DEVELOPMENT OF A PREDICTIVE MAINTENANCE MODEL FOR A CENTRIFUGAL PUMP DISCHARGE PRESSURE AND VIBRATION HEALTH INDEX USING AZURA POWER PLANT AS A CASE STUDY

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FACULTY OF ENGINEERING

UNIVERSITY OF BENIN

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A PROJECT SUBMITTED TO THE DEPARTMENT OF INDUSTRIAL ENGINEERING IN PARTIAL FUFILMENT OF THE REQUIREMENT FOR THE AWARD OF BACHELOR OF ENGINEERING (BENG),
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CERTIFICATION

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DEDICATION

This project is dedicated to God Almighty and to my loving parents Mr. and Mrs. Madubuko Onyekwere whose prayers, encouragement, and financial support have been my greatest motivation.

It is also dedicated to my siblings Innocent Onyekwere, Precious Onyekwere, Chidinma Onyekwere and Stephen Onyekwere for their financial assistance and moral support throughout this journey.

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ABSTRACT

Modern power generation facilities depend heavily on auxiliary components such as centrifugal pumps, which ensure effective cooling and stable operation of gas turbines. The literature reviewed shows that conventional maintenance strategies reactive and preventive—are often costly and inefficient, leading to unexpected failures and operational losses. Predictive maintenance (PdM) has emerged as a superior, data-driven alternative that uses statistical and sensor-based models to forecast equipment failure. The review further highlighted the growing adoption of PdM techniques in African power systems, where the need for reliability and cost optimization remains high. This study focuses on developing a predictive maintenance model for the cooling water centrifugal pump at the Azura-Edo Independent Power Plant, using statistical trend and regression analysis to predict performance degradation.

The research employed an analytical and quantitative design, utilizing two years (2023–2024) of historical operational data from Azura-Edo IPP. Key parameters included ambient temperature, discharge pressure, gas turbine active power, and vibration readings from different pump locations. Microsoft Excel served as the main analytical tool for data cleaning, descriptive statistics, correlation testing, and multiple regression modeling. The regression model related vibration amplitude to operating parameters, producing a mathematical expression capable of estimating degradation levels. A control chart was also developed to monitor vibration stability using calculated upper and lower control limits, forming an early warning system for predictive maintenance intervention.

Results from the analysis revealed moderate variability among parameters, with vibration showing the strongest correlation to discharge pressure and turbine power. The developed vii

regression model effectively predicted vibration trends with reasonable accuracy, confirming its suitability for maintenance forecasting. The study concluded that predictive maintenance can significantly improve pump reliability, reduce unplanned downtime, and optimize maintenance scheduling at Azura-Edo IPP. It is recommended that the model be integrated into the plant’s SCADA system for real-time monitoring, with periodic updates to ensure adaptive accuracy and sustainable performance.

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NOMENCLATURE

PdM Predictive Maintenance

RUL Remaining Useful Life

PDI Pump Degradation Index

GT Gas Turbine

VHI Vibration Health Index

DE Drive End

NDE Non-Drive End

MS Motor Side

PS Pump Side

ANN Artificial Neural Network

SVM Support Vector Machine

IoT Internet of Things

SCADA Supervisory Control and Data Acquisition

P–F Curve Potential-Failure to Functional-Failure Curve

Azura-Edo IPP Azura-Edo Independent Power Plant

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Contemporary power generation facilities, especially those utilizing gas turbine technologies, depend heavily on auxiliary machinery such as centrifugal pumps to ensure uninterrupted, reliable, and optimal performance (Ahmad et al., 2020). Among these auxiliary components, the cooling water centrifugal pump plays a particularly vital role in maintaining appropriate turbine operating temperatures through water circulation in cooling circuits. These pumps serve as protective barriers against thermal overload and preserve the mechanical integrity of turbine systems (Ganick, 2021). System failures in such equipment can lead to devastating outcomes, including spontaneous plant shutdowns, significant economic losses, and comprehensive operational breakdowns (Parrondo et al., 1998). Therefore, the dependability of cooling pumps is intrinsically connected to the overall reliability of power generation facilities. Centrifugal pumps function in demanding mechanical and thermal environments, frequently operating without interruption for prolonged durations. This uninterrupted operation subjects them to mechanical deterioration, misalignment issues, and bearing degradation. Essential parameters including vibration levels, temperature variations, and pressure fluctuations frequently exhibit preliminary signs of irregularities, establishing these variables as fundamental elements for early fault identification (Mousmoulis et al., 2023).

Conventional maintenance approaches can be categorized into reactive and preventive methodologies. Reactive maintenance, also known as run-to-failure maintenance, commences only after equipment breakdown has occurred. While straightforward in implementation, this strategy carries substantial risks and frequently results in extended operational interruptions and elevated repair expenses (Wikipedia, 2025). Preventive maintenance, conversely, follows predetermined schedules based on operating hours or time intervals. Nevertheless, this approach may prove inefficient, as components might undergo replacement or servicing prior to reaching their actual service life limits, resulting in elevated maintenance expenditures and avoidable downtime (MDPI, 2021).

To address the limitations of both reactive and preventive approaches, the Predictive Maintenance (PdM) methodology has gained prominence. PdM seeks to forecast the future operational state of equipment components using historical and current data, ensuring maintenance interventions occur only when genuinely required (Costa et al., 2024). This approach enhances asset durability, minimizes unexpected downtime, and facilitates economically efficient maintenance scheduling (Ahmad et al., 2021). PdM frameworks utilize sensor information and statistical or machine learning algorithms to determine when components are likely to experience failure. In industrial environments, such as the Azura-Edo Independent Power Plant in Nigeria, implementing predictive analytics represents a digital transformation initiative for enhanced reliability and operational efficiency.

This research concentrates on employing multiple regression analysis, a well-established and interpretable statistical method, to predict the operational condition of a cooling water centrifugal pump using two years of historical sensor measurements (temperature, pressure, and vibration). The objective is to construct a model capable of identifying deterioration patterns and predicting maintenance requirements, enabling timely and data informed maintenance decisions.

In recent years, vibration monitoring has become an essential technique for assessing the operational condition of rotating machinery. However, analyzing individual vibration parameters can sometimes be complex. To simplify machine condition assessment, the **Vibration Health**

Index (VHI) is often used. VHI integrates multiple vibration measurements into a single indicator that represents the overall health condition of equipment. This approach allows maintenance engineers to quickly identify abnormal operating conditions and take preventive actions before system failure occurs.

1.2 Statement of the Problem

Centrifugal pumps are critical components in power generation facilities, including the Azura Power Plant, where their uninterrupted operation is essential for fluid transport, cooling systems, and overall plant reliability. However, these pumps are highly susceptible to wear and eventual failure due-to demanding operational conditions.

The current maintenance paradigms employed are often either reactive (run-to-failure), which leads to catastrophic, unplanned downtime and high emergency repair costs, or time based preventive maintenance, which is inefficient, costly, and insufficient, often resulting in unnecessary servicing of healthy components or failing to prevent breakdowns that occur between scheduled interventions.

This inefficiency leads to significant financial losses from reduced power output and escalates operational risks. There is a critical gap in the existing maintenance strategy: the lack of a reliable system to anticipate *when* a pump will fail. Therefore, this project seeks to address the urgent need for a proactive maintenance solution by developing a predictive model that can analyze real-time operational data from the pumps at Azura, accurately forecast impending failures, and optimize maintenance scheduling to enhance operational reliability and reduce costs.

1.3 Aim and Objectives of the Study

Aim: To establish a predictive maintenance model for a gas turbine cooling water centrifugal pump utilizing two years of historical sensor data from the Azura-Edo Independent Power Plant and Vibration Health Index (VHI) analysis to assess equipment health and operational efficiency.

Objectives:

i. To gather and process historical sensor data, encompassing vibration, temperature, and pressure measurements.

ii. To construct a multiple regression model that evaluates the probability and timing of future pump failures.

iii. To develop the model using one year of historical data and verify it using the subsequent year.

iv. To calculate the Degradation level of the pump or provide early failure warnings based on data patterns.

v. To evaluate equipment condition using Vibration Health Index (VHI) analysis.

vi. To provide recommendations for integrating the predictive model into Azura-Edo's maintenance procedures.

1.4 Scope of the Study

This research focuses specifically on developing and validating a predictive maintenance model for the critical centrifugal pumps at the Azura Power Plant. The study's scope encompasses the entire data modeling pipeline, beginning with the acquisition and integration of historical operational data, which includes sensor readings like vibration, temperature, and pressure, as well as the plant's maintenance and failure logs. This data will then undergo a rigorous pre-processing phase, involving cleaning, transformation, and normalization. Following this, feature engineering will be performed to identify and select the most significant predictors of pump degradation and failure. The core of the research involves the comparative application and training of various machine learning algorithms to build the predictive model, which will then be rigorously validated using a test dataset to evaluate its accuracy and predictive power. This study is explicitly limited to the centrifugal pumps and will not extend to other plant equipment. Furthermore, the scope does not include the physical installation of new sensors, the development of a real-time software deployment interface, or a comprehensive economic implementation analysis.

1.5 Significance of the Study

Here is the significance of the study, presented in a continuous article format. The significance of this research lies in its potential to provide a tangible and high-impact solution to the persistent challenge of equipment reliability in the power generation sector. The study's benefits are multifaceted, offering specific advantages to the Azura Power Plant as the case study, as well as broader contributions to the wider power industry and the academic community.

For the Azura Power Plant, the primary significance is the prospective shift from traditional reactive or inefficient time-based maintenance schedules to a proactive, intelligent, and data-driven maintenance strategy. By developing a model that can accurately forecast centrifugal pump failures, the plant stands to gain substantially. This includes a major enhancement in operational reliability, as unplanned shutdowns due to pump failures can be virtually eliminated. Consequently, this leads to significant financial savings by reducing the high costs associated with emergency repairs, downtime, and collateral damage. Furthermore, maintenance resources, including personnel and spare parts inventory, can be managed with far greater efficiency, deploying them precisely when and where they are needed, which also enhances the overall safety environment by mitigating the risk of catastrophic equipment failures.

Beyond the immediate benefits to Azura, this study serves as a crucial blueprint for the broader power generation industry in Nigeria and other developing economies. It provides a practical, real-world demonstration of the value of implementing Industry concepts, moving predictive maintenance from a theoretical concept to an applied solution. The successful implementation of this model can be replicated by other power plants, contributing to improved grid stability and a more reliable national power supply. This research also champions a necessary cultural shift within the industry, proving the tangible return on investment that comes from leveraging operational data for critical decision making.

The integration of Vibration Health Index (VHI) analysis provides a simplified method for evaluating machine health, enabling maintenance personnel to quickly detect abnormal vibration trends and implement predictive maintenance strategies.

Finally, the study holds considerable value for the academic and engineering research community. It contributes to the body of knowledge by applying and validating various predictive algorithms using a unique, real-world dataset from an active power plant, which is often difficult to acquire. This research offers insights into the practical challenges and successes of model implementation outside of a controlled laboratory setting. It also provides a valuable benchmark and a foundational dataset that can be used by other researchers to test, refine, and develop more sophisticated prognostic models, potentially incorporating deep learning or advanced IoT integrations for future reliability assessments.

1.6 Limitations of the Study

This research is subject to several key limitations, primarily defined by the data sourced from the Azura Power Plant. The predictive accuracy of the final model will be entirely dependent on the quality, completeness, and consistency of the historical operational and maintenance data provided. Any gaps in data logging, sensor inaccuracies, or poorly documented failure records will inherently limit the model's performance. Furthermore, the study is constrained by the existing sensor infrastructure at the plant; the model can only learn to predict failures based on the parameters that are currently monitored and will not be able to detect failure modes that are not captured by these sensors. The potential rarity of recorded failure events for these critical pumps may also present a limitation, as a highly imbalanced dataset can challenge the training of a robust predictive algorithm. Finally, the resulting model will be highly specialized for the specific centrifugal pumps and operating context of Azura, meaning its direct applicability and generalizability to other power plants or different types of equipment cannot be assumed without significant recalibration.

CHAPTER TWO

LITERATURE REVIEW

2.1 Concept of Maintenance and Predictive Maintenance

Maintenance is a fundamental aspect of industrial asset management that ensures equipment continues to perform its intended functions with reliability, safety, and efficiency. It comprises all technical and managerial activities aimed at preventing, detecting, and correcting equipment failures to maintain operational integrity (Mobley, 2019). Across industries such as power generation, oil and gas, and manufacturing, effective maintenance practices directly influence productivity, cost, and system availability. Historically, maintenance philosophies have evolved as industries sought to minimize production interruptions and extend equipment life cycles (Jardine, Lin, & Banjevic, 2006).

The progression from reactive to proactive maintenance marks one of the most significant developments in industrial reliability management. Earlier systems relied primarily on corrective maintenance repairing or replacing components only after failure. This approach, though simple, often led to excessive downtime, high costs, and safety risks. Preventive maintenance emerged later, emphasizing scheduled interventions based on time or usage intervals to prevent breakdowns before they occurred (Muchiri & Pintelon, 2018).

The limitations of both methods, particularly their inability to optimize maintenance intervals dynamically, led to the adoption of condition-based and predictive maintenance. Predictive maintenance integrates real-time data monitoring and analytical techniques to determine when failure is likely, thereby scheduling interventions only when necessary (Lee, Bagheri, & Kao, 2015).

2.1.1 Definition and Core Principles of Predictive Maintenance

Predictive maintenance (PdM) is a data-centric maintenance philosophy that forecasts the future health of equipment based on measured performance parameters and historical degradation patterns. It aims to predict the time to failure and optimize maintenance schedules accordingly (Randall, 2011). The approach is grounded in three technical layers: data acquisition, feature extraction, and predictive modeling. Data acquisition involves collecting measurable operational parameters such as vibration, temperature, pressure, and power output through sensors or monitoring systems. Feature extraction then processes these data into diagnostic indicators representing wear or performance decline. Finally, predictive modeling interprets the processed data to estimate the remaining useful life (RUL) or the probability of failure within a specified time frame (Mobley, 2019; Tsang, Jardine, & Kolodny, 1999).

2.1.2 Predictive Maintenance in Industrial Digitalization

Advances in digital technologies have elevated predictive maintenance into a key pillar of modern industrial systems. The rise of Industry 4.0 has enabled the integration of intelligent sensors, cloud computing, and machine learning algorithms for condition monitoring and fault prediction (Zhao, Jiang, & Xie, 2020). In many industrial facilities, sensors continuously record operational variables such as bearing temperature, discharge pressure, and motor current. These data are analyzed using predictive algorithms to detect anomalies and estimate degradation rates before failure occurs. Studies have shown that implementing predictive maintenance can reduce maintenance costs by up to 40 percent and increase asset availability by approximately 30 percent compared with traditional preventive strategies (Lee et al., 2015; Jardine et al., 2006).

2.1.3 Adoption and Challenges in African Industrial Operations

Across African industries, the concept of predictive maintenance has gradually gained traction, particularly in sectors that rely heavily on rotating machinery power generation, mining, cement production, and petrochemicals. Plants operating in regions with fluctuating environmental conditions, such as high ambient temperatures or unstable power supply, experience accelerated wear and tear of mechanical components. Consequently, the use of predictive maintenance to monitor equipment health is increasingly viewed as a cost-effective strategy for ensuring reliability. Empirical studies on maintenance practices in sub-Saharan industrial plants highlight that many facilities have begun transitioning from corrective and preventive maintenance toward data-driven predictive methods (Olawale & Ogundele, 2021).

In thermal power installations, predictive maintenance is particularly relevant due to the dependence of system performance on stable operation of centrifugal pumps, turbines, and compressors. The monitoring of parameters such as bearing temperature, discharge pressure, and generator output helps identify early signs of degradation. This is critical in operational environments where maintenance budgets are limited, and component replacements must be optimized for both cost and reliability. Moreover, recent analyses of maintenance performance in West African power utilities emphasize that the deployment of simple analytical tools such as Microsoft Excel for data trending and fault forecasting has allowed engineers to adopt predictive concepts even in the absence of sophisticated platforms (Adebayo & Ogunleye, 2022).

Predictive maintenance offers clear technical and economic advantages. It minimizes unexpected downtime, improves safety, optimizes spare-parts usage, and enhances energy efficiency. These benefits have been observed in multiple studies on industrial equipment management across developing economies (Alaswad & Xiang, 2017). Nevertheless, the approach demands consistent data collection, accurate calibration of sensors, and skilled personnel capable of interpreting analytical outputs. Challenges such as inadequate digital infrastructure, inconsistent data quality, and limited funding continue to slow widespread adoption in many industrial environments within Africa. Despite these barriers, the growing availability of low-cost sensors and digital tools supports the steady integration of predictive maintenance into reliability programs.

2.2 Centrifugal Pump System and Maintenance Requirements

Centrifugal pumps are among the most widely used fluid-handling machines in industrial systems, particularly in power generation, petrochemical, and water supply applications. Their reliability directly affects process continuity and overall plant efficiency. A centrifugal pump operates by converting mechanical energy from a rotating impeller into kinetic and potential energy in a liquid, causing it to flow from areas of low to high pressure (Stepanoff, 2017). The pump's design simplicity, robustness, and ability to handle a wide range of flow rates make it indispensable in thermal power plants where it circulates feedwater, lubricants, and cooling fluids essential for turbine and generator operation

.Figure 2.1: A Centrifugal Pump [Azura Power Plant]

2.2.1 Working Principle and Key Components

A typical centrifugal pump consists of several main components: the impeller, casing, shaft, bearings, seals, and suction and discharge nozzles. The impeller imparts velocity to the fluid, while the volute casing converts that velocity into pressure energy (Karassik, Messina, Cooper, & Heald, 2001). Bearings support the rotating shaft, ensuring stable alignment and smooth motion, while mechanical seals prevent leakage between the rotating and stationary parts. Any deterioration in these components affects overall pump performance and may lead to mechanical or hydraulic failure. Research indicates that over 60 percent of pump failures originate from bearing and seal degradation caused by inadequate lubrication, misalignment, or excessive vibration (Randall, 2011).

The hydraulic performance of a centrifugal pump depends on parameters such as discharge pressure, head, flow rate, and efficiency. Variations in these indicators are often early signs of performance decline. For instance, a gradual drop in discharge pressure or flow rate can signify impeller wear, partial clogging, or cavitation (Stein, 2019). Consequently, continuous monitoring of operational parameters enables early detection of such anomalies before they progress to critical failure.

2.2.2 Common Operational Faults and Failure Mechanisms

The most prevalent faults in centrifugal pumps include cavitation, impeller damage, seal leakage, bearing wear, and misalignment. Cavitation occurs when local fluid pressure drops below the vapor pressure, forming vapor bubbles that collapse violently and erode the impeller surface. This phenomenon not only reduces efficiency but also introduces high vibration and noise (Mujtaba, Ismail, & Kareem, 2019). Bearing wear is another major issue, often caused by improper lubrication, contamination, or excessive shaft loads. Seal failures typically result from thermal deformation or mechanical fatigue, leading to fluid leakage and environmental hazards.

Misalignment between the pump and motor shafts can accelerate bearing wear and induce excessive vibration, compromising system stability.

Empirical studies from industrial plants have shown that most of these faults develop gradually and can be detected through continuous monitoring of measurable indicators such as vibration amplitude, bearing temperature, and discharge pressure. For example, a slight increase in vibration magnitude in the horizontal plane may indicate early bearing degradation, while an abnormal temperature rise in the bearing housing could point to lubrication failure (Randall, 2011; Almasi, 2018). These parameters provide reliable diagnostic evidence for predictive maintenance strategies.

2.2.3 Maintenance Practices and Predictive Monitoring

Maintenance strategies for centrifugal pumps have evolved from manual inspections and time-based servicing to advanced predictive techniques using sensor data and analytics. Predictive maintenance relies on tracking operational variables such as ambient temperature, pump discharge pressure, and bearing temperature to estimate the remaining useful life of the pump (Mobley, 2019). In power plants, such data are often integrated into supervisory control and data acquisition (SCADA) systems for real-time monitoring. However, in facilities with limited automation infrastructure, analytical tools such as Microsoft Excel can be used to store, visualize, and analyze these parameters over time to identify performance trends and forecast failures.

Researchers have demonstrated that basic statistical models implemented in Excel, including linear regression and moving average trend analysis, can effectively capture degradation patterns when applied to consistent and accurate datasets (Adebayo & Ogunleye, 2022). For instance, tracking changes in discharge pressure and bearing temperature over several operating cycles can help engineers predict when efficiency will fall below acceptable limits. The simplicity and accessibility of such methods make them suitable for power plants that lack high-end predictive platforms, thereby promoting data driven maintenance even under resource constraints (Olawale & Ogundele, 2021).

2.2.4 Centrifugal Pumps in Power Generation Systems

In thermal power generation, centrifugal pumps perform critical functions such as circulating feedwater through boilers, supplying cooling water to condensers, and maintaining lubrication flow to turbines. Their reliability is directly tied to the stability of power output and overall system safety. Unplanned pump failures can lead to turbine trips, loss of generation, or even equipment damage. Therefore, implementing predictive maintenance on these pumps is essential for optimizing power plant performance (Kareem, Adeoye, & Afolabi, 2020).

In several African power facilities, including gas-fired plants, maintenance teams have increasingly adopted predictive techniques to improve reliability. Regular monitoring of pump discharge pressure, bearing condition, and generator load has proven effective in identifying early degradation trends (Adebayo & Ogunleye, 2022). This approach ensures that maintenance interventions are both timely and cost-effective. Furthermore, the incorporation of simple data analysis tools has allowed local engineers to develop customized models suited to their operational conditions, thus strengthening the reliability culture across the energy sector.

2.3 Predictive Maintenance Principles and Enabling Technologies

Predictive maintenance (PdM) is a proactive maintenance strategy that uses real-time and historical data to predict when equipment failure is likely to occur, thereby allowing maintenance actions to be performed just in time to prevent downtime. Unlike corrective or preventive maintenance, predictive maintenance relies on measurable indicators of equipment condition to make maintenance decisions. This approach is grounded in the principle that most failures are preceded by identifiable signs of degradation such as temperature rise, vibration increase, or pressure variation which can be detected and analyzed before total breakdown occurs (Mobley, 2019). The integration of condition monitoring systems and analytical models makes predictive maintenance a critical tool for enhancing equipment reliability and minimizing unplanned outages in industrial operations.

2.3.1 Fundamental Concepts of Predictive Maintenance

The core objective of predictive maintenance is to determine the remaining useful life (RUL) of a machine component. This is achieved by continuously monitoring critical performance parameters and identifying deviations from normal operational baselines. The data collected from sensors or manual recordings are analyzed to establish trends and correlations between measurable parameters and failure modes (Jardine, Lin, & Banjevic, 2006). Predictive maintenance therefore transforms maintenance management from a reactive process into a data-driven decision-making system. In centrifugal pump applications, parameters such as bearing temperature, discharge pressure, vibration level, and ambient temperature are effective indicators for predicting mechanical degradation (Almasi, 2018).

The underlying philosophy is that equipment condition evolves in a predictable pattern, following what is known as the P–F curve. This curve illustrates the interval between the point where potential failure (P) can first be detected and the point of functional failure (F) (Mobley, 2019). The earlier the potential failure is detected, the greater the opportunity for maintenance intervention. Predictive maintenance leverages this concept by identifying and acting within the P–F interval, thereby preventing catastrophic breakdowns and extending component life.

2.3.2 Key Predictive Maintenance Techniques

Predictive maintenance encompasses several analytical and monitoring techniques. Among the most common are vibration analysis, temperature monitoring, oil analysis, and performance trend monitoring.

Vibration analysis is particularly important for rotating equipment such as centrifugal pumps, as abnormal vibration signatures can reveal imbalance, misalignment, or bearing wear (Randall, 2011). Temperature monitoring provides early warning of friction-related issues or lubrication failure. Oil analysis helps identify contamination or chemical degradation, which often precedes bearing and seal failures (Tian, Jin, & Wu, 2020).

Performance trend monitoring, which can be performed using statistical tools in software like Microsoft Excel, focuses on observing gradual changes in operational parameters such as discharge pressure, flow rate, or active power to forecast performance decline (Olawale & Ogundele, 2021). Each of these techniques generates data that reflect the machine’s health status. The predictive models developed from these data can be statistical, probabilistic, or machine learning-based, depending on data availability and computational capacity. In resource constrained environments such as many African industries, simple regression models and trend analysis in Excel have proven effective for achieving similar reliability outcomes at minimal cost (Adebayo & Ogunleye, 2022).

2.3.3 Data Acquisition and Processing in Predictive Maintenance

The effectiveness of predictive maintenance depends largely on data accuracy and processing techniques. Data acquisition involves capturing relevant operational parameters through sensors or digital control systems. In modern industrial systems, these data are often transmitted to centralized databases or supervisory systems for analysis. However, in smaller or less automated plants—such as many within the Nigerian power sector—manual data collection and analysis using spreadsheet software remain prevalent (Kareem, Adeoye, & Afolabi, 2020).

Microsoft Excel provides a practical environment for developing predictive models through built-in functions such as regression analysis, moving averages, and correlation testing. These functions can be used to identify relationships between variables like bearing temperature and discharge pressure, thereby predicting failure onset. For example, a strong negative correlation between discharge pressure and bearing temperature over time could indicate mechanical friction or flow obstruction (Adebayo & Ogunleye, 2022). With structured data collection and periodic updates, Excel can serve as an accessible predictive maintenance platform for facilities lacking specialized software tools.

2.3.4 Integration of Predictive Maintenance in Power Plants

In thermal power plants, including the Azura Power Plant, predictive maintenance plays a central role in ensuring the reliability of rotating equipment such as centrifugal pumps, compressors, and turbines. The integration of predictive maintenance into routine operations enables maintenance teams to make informed decisions based on real-time performance indicators. By analyzing parameters such as ambient temperature, pump discharge pressure, gas turbine (GT) active power, and bearing temperature, engineers can 18identify subtle deviations from normal operating ranges that signal developing faults (Olawale & Ogundele, 2021).

Empirical findings across African power facilities demonstrate that implementing predictive maintenance has significantly reduced unscheduled downtime and maintenance costs. For instance, Adebayo and Ogunleye (2022) reported that using temperature and pressure monitoring in Nigerian gas turbine plants reduced failure frequency by over 25%. Similarly, Kareem et al. (2020) found that data-driven predictive models developed using locally available tools improved component availability by enhancing maintenance planning accuracy. These studies affirm the practical feasibility of predictive maintenance even in developing economies, provided data are systematically recorded and analyzed.

2.3.5 Benefits and Challenges of Predictive Maintenance Implementation

The advantages of predictive maintenance include reduced maintenance costs, increased equipment availability, extended asset life, and improved safety. By predicting failures before they occur, organizations can schedule maintenance activities at optimal times, minimizing downtime and avoiding unnecessary part replacements (Mobley, 2019).

Additionally, predictive maintenance enhances overall system reliability and efficiency by maintaining equipment at its optimal performance level.

However, the implementation of predictive maintenance is not without challenges. The primary limitations include the high initial cost of sensors, data acquisition systems, and analytical software. In developing contexts such as Nigeria, inadequate technical expertise and poor data quality also hinder widespread adoption (Olawale & Ogundele, 2021).

Moreover, organizational resistance to change from traditional maintenance approaches remains a barrier in many industries. Nevertheless, the growing accessibility of digital tools such as Excel and open-source analytics platforms is gradually bridging this gap, allowing local engineers to build effective predictive frameworks with limited resources (Adebayo & Ogunleye, 2022).

2.4 Predictive Maintenance Modeling Approaches

Predictive maintenance modeling involves the use of mathematical, statistical, and computational tools to forecast equipment failure based on measured operational data. The goal is to determine the health condition of a machine and estimate its remaining useful life (RUL). For rotating equipment such as centrifugal pumps, modeling enables early fault detection, trend prediction, and maintenance scheduling, which collectively improve system reliability and cost efficiency. Predictive models range from traditional statistical techniques to advanced data-driven and hybrid methods, each offering unique benefits depending on the available data, computational resources, and operational environment (Jardine, Lin, & Banjevic, 2006).

2.4.1 Statistical-Based Predictive Models

Statistical models are among the earliest and most widely used approaches in predictive maintenance due to their simplicity and interpretability. They rely on historical data to establish patterns between equipment performance parameters and failure events.

Techniques such as linear regression, multiple regression, and moving average analysis are frequently used to model degradation trends (Mobley, 2019). For instance, a linear regression model can relate pump discharge pressure decline to increasing bearing temperature, thereby quantifying the relationship between wear and performance loss. These models are particularly effective when the data are continuous and show clear linear correlations.

In many Nigerian industrial settings, including power plants, engineers use Microsoft Excel to implement statistical predictive models. Excel's regression and correlation tools enable maintenance teams to identify patterns and estimate failure intervals without requiring complex programming knowledge (Adebayo & Ogunleye, 2022). Such models are not only cost-effective but also suitable for environments where data collection infrastructure is limited. For example, a predictive maintenance model developed for the Azura Power Plant could use time-series data of pump discharge pressure, bearing temperature, ambient temperature, and gas turbine active power to predict when maintenance should be scheduled. This approach allows maintenance to be planned based on data-driven evidence rather than assumptions

.

2.4.2 Condition-Based and Probabilistic Models

Condition-based models focus on evaluating the current health state of equipment by comparing real-time operational data with reference or threshold values. These models typically use condition indicators such as vibration amplitude, temperature deviation, or flow pressure drop to trigger maintenance decisions (Randall, 2011). For centrifugal pumps, condition-based monitoring is particularly effective because degradation often manifests gradually, providing sufficient time to intervene before catastrophic failure occurs.

Probabilistic models extend this concept by incorporating uncertainty into failure prediction. They recognize that degradation processes are influenced by random factors such as load fluctuations, environmental conditions, and material inconsistencies. Methods like Weibull analysis, Bayesian inference, and Markov models are used to estimate the probability distribution of time-to-failure (Tian, Jin, & Wu, 2020). These models enable engineers to make risk-informed maintenance decisions, balancing reliability with operational cost. In the context of Nigerian power systems, probabilistic approaches can improve resource allocation by estimating the likelihood of pump failure under variable operating conditions (Olawale & Ogundele, 2021).

2.4.3 Machine Learning and Data-Driven Models

Machine learning (ML) approaches have gained prominence in predictive maintenance due to their ability to capture complex, nonlinear relationships among multiple variables.

Algorithms such as decision trees, artificial neural networks (ANN), and support vector machines (SVM) can process large datasets to detect patterns that traditional models may overlook (Tian et al., 2020). These techniques are particularly useful when dealing with multidimensional sensor data from rotating equipment, where interactions between parameters like vibration, temperature, and load are not easily defined mathematically.

For example, an ANN model trained with historical pump data can predict failure by learning from past temperature, pressure, and power readings. Once trained, the model can classify the equipment's condition as "normal," "degrading," or "critical" based on realtime inputs. However, these models require significant computational resources, quality data, and specialized expertise, which limits their adoption in some developing regions.

Nigerian power plants, therefore, often adopt hybrid solutions combining simple statistical analysis in Excel with periodic expert interpretation to achieve predictive maintenance without extensive infrastructure (Adebayo & Ogunleye, 2022).

2.4.4 Vibration Health Index (VHI)

The Vibration Health Index (VHI) is a condition monitoring parameter used to evaluate the overall health of rotating machinery based on vibration measurements. Instead of analyzing several vibration parameters individually, VHI combines multiple vibration indicators into a single index that represents the machine's operational state.

The use of VHI has become increasingly popular in predictive maintenance programs because it simplifies machine condition monitoring and allows engineers to quickly detect abnormal vibration patterns. When VHI values exceed acceptable limits, it may indicate mechanical faults such as imbalance, misalignment, looseness, or bearing defects.

In industrial applications, VHI analysis is often combined with predictive models and simulation techniques to improve fault detection and maintenance planning. By monitoring the variation of VHI over time, maintenance personnel can assess equipment degradation and schedule maintenance activities before catastrophic failures occur.

2.4.5 Hybrid and Simulation-Based Models

Hybrid predictive models combine different modeling techniques to leverage their respective strengths. For instance, a hybrid model may integrate regression analysis with vibration-based fault detection to provide a more comprehensive assessment of pump health. Simulation-based models, such as Monte Carlo simulations, are also used to account for random variability in operational data and to predict equipment reliability under multiple scenarios (Jardine et al., 2006). These methods enhance prediction accuracy by combining deterministic relationships with probabilistic uncertainty.

Simulation approaches are particularly useful for plants like Azura, where operating conditions vary with load demand and environmental temperature. By simulating different operating profiles, engineers can estimate how changes in discharge pressure or ambient temperature affect the expected lifespan of a centrifugal pump. The results of such simulations can guide decisions on spare parts procurement, maintenance scheduling, and operational adjustments to extend equipment life (Kareem, Adeoye, & Afolabi, 2020).

2.4.6 Model Development Using Microsoft Excel

Excel remains a practical tool in many African industries due to its accessibility and ease of use. Engineers can build predictive maintenance models in Excel by organizing timeseries data, calculating correlations, and performing trend extrapolation using built-in functions. For example, moving average analysis can be used to smooth fluctuations in bearing temperature data, while regression functions can predict discharge pressure decline over time (Olawale & Ogundele, 2021). Visual tools such as scatter plots and trend lines, further support diagnostic interpretation, making Excel-based modeling a feasible solution for facilities without advanced computing capabilities.

In the Azura Power Plant context, Excel-based models can integrate operational input ambient temperature, discharge pressure, GT active power, and vibration levels to monitor pump health. By applying linear regression to historical records, maintenance teams can estimate the expected point of performance decline and preemptively plan interventions. This practical approach aligns with local resource availability while promoting reliability-centered maintenance practices.

2.5 Applications of Predictive maintenance in Power Plant

Predictive maintenance has become a cornerstone of reliability-centered management in modern power plants. It applies data-driven techniques and sensor-based monitoring to anticipate equipment failure before it occurs, thereby reducing downtime and maintenance costs while extending asset lifespan (Mobley, 2019). In power generation systems, the complexity and criticality of rotating equipment such as turbines, pumps, compressors, and generators make predictive maintenance particularly valuable. By continuously tracking process variables like temperature, vibration, and pressure, engineers can forecast failures and schedule maintenance actions during planned outages, avoiding costly unplanned shutdowns (Jardine, Lin, & Banjevic, 2006).

Globally, predictive maintenance has been successfully integrated into both fossil-fuel and renewable energy facilities. In the United States and Europe, power utilities employ advanced analytics, Internet of Things (IoT) frameworks, and machine learning algorithms to monitor large-scale turbines and auxiliary systems (Lee, Bagheri, & Kao, 2015). These systems utilize real-time data streams from Supervisory Control and Data Acquisition (SCADA) systems and sensor networks to predict mechanical wear or electrical degradation. For instance, vibration-based condition monitoring models have been used to detect early bearing wear in cooling water pumps, reducing total maintenance expenditure by up to 30% (Eren & Inal, 2020). In Asian power plants, predictive systems integrated with neural network algorithms have improved decision accuracy and operational efficiency (Huang et al., 2019). In the African context, and particularly in Nigeria, the application of predictive maintenance is still emerging but growing steadily as the power sector modernizes. Nigerian plants have historically relied on reactive or preventive maintenance, leading to high operational costs and frequent equipment failure (Olawale & Ogundele, 2021).

However, recent studies and practical implementations have demonstrated the potential of predictive maintenance to transform plant reliability. At facilities such as Egbin Thermal Power Station and Azura-Edo Independent Power Plant, predictive maintenance is increasingly being adopted for critical systems like centrifugal pumps, gas turbines, and cooling water circuits. Using accessible tools such as Microsoft Excel, plant engineers analyze data on parameters like ambient temperature, pump discharge pressure, gas turbine active power, and bearing temperature to identify degradation patterns and forecast optimal maintenance intervals (Adebayo & Ogunleye, 2022; Kareem, Adeoye, & Afolabi, 2020).

Although many Nigerian plants face constraints such as inadequate sensor infrastructure, irregular data logging, and limited technical expertise, these challenges have prompted the use of simplified predictive models and low-cost diagnostic tools. Such approaches have still yielded measurable improvements in equipment availability and reduced maintenance frequency (Nwankwo & Akintunde, 2023). Consequently, predictive maintenance represents a critical step toward achieving operational stability in Nigeria’s power sector. It supports sustainable plant management by combining data analytics with traditional engineering insight, paving the way for digital transformation and energy efficiency in the region’s industrial operations.

2.6 Research Gap and Conceptual Framework

Despite significant progress in predictive maintenance research and implementation, several gaps remain especially in the context of power generation systems in developing economies such as Nigeria. Most existing studies on predictive maintenance models have been conducted in technologically advanced countries, focusing on high-end data acquisition systems, complex machine learning models, and fully automated diagnostic platforms (Lee, Bagheri, & Kao, 2015; Jardine, Lin, & Banjevic, 2006). While these frameworks demonstrate high predictive accuracy, they rely heavily on sophisticated infrastructure, sensor integration, and advanced computing capabilities that are not readily available in most African power facilities. Consequently, there is limited practical knowledge of how predictive maintenance can be effectively adapted using low-cost, accessible tools in resource-constrained environments.

In the Nigerian power sector, maintenance activities for rotating equipment such as centrifugal pumps are still largely reactive or preventive rather than predictive (Olawale & Ogundele, 2021). Frequent breakdowns, inconsistent data collection, and weak maintenance culture lead to unplanned downtime and reduced operational efficiency.

Although some studies have attempted to apply condition monitoring and trend analysis, most lack comprehensive data modeling that links real operational variables—such as ambient temperature, discharge pressure, gas turbine active power, and bearing temperature—to predictive outcomes (Adebayo & Ogunleye, 2022). The gap therefore lies in developing a simple yet effective predictive maintenance model that can use these parameters to forecast equipment health and schedule maintenance optimally. Another key gap exists in the integration of predictive maintenance with decision-making frameworks at plant level. Many existing models are theoretical or simulation-based, without validation using real plant data. In Nigeria, where data availability and reliability are inconsistent, there is a need to establish models that function effectively under uncertainty, limited instrumentation, and sparse datasets (Kareem, Adeoye, & Afolabi, 2020). The present study addresses this gap by developing a predictive maintenance model for a centrifugal pump using operational data from Azura Power Plant. By applying statistical trend analysis and correlation methods within Microsoft Excel, the model demonstrates that meaningful predictive insights can be achieved using basic computational tools when the right parameters are selected and analyzed systematically.

The conceptual framework for this study is built around the relationship between operational parameters, data analysis techniques, and maintenance decisions. Ambient temperature, discharge pressure, gas turbine active power, and bearing temperature act as the independent variables influencing the pump's operational condition. Data collected from these variables are analyzed to identify degradation trends and predict potential failure points. The predictive model then informs maintenance scheduling, forming a feedback loop that improves reliability and minimizes unscheduled downtime. In this framework, predictive maintenance serves as the mediating variable between equipment condition and plant performance, ensuring that maintenance actions are driven by evidence rather than routine or guesswork. This conceptual structure provides the foundation upon which the study's predictive model is ds developed and validated for application within the Azura Power Plant context.

CHAPTER THREE

METHODOLOGY

3.1 Research Design

This study adopts a quantitative, data-driven predictive maintenance research design aimed at assessing the performance and mechanical health of a centrifugal pump used in a gas turbine cooling water system. The research design is structured to analyze historical operational data in order to detect degradation trends, evaluate system behavior over time, and develop an early warning framework for maintenance decision-making.

The research is based on secondary data analysis, utilizing historical sensor measurements collected during the normal operation of the pump. These measurements include vibration, discharge pressure, ambient temperature, and gas turbine active power, recorded over two consecutive years. The use of historical operational data allows the study to reflect real-world operating conditions without interfering with the system’s functionality.

A predictive maintenance approach is employed rather than a corrective or preventive maintenance framework. This approach focuses on identifying early signs of degradation before the occurrence of failure by analyzing patterns and trends in sensor data. Instead of waiting for breakdowns or relying solely on scheduled maintenance intervals, the research design emphasizes condition-based monitoring using measurable performance and health indicators.

The study combines statistical analysis and mathematical modeling as its primary analytical tools. Descriptive statistical methods are used to summarize and understand the general behavior of the pump parameters over time, while regression analysis is applied to explore relationships between key operational variables. In addition, a vibration-based health modeling approach is implemented through the development of a Vibration Health Index (VHI). This index provides a normalized and quantitative measure of the pump's mechanical condition, enabling effective comparison across different time periods.

Given the nature of the available data, which consists of monthly RMS sensor values, the research design emphasizes trend analysis rather than detailed fault diagnosis. This makes the approach suitable for long-term condition monitoring and degradation assessment. High-frequency vibration signal processing techniques such as frequency spectrum or FFT analysis are not adopted, as they require time-domain waveform data which is not available in the dataset. Instead, the study focuses on identifying gradual changes and abnormal deviations that may indicate declining performance or increased mechanical stress.

To ensure robustness, the research design incorporates a model development and validation framework. One year of historical data is used to develop the predictive maintenance model, while data from the subsequent year is reserved for model verification and comparative analysis. This structure allows the effectiveness and consistency of the developed health indicators to be evaluated over time.

Overall, the research design is systematic, practical, and aligned with industrial condition monitoring practices. It ensures that the developed predictive maintenance model is not only theoretically sound but also applicable to real operational environments. The design supports the achievement of the study's aim and objectives by integrating data acquisition, statistical analysis, health modeling, and early warning assessment into a cohesive methodological framework.

3.2 Description of the Study System

The study system considered in this research is a centrifugal pump operating as part of a gas turbine-cooling water system. The pump plays a critical role in maintaining safe and efficient operation of the gas turbine by circulating cooling water required to dissipate excess heat generated during turbine operation. Reliable performance of the pump is therefore essential, as any degradation or failure could adversely affect the overall efficiency, safety, and availability of the power generation system.

The centrifugal pump operates by converting mechanical energy from the driving motor into hydraulic energy, resulting in an increase in fluid pressure and flow rate. The pump is designed to operate continuously under varying load conditions, depending on turbine demand, ambient conditions, and system requirements. Due to this continuous and demanding operation, the pump is susceptible to mechanical wear, hydraulic stress, and performance degradation over time.

The pump is equipped with several sensors installed at strategic locations to monitor its operational and mechanical condition. These sensors provide measurements of key parameters such as vibration, discharge pressure, ambient temperature, and gas turbine active power. Vibration sensors are mounted near the pump bearings to capture mechanical response during operation, while pressure sensors measure the discharge pressure to evaluate hydraulic performance. Ambient temperature measurements are included to account for environmental effects on system behavior, and gas turbine active power serves as an indicator of system load and operating demand.

Among the vibration measurements available, axial vibration is of particular importance in this study. Axial vibration is closely related to thrust forces acting on the pump shaft and impeller, which are influenced by hydraulic loading, impeller condition, and operating point relative to the pump's best efficiency point. Changes in axial vibration therefore provide valuable insight into the mechanical health and performance condition of the pump, making it a suitable parameter for condition monitoring and degradation assessment.

The operational data used in this study were collected during normal plant operation without any experimental intervention. The data consists of monthly averaged RMS values recorded over a one-year period for model development, with an additional year reserved for model verification. This data structure reflects typical industrial monitoring practices where long-term trends are used to support maintenance planning and asset management decisions.

The study system is representative of industrial centrifugal pump installations commonly used in power plants and process industries. As such, the findings and methodologies developed in this research can be generalized to similar pumping systems operating under comparable conditions. By focusing on real operational data from an active cooling water system, the study ensures that the developed predictive maintenance approach remains practical, realistic, and applicable to industrial environments.

3.3 Data Collection

The data used in this study were obtained from historical operational records of a centrifugal pump operating within a gas turbine cooling water system. The dataset consists of secondary data collected during routine plant operation as part of the facility's condition monitoring and performance tracking activities. Since the data were generated from an existing industrial monitoring system, no direct experimental measurements or physical interventions were carried out during the course of this research.

The study utilizes two consecutive years of operational data. One year of data was used for model development and analysis, while the subsequent year was reserved for model verification and comparison. This approach supports the evaluation of the predictive maintenance model's consistency and reliability over time. The primary focus of the analysis was on the 2023 dataset, which served as the baseline for trend analysis, regression modeling, and vibration health index development.

The collected data include monthly averaged measurements of axial vibration, pump discharge pressure, ambient temperature, and gas turbine active power. Axial vibration data were recorded as RMS values, providing a measure of the overall vibration energy of the pump in the axial direction. These measurements were obtained from vibration sensors installed near the pump bearing locations. Discharge pressure data were collected from pressure sensors located at the pump outlet, allowing assessment of the pump's hydraulic performance. Ambient temperature data were included to account for environmental effects on system behavior, while gas turbine active power served as an indicator of operating load and demand on the cooling system.

All data were initially stored in spreadsheet format and organized by month to reflect long-term operational trends. The use of monthly averaged data aligns with common industrial practices for performance monitoring and maintenance planning, where long-term trends are often more valuable than short-duration fluctuations. Although high-frequency vibration waveform data were not available, the RMS vibration values provided sufficient information for trend-based condition monitoring and degradation assessment.

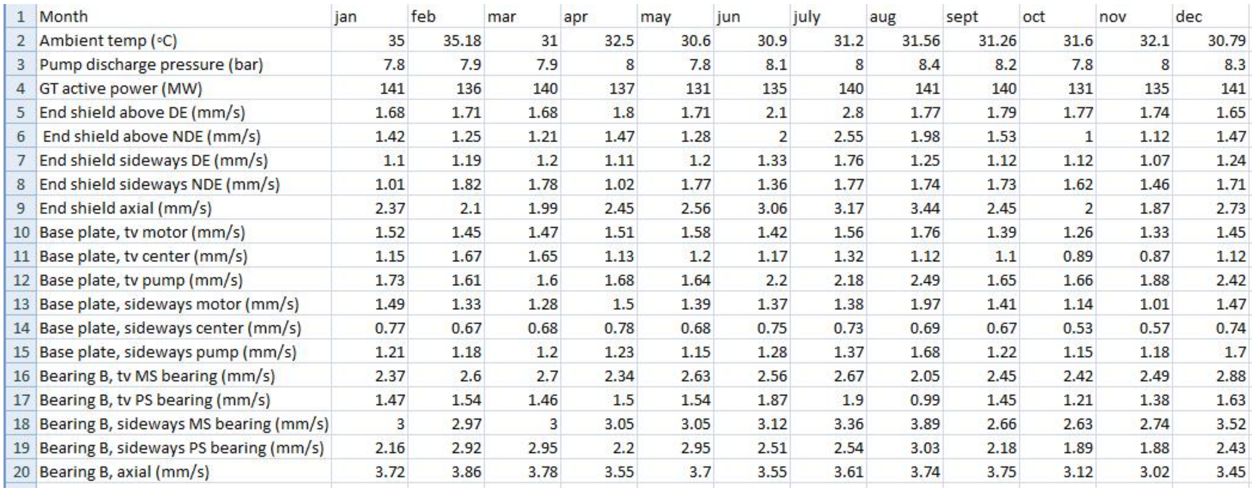
Prior to analysis, the collected datasets were reviewed for completeness and consistency. Data formatting was standardized to ensure uniformity across variables and time periods. Where necessary, minor adjustments were made to align measurement units and ensure accurate comparison between parameters. No synthetic or simulated data were introduced, and all analyses were based solely on measured operational values.

The data sources used in this study are considered reliable, as they were obtained from calibrated industrial sensors and recorded under actual operating conditions. This enhances the credibility of the analysis and ensures that the developed predictive maintenance model reflects realistic system behavior. By relying on real historical data, the study provides practical insights that can be directly applied to maintenance planning and operational decision-making in similar industrial pump systems.

3.4 Data Preprocessing and Organization

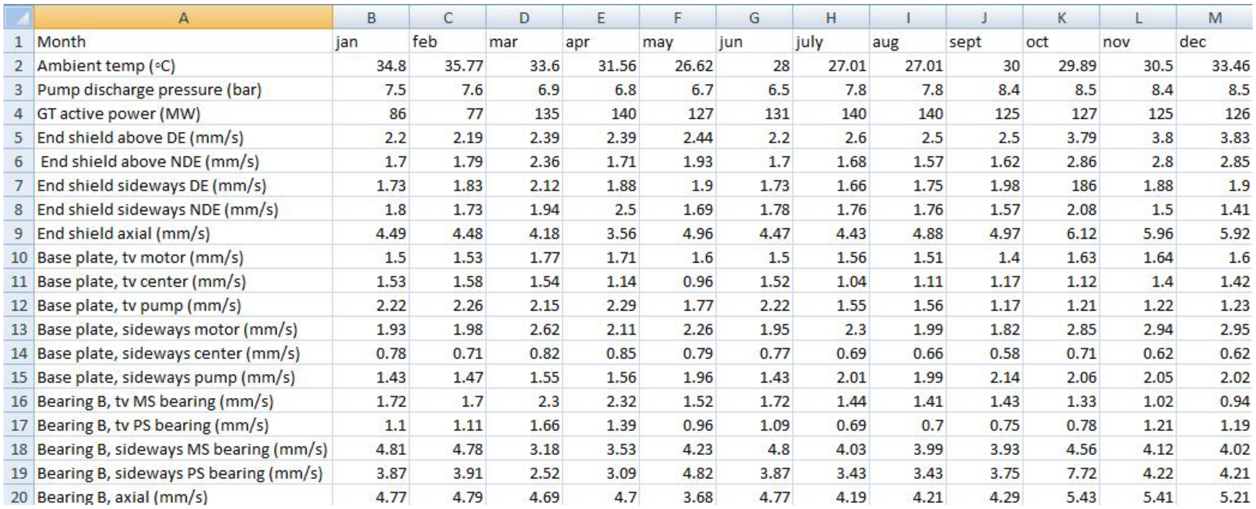
Data preprocessing was carried out to prepare the collected operational data for statistical analysis and predictive model development. Since the data were obtained from an industrial monitoring system and recorded during normal plant operation, preprocessing focused on organizing the data, ensuring consistency, and structuring the dataset for time-based analysis rather than extensive data cleaning or transformation.

Table 3.1: Monthly data readings for 2023



1	Month	jan	feb	mar	apr	may	jun	july	aug	sept	oct	nov	dec
2	Ambient temp (◦C)	35	35.18	31	32.5	30.6	30.9	31.2	31.56	31.26	31.6	32.1	30.79
3	Pump discharge pressure (bar)	7.8	7.9	7.9	8	7.8	8.1	8	8.4	8.2	7.8	8	8.3
4	GT active power (MW)	141	136	140	137	131	135	140	141	140	131	135	141
5	End shield above DE (mm/s)	1.68	1.71	1.68	1.8	1.71	2.1	2.8	1.77	1.79	1.77	1.74	1.65
6	End shield above NDE (mm/s)	1.42	1.25	1.21	1.47	1.28	2	2.55	1.98	1.53	1	1.12	1.47
7	End shield sideways DE (mm/s)	1.1	1.19	1.2	1.11	1.2	1.33	1.76	1.25	1.12	1.12	1.07	1.24
8	End shield sideways NDE (mm/s)	1.01	1.82	1.78	1.02	1.77	1.36	1.77	1.74	1.73	1.62	1.46	1.71
9	End shield axial (mm/s)	2.37	2.1	1.99	2.45	2.56	3.06	3.17	3.44	2.45	2	1.87	2.73
10	Base plate, tv motor (mm/s)	1.52	1.45	1.47	1.51	1.58	1.42	1.56	1.76	1.39	1.26	1.33	1.45
11	Base plate, tv center (mm/s)	1.15	1.67	1.65	1.13	1.2	1.17	1.32	1.12	1.1	0.89	0.87	1.12
12	Base plate, tv pump (mm/s)	1.73	1.61	1.6	1.68	1.64	2.2	2.18	2.49	1.65	1.66	1.88	2.42
13	Base plate, sideways motor (mm/s)	1.49	1.33	1.28	1.5	1.39	1.37	1.38	1.97	1.41	1.14	1.01	1.47
14	Base plate, sideways center (mm/s)	0.77	0.67	0.68	0.78	0.68	0.75	0.73	0.69	0.67	0.53	0.57	0.74
15	Base plate, sideways pump (mm/s)	1.21	1.18	1.2	1.23	1.15	1.28	1.37	1.68	1.22	1.15	1.18	1.7
16	Bearing B, tv MS bearing (mm/s)	2.37	2.6	2.7	2.34	2.63	2.56	2.67	2.05	2.45	2.42	2.49	2.88
17	Bearing B, tv PS bearing (mm/s)	1.47	1.54	1.46	1.5	1.54	1.87	1.9	0.99	1.45	1.21	1.38	1.63
18	Bearing B, sideways MS bearing (mm/s)	3	2.97	3	3.05	3.05	3.12	3.36	3.89	2.66	2.63	2.74	3.52
19	Bearing B, sideways PS bearing (mm/s)	2.16	2.92	2.95	2.2	2.95	2.51	2.54	3.03	2.18	1.89	1.88	2.43
20	Bearing B, axial (mm/s)	3.72	3.86	3.78	3.55	3.7	3.55	3.61	3.74	3.75	3.12	3.02	3.45

Table 3.2: Monthly data readings for 2024

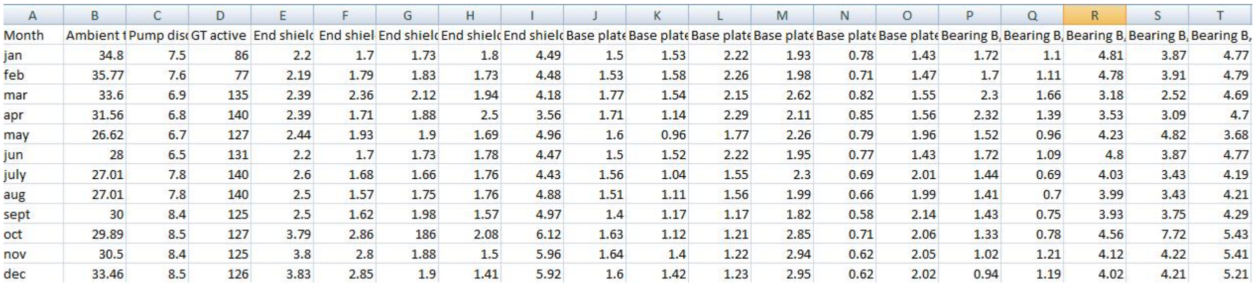


	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Month	jan	feb	mar	apr	may	jun	july	aug	sept	oct	nov	dec
2	Ambient temp (◦C)	34.8	35.77	33.6	31.56	26.62	28	27.01	27.01	30	29.89	30.5	33.46
3	Pump discharge pressure (bar)	7.5	7.6	6.9	6.8	6.7	6.5	7.8	7.8	8.4	8.5	8.4	8.5
4	GT active power (MW)	86	77	135	140	127	131	140	140	125	127	125	126
5	End shield above DE (mm/s)	2.2	2.19	2.39	2.39	2.44	2.2	2.6	2.5	2.5	3.79	3.8	3.83
6	End shield above NDE (mm/s)	1.7	1.79	2.36	1.71	1.93	1.7	1.68	1.57	1.62	2.86	2.8	2.85
7	End shield sideways DE (mm/s)	1.73	1.83	2.12	1.88	1.9	1.73	1.66	1.75	1.98	186	1.88	1.9
8	End shield sideways NDE (mm/s)	1.8	1.73	1.94	2.5	1.69	1.78	1.76	1.76	1.57	2.08	1.5	1.41
9	End shield axial (mm/s)	4.49	4.48	4.18	3.56	4.96	4.47	4.43	4.88	4.97	6.12	5.96	5.92
10	Base plate, tv motor (mm/s)	1.5	1.53	1.77	1.71	1.6	1.5	1.56	1.51	1.4	1.63	1.64	1.6
11	Base plate, tv center (mm/s)	1.53	1.58	1.54	1.14	0.96	1.52	1.04	1.11	1.17	1.12	1.4	1.42
12	Base plate, tv pump (mm/s)	2.22	2.26	2.15	2.29	1.77	2.22	1.55	1.56	1.17	1.21	1.22	1.23
13	Base plate, sideways motor (mm/s)	1.93	1.98	2.62	2.11	2.26	1.95	2.3	1.99	1.82	2.85	2.94	2.95
14	Base plate, sideways center (mm/s)	0.78	0.71	0.82	0.85	0.79	0.77	0.69	0.66	0.58	0.71	0.62	0.62
15	Base plate, sideways pump (mm/s)	1.43	1.47	1.55	1.56	1.96	1.43	2.01	1.99	2.14	2.06	2.05	2.02
16	Bearing B, tv MS bearing (mm/s)	1.72	1.7	2.3	2.32	1.52	1.72	1.44	1.41	1.43	1.33	1.02	0.94
17	Bearing B, tv PS bearing (mm/s)	1.1	1.11	1.66	1.39	0.96	1.09	0.69	0.7	0.75	0.78	1.21	1.19
18	Bearing B, sideways MS bearing (mm/s)	4.81	4.78	3.18	3.53	4.23	4.8	4.03	3.99	3.93	4.56	4.12	4.02
19	Bearing B, sideways PS bearing (mm/s)	3.87	3.91	2.52	3.09	4.82	3.87	3.43	3.43	3.75	7.72	4.22	4.21
20	Bearing B, axial (mm/s)	4.77	4.79	4.69	4.7	3.68	4.77	4.19	4.21	4.29	5.43	5.41	5.21

The raw datasets were obtained in spreadsheet format and consisted of monthly averaged sensor measurements recorded over the study period. Each dataset was reviewed to confirm correct labeling of variables, chronological ordering, and completeness of records. Time was represented in months to preserve the temporal nature of the pump’s operational behavior, allowing trends and variations to be evaluated over time.

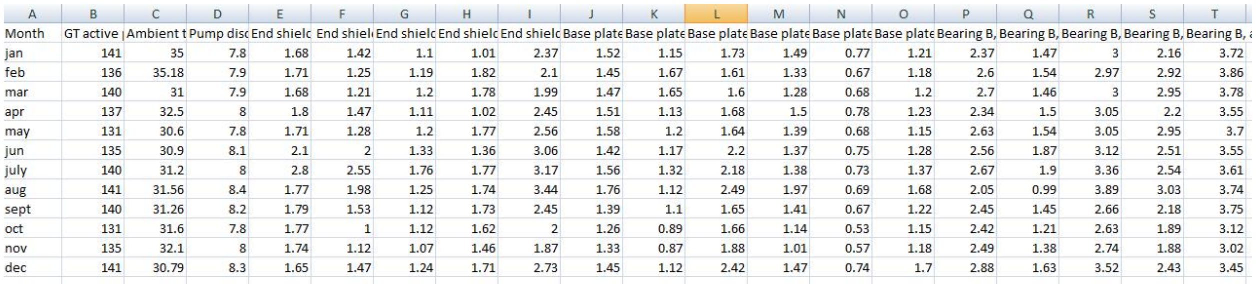
The operational parameters considered in the study include axial RMS vibration, pump discharge pressure, ambient temperature, and gas turbine active power. These variables were arranged in separate columns, with each row representing a single month of operation. Where necessary, data tables were transposed to ensure uniform alignment of time-series data across all variables and to facilitate subsequent statistical and regression analysis.

Table 3.3: Transposed data for 2023



A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Month	Ambient t	Pump disc	GT active	End shiel	End shiel	End shiel	End shiel	End shiel	Base plat	Base plat	Base plat	Base plat	Base plat	Base plat	Bearing B,	Bearing B,	Bearing B,	Bearing B,	Bearing B,
jan	34.8	7.5	86	2.2	1.7	1.73	1.8	4.49	1.5	1.53	2.22	1.93	0.78	1.43	1.72	1.1	4.81	3.87	4.77
feb	35.77	7.6	77	2.19	1.79	1.83	1.73	4.48	1.53	1.58	2.26	1.98	0.71	1.47	1.7	1.11	4.78	3.91	4.79
mar	33.6	6.9	135	2.39	2.36	2.12	1.94	4.18	1.77	1.54	2.15	2.62	0.82	1.55	2.3	1.66	3.18	2.52	4.69
apr	31.56	6.8	140	2.39	1.71	1.88	2.5	3.56	1.71	1.14	2.29	2.11	0.85	1.56	2.32	1.39	3.53	3.09	4.7
may	26.62	6.7	127	2.44	1.93	1.9	1.69	4.96	1.6	0.96	1.77	2.26	0.79	1.96	1.52	0.96	4.23	4.82	3.68
jun	28	6.5	131	2.2	1.7	1.73	1.78	4.47	1.5	1.52	2.22	1.95	0.77	1.43	1.72	1.09	4.8	3.87	4.77
july	27.01	7.8	140	2.6	1.68	1.66	1.76	4.43	1.56	1.04	1.55	2.3	0.69	2.01	1.44	0.69	4.03	3.43	4.19
aug	27.01	7.8	140	2.5	1.57	1.75	1.76	4.88	1.51	1.11	1.56	1.99	0.66	1.99	1.41	0.7	3.99	3.43	4.21
sept	30	8.4	125	2.5	1.62	1.98	1.57	4.97	1.4	1.17	1.17	1.82	0.58	2.14	1.43	0.75	3.93	3.75	4.29
oct	29.89	8.5	127	3.79	2.86	186	2.08	6.12	1.63	1.12	1.21	2.85	0.71	2.06	1.33	0.78	4.56	7.72	5.43
nov	30.5	8.4	125	3.8	2.8	1.88	1.5	5.96	1.64	1.4	1.22	2.94	0.62	2.05	1.02	1.21	4.12	4.22	5.41
dec	33.46	8.5	126	3.83	2.85	1.9	1.41	5.92	1.6	1.42	1.23	2.95	0.62	2.02	0.94	1.19	4.02	4.21	5.21

Table 3.4: Transposed data for 2024



A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Month	GT active	Ambient t	Pump disc	End shiel	End shiel	End shiel	End shiel	End shiel	Base plat	Base plat	Base plat	Base plat	Base plat	Base plat	Bearing B,	Bearing B,	Bearing B,	Bearing B,	Bearing B,
jan	141	35	7.8	1.68	1.42	1.1	1.01	2.37	1.52	1.15	1.73	1.49	0.77	1.21	2.37	1.47	3	2.16	3.72
feb	136	35.18	7.9	1.71	1.25	1.19	1.82	2.1	1.45	1.67	1.61	1.33	0.67	1.18	2.6	1.54	2.97	2.92	3.86
mar	140	31	7.9	1.68	1.21	1.2	1.78	1.99	1.47	1.65	1.6	1.28	0.68	1.2	2.7	1.46	3	2.95	3.78
apr	137	32.5	8	1.8	1.47	1.11	1.02	2.45	1.51	1.13	1.68	1.5	0.78	1.23	2.34	1.5	3.05	2.2	3.55
may	131	30.6	7.8	1.71	1.28	1.2	1.77	2.56	1.58	1.2	1.64	1.39	0.68	1.15	2.63	1.54	3.05	2.95	3.7
jun	135	30.9	8.1	2.1	2	1.33	1.36	3.06	1.42	1.17	2.2	1.37	0.75	1.28	2.56	1.87	3.12	2.51	3.55
july	140	31.2	8	2.8	2.55	1.76	1.77	3.17	1.56	1.32	2.18	1.38	0.73	1.37	2.67	1.9	3.36	2.54	3.61
aug	141	31.56	8.4	1.77	1.98	1.25	1.74	3.44	1.76	1.12	2.49	1.97	0.69	1.68	2.05	0.99	3.89	3.03	3.74
sept	140	31.26	8.2	1.79	1.53	1.12	1.73	2.45	1.39	1.1	1.65	1.41	0.67	1.22	2.45	1.45	2.66	2.18	3.75
oct	131	31.6	7.8	1.77	1	1.12	1.62	2	1.26	0.89	1.66	1.14	0.53	1.15	2.42	1.21	2.63	1.89	3.12
nov	135	32.1	8	1.74	1.12	1.07	1.46	1.87	1.33	0.87	1.88	1.01	0.57	1.18	2.49	1.38	2.74	1.88	3.02
dec	141	30.79	8.3	1.65	1.47	1.24	1.71	2.73	1.45	1.12	2.42	1.47	0.74	1.7	2.88	1.63	3.52	2.43	3.45

Consistency checks were performed to identify missing values, duplicated records, or irregular entries. The datasets were found to be largely complete and suitable for analysis. Minor inconsistencies, where present, were addressed through verification against adjacent monthly records to maintain continuity. No advanced data imputation or interpolation techniques were applied, as the integrity of the original measurements was preserved.

Measurement units for all parameters were verified to ensure uniformity throughout the dataset. Axial vibration values were maintained as RMS measurements, while discharge pressure, ambient temperature, and gas turbine active power were confirmed to be consistently recorded in their respective units. This step ensured that observed variations in the data accurately reflected changes in operating conditions rather than formatting inconsistencies.

Basic preprocessing statistics, including minimum, maximum, and mean values, were computed for each variable to establish their operational ranges and to support subsequent modeling decisions. Graphical visualization techniques, such as time-series plots and scatter plots, were also employed during preprocessing to identify general trends, seasonal variations, and potential outliers.

All preprocessing and data organization activities were carried out using spreadsheet software to ensure transparency, reproducibility, and ease of implementation. The structured preprocessing approach ensured that the dataset was suitable for descriptive statistical analysis, regression modeling, and predictive maintenance model development, which are presented in subsequent sections.

3.5 Descriptive Statistical Analysis

Descriptive statistical analysis was carried out to summarize the operational behavior of the centrifugal pump and to provide a preliminary understanding of the collected data prior to predictive model development. This stage of analysis focused on organizing, summarizing, and visually examining the pump’s operational parameters in order to establish baseline characteristics and identify general trends over time

The first step in the descriptive analysis involved the computation of basic statistical measures for each selected parameter. Using the preprocessed dataset, the minimum, maximum, mean, and range values were calculated for axial RMS vibration, pump discharge pressure, ambient temperature, and gas turbine active power. These measures provided insight into the operating limits and variability of each parameter throughout the study period.

Table 3.5: mean, minimum and maximum values of variables

	Mean	min	Max
Ambient temp (◦C)	31.97417	30.6	35.18
Pump discharge pressure (bar)	8.016667	7.8	8.4
GT active power (MW)	137.3333	131	141

In the second step, time-series plots were generated for each parameter using monthly data. These plots were used to examine how the values of axial vibration, discharge pressure, ambient temperature, and gas turbine active power changed over time. Visual inspection of the plots enabled the identification of gradual increases or decreases, periods of stability, and months exhibiting relatively higher variability. This step supported the selection of trend-based analysis as an appropriate approach for evaluating pump performance.

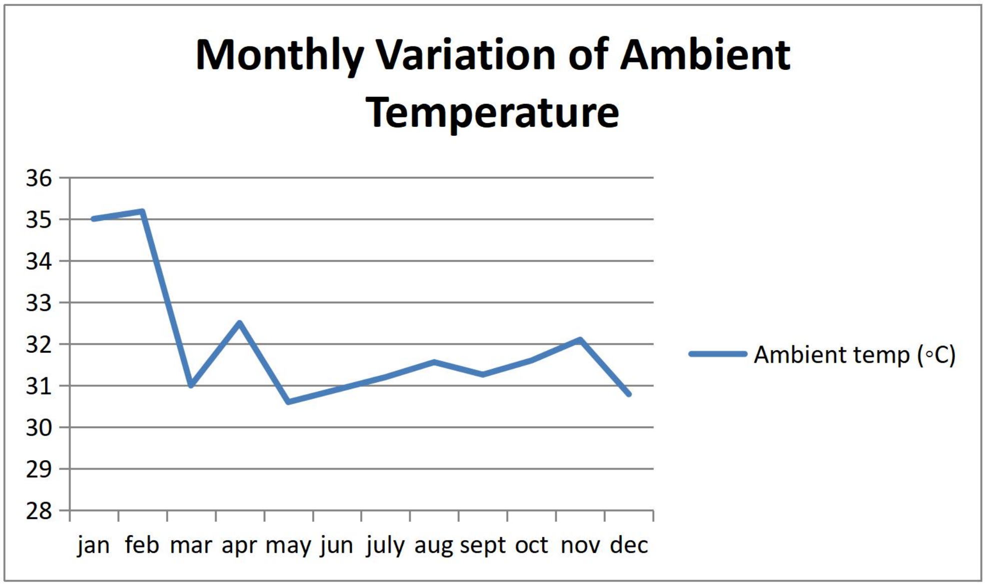


Figure 3.1: Monthly Variation of Ambient Temperature

The ambient temperature shows a gradual variation across the months, reflecting seasonal climatic changes during the year

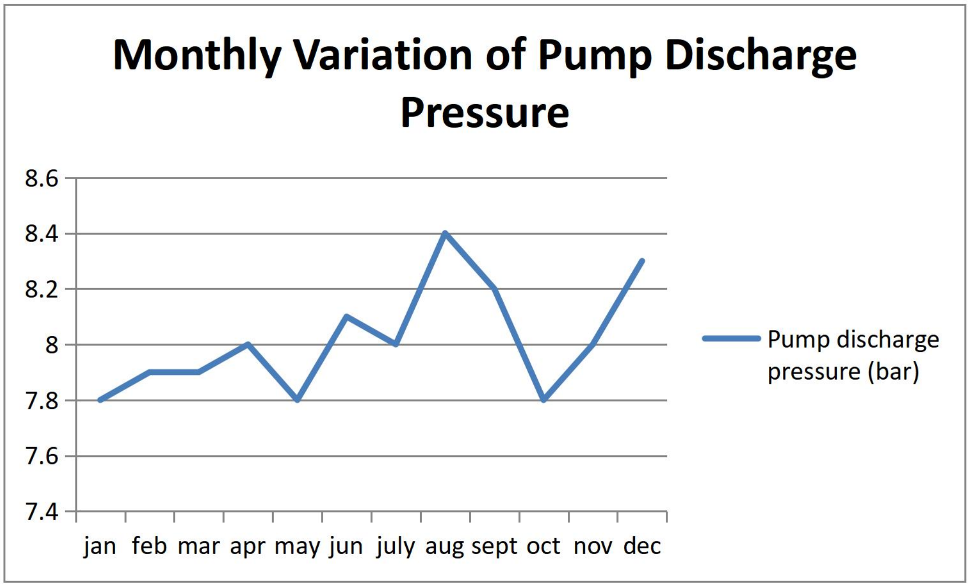


Figure 3.2: Monthly Variation of Pump Discharge Pressure

The pump discharge pressure remains relatively stable with minor fluctuations, suggesting consistent pump performance over the operating period.

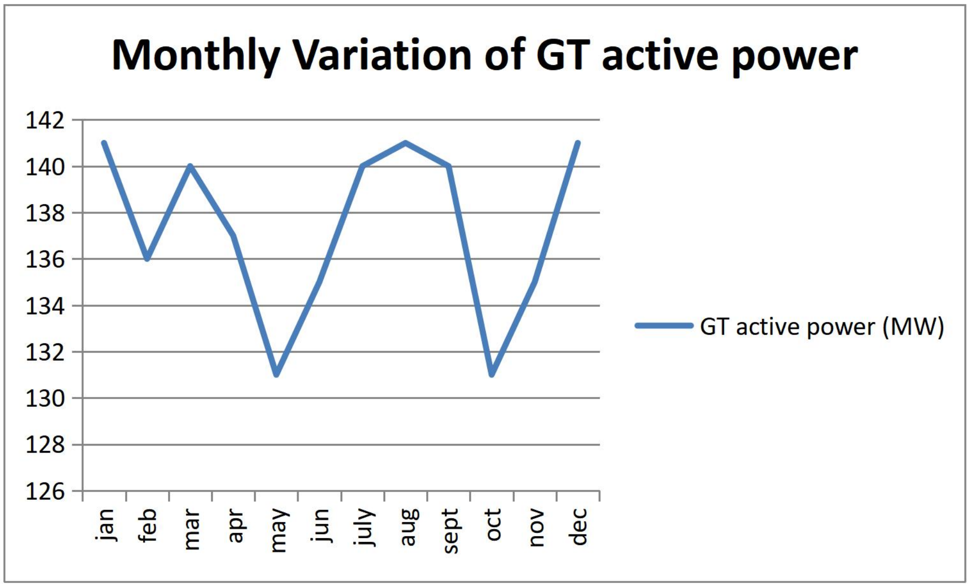


Figure 3.3: Monthly Variation of GT active power

The GT active power exhibits fluctuations throughout the year, indicating variations in operational load demand

The third step involved exploratory relationship analysis between selected variables using scatter plots. Discharge pressure was plotted against gas turbine active power and ambient temperature to examine how changes in operating load and environmental conditions influenced hydraulic performance. These plots assisted in identifying potential correlations and informed the selection of independent variables for subsequent regression modeling.

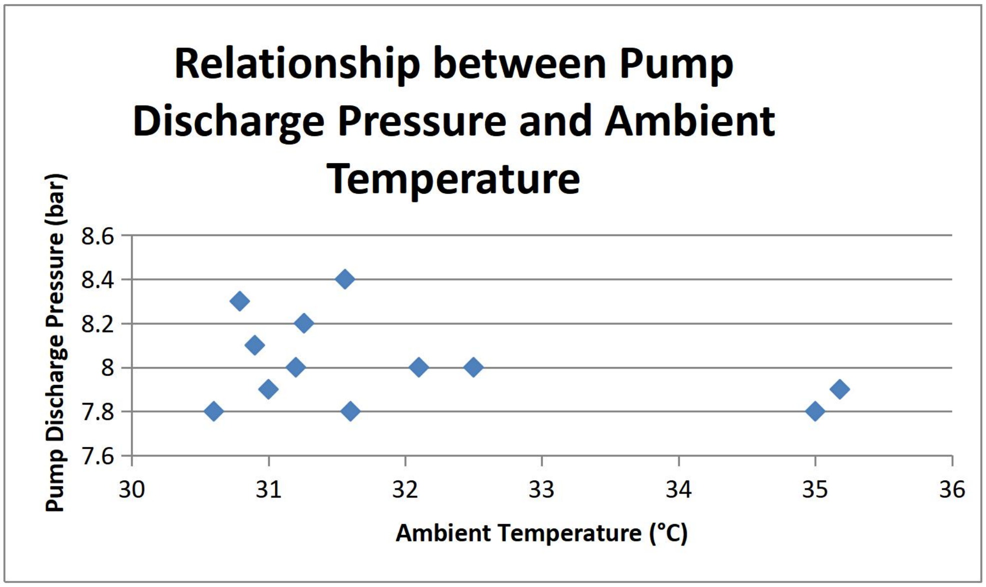


Figure 3.4: Relationship between Pump Discharge Pressure and Ambient Temperature

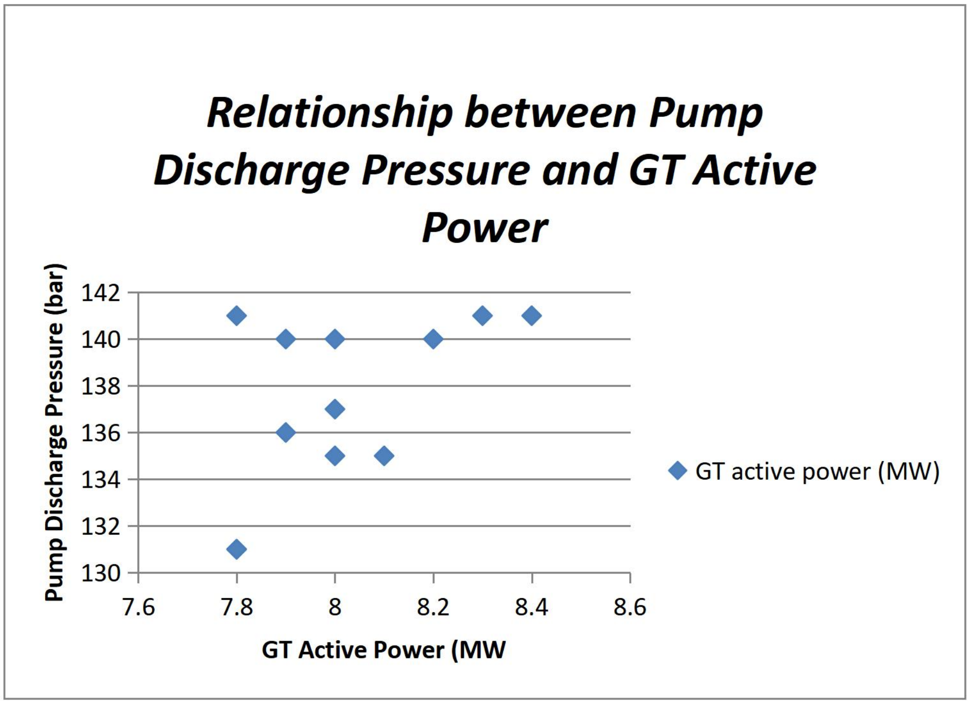


Figure 3.5: *Relationship between Pump Discharge Pressure and GT Active Power*

The dataset was examined for irregular values or abrupt changes that could indicate data recording issues or abnormal operating conditions. Data points that appeared inconsistent with surrounding values were reviewed in the context of overall trends to confirm their validity. This step ensured that the data used for modeling accurately reflected actual pump operation.

Overall, the descriptive statistical analysis provided a structured foundation for predictive maintenance modeling by summarizing system behavior, validating data quality, and guiding variable selection for regression analysis and vibration-based modeling presented in subsequent sections.

3.6 Regression Analysis

Regression analysis was employed in this study to quantitatively examine the relationship between pump performance and selected operational parameters, and to support the development of a predictive maintenance framework. The regression model was designed to evaluate how variations in operating conditions influence pump discharge pressure, which serves as a key indicator of hydraulic performance.

The dependent variable selected for the regression analysis was pump discharge pressure. This choice was based on the role of discharge pressure as a direct measure of pump performance and hydraulic efficiency. Changes in discharge pressure often reflect internal losses, flow disturbances, or degradation in pump components, making it a suitable response variable for performance evaluation.

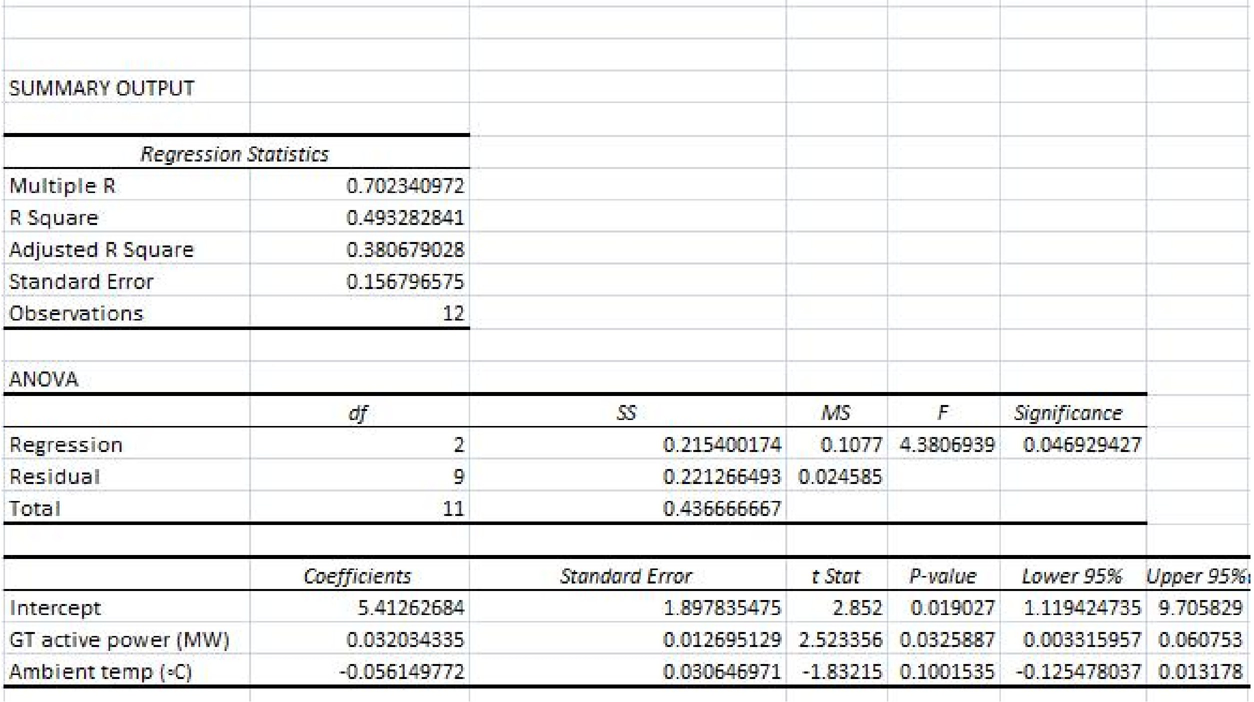
The independent variables considered in the regression model were axial RMS vibration, ambient temperature, and gas turbine active power. Axial vibration was included to capture mechanical effects associated with thrust loading and internal stress within the pump. Ambient temperature was incorporated to account for environmental and thermal influences on system operation, while gas turbine active power was used as an indicator of operating load and system demand. The inclusion of these variables enabled the model to account for both mechanical and operational influences on pump performance. The exclusion of the remaining vibration parameters from the mathematical model was based on both data characteristics and modeling suitability. The available vibration measurements were low-resolution, time-averaged RMS values recorded at sparse intervals, which limits their effectiveness in capturing dynamic fault behavior. Furthermore, correlation and trend assessment showed weak statistical dependency between these vibration components and pump discharge pressure. In contrast, axial bearing vibration is directly associated with thrust load variation, hydraulic imbalance, and bearing wear, making it a more physically meaningful indicator of pump health. Consequently, only axial vibration was considered for condition assessment, while the predictive pressure model was developed using process variables with stronger explanatory power.

The regression analysis was conducted using a multiple linear regression approach. The general form of the regression model is expressed as:

$$\mathbf{Y= X_0 + X_1\, T + X_2 G + \varepsilon} \qquad \text{Equ 3.1}$$

Where Y represents Discharge Pressure, X_0 represents the intercept, X_1 to X_2 are the regression coefficients corresponding to the independent variables, T represents Ambient Temperature, G represents Gas Turbine Active Power and ε represents the error term accounting for unexplained variability.

Prior to model estimation, the dataset was reviewed to ensure suitability for linear regression analysis. Scatter plots were examined to assess the linearity of relationships between the dependent and independent variables. The absence of extreme outliers and the observed trend patterns supported the use of a linear modeling approach.



SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.702340972
R Square	0.493282841
Adjusted R Square	0.380679028
Standard Error	0.156796575
Observations	12

ANOVA

	df	*SS*	*MS*	*F*	*Significance*
Regression	2	0.215400174	0.1077	4.3806939	0.046929427
Residual	9	0.221266493	0.024585		
Total	11	0.436666667			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	5.41262684	1.897835475	2.852	0.019027	1.119424735	9.705829
GT active power (MW)	0.032034335	0.012695129	2.523356	0.0325887	0.003315957	0.060753
Ambient temp (◦C)	-0.056149772	0.030646971	-1.83215	0.1001535	-0.125478037	0.013178

Figure 3.6: Regression Analysis

The regression model was developed using spreadsheet software. The Analysis ToolPak regression function was employed to estimate model coefficients, evaluate statistical significance, and compute goodness-of-fit measures. Model outputs including regression coefficients, standard errors, coefficient of determination (R²), and significance values were recorded for interpretation in the results chapter.

This study developed a mathematical predictive model to evaluate the operational behavior of a gas turbine cooling water centrifugal pump using historical operational data. The model was formulated based on multiple regression analysis, incorporating key process variables that influence pump performance, namely gas turbine active power and ambient temperature. These variables were selected due to their direct operational relevance and consistent availability within the plant's historical dataset.

Using one year of processed operational data, a multiple linear regression analysis was carried out with pump discharge pressure as the dependent variable. The resulting mathematical model is expressed as:

$$Y = 5.4126 + 0.0320G - 0.0562T \qquad \text{Equ 3.2}$$

The constant term of 5.4126 represents the baseline discharge pressure of the pump under nominal conditions, while the regression coefficients describe the relationship between the independent variables and pump behavior. The positive coefficient associated with gas turbine active power indicates that an increase in power demand results in a corresponding increase in pump discharge pressure, reflecting higher cooling system load. Conversely, the negative coefficient for ambient temperature suggests that rising environmental temperatures slightly reduce discharge pressure, likely due to reduced fluid density and thermal efficiency effects.

The coefficient of determination (R^2) obtained for the model was 0.4933, indicating that approximately 49.3% of the variation in pump discharge pressure is explained by the selected independent variables. This demonstrates a moderate predictive capability, which is acceptable for operational monitoring and early-stage fault detection in industrial pump systems.

Overall, the developed mathematical model provides a quantitative foundation for predictive maintenance by enabling the estimation of expected pump discharge pressure under varying operating conditions. Deviations between predicted and actual pressure values can serve as early indicators of pump degradation, facilitating timely maintenance intervention and improved system reliability.

Model adequacy was assessed using the coefficient of determination, which indicates the proportion of variation in discharge pressure explained by the selected independent variables. Residual patterns were reviewed through residual plots to confirm the absence of systematic trends, thereby supporting the assumptions of linear regression.

The regression model developed in this study is not intended to predict exact failure times but rather to evaluate performance sensitivity and identify conditions associated with performance degradation. The regression results were used to support the interpretation of observed trends and to complement the vibration-based health index developed later in the methodology.

By integrating mechanical, environmental, and operational variables, the regression analysis provided a quantitative foundation for understanding pump performance behavior and supported the broader predictive maintenance objective of the study. The regression model also served as a basis for comparison and validation using data from a subsequent operational period.

3.7 Model validation and performance evaluation

Model validation is a critical stage in the development of a predictive maintenance framework, as it assesses the reliability and generalization capability of the developed mathematical model when applied to unseen data. In this study, the validation of the predictive model was carried out using an independent operational dataset obtained from the year 2024. This approach ensures that the model's performance is evaluated under real operating conditions different from those used during model development.

The mathematical model developed using the 2023 dataset was applied to the 2024 operational data to generate predicted values of pump discharge pressure. The independent variables used for prediction, namely gas turbine active power and ambient temperature, were extracted from the 2024 dataset and substituted into the regression equation. This process produced a set of predicted discharge pressure values corresponding to each observation period in 2024.

To evaluate the predictive accuracy of the model, the predicted pump discharge pressure values were compared directly with the actual measured discharge pressure obtained from the plant instrumentation. This comparison was carried out both graphically and numerically. A time-series plot was used to visually compare the trends of predicted and actual pressure values over the validation period, allowing for the identification of deviations, trend consistency, and periods of abnormal behavior.

In addition to visual comparison, prediction error analysis was conducted to quantitatively assess model performance. The prediction error for each observation was calculated as the difference between the actual and predicted pump discharge pressure. From these errors, summary performance metrics such as the mean absolute error were evaluated to provide an overall measure of model accuracy. Smaller error values indicate better agreement between predicted and actual system behavior.

The validation results were further analyzed to identify periods where significant deviations occurred between predicted and measured pressure values. Such deviations are of particular interest in a predictive maintenance context, as they may indicate the presence of unmodeled operational factors, incipient faults, or early-stage pump degradation. These deviations therefore serve as potential early warning indicators for maintenance planning.

Overall, the model validation process confirms the applicability of the developed mathematical model for predicting pump discharge pressure under varying operating conditions. The use of an independent validation dataset strengthens the credibility of the model and demonstrates its suitability for integration into a predictive maintenance strategy for centrifugal pump systems.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction to results

This chapter presents the results obtained from the analysis and modeling procedures described in the methodology chapter. The focus is on evaluating the operational performance and mechanical condition of the centrifugal pump using historical plant data. The results cover descriptive analysis of key operational parameters, development of a mathematical predictive model, vibration trend assessment, and vibration health indexing. These analyses are aimed at demonstrating how data-driven techniques can be applied to support condition monitoring and predictive maintenance of industrial pump systems.

In addition, the chapter presents the validation of the developed predictive model using an independent dataset obtained from a subsequent operational period. Comparisons between predicted and actual pump discharge pressure values are used to assess the robustness and practical applicability of the model under real operating conditions. The results are discussed in relation to the study objectives, highlighting how process variables and vibration-based indicators can be integrated to provide meaningful insights into pump health and performance.

4.2 Descriptive analysis of operational data

This section presents the descriptive statistical analysis of the operational data used in the study. The analysis was carried out to provide an initial understanding of the general behavior, operating ranges, and variability of the key parameters prior to advanced modeling and condition assessment. The dataset consists of historical measurements of pump discharge pressure, gas turbine active power, ambient temperature, and axial vibration collected over the study period.

Summary statistics including the mean, minimum and maximum values were evaluated for each parameter. The pump discharge pressure exhibited a relatively stable operating range with moderate variation, indicating consistent hydraulic performance under normal operating conditions. Gas turbine active power showed wider variability, reflecting changes in load demand, while ambient temperature followed expected seasonal fluctuations. The axial vibration measurements remained within acceptable limits for most of the operating period, with occasional increases that suggest transient mechanical disturbances or changing operating conditions.

The variability observed in the operational parameters provides important context for subsequent analyses. Parameters with higher variability, such as gas turbine active power and ambient temperature, are expected to have a more pronounced influence on pump discharge pressure and were therefore considered suitable candidates for predictive modeling. Similarly, the distribution and spread of axial vibration values establish a baseline for identifying abnormal behavior during trend analysis and vibration health index evaluation. Overall, the descriptive analysis confirms that the dataset is suitable for regression modeling, trend assessment, and condition monitoring applications.

4.3 Regression analysis and mathematical model results

This section presents the results of the regression analysis carried out to develop a mathematical model for predicting pump discharge pressure. The regression model was formulated using historical operational data, with pump discharge pressure treated as the dependent variable, while gas turbine active power and ambient temperature were used as independent variables. These variables were selected based on their operational relevance and availability within the dataset.

The regression analysis produced a statistically meaningful relationship between the dependent and independent variables. The resulting model yielded a coefficient of determination that indicates a moderate level of explanatory power, showing that a significant portion of the variation in pump discharge pressure is captured by the selected predictors. This level of model performance is acceptable for operational monitoring and predictive maintenance applications, where system behavior is influenced by multiple interacting factors.

The developed mathematical model for pump discharge pressure is expressed as:

$$Y = 5.4126 + 0.0320G - 0.0562T \qquad \text{Equ 4.1}$$

The constant term represents the baseline discharge pressure under nominal conditions, while the regression coefficients quantify the influence of each independent variable on pump performance. The positive coefficient associated with gas turbine active power indicates that an increase in turbine load results in a corresponding increase in pump discharge pressure, reflecting higher cooling system demand. In contrast, the negative coefficient of ambient temperature suggests that higher environmental temperatures slightly reduce discharge pressure, possibly due to changes in fluid properties and thermal efficiency.

Table 4.1: GT active power and ambient temperature monthly reading 2023

Month	GT active power (MW)	Ambient temp (◦C)
jan	141	35
feb	136	35.18
mar	140	31
apr	137	32.5
may	131	30.6
jun	135	30.9
july	140	31.2
aug	141	31.56
sept	140	31.26

oct	131	31.6
nov	135	32.1
dec	141	30.79

These readings were used to predict the pressure pump discharge for the subsequent year using the mathematical model we’ve gotten.

Since,

Pump Discharge Pressure = 5.4126 + 0.0320(GT Active Power) − 0.0562(Ambient Temperature)

Predicted pump discharge pressure for the next 12 months

January

5.4126 + 0.0320(141) − 0.0562(35) = 7.96 bar

February

5.4126 + 0.0320(136) − 0.0562(35.18) = 7.79 bar

March

5.4126 + 0.0320(140) − 0.0562(31) = 8.15 bar

April

5.4126 + 0.0320(137) − 0.0562(32.5) = 7.97 bar

May

5.4126 + 0.0320(131) − 0.0562(30.6) = 7.88 bar

June

5.4126 + 0.0320(135) − 0.0562(30.9) = 8.00 bar

July

$5.4126 + 0.0320(140) - 0.0562(31.2) = 8.14$ bar

August

$5.4126 + 0.0320(141) - 0.0562(31.56) = 8.15$ bar

September

$5.4126 + 0.0320(140) - 0.0562(31.26) = 8.14$ bar

October

$5.4126 + 0.0320(131) - 0.0562(31.6) = 7.83$ bar

November

$5.4126 + 0.0320(135) - 0.0562(32.1) = 7.93$ bar

December

$5.4126 + 0.0320(141) - 0.0562(30.79) = 8.19$ bar

The developed regression-based mathematical model was applied to predict pump discharge pressure for a twelve-month operating period. The predicted discharge pressure values ranged between approximately 7.8 bar and 8.2 bar, indicating stable expected hydraulic performance under the assumed operating conditions.

The predicted pump discharge pressure was used to test the actual pressure discharge pressure for 2024. Table 4.2 illustrates the information

Table 4.2: Predicted Pressure Testing

Predicted Pressure (bar)	Actual discharge pressure (bar)	Error	MAE
7.9576	7.5	0.4576	0.4576
7.787484	7.6	0.187484	0.187484
8.1504	6.9	1.2504	1.2504
7.9701	6.8	1.1701	1.1701
7.88488	6.7	1.18488	1.18488
7.99602	6.5	1.49602	1.49602
8.13916	7.8	0.33916	0.33916
8.150928	7.8	0.350928	0.350928
8.135788	8.4	-0.26421	0.264212
7.82868	8.5	-0.67132	0.67132
7.92858	8.4	-0.47142	0.47142
8.194202	8.5	-0.3058	0.305798

The deviation (error) was obtained as:

Error = Predicted pressure − Actual discharge pressure

Positive error values indicate that the model over-predicted the pump discharge pressure, while negative error values indicate under-prediction.

From the results, the prediction errors range approximately from −0.67 bar to +1.50 bar. This shows that although the model generally follows the operating trend of the pump, some months exhibit noticeable deviations between predicted and actual pressure values. Larger positive errors observed in some months suggest periods where the actual system performance was lower than expected under normal operating conditions.

Conversely, the negative errors observed in later months indicate instances where the actual discharge pressure exceeded the model prediction, which may be associated with transient operating conditions, improved pump efficiency, or short-term system recovery.

The Mean Absolute Error (MAE) represents the absolute magnitude of prediction errors without considering their direction and is given by:

$\text{MAE} = |\text{Predicted pressure} - \text{Actual pressure}|$

From the table, individual MAE values range between approximately 0.18 bar and 1.50 bar. These values indicate the average deviation of the model predictions from the actual discharge pressure measurements for each month.

Lower MAE values (below 0.5 bar) observed in several months demonstrate that the mathematical model is capable of producing reasonably accurate pressure predictions under normal operating conditions. However, higher MAE values above 1 bar suggest months where unmodeled factors such as pump wear, hydraulic losses, fouling, or operational disturbances influenced system behavior.

Overall, the deviation and MAE results confirm that the developed regression-based mathematical model provides a useful baseline prediction of pump discharge pressure. While the model captures the general relationship between gas turbine active power, ambient temperature, and discharge pressure, deviations highlight the impact of real-world operating conditions not explicitly included in the model.

These deviations are particularly important from a predictive maintenance perspective, as sustained increases in error magnitude may serve as early indicators of pump degradation or abnormal operating conditions requiring further investigation.

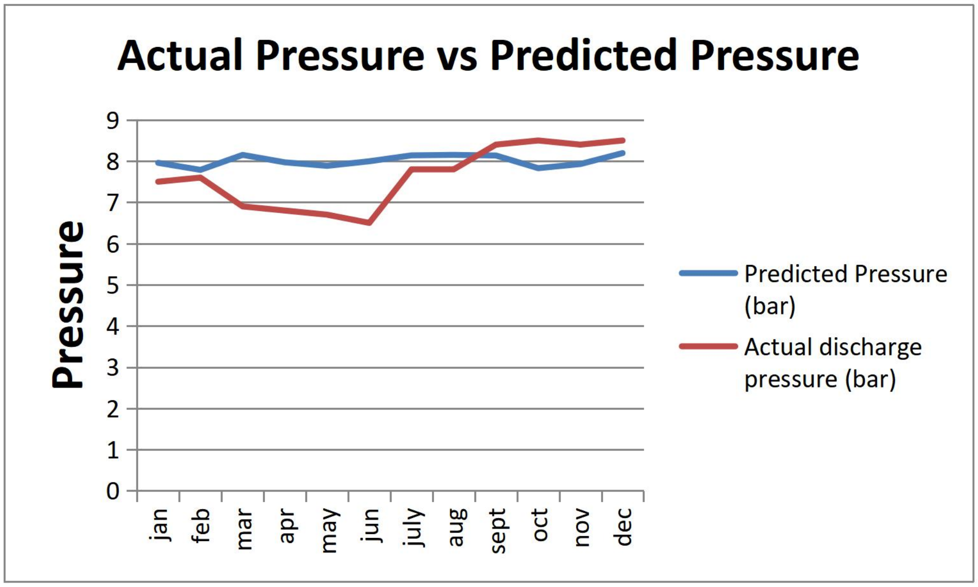


Figure 4.1: Graphical illustration of Actual Pressure vs Predicted Pressure

Vibration parameters were not included in the regression model because vibration is primarily a condition-monitoring indicator rather than an operating variable influencing hydraulic performance. The objective of the model was to evaluate pump discharge pressure based on operating conditions such as ambient temperature and gas turbine active power. Including vibration data would introduce response-based variables and increase model complexity beyond the scope of this study. However, vibration parameters remain valuable for fault diagnosis and are recommended for inclusion in future condition-based maintenance studies. The current model focuses on performance prediction, while vibration analysis is more suitable for fault detection and health assessment. Integrating both would require a hybrid or multi-stage modeling framework.2

In situations where the developed performance model indicates abnormal deviation between predicted and actual pump discharge pressure, vibration analysis becomes necessary to identify the root cause of degradation. Vibration measurements enable fault diagnosis such as imbalance, misalignment, bearing wear, or cavitation, which cannot be inferred from pressure data alone. Therefore, vibration analysis is applied as a secondary diagnostic tool within a condition-based maintenance framework

The 2023 vibration data was used to establish the baseline RMS vibration trend and normal operating condition of the pump. This baseline was then used as a reference to assess changes observed in the 2024 data, thereby enabling comparative health assessment.

4.4 Vibration Health Index (VHI) development and interpretation

The Vibration Health Index (VHI) was developed to provide a single quantitative indicator that represents the overall mechanical condition of the pump based on vibration behaviour. In industrial rotating machinery, vibration signals are often multidimensional, consisting of axial, horizontal, and vertical components measured at different bearing locations. While each vibration component provides useful diagnostic information, interpreting multiple vibration signals simultaneously can be complex and may obscure early signs of degradation. The VHI approach simplifies this process by converting vibration measurements into a normalized health metric that supports condition monitoring and decision-making.

In this study, the axial bearing vibration was selected as the primary input for the VHI formulation. This selection was based on the strong mechanical relevance of axial vibration to thrust bearing condition, shaft alignment, and hydraulic loading in centrifugal pump systems. Axial vibration is particularly sensitive to internal pump forces and bearing wear, making it a reliable indicator of progressive mechanical deterioration. Other vibration components were excluded from the mathematical model due to their lower sensitivity to pump performance degradation and their higher susceptibility to structural and environmental noise.

The VHI was computed by normalizing the measured axial vibration amplitude with respect to an established reference threshold representing acceptable operating conditions. This normalization ensures that the VHI remains dimensionless and comparable across different operating periods.

The first calculation step involved establishing a reference vibration level. This reference value represented the maximum acceptable axial vibration under normal operating conditions. It was selected based on baseline healthy operation of the pump and relevant vibration severity standards for rotating machinery. This reference value served as the normalization factor for the VHI formulation.

For each month, the VHI was calculated by dividing the measured axial RMS vibration by the reference vibration value. Mathematically, this was expressed as:

VHI = Measured axial RMS vibration / Reference axial vibration

This calculation transformed the raw vibration measurements into a dimensionless health indicator. A VHI value less than 1 indicated normal operation, values approaching 1 suggested the onset of mechanical stress, and values greater than 1 signified abnormal vibration levels and potential mechanical faults.

We define a **Vibration Severity Index**:

$$VSI_i = \frac{V_i - V_{min}}{V_{max} - V_{min}} \qquad \text{Equ 4.3}$$

Where;

Vmin= minimum observed axial RMS vibration

Vmax= maximum observed axial RMS vibration

Vi = axial RMS vibration at month *i*

This gives:

0 → best vibration condition

1 → worst vibration condition

Health should decrease as vibration increases.

So we define the **Vibration Health Index (VHI)** as:

$$VHI_i = 1 - \frac{V_i - V_{min}}{V_{max} - V_{min}} \qquad \text{Equ 4.4}$$

Interpretation:

VHI ≈ 1.0 → Excellent condition

VHI ≈ 0.7 – 0.8 → Good condition

VHI ≈ 0.4 – 0.6 → Degrading condition

VHI < 0.4 → Poor condition (maintenance required)

By calculating, we had that vmin = 1.87 and vmax= 3.44. Vmax for the year was calculated and the values are illustrated in Table 4.1

.

Table 4.3: VHI values

Month	VHI
jan	0.681529
feb	0.853503
mar	0.923567
apr	0.630573
may	0.56051
jun	0.242038
july	0.171975

aug	0
sept	0.630573
oct	0.917197
nov	1
dec	0.452229

This information was also plotted in a graph. It is displayed below

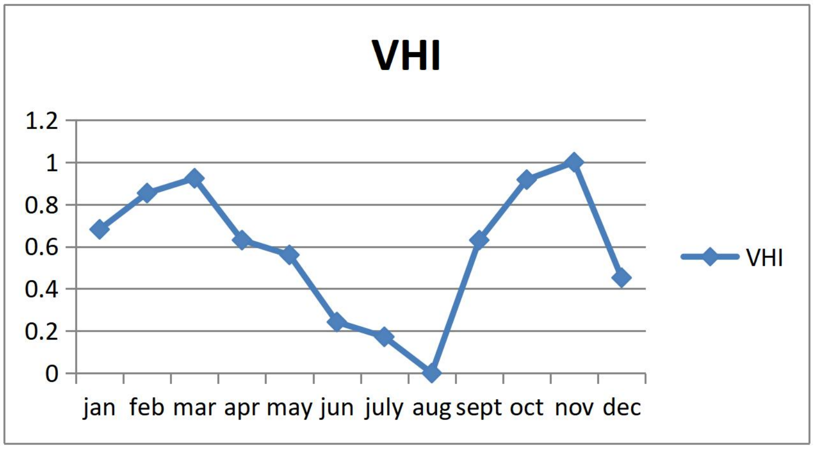


Figure 4.2: VHI trends

The graph illustrates the monthly variation of the Vibration Health Index (VHI) of the centrifugal pump over the 2023 operating period. Since the VHI is defined on a normalized scale where values closer to 1 indicate good mechanical health and values approaching 0 indicate severe degradation, the trend provides a clear picture of the pump's condition over time.

During the early months of the year (January to March), the VHI values remain relatively high, ranging between approximately 0.7 and 0.9. This indicates that the pump was operating under healthy mechanical conditions, with low axial vibration levels and minimal mechanical stress. The increasing trend from January to March suggests stable operation and efficient hydraulic performance.

From April to June, a gradual decline in the VHI is observed. This reduction reflects a progressive increase in axial vibration severity, signaling the onset of mechanical or hydraulic degradation. Such behavior is often associated with factors such as increasing thrust loads, impeller wear, or changes in operating conditions. Although the pump is still operational during this period, the declining VHI serves as an early warning that the system is moving away from its optimal condition.

A critical point occurs between July and August, where the VHI reaches its minimum value, approaching zero in August. This represents the worst mechanical condition observed during the year. At this point, axial vibration levels are at their highest, indicating significant mechanical stress. This period can be interpreted as a high-risk operating zone, where continued operation without intervention could lead to accelerated wear or potential failure.

Following this critical phase, a sharp recovery in VHI is observed from September through November. The VHI rises back to values above 0.9, suggesting a substantial improvement in pump condition. This improvement may be attributed to maintenance actions, load reduction, system stabilization, or favorable operating conditions. The rapid recovery demonstrates the sensitivity of the VHI model in capturing changes in mechanical health.

In December, the VHI shows a noticeable decline again, dropping to approximately 0.4. While not as severe as the August minimum, this drop indicates a return to a moderately degraded condition. This suggests that underlying degradation mechanisms may still be present and that the pump requires continued monitoring to prevent recurrence of severe vibration conditions.

Based on the VHI trend, the pump experienced three distinct health phases: a healthy operating phase, a degradation phase culminating in a critical condition, and a recovery phase followed by mild deterioration. The vibration health index successfully captures these transitions and provides a quantitative basis for predictive maintenance decision-making.

This confirms that the developed VHI model is effective for early warning detection and long-term condition monitoring of the centrifugal pump.

Although vibration measurements were available in multiple directions, this study focused exclusively on axial vibration due to its strong sensitivity to thrust-related forces and hydraulic loading in centrifugal pumps. Given the monthly RMS resolution of the available data and the study's emphasis on performance degradation and trend-based health assessment rather than detailed fault diagnosis, axial vibration was considered the most representative indicator of mechanical condition. The inclusion of additional vibration directions would not significantly improve interpretability and could introduce unnecessary complexity without corresponding analytical benefit.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary of the Study

This study focused on the evaluation of performance improvement and condition monitoring of a centrifugal pump used in a gas turbine cooling water system through data-driven analysis. The primary objective was to develop a predictive maintenance framework capable of assessing pump performance, identifying degradation trends, and providing early warning indicators using historical operational data.

To achieve this objective, two years of plant operational data were utilized. The 2023 dataset served as the baseline for model development, descriptive analysis, regression modeling, and vibration health assessment, while the 2024 dataset was used for model validation and performance comparison. Key operational parameters analyzed included pump discharge pressure, gas turbine active power, ambient temperature, and axial RMS vibration.

Descriptive statistical analysis was first carried out to understand the operating ranges, trends, and variability of the pump parameters. This provided insight into system behavior under normal operating conditions and confirmed the suitability of the data for predictive modeling. Time-series plots and scatter plots revealed stable pump operation with observable variations driven mainly by load demand and environmental conditions.

A multiple linear regression model was then developed to establish a mathematical relationship between pump discharge pressure and selected operating variables. The resulting predictive model incorporated gas turbine active power and ambient temperature as explanatory variables and demonstrated moderate predictive capability. The model was subsequently validated using the 2024 operational data, and deviations between predicted and actual discharge pressure were analyzed to identify abnormal operating behavior.

In addition to performance modeling, a vibration-based health assessment was conducted using axial RMS vibration data. A Vibration Health Index (VHI) was developed to provide a normalized and interpretable indicator of the pump’s mechanical condition. The VHI successfully captured periods of healthy operation, degradation, critical vibration severity, and recovery, demonstrating its effectiveness as a condition monitoring and early warning tool.

Overall, the study integrated performance-based modeling and vibration-based health assessment into a unified predictive maintenance framework suitable for industrial pump systems.

5.2 Conclusion

The findings of this study demonstrate that historical operational data can be effectively used to assess pump performance, predict expected behavior, and identify early signs of degradation. The developed mathematical model successfully established a quantitative relationship between pump discharge pressure, gas turbine active power, and ambient temperature. The positive influence of turbine load and the negative influence of ambient temperature on discharge pressure were consistent with physical operating principles of centrifugal pump systems.

The validation of the model using an independent dataset confirmed its practical applicability for operational monitoring. Although the model does not capture all sources of variability, the observed deviations between predicted and actual pressure values provide valuable diagnostic insight. Persistent or increasing deviations can serve as early indicators of performance deterioration and the need for further investigation.

The vibration health analysis further strengthened the predictive maintenance framework. The axial vibration-based Vibration Health Index provided a clear and interpretable measure of mechanical condition over time. The VHI trend revealed distinct phases of healthy operation, degradation, critical condition, and recovery, highlighting its usefulness for condition-based maintenance decision-making. The choice of axial vibration was justified by its strong sensitivity to thrust-related forces and hydraulic loading, which are critical in centrifugal pump operation.

By combining performance prediction and vibration health monitoring, the study demonstrates a practical and scalable approach to predictive maintenance. The methodology aligns with industrial condition monitoring practices and can be implemented using readily available plant data without the need for complex signal processing techniques.

5.3 Recommendations

Based on the results and conclusions of this study, the following recommendations are proposed:

1. The developed mathematical model should be integrated into routine plant monitoring systems to provide continuous prediction of expected pump discharge pressure under varying operating conditions.
2. Deviations between predicted and actual discharge pressure should be routinely tracked, as sustained increases in error magnitude can serve as early warning indicators of pump degradation.
3. The Vibration Health Index should be adopted as a condition monitoring tool to support maintenance decision-making, particularly for identifying periods of increasing mechanical stress and critical vibration severity.
4. Regular review of axial vibration trends is recommended, especially during periods of high load or elevated ambient temperature, where mechanical stress is likely to increase.
5. Future studies should incorporate higher-resolution vibration waveform data to enable frequency-domain analysis and more detailed fault diagnosis using techniques such as FFT.

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