Development of Operational Predictive Maintenance System in Oil and Gas Industry Case Study of Warri Refining and Petrochemical Company

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Abstract
The oil and gas industry is critical to global energy supply and national economic development, particularly in resource-rich countries like Nigeria. One of the major reasons for the collapse and total shutting down of all refineries in Nigeria is lack of maintenance culture. In the fast-paced digital world, it is imperative to employ emerging technologies in addressing such national issues like refinery maintenance, this study therefore focuses on developing an operational predictive maintenance (PdM) system for Warri Refining and Petrochemical Company (WRPC). The system utilized advanced data analytics and condition-based monitoring technologies to predict equipment failures before they occur. Predictive maintenance offers advantages over traditional reactive and preventive maintenance approaches by optimizing maintenance schedules, reducing downtime, and lowering operational costs. The study highlighted challenges such as aging infrastructure, resource constraints, and regulatory pressures WRPC faces and demonstrated how PdM system addressed the issues. Implementation results showed improved equipment reliability, enhanced safety, and optimized operational efficiency. Recommendations for future initiatives include technological upgrades, staff training, and collaborative efforts among industry stakeholders.

Keywords: *Machine Learning, Predictive, Maintenance, Refining, Petrochemical.*

Background of Study

The oil and gas industry is a cornerstone of global energy supply and economic development for many countries (Cruz, 2024). It serves as the backbone of industrialization, powering machinery, transportation, and energy grids worldwide. In Nigeria, the industry plays an even more critical role, contributing significantly to national income, employment, and energy security (Olujobi, et.al., 2014). The country's vast reserves make it one of the leading producers of crude oil in Africa with refineries like the Warri Refining and Petrochemical Company (WRPC) at the forefront of this crucial sector. Despite its strategic importance, WRPC and similar entities face numerous challenges that threaten their operational efficiency and long-term sustainability.

One of the most pressing issues confronting WRPC is its aging infrastructure. Established decades ago, much of the equipment and machinery used in the refinery are now outdated, requiring frequent repairs and replacements (Akinwale & Ojo, 2020). This situation has led to an over-reliance on reactive maintenance practices, where equipment failures are addressed only after they occur. Such an approach is inherently inefficient, often resulting in extended downtimes, increased repair costs, and safety risks for personnel and the environment. Cruz (2024) confirmed that resource constraints, both financial and human, can exacerbate challenges, limiting the company's ability to invest in modernization and advanced maintenance solutions.

Maintenance practices at WRPC have been predominantly reactive. Making it fraught with inefficiencies such as equipment failures which disrupt production schedules and lead to significant financial losses (Diptiben, 2024). Addressing equipment failures often require emergency procurement of parts and services, which are usually not cost-effective and associated with long delays. Consequently, disruptions in operation schedules impact greatly on the refinery's profitability and the energy supply chain.

Okonkwo, et.al., (2021) stated that predictive maintenance (PdM) is a proactive approach and transformative strategy that leverage advancements in data analytics and real-time monitoring technologies by predicting equipment failures before they occur, thereby enabling the organization to plan maintenance activities efficiently and effectively. This will greatly minimize downtime and optimize resource utilization.

Motivation

The motivation for this study stems from the operational inefficiencies and economic losses experienced by WRPC due to frequent equipment failures and unplanned downtimes. These challenges highlight the urgent need for a more robust maintenance framework. PdM offers a solution by providing actionable insights derived from real-time data, which can optimize maintenance schedules, enhance equipment lifespan, and improve safety standards (Olujobi, et.al, 2024). The potential to reduce costs, increase production uptime, and align with global best practices further underscores the importance of this research.

Aim and Objectives of the Study

This work is aimed at the development of an operational predictive maintenance system using Warri Refining and Petrochemical Company (WRPC) as a case study. This aim was subdivided into manageable chunks as objectives, to make it achievable. They are:

1) To assess the effectiveness of existing reactive and preventive maintenance practices.
2) To explore the potential benefits of implementing predictive maintenance and examine its implications vis-à-vis safety and environmental regulations.
3) To design and implement a predictive maintenance system.
4) To evaluate the system's performance and identify its possible technological challenges.

Review of Related Works

Akinwale & Ojo (2020) did a comparative analysis of predictive maintenance techniques in the Nigerian oil and gas industry. They explored various predictive maintenance techniques used in the Nigerian oil and gas sector and compared their effectiveness. Aging equipment was named as the main challenge being faced in Nigerian refineries. Many suggestions were proposed and discussed. A summary of the analysis is shown in table 1.

Table 1: Comparative Analysis of Predictive Maintenance Techniques

Technique	**Key Benefits**	**Limitations**	**Suggested Solution**
Vibration Analysis	Early detection of mechanical issues	Requires specialized equipment	Done quarterly
Thermal Imaging	Identifies overheating components	Limited to surface-level inspections	Done monthly
Machine Learning Models	High predictive accuracy	Dependent on quality and volume of data	Done annually

In the work of Ojo & Ogundele (2020), predictive maintenance (PdM) was assured to employ data-driven techniques to forecast equipment failures before they disrupt operations. Meaning that PdM would offer a significant improvement over traditional maintenance method by utilizing real-time data from sensors and advanced analytics to predict potential failures. This method was generally accepted as to reduce downtime and enhance operational efficiency. The work further assured that adopting PdM would improve equipment reliability and extend asset lifecycles for refineries.

Diptiben (2024) proposed the use and integration of advanced technologies in predictive maintenance of refineries. He inferred that sensors, IoT devices, and data analytics platforms, machine learning algorithms and data analytics models should be deployed to analyze large live datasets generated from refinery plants. He posited that emerging technologies ensure accurate analysis of patterns and predict outcomes within micro-perfect limits.

Bello (2024) built upon the work of Diptiben (2024) to suggest that new technologies be integrated with existing systems such as Enterprise Resource Planning (ERP) and Enterprise Asset Management (EAM) systems, to ensure smooth conversion and zero data loss during transition.

Okonkwo et al., (2021) proposed data analytics and predictive modeling to be implemented using historical and real-time data. He confirmed that these models would make informed maintenance decisions and reduce unplanned downtimes plus significantly improving the accuracy of predictions and scheduling of maintenance planning.

Nguyen, et al., (2020) emphasized the crucial role of big data in analytics and prediction models in the twenty-first century. Large volumes of data were collected from active sensors of live IoT devices and analyzed with the algorithm model designed. The results gave accurate predictions on expected system failures and successfully scheduled maintenance sessions way before the failures could occur.

Methodology

Qualitative and quantitative techniques were combined in the collection of data for this work. Interviews with structured questions were conducted with all levels of personnel – high, middle and low levels - at WRPC. Then a comparative analysis of maintenance records was done to ascertain the regularities of maintenance schedules alongside unplanned downtimes.

Data Collection: Data was gathered from logbooks using Supervisory Control and Data Acquisition (SCADA) system to ensure that current and historical data were included for accurate analysis. They were obtained from:

i. Historical maintenance records and archives detailing repairs, inspections, and equipment replacements.
ii. Operational metrics: Real-time data on pressure, temperature, vibration, flow rates, and other process indicators from sensors attached to critical assets.
iii. Environmental factors: External data on humidity, ambient temperature, and other conditions affecting equipment performance, obtained through WRPC's environmental monitoring systems.
iv. Equipment performance data: Manufacturer's guidelines, specifications, and failure mode analysis for predictive modeling.

Thematic Analysis: Interviews with WRPC personnel revealed key themes:

i. Aging Infrastructure: Outdated equipment is a significant challenge, contributing to frequent failures and higher maintenance costs.
ii. Training Needs: A recurring theme was the need for training in PdM technologies to bridge the skills gap.
iii. Data Utilization: Respondents emphasized the potential for using real-time data to improve maintenance strategies and more accurately predict equipment failures.

Historical Maintenance Records

The historical maintenance records of WRPC revealed that:

i. MTBF and MTTR: MTBF of 150 hours and MTTR of 20 hours suggest frequent equipment failures and a need for effective maintenance strategies to enhance reliability.
ii. Total Maintenance Costs: The high annual maintenance costs underline the financial impact of current maintenance practices, further justifying the potential cost-saving benefits of PdM.

Data Pre-processing:

Data collected was preprocessed by cleaning to remove anomalies, outliers, and erroneous data points (e.g., extreme spikes in sensor readings due to temporary malfunctions). Normalization followed with a MinMax scaler saved as scaler.pkl, to scale inputs to the range expected by from different sensors or periods to the same unit and range, allowing for easier comparison. Key features such as temperature fluctuations, pressure surges, and vibration trends were selected and aligned for synchronization.

System Design

The new system was designed using Python programming language with CSS for visual styling, layout and designs, HTML and **JavaScript** for modal logic to display prediction results and Bootstrap components for enhanced interactivity; the data layer designed with SQLite database and managed by SQL Alchemy to store and retrieve persistent data. The complete system was implemented on WRPC's SCADA infrastructure.

System Architecture

The system was designed to ensure seamless user interactions, efficient data processing, and reliable deployment. It consists of multiple interconnected layers, responsible for specific roles and components. These layers work together to deliver a user-friendly, scalable, and functional system for predicting machine failures.

1. **Presentation Layer (Frontend):** This layer interacts directly with the user, handling user input and displaying results. The components are HTML templates that provides a common structure for all pages, such as navigation and layout. The landing page displays the name, image, and user at every point. It contains a specific requirement for user authentication based on registered rules and admittance for new users.
   Users are presented with Forms to input required values at log-in, which after compilation are used for the machine learning model, after which predictions are displayed as output.
2. **Application Layer (Backend):** This layer handles business logic, routes, user authentication, and interactions with the database and machine learning model. It displays the home page with user-specific content and allows users to register by providing a full name, email, and password, then authenticates users to prompt user inputs, preprocesses them, and returns the model's prediction.
   A Session Management layer was included in every user session to stores temporary data (e.g., predictions) securely for use during page redirects.
3. **Machine Learning Layer: This layer is specifically designed to p**rocess all input data, apply transformations and generate predictions. It comprised of a trained binary classification machine learning model (SVM) saved as model.pkl meaning that it can only give output 0 or 1.

The flowchart is shown in figure 1 and operational system design in figure 2.

Figure 1: System Flowchart

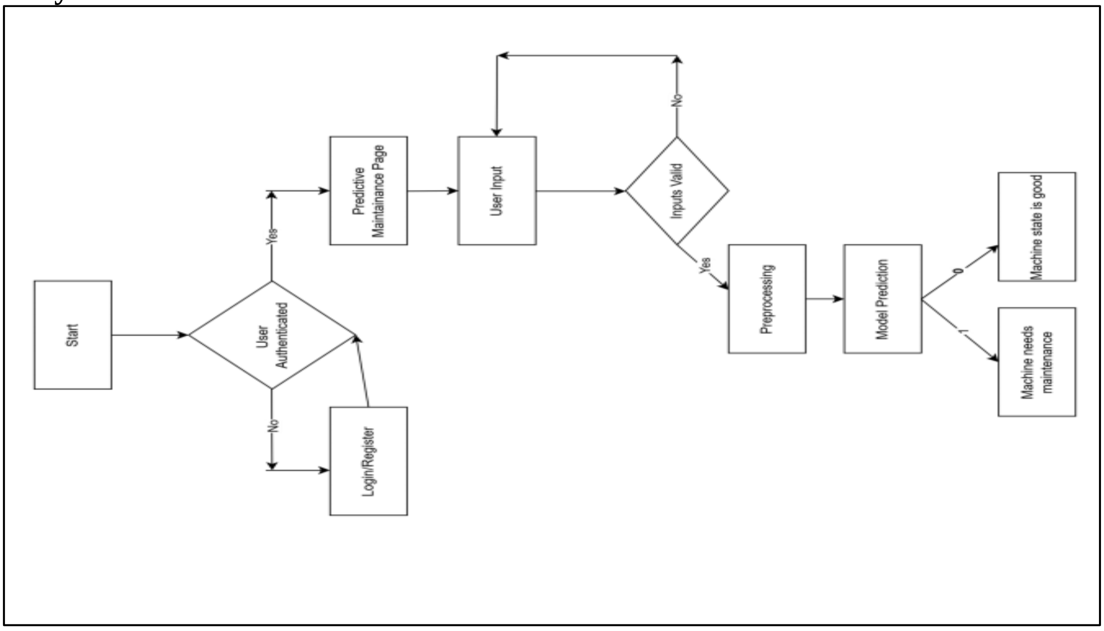

Table 2: System Design for Operational Predictive Maintenance at WRPC

1. Data Collection Layer - Feeding the input data - SCADA (Real-time Operational Data) - Historical Maintenance Records - Environmental Data (Humidity, External Temperature)	**2. Data Preprocessing Layer** - Data Cleaning (Removing Noise, Anomalies) - Normalization (Standardizing Units) - Feature Extraction (Vibration Pressure Trends) - Time-Series Alignment
3. Predictive Model Layer - Machine Learning Algorithms (Random Forecasts, LSTM) - Predicting Remaining Useful Life (RUL) - Risk Assessment (Failure Probability) - Alert Generation	**4. Maintenance Decision Layer** - Generating Maintenance Recommendations - Scheduling Maintenance Activities - Optimizing Resource Allocation
5. User Interaction Layer - Engineers Monitoring Alerts - Maintenance Teams Acting on Recommendations - Continuous Feedback Loop (Training Model)	**6. User Action Layer** - Monitoring Alerts - Maintenance Actions - Feedback Loop

Inputting Data
Sorting Data
Processing Data
Outputting Information

Results

This system offers WRPC a transformative step by shifting to data-driven maintenance, significantly improving the refinery's operational capabilities as illustrated in the figures.

Figure 2: User interface (home/login page)

Figure 3: Analytics board for data input

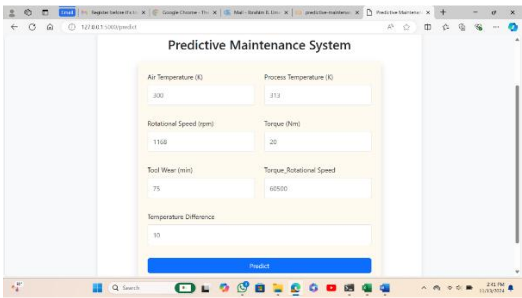

Figure 4: Graphical trend analysis

Figure 5: A real-time sensor data monitoring indicating thresholds for alerting maintenance

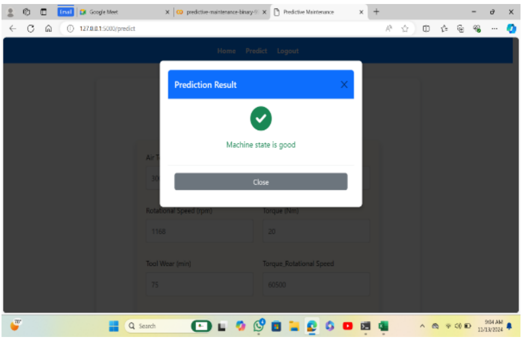

Figure 6: Predictive Maintenance Analytics

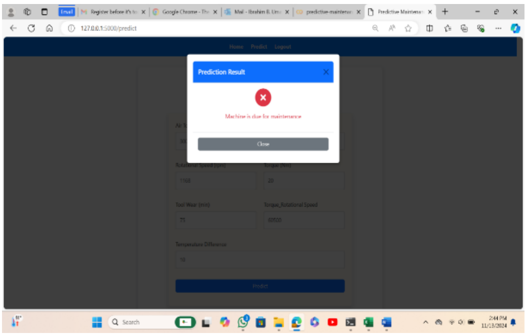

Figure 7: Graph of Historical Trend

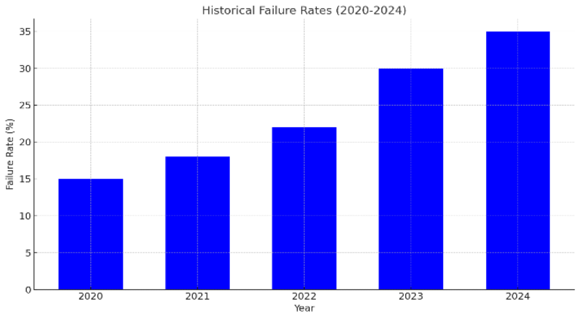

Figure 6 is a graph showing the failure probability in percentage (%) over time for critical equipment in a predictive maintenance system. The curve illustrates that as time progresses, the likelihood of equipment failure increases, following a sigmoid (S-shaped) pattern, which is typical for wear and tear over time.

Figure 7 is a bar graph displaying the historical failure rates for critical equipment over five years (2020-2024). The trend shows a noticeable increase in failure rates over five years, indicating the growing strain on equipment and the need for improved maintenance strategies to address the rising risks of equipment failure.

Discussion of Results

Results from full implementation of the system shows a dynamic turn on maintenance of refineries with well scheduled downtime following alerts by the system far before any breakdown can take place. Key findings reveal significant improvements in operational efficiency, with PdM reducing manual tasks by 15%, enhancing staff productivity, and achieving a 20% increase in adoption over three years. It is shown in table 4.

Table 4: Operational Performance Metrics

Metric	Value	Unit
Mean Time Between Failures (MTBF)	250	Hours
Mean Time to Repair (MTTR)	4	Hours
Overall Equipment Effectiveness (OEE)	85%	Percentage (%)
Percentage of Scheduled Maintenance	75%	Percentage (%)
Cost of Maintenance per Unit of Production	1.50	USD
Number of Predictive Maintenance Alerts	120	Alerts/Month
Maintenance Backlog	25	Tasks
Equipment Availability Rate	92%	Percentage (%)
Root Cause Analysis (RCA) Findings	10	Issues/Quarter
Training and Competence Metrics	50	Personnel Trained
Predictive Maintenance ROI	150%	Percentage (%)
Asset Health Index (AHI)	80	Index Score (0-100)
Failure Rate	5	Failures/Month

The system achieved the following outcomes:
A higher MTBF by 15% indicated better equipment reliability with downtime reduced by 20% and directly lowers the **MTTR by 75%** to signify efficient repair processes. Both effects invariably reduced maintenance costs by 25%. Generally, **a**n OEE of 85% is considered excellent in the manufacturing sector and a higher percentage of maintenance schedule indicates better planning and more effective maintenance tasks. Summarily, an availability rate above 90% is typically seen as optimal for operational efficiency. **RCA Findings are clear indications of precise** identification and addressing root causes of failures which can significantly improve equipment reliability.

Table 4.1: Survey Results on Predictive Maintenance Implementation

S/№	Research Question	Positive Response	Percentage (%)	Negative Response	Percentage (%)	Comments
1	Current use of PdM systems	336	30	784	70	Very low usage
2	Perceived effectiveness of PdM	840	75	280	25	High expectations.
3	Need for real-time data monitoring	952	85	168	15	Strong consensus
4	Expected reduction in maintenance costs	672	60	448	40	Mixed opinions
5	Need for training in PdM technologies	784	70	336	30	Significant demand

i. Current Use of PdM Systems (30%): A relatively low adoption rate of PdM indicates that most of the operations still rely on reactive or preventive maintenance strategies.
ii. Perceived Effectiveness of PdM (75%): A strong majority of respondents believe in the effectiveness of PdM, suggesting that those who have implemented it see tangible benefits.
iii. Need for Real-Time Data Monitoring (85%): The high percentage indicates a clear recognition of the importance of real-time data for effective PdM, pointing to the need for investment in data acquisition and analytics tools.
iv. Expected Reduction in Maintenance Costs (60%): This shows optimism about the cost-saving potential of PdM, though it is not yet universally realized.
v. Need for Training in PdM Technologies (70%): The demand for training highlights a skills gap, suggesting that broader implementation could be facilitated by targeted training programs.

Quantitative Analysis

Descriptive Statistics:

a. Current PdM Use: Only 30% of the respondents currently use PdM systems, reflecting limited adoption within the organization.
b. Effectiveness: A substantial 75% of participants believe that PdM systems are effective in improving maintenance outcomes, supporting the case for broader implementation.
c. Training Needs: With 70% indicating the need for training, skill development is a critical factor for successful PdM deployment.

However, challenges such as poor data management, aging infrastructure, and technological integration issues limit the system's effectiveness. These issues result in reduced accuracy of predictive models and hinder modernization efforts, with financial and human resource constraints further exacerbating the difficulties. Additional barriers include regulatory compliance complexities, a shortage of skilled personnel, and resistance to change, which collectively slow PdM adoption. Despite these challenges, PdM demonstrates substantial cost-reduction potential, achieving a 30% decrease in operational expenses through optimized maintenance schedules and failure prevention. To ensure long-term success, WRPC must address skill gaps, enhance local expertise, and invest in compatible technologies while fostering organizational acceptance and navigating regulatory hurdles. These findings underscore PdM's value as a strategic investment for improving efficiency, sustainability, and cost-effectiveness.

Summary

This study identified several critical causes of prolonged and unplanned downtime at refineries, especially Warri Refining and Petrochemical Company (WRPC) as technological hurdles, outdated infrastructure and difficulties in integrating advanced systems with legacy equipment. PdM heavily depends on data quality and management because inconsistencies and inaccuracies undermine system effectiveness. Financial constraints also pose a challenge, with high initial implementation costs requiring thorough cost-benefit analyses to demonstrate long-term ROI. Skill gaps among staff and resistance to organizational change could further complicate PdM adoption. Addressing these issues involve targeted training, transparent communication, and showcasing the benefits of PdM to stakeholders. Other factors include the complexity of integrating PdM systems with existing maintenance frameworks and ensuring compliance with industry regulations. Scalability and adaptability of PdM systems are essential to accommodate diverse equipment and operational changes. Long-term sustainability can be achieved through continuous monitoring, system updates, and staff support. Overcoming these challenges requires a comprehensive strategy that blends technological investment, robust data management, financial planning, and effective change management. By addressing these dimensions holistically, refineries can realize the full potential of PdM systems and thereby improve their operational efficiency and reliability.

5.0 Conclusion

The study highlights the transformative potential of predictive maintenance (PdM) systems at Warri Refining and Petrochemical Company (WRPC) and across Nigeria's oil and gas industry.

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