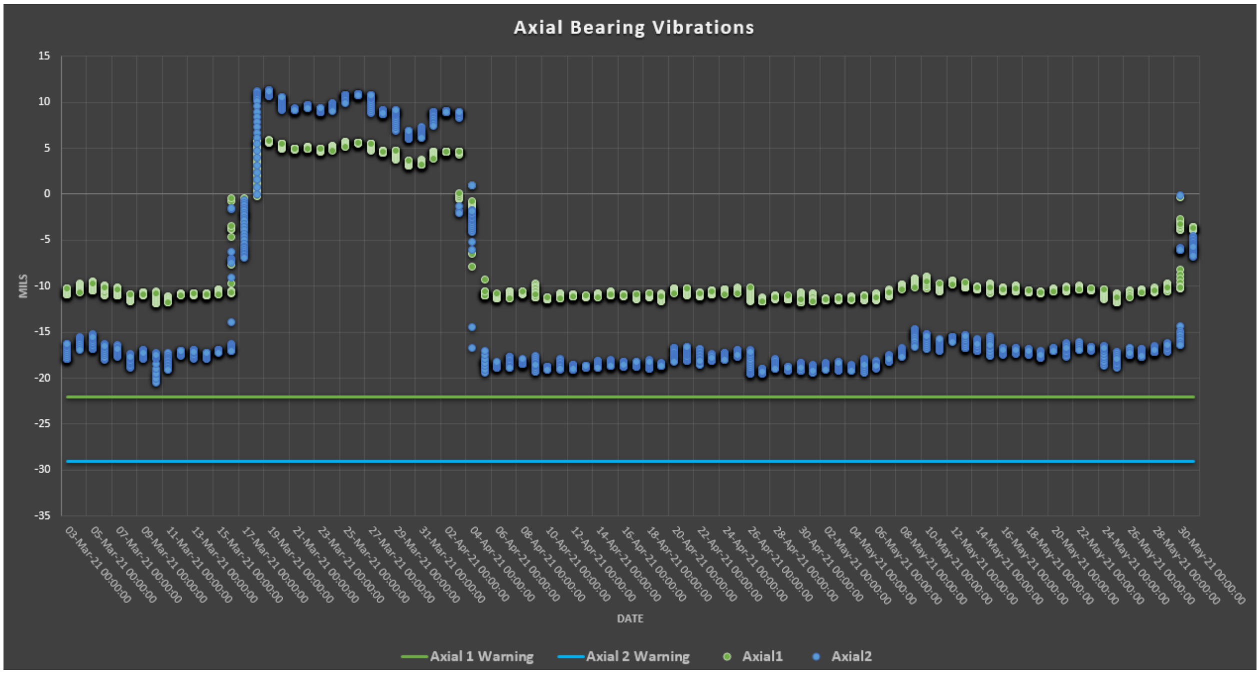

Figure 4.3. Axial Bearing Vibration

The dashboard has scatter plots for all bearing vibrations in both the X and Y directions, showing similar scatter plots and warning lines at 4 mils. The dashboard has scatter plots of all bearing temperatures with alarm levels at 225 °F, and all stator temperatures with alarms at 275 °F. Finally, the dashboard also has a scatter plot for the steam seal pressure, with two warning lines, located at 1.5 psi and 7 psi respectively.

In addition to line graphs, the dashboard also uses average values, minimum and maximum values, and alarm ranges to give status warning of data discrepancies. Figure 4.4 shows the dashboard table of statistical results and status for the measured variables. Users see the variable description or name, the unit of measurement, the start date's average and extrema, the start week's average, the first 30 day's average and extrema, and the total 90-day average. Data with warning levels has a status indicator. When data reported is within the specified range the "OK" status is displayed as a green cell. A component that falls outside of specific limits shows results in a red cell with a "Warning" label displayed. Components that do not have specified manufacturer or operational limits do not offer this feature, display as not applicable, or "N/A" and remain grey.

			Start Date			Start Week	1 Month			3 Months	
Variable		Unit	Average	Minimum	Maximim	Average	Month's Average	Minimum	Maximim	Average	Status
Bearing 1	X Direction	mils	0.000	0.000	0.000	0.179	0.199	0.000	0.310	0.161	OK
	Y Direction	mils	0.001	0.000	0.018	0.233	0.242	0.000	0.431	0.192	OK
Bearing 2	X Direction	mils	0.000	0.000	0.000	0.197	0.240	0.000	0.313	0.191	OK
	Y Direction	mils	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	OK
Bearing 3	X Direction	mils	0.000	0.000	0.000	0.211	0.241	0.000	0.388	0.194	OK
	Y Direction	mils	0.802	0.786	0.813	0.760	0.759	0.706	0.813	0.772	OK
Bearing 4	X Direction	mils	0.000	0.000	0.000	0.228	0.276	0.000	0.313	0.225	OK
	Y Direction	mils	0.000	0.000	0.000	0.204	0.236	0.000	0.250	0.191	OK
Axial1		mils	-3.769	-3.926	-3.573	-9.268	-10.216	-11.807	-0.364	-7.528	OK
Axial2		mils	-5.870	-6.804	-4.598	-14.912	-16.666	-18.881	-0.221	-12.123	OK
Bearing 1	Temperature 1	°F	143.297	124.333	158.917	162.323	171.987	121.096	179.794	163.382	OK
	Teperature 2	°F	139.108	121.778	151.341	163.153	174.086	118.469	178.755	163.736	OK
Bearing 2	Temperature 1	°F	117.139	111.205	122.310	152.638	152.638	111.205	171.767	151.389	OK
	Teperature 2	°F	116.486	110.310	121.554	148.086	158.771	110.310	162.734	145.795	OK
Bearing 3	Temperature A	°F	111.722	98.309	122.635	150.214	163.050	98.309	167.623	147.333	OK
	Teperature B	°F	94.302	80.829	105.184	132.402	145.029	80.829	149.681	129.502	OK
	Temperature C	°F	118.554	100.647	124.837	145.202	155.203	100.647	159.102	141.545	OK
	Teperature D	°F	71.419	57.998	81.246	102.555	112.606	57.998	116.004	104.211	OK
Bearing 4	Temperature A	°F	114.418	100.686	124.522	159.048	174.280	100.686	179.151	157.597	OK
	Teperature B	°F	113.603	99.951	123.399	158.517	173.981	99.951	178.265	157.503	OK
	Temperature C	°F	112.029	98.348	122.017	142.163	152.009	98.348	155.302	138.838	OK
	Teperature D	°F	110.763	97.112	120.683	140.657	150.334	97.112	153.735	137.295	OK
Bearing Combined Drain	Temperature 1	°F	100.558	86.079	118.189	127.745	135.481	86.079	140.420	123.847	N/A
	Teperature 2	°F	97.210	87.028	110.283	112.665	117.126	87.028	125.327	108.744	N/A
Steam Seal	Temperature	°F	86.127	83.606	96.421	418.926	530.870	83.606	629.236	451.188	N/A
Sator Temperature 1		°F	98.510	95.235	102.897	126.955	127.576	95.235	150.563	117.485	OK
Sator Temperature 2		°F	100.516	97.154	104.545	128.973	129.343	97.154	154.115	119.258	OK
Sator Temerpature 3		°F	101.386	98.346	105.217	129.202	129.570	98.346	153.741	119.601	OK
Sator Temperature 4		°F	101.386	98.346	105.217	129.202	129.570	98.346	153.741	119.601	OK
Sator Temperature 5		°F	99.462	96.344	103.085	125.649	125.943	96.344	149.747	116.322	OK
Sator Temperature 6		°F	99.200	96.416	102.691	124.475	124.689	96.416	148.134	115.326	OK
Sator Overspeed		RPM	4.279	0.000	9.500	2898.001	3360.942	0.000	3601.028	2768.997	OK
Hot Well Level		in Hg	5.248	3.528	6.873	1.024	0.512	0.512	6.873	1.779	N/A
Hot Well Level FCV		%	0.305	0.305	0.305	0.161	0.125	0.125	0.305	0.149	N/A
Gen CW Valve		%	0.305	0.305	0.305	0.106	0.073	0.073	0.305	0.063	N/A
Cond Valve		%	100.000	100.000	100.000	62.086	62.160	62.160	100.000	70.439	N/A
Cond Pump Flow		gpm	68.769	67.859	69.550	419.819	472.631	472.631	503.948	401.054	N/A
Steam Seal Pressure		PSI	-0.125	-0.125	-0.125	2.792	3.218	3.218	3.561	2.622	OK
Tower Water Flow		GPM	7078.807	1.455	15271.107	14543.447	14365.494	14365.494	18404.958	11362.072	N/A
Heat Rate		Btu/kW	0.000	0.000	0.000	9345.008	11355.565	11355.565	20274.813	10228.150	N/A

Figure 4.4. Statistical Data Analysis`

Steam data is controlled by the operators and based on the campus demand for electricity, and steam. Therefore, there is intrinsic variability within the pressure, temperature, and velocity data for 650 pound, 125 pound and 15 pound steam. These data points are not visually trended nor displayed in the analysis table. Instead, steam is shown as a separate table that lists the start day's average and the start week's average.

Steam				
Start Date's Average				
Variable	**Unit**	**650 lb**	**125 lb**	**15 lb**
Flow	KPPH	53.861	-0.425	51.519
Temperature	°F	533.472	130.175	255.780
Pressure	PSI	4.006	457.761	
Week's Average				
Flow	KPPH	112.504	-1.382	26.929
Temperature	°F	710.099	128.649	250.950
Pressure	PSI	470.618	524.382	

Figure 4.5. Steam Averages

4.4 Chapter Four Summary

Chapter four described the results of the TG1 dashboard, which alerts Wade personnel to data discrepancies within 90 days of data, taken hourly. The dashboard is built in Microsoft Excel, and sourcing TG1 operation and performance data from OSIsoft's Pi Data Historian. As predictive software comes at great costs, Excel offers the ability to collect, analysis, and customize TG1 data needs, on a platform that is already used at the utility plant. Big data from TG1 shows quantifiable proof of machine health and can be used to forecast and predict maintenance needs in the future. The workbook consists of six pages, the first being the dashboard, and the following five pages being the supporting data. Data is traced and recorded in the workbook by assigned variable names and tags which allow the interconnectivity between Excel and PI Data Historian. The dashboard users enter a starting date, as prompted, and the workbook back-calculates 90 days of data, updating trends and tables. The planning, forecasting, and purchasing involved for energy and utility production involves a wide range of employees, with varying levels of statical analysis skills. The dashboard incorporates 48 variables associated with the operation and performance of TG1, making simple visual trends as well as take the averages and extrema, and provided status updates. The dashboard offers users a look at the daily steam metrics, megawatt production, and heat rate, alongside the operation variables of vibrations, temperatures, and pressures. The dashboard offers a simple, yet customizable platform to navigate big data for TG1, alerting to discrepancies before the errors impact production.

CHAPTER 5: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Chapter Five offered concluding remarks and provides suggestion for future work and adaptations. This chapter reviews the proposed research questions discussing the dashboard metrics, and remarks on employee accessibility, data collections and adaptability. The dashboard is built in an Excel workbook that sources operational and performance data for TG1 at the Wade Utility plant. Trending and analyzing available data, the dashboard alerts to data discrepancies while minute. Using advanced warning, employees at Wade Utility Plant can plan for outages, managing time, finances and resources while ensuing reliable utility services from TG1.

5.1 Dashboard Metrics

The purpose of this research is to utilize the existing condition, monitoring, and operational data for TG1 at the Wade Utility Plant to create a dashboard justifying reliability and promoting the practices of predictive maintenance. Unexpected downtime can be detrimental in meeting demand needs and production expectations, in addition to a waste of employee time and company finances. This research study creates a dashboard referencing “big data” associated with the operation and performance of TG1. Predictive maintenance is data-centric, and for optimal results, the dashboard is a balance of form and function while being easily understood. With this in mind, simple statics and data visualization took precedence as an effective way to highlight patterns and outliers. The success of this dashboard is in being accessible, comprehensive, and adaptable, giving insight into early error detection, allowing Wade’s employees time to plan and prepare for repairs. Furthermore, the dashboard approach in navigating “big data” can be applied to other equipment and systems for future predictive maintenance strategies.

5.1.1 Accessibility to Employees

Ensuring the health and maintenance needs of equipment is critical for reliable utility services at the Wade Utility Plant. The dashboard is built using Microsoft Excel, a software capable of collecting, documenting, and analyzing essential metrics to justify maintenance and proof of reliability in TG1. While navigating big data is vital in predictive maintenance, it is equally essential for data to be comprehendible. The Excel software is an optimal choice. It offers the ability to collect, document, and analyze data for TG and already licensed and installed on machines across the utility plant; creating the dashboard came at zero cost for Wade. The planning, forecasting, and purchasing for energy and utility production involves employees with a wide range of skills sets, backgrounds, and educations. As Excel is also a primary platform used to answer and catalog operational, engineering, and financial data at the Plant, there is only a slight learning curve necessary for software navigation department wide.

5.1.2 Comprehensive Data Collection

As discussed in Chapter Four, the predictive dashboard displays real-time and historical metrics for sub-sections of an operational turbine generator, creating a powerful tool for predictive maintenance strategies. The dashboard is built in a Microsoft Excel file, focusing on four primary areas of data: vibrations, temperatures, operational data, and production data. For organization, ease of use, and computation purposes, the Excel workbook has a page for the dashboard and supporting pages for data arrays and analysis. The sheets for vibrations, temperatures, operational and performance data link to PI Historian using "tag" names assigned in the PI system. Each tag name is associated with a measurement or calculation in or made from the operation of the turbine generator itself. The data is pulled into an array that lists a variable name, variable description, PI tag, date and time, and the associated variable point. As a user-friendly way to navigate big data, the dashboard utilizes scatter plots and line graphs to display information visually. For comparative measures, the dashboard also uses average values and minimum and maximum values for each day, week, 30-day time period, and 90-day time period. Finally, for data with specified alarm or alarm ranges, the dashboard also features a daily status value. The "OK" status is displayed as a green cell, "Warning" is displayed in a red cell, and "N/A" remains a gray cell.

For a total, 48 variables and more than 100,000 data points are used as metrics for TG1 performance and maintenance needs. These variables are read from sensing equipment on TG1 or auxiliary equipment, critical for the turbine generator's operation. As mentioned in Chapter 3.1, Heat Rate Computation, heat rate is the turbine generator's operation efficiency, the total amount of energy required to produce one kilowatt-hour. Alongside the heat rate and megawatt production, velocity, temperature, and pressure of the 650 psi, 125 psi, and 15 psi steam measurements are also critical performance metrics. Section 2.5 introduces key physical components in a turbine generator, and PI Historian has retrievable data, including the steam seal, stators, and bearings.

The steam seal has a retrievable pressure reading, the stators have six temperature readings, and an over-speed alarm read as rotations per minute. Finally, six total bearings offer fourteen temperature variables and ten vibrational readings. Lastly, auxiliary equipment and systems incorporated into the dashboard for TG1 include the hot well level, chilled water valve, condensate valve, pump, and cooling tower water, flow into the TG1 system. Faults in these components introduce the potential for operational errors in the turbine generator.

5.1.3 Adaptability

The predictive maintenance dashboard is customized to TG1 with 48 specific variables chosen, built to retrieve data in 90-day periods. The dashboard sheet is supported by five data sheets that resource information from PI historian. The workbook is constructed modularly, allowing users to trace and track a specific variable or set of variables outside of the dashboard page, with a specific tag, name, and description which is kept consistent throughout. Advanced trending and statistics are available through Excel, and the 90-day window can be adjusted for outage planning and forecasting. Tags are also easily added if the data is available in PI. The workbook can be easily molded and modified for future planning and additions. The workbook may also act as an example or outline, copied for other critical equipment at the Wade Utility Plant.

5.2 Recommendations and Future Work

Predictive maintenance is data-centric. Theoretically, the more operational and performance metrics made available and tracked, be more insight on the health of the turbine generator is available. The working tags available for TG1 and auxiliary equipment are utilized in this research study.

The dashboard is set to use data collected in hourly increments for 90 days. These parameters can be adjusted. Future work could pull in daily, monthly, or yearly data to better understand operational and performance trends.

As this Excel workbook is accessible for all employees at Wade, the dashboard displays statistical averaging, minimums, maximums, and data visualization using scatterplots and line graphs highlight patterns and outliers. The analysis and graphical representation in the workbook can be taken to a narrowed and advanced level. The workbook has the potential to be customized should operations, engineering, management, or financial planning required different metrics when forecasting maintenance.

Lubrication data is an important metric for TG1 and was not available. Important metrics to consider including particle count, viscosity, moisture content, and ISO rating during routine testing for TG1 at Wade Utility plant. This information is not available through PI historian is available in written records.

5.3 Chapter Five Summary

Chapter Five provided concluding remarks on this research study offering summaries of research questions and providing future work suggestions for continued research. The dashboard collects available data for TG1 using the interconnectivity of a physical system and cyber data. The dashboard is built in Excel, a platform that is both available and accessible to employees at the Wade Utility Plant. Having inclusivity and planning in-mind, the dashboard displays data visually though scatter plots, showing operating data and warnings. The dashboard also offers a simple statical study of the days, weeks, 30 day and 90 averages and extrema. Finally, with applicable, the dashboard also shows an easy-to-follow status of the variable, with a green “OK” status with data is within reason, and a red “Warning” which results in data changes outside of the satisfactory range. The workbook is unlocked, and can be changes, edited, and expanded upon, should the user feel it is necessary. Future work suggestions include expansion of data, both in number of variables and in also in time frame. This offers customization for better evaluation of regarding the equipment health and maintenance needs of TG1.

LIST OF REFERENCES

Akers, H., Dickinson, J., & Skooglund, J. (1968). Operation and protection of large steam turbine generators under abnormal conditions. *IEEE Transactions on Power Apparatus and Systems, PAS-87*(4), 1180-1188. doi:10.1109/tpas.1968.292097

Alaswad, S., & Xiang, Y. (2017). A review on condition-based maintenance optimization models for stochastically deteriorating system. *Reliability Engineering & System Safety, 157*, 54-63. doi:10.1016/j.ress.2016.08.009

Annual Survey of Manufactures: Summary Statistics for Industry Groups and Industries in the U.S.: 2018. (2018, April). https://data.census.gov/cedsci/table?q=am1831.

Arno, R., Dowling, N., & Schuerger, R. (2015). Equipment failure CHARACTERISTICS & RCM for optimizing maintenance cost. *2015 IEEE/IAS 51st Industrial & Commercial Power Systems Technical Conference (I&CPS)*. doi:10.1109/icps.2015.7266415

Au-Yong, C. P., Ali, A. S., & Ahmad, F. (2016). Relationship between Predetermined Maintenance Interval and Maintenance Performance. *Applied Mechanics and Materials*, *845*, 305–310. doi: 10.4028/www.scientific.net/amm.845.305

Bengtsson, M., & Lundström, G. (2018). On the importance of combining "the new" with "the old" – one important prerequisite for maintenance in industry 4.0. *Procedia Manufacturing, 25*, 118-125. doi:10.1016/j.promfg.2018.06.065

Bigret, R. (2001). *Fluid bearing*. Fluid Bearing - an overview | ScienceDirect Topics. Retrieved August 30, 2021, from https://www.sciencedirect.com/topics/materials-science/fluid-bearing.

Blažević, S., Mrzljak, V., Anđelić, N., & Car, Z. (2019). Comparison of energy flow stream and isentropic method for steam turbine energy analysis. *Acta Polytechnica*, *59*(2), 109-125. doi:10.14311/ap.2019.59.0109

Britannica, The Editors of Encyclopedia (n.d.). *Amplitude*. *Encyclopedia Britannica*. https://www.britannica.com/science/amplitude-physics

Britannica, The Editors of Encyclopedia (n.d.). *Frequency*. *Encyclopedia Britannica*. https://www.britannica.com/science/amplitude-physics

Christensen, C., Raynor, M., & McDonald, R. (2015, December). What is disruptive innovation? *Harvard Business Insider*, 44-53. Retrieved August 2, 2021, from https://hbr.org/2015/12/what-is-disruptive-innovation

Christiansen, B. (2019, October 10). A Comprehensive Guide To Corrective Maintenance. Retrieved April 23, 2020, from https://limblecmms.com/blog/corrective-maintenance/

Coleman, C., Damodaran, S., & Deuel, E. (2017). *Predictive maintenance and the smart factory*. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/process-and-operations/us-cons-predictive-maintenance.pdf.

Corrective Maintenance Comparisons. (n.d.). Retrieved April 27, 2020, from https://www.proaxion.io/corrective-maintenance

Douglas, T. S. (2018, April). *The Costs and Benefits of Advanced Maintenance in Manufacturing*. National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AMS.100-18.

Electricity explained Magnets and Electricity. (2020, January 08). Retrieved August 01, 2020, from https://www.eia.gov/energyexplained/electricity/magnets-and-electricity.php

Electricity explained The science of electricity. (2020, January 08). Retrieved August 01, 2020, from https://www.eia.gov/energyexplained/electricity/the-science-of-electricity.php

Fenton, R., Gott, B., & Maughan, C. (1992). Preventative maintenance of turbine-generator stator windings. *IEEE Transactions on Energy Conversion, 7*(1), 216-222. doi:10.1109/60.124563

Fitch, B. (2013, December 17). Oil Analysis Explained. Retrieved April 27, 2020, from https://www.machinerylubrication.com/Read/29598/oil-analysis-report

Haugen, S., Vinnem, J., Kongsvik, T., Barros, A., & Gulijk, C. V. (2018). Reliability-based maintenance optimization for the leased equipment with deterioration depending on age and usage. In *Safety and Reliability safe societies in a changing world* (1st ed., pp. 653-661). Boca Raton, FL: Routledge, an imprint of Taylor and Francis.F

Hurley, K., & Shamieh, J. (2020, August 15). Enthalpy. Retrieved October 13, 2020, from https://chem.libretexts.org/Bookshelves/Physical_and_Theoretical_Chemistry_Textbook_Maps/Supplemental_Modules_(Physical_and_Theoretical_Chemistry)/Thermodynamics/Energies_and_Potentials/Enthalpy

Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing, 20*(7), 1483-1510. doi:10.1016/j.ymssp.2005.09.012

Landis, F., & Budenholzer, R. (2017, March 27). Steam Turbines. Retrieved July 22, 2020, from https://www.britannica.com/technology/turbine/Steam-turbines

Levitt, J. (2011). *Complete guide to preventive and predictive maintenance*. New York: Industrial Press.

Maheshwari, M., & Singh, O. (2019). Comparative evaluation of different combined cycle configurations having simple gas turbine, steam turbine and ammonia water turbine. *Energy, 168*, 1217-1236. doi:10.1016/j.energy.2018.12.008

Malik, M. A. (1979). Reliable preventive maintenance scheduling. *A I I E Transactions, 11*(3), 221-228. doi:10.1080/05695557908974463

Marr, B. (2019, July 11). What is industry 4.0? Here's a super easy explanation for anyone. Retrieved August 02, 2021, from https://www.forbes.com/sites/bernardmarr/2018/09/02/what-is-industry-4-0-heres-a-super-easy-explanation-for-anyone/?sh=58402f2d9788

Merriam-Webster. (n.d.). British thermal unit. In *Merriam-Webster.com dictionary*. Retrieved August 2, 2021, from https://www.merriam webster.com/dictionary/British%20thermal%20unit

Merriam-Webster. (n.d.). Internet of Things. In *Merriam-Webster.com dictionary*. Retrieved August 2, 2021, from https://www.merriam-webster.com/dictionary/Internet%20of%20Things

Merriam-Webster. (n.d.). Metric. In *Merriam-Webster.com dictionary*. Retrieved August 2, 2021, from https://www.merriam-webster.com/dictionary/metric

Merriam-Webster. (n.d.). Resonance. In *Merriam-Webster.com dictionary*. Retrieved August 2, 2021, from https://www.merriam-webster.com/dictionary/resonance

Merriam-Webster. (n.d.). Turbine generator. In *Merriam-Webster.com dictionary*. Retrieved August 2, 2021, from https://www.merriam-webster.com/dictionary/turbine%20generator

Merriam-Webster. (n.d.). Watt. In *Merriam-Webster.com dictionary*. Retrieved August 2, 2021, from https://www.merriam-webster.com/dictionary/watt

Mobley, R. (2002). *An introduction to predictive maintenance* (2nd ed., Plant Engineering). Amsterdam ; New York: Butterworth-Heinemann.

Munirathinam, S. (2020). Industry 4.0: Industrial Internet of Things (iiot). *Advances in Computers,* 129-164. doi:10.1016/bs.adcom.2019.10.010

Passlick, J., Dreyer, S., Olivotti, D., Grützner, L., Eilers, D., & Breitner, M. H. (2020). Predictive maintenance as an internet of things enabled business model: A taxonomy. *Electronic Markets, 31*(1), 67-87. doi:10.1007/s12525-020-00440-5

Pennacchi, P. (2017). Introduction of advanced technologies for steam turbine bearings. In 1434625076 1042137702 T. Tanuma (Author), *Advances in steam turbines for modern power plants* (pp. 321-378). Amsterdam: Woodhead Publishing.

Persigehl, B., Gellermann, T., Thumm, S., & Stoiber, J. (2020). Possibilities and limitations of early fault detection in gas turbines. *Volume 5: Controls, Diagnostics, and Instrumentation; Cycle Innovations; Cycle Innovations: Energy Storage*. doi:10.1115/gt2020-16251

Petherus, V., Nirbito, W., & Nurhantoko, H. (2019). Application of predictive maintenance technique with vibration monitoring method for analysis of damage trend and damage diagnosis at make up water pump On Pltgu installation. *AIP Conference Proceedings*, *2088*(1). doi:10.1063/1.5095337

PI System: Operational Intelligence-Data Infrastructure (n.d.) Retrieved November 07, 2020 from http://www.osisoft.com/

QA Platforms. (2019, November 12). Maintenance Testing. Retrieved April 23, 2020, from https://qa-platforms.com/maintenance-testing/

Ramaraj, S. (2018). Turbine Generator [PowerPoint slides]

Reimche, W., Südmersen, U., Pietsch, O., Scheer, C., & Bach, F. W. (2003). Basics of vibration monitoring for fault detection and process control. *Rio de Janeiro, Brazil*, *6*, 2-6.

Selcuk, S. (2016). Predictive maintenance, its implementation and latest trends. *Institution of Mechanical Engineers*, *231*(9). doi: 10.1177/095449054156160

Shang, L., Si, S., Cai, Z., & Wang, X. (2018). Reliability-based maintenance optimization for the leased equipment with deterioration depending on age and usage. In 1433954497 1041738640 S. Haugen, 1433954498 1041738640 A. Barros, 1433954499 1041738640 C. V. Gulijk, 1433954500 1041738640 T. Kongsvik, & 1433954501 1041738640 J. E. Vinnem (Authors), *Safety and reliability: Safe societies in a changing world: Proceedings Of ESREL 2018, JUNE 17-21, 2018, Trondheim, Norway*. Boca Raton: CRC Press.

Silaipillayarputhur, K. (2016). Maintenace engineering in process plants. *MATEC Web of Conferences*, *77*, 10007. doi:10.1051/matecconf/20167710007

Soliman, M. (2020, December 14). Machinery oil analysis & CONDITION MONITORING: A practical guide to sampling and ANALYZING oil to Improve EQUIPMENT RELIABILITY. Retrieved July 19, 2021, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3748009

Soliman, M. (2021). *Vibration Basics and Machine Reliability Simplified: A Practical Guide to Vibration Analysis*. Retrieved from https://ssrn.com/abstract=3752458

Steam Turbine Basic Parts. (2018, February 11). Retrieved July 19, 2020, from http://www.mechanicalengineeringsite.com/steam-turbine-basic-parts/

Steam Turbine Generator Maintenance Programs. (2016). Retrieved July 27, 2020, from https://www.elliottturbo.com/Files/Admin/Literature/Literature%20Updates%20June2017/SVS.4090.0516---Maintenance-Agreement.pdf

Stenström, C., Norrbin, P., Parida, A., & Kumar, U. (2015). Preventive and corrective maintenance – cost comparison and cost–benefit analysis. *Structure and Infrastructure Engineering*, *12*(5), 603-617. doi:10.1080/15732479.2015.1032983

Sullivan, G., Pugh, R., Melendez, A., & Hunt, W. (2010, August). *Operations & Maintenance Best Practices A Guide to Achieving Operational Efficiency*. US Department of Energy. https://www.energy.gov/sites/prod/files/2013/10/f3/omguide_complete.pdf.

Swanson, L. (2001). Linking maintenance strategies to performance. *International Journal of Production Economics*, *70*(3), 237–244. doi: 10.1016/s0925-5273(00)00067-0

Trout, J. (2008, July 7). Preventive Maintenance: An Overview. Retrieved April 23, 2020, from https://www.reliableplant.com/Read/12494/preventive-maintenance

Trout, J. (2019, June 27). Vibration Analysis Explained. Retrieved April 27, 2020, from https://www.reliableplant.com/vibration-analysis-31569

Vibration Analysis. (n.d.). Retrieved April 27, 2020, from https://vibralign.com/resources/concepts/vibration-analysis/

Wade Utility Plant. Figure 2.1 TG1 Installation stock photo (n.d.)

Wang, Y., Deng, C., Wu, J., Wang, Y., & Xiong, Y. (2014). A corrective maintenance scheme for engineering equipment. *Engineering Failure Analysis, 36*, 269-283. doi: 10.1016/j.engfailanal.2013.106