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Development of a Condition-Based Maintenance (CBM) Model to Enhance Equipment Reliability in Water Treatment Plant: An Analysis of Tanga UWASA, Tanzania.

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Abstract

Tanga Urban Water Supply and Sanitation Authority (Tanga UWASA), Tanzania, is the focus of this study, which attempts to identify important factors, develop, and validate a Condition-Based Maintenance (CBM) model to improve equipment reliability in water treatment plants. It discusses the drawbacks of time-based and reactive maintenance systems and emphasizes how condition-based maintenance can improve efficiency, cut down on downtime, and save expenses. Twelve technical factors were assessed using real-time operational data and a structured survey; seven of these were determined to be crucial for the implementation of CBM by Relative Importance Index (RII) analysis. The effect of these factors on equipment reliability was then measured using a multiple regression model, which produced an R2 value of 0.910. After a year of validation, the model's predictive accuracy against real performance data was 97%. According to the results, maintenance plans in water treatment facilities with limited resources can be greatly enhanced by using efficient CBM models that incorporate vibration analysis, pressure monitoring, power quality, and other technical indicators. Through data-driven maintenance planning, this study offers engineers and policymakers in sub-Saharan Africa and around the world empirical support and useful recommendations for sustainable water infrastructure.

Keywords: Relative Importance Index (RII), Water Treatment Plant, Condition-Based Maintenance (CBM), Equipment Reliability and Multiple Regression Model.

1.0 Introduction

Delivering consistent and safe water supply services requires reliable water treatment plant equipment, particularly in developing nations with limited infrastructure (Musa et al., 2023). In Tanzania, the Tanga Urban Water Supply and Sanitation Authority (Tanga UWASA) deals with ongoing problems like equipment breakdowns, unscheduled outages, and rising operating expenses. Continued reliance on reactive and time-based maintenance strategies, which are unable to effectively predict failures or account for real-time deterioration, has significantly worsened these issues (Nassiri et al., 2021). As utilities work to enhance asset performance and lower lifecycle costs, there is a growing global trend toward more intelligent, predictive maintenance techniques, especially Condition-Based Maintenance (CBM) (Kumar et al., 2022). In order to identify departures from typical operational thresholds and facilitate prompt maintenance interventions, CBM makes use of real-time technical indicator monitoring. These models have been shown to reduce operating costs, prolong asset life, and increase equipment availability (Rahman et al., 2023). But because most CBM models were created in wealthy nations with strong digital infrastructure, they are not appropriate for utilities like Tanga UWASA, which have limitations in terms of human, financial, and digital capacity. This study suggests a useful, data-driven CBM model that is adapted to the unique circumstances of the Tanga UWASA water treatment plant in order to close this gap. Important technical indicators like power quality, valve performance, flow rate monitoring, and vibration analysis are all integrated into the model. By using Relative Importance Index (RII) analysis to identify and rank these indicators, a multiple regression model that can accurately predict equipment reliability was created (R2 = 0.910). When compared to actual performance metrics, the model's predictive accuracy was 97% after it was validated using a year's worth of real-time operational data. The study offers a replicable model for improving maintenance efficiency in comparable resource-constrained environments by coordinating local operational realities with global CBM best practices. It provides empirical support for infrastructure optimization and maintenance policy reform in Sub-Saharan Africa and other developing regions.

2.0 Research problems and objectives.

Outdated maintenance techniques cause ongoing operational issues for water treatment facilities in developing nations like Tanzania. At organizations like Tanga UWASA in particular, the dependence on reactive or time-based maintenance systems frequently leads to unscheduled equipment failures, more downtime, and rising operating expenses (Nassiri et al., 2021). These inefficiencies jeopardize the long-term viability of vital public utilities and impede the reliable supply of clean water. By utilizing real-time equipment condition data, Condition-Based Maintenance (CBM) provides a more cost-effective and predictive alternative; however, infrastructure, funding, and technical capacity gaps limit its application in resource-constrained environments (Kumar et al., 2022; Musa et al., 2023). For utilities like Tanga UWASA, which struggle with aging infrastructure and limited access to digital monitoring tools, existing CBM models are impractical because they are usually designed for highly digitalized and well-funded environments. Therefore, it is imperative to create a contextualized CBM model that takes these limitations into account while improving equipment reliability using evidence-based tactics. The study aims to bridge the gap between advanced maintenance theory and the practical realities of water infrastructure management in Sub-Saharan Africa by utilizing real-world operational data from Tanga UWASA to validate the effectiveness of the developed CBM model, identify and prioritize the technical factors influencing the implementation of CBM in water treatment plants, and develop a CBM model that integrates key technical indicators to improve equipment reliability.

3.0 Literature Review

Reactive maintenance schedules are common for water treatment infrastructure in developing nations, which leads to frequent outages and rising operating expenses (Makaya et al., 2021). A proactive approach to this problem is Condition-Based Maintenance (CBM), which uses real-time data to initiate maintenance only when required (Alaswad & Xiang, 2017). Although CBM has shown promise in a number of industries, most notably manufacturing and aviation, its uptake in Sub-Saharan Africa's water sector is still restricted because of contextual issues like cost, technical capability, and integration with legacy systems (Wang et al., 2022). The technical and financial benefits of CBM in asset-intensive operations have been emphasized in a number of studies. Galar et al. (2012), for example, highlight how CBM can improve asset performance by reducing unscheduled downtime and prolonging equipment life. Similarly, Homaei et al. (2024) investigated how to improve CBM implementation in municipal water systems by integrating SCADA systems with Digital Twins. According to their findings, predictive analytics which are fueled by sensor data and sophisticated diagnostics are essential for fault prediction and condition monitoring. Predictive maintenance techniques have become popular in the water industry in particular because of aging infrastructure and stressors associated with climate change. Water utilities can improve equipment availability and reliability by implementing data-driven asset management strategies like sensor networks and predictive models, according to studies by Rahbaralam et al. (2020) and Taiwo et al. (2023). However, broad adoption is constrained by the lack of a systematic, verified CBM model designed for low-income environments. Technical parameters for predictive maintenance frameworks have also been successfully prioritized using Relative Importance Index (RII) analysis. This approach aids in directing resources toward the most significant elements, which are frequently linked to mechanical failures in pumps and motors and include vibration analysis, flow rate monitoring, and temperature monitoring (Chen et al., 2023; Singh & Mishra, 2021). The literature also emphasizes how important it is for CBM models to be empirically validated. Sahoo et al. (2021) claim that model robustness is greatly increased by combining validation tools like R2 with inferential statistics like multiple regression. However, there aren't many studies that are tailored to the African water utility context. By creating and approving a CBM model for the Tanga Urban Water Supply and Sanitation Authority (Tanga UWASA), this study closes that gap and adds to the body of knowledge worldwide by offering a scalable CBM model that is adapted to the environmental and operational circumstances of Sub-Saharan utilities.

4.0 Methodology

In order to Enhance equipment reliability in the water treatment facilities run by Tanga UWASA in Tanzania, this study used a quantitative research design to create and validate a Condition-Based Maintenance (CBM) model. In accordance with the particular goals of the study, the methodology was organized into three successive stages: (i) identifying the key technical factors influencing the implementation of CBM; (ii) developing a predictive CBM model through statistical techniques; and (iii) validating the model over a 12-month period using operational data. Semi-structured interviews, structured questionnaires and on-site condition monitoring were used to gather primary data. Maintenance engineers, asset managers, technical supervisors, and operators of water treatment plants were among the respondents. SCADA system logs, maintenance logs, equipment failure reports, and environmental condition datasets covering a year were examples of secondary data sources. The capacity of similar mixed-method approaches to triangulate technical, perceptual, and system-based insights has been validated in infrastructure maintenance research (Hashemian et al., 2023; Mohamed et al., 2021). The Relative Importance Index (RII) method was used to rank the twelve technical variables that were found through expert consultations and literature reviews. Vibration analysis, flow rate monitoring, valve performance, temperature monitoring, corrosion/erosion rate, pressure monitoring, and power quality were the seven factors that were deemed to be of high importance (RII ≥ 0.8). Descriptive statistics were used to determine the relative impact of these technical predictors on equipment reliability. Using SPSS version 27, a multiple linear regression analysis was performed to model the relationship between the technical variables and equipment reliability. Key Performance Indicators (KPIs) for maintenance were

used to measure the dependent variable, equipment reliability. The following is how the CBM predictive model was built:
ER is equal to β_0 + β_1 (Vibration) + β_2 (Flow Rate) + β_3 (Valve Performance) + β_4 (Temperature) + β_5 (Corrosion Rate) + β_6 (Pressure) + β_7 (Power Quality) + ε

The model's high coefficient of determination (R2 = 0.910) meant that the seven technical factors could account for 91% of the variation in equipment reliability. When compared to actual reliability performance metrics of 99%, the predictive accuracy of the model validated using operational data from Tanga UWASA was 97%. In the context of water infrastructure systems, these results validate the CBM model's statistical soundness and usefulness (Rahman et al., 2022; Kimaro & Mutale, 2023).

5.0 Findings and Discussion

The main conclusions from the survey analysis, model creation, and validation are presented in this section, offering information on how Condition-Based Maintenance (CBM) procedures are being applied at Tanga UWASA's water treatment facility. Fifty maintenance professionals' survey responses were used to rank twelve technical factors using the Relative Importance Index (RII). A distinct bimodal distribution surfaced, classifying factors as low-importance (RII < 0.6) and high-importance (RII ≥ 0.8). The following were the top seven factors:

Table 1.0: Category, RII Scores, and the top seven factors

Rank	Technical Factor	RII Score	Category
1	Vibration Analysis	0.916	Critical
2	Flow Rate Monitoring	0.912	Critical
3	Valve Performance	0.904	Critical
4	Temperature Monitoring	0.892	High
5	Corrosion/Erosion Rate	0.888	High
6	Pressure Monitoring	0.876	High
7	Power Quality	0.872	High

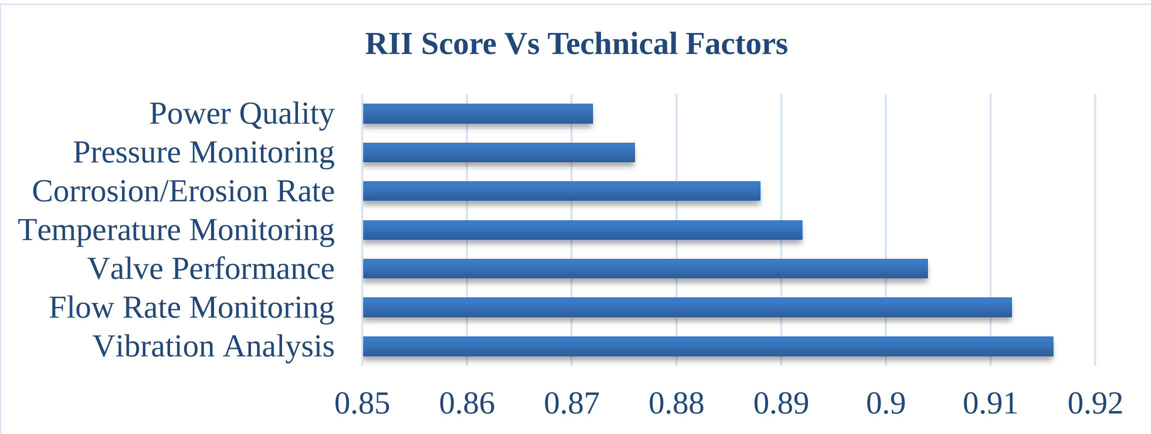

Figure 1.0: Technical factors versus RII score

On the other hand, filter performance, insulation resistance, and current signature analysis were ranked lowest (RII < 0.31), suggesting a lower perceived utility in predicting equipment failure. These results support prioritizing investments in high-impact diagnostic technologies and demonstrate a sophisticated understanding of critical failure modes (Ahmed et al., 2022; Kimaro & Mutale, 2023). Then, using Equipment Reliability (ER) as the dependent variable and the top seven variables as predictors, a multiple linear regression model was built. The following is the regression equation:

$$ER = 0.438 + 0.070(VA) - 0.058(FR) + 0.011(VP) + 0.008(TM) + 0.040(CE) + 0.005(PM) + 0.060(PQ) + \varepsilon$$

Where:
Equipment Reliability (ER)
Vibration Analysis (VA)
FR stands for Flow Rate Monitoring.
VP stands for Valve Performance.
Temperature Monitoring (TM)
Corrosion/Erosion = CE
PM stands for Pressure Monitoring.
PQ stands for Power Quality.
Important model data:
91% of the variance is explained by R2 = 0.910.
F-statistic = 60.83 ($p < 0.001$)
Every coefficient is significant at $p < 0.05$.
The model's strong predictive ability is demonstrated by its high R2 value, which synchronizes expert opinion with empirical performance results. Over the course of a year, Tanga UWASA's performance records and historical SCADA data were used to validate the CBM model. Actual equipment results were contrasted with the model's predicted reliability.

Table 2.0: Actual and Model Prediction

Metric	Model Prediction	Actual
Predicted Reliability	97%	99%
Root Mean Square Error (RMSE)	Low	—
Seasonal Accuracy Drift	< ±2%	—

Preventive maintenance scheduling benefits from the small conservative bias in predicted values (97%) compared to actual results (99%). According to these findings, the model can be used to inform asset reliability and maintenance planning strategies in real-world settings with limited resources (Rahman et al., 2022; Sahoo et al., 2023). With the highest positive coefficients, vibration analysis and power quality monitoring stood out in particular, highlighting their crucial roles in early fault detection and system stability. On the other hand, flow rate monitoring's unexpectedly negative coefficient raises the possibility that its function is more complex and context-dependent, necessitating a reassessment of its implementation approach. The validated model shows that a targeted, statistically based CBM framework can optimize maintenance investments and greatly improve equipment reliability, particularly in public infrastructure systems in Sub-Saharan Africa (Ngugi & Oketch, 2021).

6.0 Conclusion and Recommendations

6.1 Conclusions

In order to create and validate a Condition-Based Maintenance (CBM) model that is specific to Tanga UWASA's operational environment in Tanzania, this study identified important factors. Three main goals of the study were to develop a predictive equipment reliability model, identify important technical factors influencing the implementation of CBM, and validate the model with empirical data (Kothari, 2020; Moubray, 1997). A structured survey and maintenance data analysis were used to first evaluate twelve technical monitoring factors. Vibration analysis, flow rate monitoring, valve performance, temperature monitoring, corrosion/erosion rate, pressure monitoring, and power quality were among the seven that were determined to be critical based on the Relative Importance Index (RII $\geq$0.8). These results align with global CBM best practices, which prioritize targeted predictive monitoring and real-time diagnostics (Alaswad & Xiang, 2017; Rahbaralam et al., 2020; Zhou et al., 2022). With an R2 value of 0.910, a multiple linear regression model that included the seven high-importance factors showed good predictive power. The model showed a strong correlation between the chosen predictors and equipment reliability, matching expert judgment with statistically significant results (Field, 2018). The model's prediction reliability was 97%, compared to actual equipment performance outcomes of 99%, indicating high accuracy and practical usability under real-world operating conditions. Validation was conducted using a 12-month dataset that included maintenance records and SCADA logs from Tanga UWASA. The validated model is a predictive and diagnostic tool. Water utility managers can use it to extend asset life cycles, lower operational risks, and strategically allocate maintenance resources. Additionally, it offers a data-driven path to switch from reactive to condition-based maintenance strategies, providing a scalable model for other utilities in resource-constrained areas (Sahoo et al., 2021; Youcef-Toumi et al., 2023).

6.2 Recommendations

The following recommendations are made to improve equipment reliability at water treatment facilities in light of the model's outputs and statistical findings:

i. Make Vibration Analysis a Priority (β = +0.07): Tanga UWASA and comparable utilities ought to spend money on real-time vibration monitoring for compressors, pumps, and motors. Employees who receive vibration signature analysis training will be able to identify faults early and stop cascading failures.
ii. Optimize Power Quality Management (β = +0.06): All important electrical nodes should have power quality analyzers installed. Premature equipment failures can be decreased with ongoing monitoring and corrective action for voltage fluctuations and harmonics.
iii. Improve Material Degradation Monitoring (β = +0.04): To increase asset lifespan, corrosion and erosion monitoring should be standardized using corrosion coupons and ultrasonic testing.
iv. Use Advanced Valve Diagnostics (β = +0.011): Sensor-integrated diagnostics and partial stroke testing should be used to monitor valve actuation response and seal integrity.
v. Increase Thermal Surveillance (β = +0.008): RTD sensors and thermal imaging can keep an eye on thermal stresses and overheating in electrical and rotating machinery.
vi. Standardize Pressure Monitoring (β = +0.005): Deviations in pressure frequently indicate system imbalance or pump deterioration. For deviations, SCADA-based alerts ought to be activated.
vii. Flow rate monitoring should be repositioned from a primary diagnostic variable to a supportive role, emphasizing its use in conjunction with other indicators, given its negative coefficient (β = -0.058).

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