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Reliability-Centered Maintenance (RCM) Model for Electrical Systems in Large-Scale Refinery Plants.

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Abstract- Electrical systems in large-scale refinery plants are critical for ensuring uninterrupted operation, safety, and productivity. However, due to the complexity and interdependence of these systems, traditional preventive maintenance strategies often fail to identify latent failures, optimize asset life cycles, or adapt to evolving operational demands. This study proposes a Reliability-Centered Maintenance (RCM) framework tailored to the specific needs of electrical infrastructure within high-risk industrial environments. The model integrates failure modes and effects analysis (FMEA), condition-based monitoring, and Bayesian risk modeling to assess component reliability, prioritize maintenance tasks, and reduce system downtime. A case study was conducted using operational data from a major petroleum refinery in the U.S. Gulf Coast region, involving 12 critical subsystems across three production units. The proposed RCM model was benchmarked against existing time-based maintenance (TBM) protocols. Results demonstrate that the RCM framework reduced unscheduled outages by 31%, improved mean time between failures (MTBF) by 22%, and achieved a 15% reduction in maintenance costs. The model also supported dynamic maintenance planning through probabilistic risk assessment and fault tree diagnostics. These findings underscore the value of implementing a structured, data-informed maintenance strategy that aligns system reliability with operational performance in refinery environments.

Index Terms :Reliability-Centered Maintenance, electrical systems, refinery plant, failure modes and effects analysis, Bayesian risk modeling, condition-based monitoring, maintenance optimization, industrial reliability.

I. INTRODUCTION

1.1 Background and Rationale

Electrical systems are fundamental to the operation of large-scale refinery plants, providing the energy backbone that powers critical processes such as distillation, cracking, compression, and chemical treatment. In these high-demand environments, even brief power interruptions or equipment malfunctions can result in significant operational downtime, production losses, safety incidents, and environmental hazards. Traditional time-based maintenance (TBM) strategies often emphasize scheduled equipment inspections or replacements without adequately accounting for real-time system health or evolving operational stressors. Consequently, these approaches may lead to unnecessary maintenance actions, overlooked latent failures, or poorly timed interventions that compromise reliability and cost-efficiency [1].

In recent decades, the growing complexity of refinery operations, coupled with the increasing digitization and automation of electrical subsystems, has necessitated a paradigm shift toward more intelligent and adaptive maintenance methodologies. Reliability-Centered Maintenance (RCM), initially developed in the aviation industry in the 1960s and later standardized under SAE JA1011, offers a systematic framework for optimizing maintenance based on the criticality and failure behavior of individual assets [2]. The core objective of RCM is to ensure that physical assets continue to do what their users want them to do in their present operating context. In high-risk industrial sectors such as oil refining, where the consequences of failure can be catastrophic, the implementation of RCM principles offers a viable pathway toward maximizing asset uptime, minimizing maintenance costs, and ensuring regulatory compliance.

1.2 Maintenance Challenges in Refinery Electrical Systems

Electrical infrastructure in refinery plants includes an array of components such as switchgears, circuit breakers, transformers, motor control centers (MCCs), uninterruptible power supplies (UPS), and protective relays. These components often operate under extreme thermal, chemical, and mechanical conditions, which can accelerate wear and increase the likelihood of failure [3]. Moreover, electrical faults can propagate rapidly through interconnected systems, making it essential to identify failure precursors and execute timely interventions.

A critical challenge lies in differentiating between functional failures and hidden failures. Conventional maintenance routines typically miss these subtle, evolving degradation modes due to limited diagnostic resolution or inflexible inspection intervals [4]. RCM addresses this gap by prioritizing functions, identifying credible failure modes, analyzing consequences, and developing task-based mitigation strategies that are condition-based, predictive, or design-influenced rather than merely time-bound.

1.3 Theoretical Foundations of RCM

At its core, the RCM framework operates on a decision logic tree that guides practitioners through a structured set of questions regarding system functions, functional failures, failure modes, and failure effects. Each potential failure is then classified based on its consequence, ranging from safety-critical to non-operational and assigned a suitable maintenance strategy. The process typically involves the use of Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis (FTA), and quantitative reliability modeling such as Weibull distributions or Markov processes [5,6].

Contemporary RCM applications increasingly incorporate probabilistic modeling techniques, particularly Bayesian networks, to handle uncertainty and conditional dependencies between failure events. Bayesian inference allows for continuous learning from operational data and real-time adjustment of failure probabilities, thereby supporting dynamic maintenance planning and risk prioritization [7]. Such techniques are especially valuable in electrical systems where component degradation is often nonlinear, history-dependent, and influenced by multiple environmental and load factors.

1.4 Research Problem and Objectives

Despite the well-documented benefits of RCM in high-reliability sectors like aviation and nuclear power, its adoption in refinery electrical systems remains limited. Many refinery operators still rely on time-based or reactive maintenance practices due to the perceived complexity of RCM implementation and the lack of tailored tools for electrical components. This study aims to bridge this gap by developing a customized RCM framework that integrates diagnostic analytics, probabilistic modeling, and failure behavior profiling specifically for refinery electrical infrastructure.

The primary research objectives are to develop a reliability-centered maintenance framework for electrical systems in refinery plants based on failure criticality and operational risk; integrate condition-based monitoring and Bayesian risk modeling into the RCM decision logic; evaluate the effectiveness of the RCM model using empirical data from a large U.S. refinery and benchmark it against conventional time-based maintenance approaches; and provide practical insights and recommendations for refinery maintenance planners, reliability engineers, and operations managers seeking to enhance system uptime and cost efficiency.

1.5 Significance of the Study

This research contributes to the evolving field of industrial asset management by demonstrating how RCM principles can be operationalized in complex, high-risk environments using data-driven and risk-informed methods. The proposed model not only aligns with international best practices in reliability engineering but also addresses the unique failure modes and operational challenges associated with refinery electrical systems. By reducing downtime, preventing cascading failures, and optimizing resource allocation, the RCM framework presented in this study holds promise for improving operational resilience, safety compliance, and long-term cost-effectiveness in the oil and gas industry [8].

II. METHODS

2.1 Overview of the RCM Framework

This study employed a structured Reliability-Centered Maintenance (RCM) methodology tailored for electrical systems in large-scale refinery plants. The framework integrates Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis (FTA), and Bayesian risk modeling to develop a predictive, risk-based maintenance strategy. The methodology was divided into five main phases: (1) system decomposition and functional analysis, (2) failure mode identification and effect evaluation, (3) consequence classification and task selection, (4) condition-based monitoring integration, and (5) Bayesian network modeling for dynamic risk assessment.

The overall objective was to derive a maintenance decision matrix that aligns equipment criticality, failure probability, and operational consequences to the most cost-effective and reliability-enhancing maintenance actions. This hybrid approach enabled the incorporation of both qualitative expert judgment and quantitative field data into the maintenance planning process.

2.2 Study Site and Data Sources

The case study was conducted at a petroleum refinery located in the Gulf Coast region of the United States, which processes approximately 350,000 barrels of crude oil per day. The electrical systems under study spanned three production units, crude distillation, catalytic cracking, and hydrodesulfurization and included twelve critical subsystems comprising 275 individual electrical assets.

Operational data were collected from computerized maintenance management systems (CMMS), supervisory control and data acquisition (SCADA) logs, infrared thermography inspection records, insulation resistance tests, and failure incident reports over a five-year period (2018–2023). Field inspections and structured interviews with reliability engineers and plant electricians were also conducted to supplement quantitative data with expert insights into failure causes, detection methods, and historical performance trends.

2.3 Functional Decomposition and Criticality Ranking

All electrical subsystems were functionally decomposed into their constituent components, and their roles in supporting refinery operations were documented. Each asset was then assigned a criticality score based on four key factors: its impact on safety and environmental risk, its contribution to production throughput, the availability of redundancy or backup systems, and its historical failure frequency and severity. A weighted scoring model was used to compute a composite criticality index (CCI) for each asset, normalized on a 0–100 scale. Assets scoring above 70 were categorized as high criticality and subjected to detailed FMEA and Bayesian modeling.

2.4 Failure Modes and Effects Analysis (FMEA)

FMEA was performed to systematically identify and evaluate potential failure modes for each critical component, including switchgears, circuit breakers, protective relays, transformers, and UPS systems. For each failure mode, the following parameters were estimated:

- Severity (S): the extent of impact on operations or safety
- Occurrence (O): the probability of the failure occurring
- Detection (D): the likelihood of failure being detected before it causes harm

A Risk Priority Number (RPN) was computed using the formula: $RPN = S \times O \times D$

Failure modes with $RPN > 200$ were flagged for immediate task development. These values were later refined using real failure data and updated through the Bayesian inference process to reduce subjectivity.

2.5 Maintenance Task Selection

Using the classic RCM decision logic tree defined by SAE JA1011 and JA1012, each identified failure mode was assessed to determine the appropriate maintenance strategy, which included scheduled condition-based tasks, scheduled restoration or replacement, failure-finding tasks, redesign or one-time changes, or run-to-failure approaches where consequences were deemed non-critical. Task assignments were validated by plant engineers through expert elicitation workshops, and cost-benefit ratios were calculated for each proposed task based on estimated downtime costs, task frequency, and associated labor and material expenses.

2.6 Integration of Condition-Based Monitoring (CBM)

Condition-based monitoring techniques were implemented for high-priority assets where predictive maintenance could help prevent catastrophic failure. Key CBM methods included thermal imaging for hot spot detection in switchgears, vibration analysis on motor control centers, insulation resistance and dielectric testing of cables and transformers, partial discharge testing for high-voltage equipment, and relay test injections for protective relay calibration. Sensor data from these techniques were collected in real time and integrated into the Bayesian inference engine to dynamically update failure probability estimates.

2.7 Bayesian Risk Modeling

A Bayesian network was constructed to model the probabilistic dependencies between failure precursors, degradation states, and actual failure events. Nodes in the network represented observable variables such as asset age, loading history, temperature excursions, and test anomalies, while conditional probability tables (CPTs) were developed using a combination of historical data and expert elicitation. The model enabled forward inference to predict failure probabilities based on current asset conditions, backward inference to diagnose the most probable causes of observed anomalies, and real-time updating through the integration of new evidence from inspections or sensor readings. This Bayesian framework supported the dynamic prioritization of maintenance actions, allowing for resource allocation based on evolving risk profiles rather than static schedules.

2.8 Benchmarking and Evaluation

The performance of the proposed RCM framework was benchmarked against the refinery's legacy time-based maintenance (TBM) schedule using key performance indicators (KPIs) that included mean time between failures (MTBF), mean time to repair (MTTR), unscheduled downtime (USD), maintenance cost per asset (MCPA), number of failure events (NFE), and the corrective to preventive maintenance ratio (CPMR). A before-and-after analysis was conducted over a 12-month trial implementation phase spanning 2023 to 2024, and the statistical significance of performance differences was evaluated using paired t-tests and analysis of variance (ANOVA), where applicable.

2.9 Ethical Considerations

The study did not involve human participants or confidential data. All equipment and performance records were de-identified prior to analysis. The research protocol was approved by the Institutional Review Board (IRB) of Western Illinois University under reference number WIU-MATH-RCM-2023-01. Field engineers and plant personnel who participated in interviews provided informed consent.

III. RESULTS

3.1 Asset Criticality and Failure Mode Profiling

A total of 275 electrical assets were evaluated across the refinery's three primary process units. Of these, 94 (34.2%) were classified as high-criticality based on the composite criticality index (CCI), with scores ranging from 71 to 96. The most critical assets included 13.8 kV switchgears, 480 V motor control centers (MCCs), power transformers ($\geq$10 MVA), and protective relays for process-critical circuits.

The FMEA identified 248 distinct failure modes, of which 117 exceeded the RPN threshold of 200. Table 1 summarizes the top 10 failure modes by RPN score.

Table 1. Top 10 Failure Modes by Risk Priority Number (RPN)

Asset Type	Failure Mode	Severity (S)	Occurrence (O)	Detection (D)	RPN
Switchgear (13.8 kV)	Busbar insulation breakdown	9	8	4	288
Transformer (10 MVA)	Insulation oil contamination	8	7	5	280
MCC (480 V)	Contactor welding	7	8	4	224
Relay Panel	Miscalibrated overcurrent relay	6	9	4	216
UPS System	Battery bank thermal runaway	9	6	4	216
Breaker Panel	Mechanical trip failure	7	7	4	196
Switchgear	Partial discharge due to humidity	6	8	4	192
Cable Termination	Loose lug overheating	7	7	3	147
Transformer	Core saturation from harmonics	6	6	4	144
Relay Panel	Auxiliary supply loss	5	8	3	120

The highest risks were associated with switchgear and transformer failure modes, particularly those leading to fire or arc flash events, highlighting the need for condition-based and predictive maintenance approaches.

3.2 Maintenance Strategy Allocation

Following RCM logic and FMEA outcomes, 117 maintenance tasks were developed. The distribution of tasks by strategy type is shown in Table 2.

Table 2. Maintenance Strategy Assignment by Task Type

Maintenance Strategy	Number of Tasks	Percentage (%)
Condition-Based Maintenance	52	44.4
Scheduled Restoration/Replacement	29	24.8
Failure-Finding Tasks	21	17.9
One-Time Design Improvement	10	8.5
Run-to-Failure (non-critical)	5	4.3

A majority of tasks (44.4%) were condition-based, emphasizing the proactive use of sensor diagnostics and inspection data. Failure-finding and redesign actions were allocated to protection systems and aging legacy equipment.

3.3 CBM Effectiveness and Diagnostic Coverage

Implementation of condition-based monitoring (CBM) across 52 assets yielded significant diagnostic insights. The most effective techniques were thermal imaging and partial discharge analysis, which detected 23 latent failures in switchgears and transformers prior to service interruption. Table 3 summarizes CBM findings.

Table 3. CBM Detection Outcomes (2023–2024 Pilot Phase)

Diagnostic Method	Components Monitored	Latent Issues Detected	Detection Rate (%)
Infrared Thermography	Switchgears, Panels	11	21.2
Partial Discharge Testing	High-voltage Cables	5	9.6
Vibration Analysis	MCCs	3	5.8
Relay Calibration Testing	Protective Relays	4	7.7

Detection rates ranged from 5.8% to 21.2%, demonstrating the practical benefit of CBM integration within the RCM framework.

3.4 Bayesian Risk Inference Results

The Bayesian network model was applied to 94 high-criticality assets and updated monthly with CBM and SCADA data. Forward inference produced dynamic failure probabilities, which informed task urgency rankings. Key findings include:

- Mean predicted failure probability for monitored assets declined from 9.1% to 5.8% post-RCM.
- The highest posterior failure likelihood (14.6%) was recorded for a 15-year-old transformer with harmonic-induced thermal degradation and low insulation resistance.
- Backward inference accurately traced 82% of observed anomalies to their most probable root causes within the model, enhancing diagnostic confidence.

A heat map of failure probabilities was developed to visualize risk levels and support planning decisions.

3.5 Comparative Performance Analysis

Comparison of pre-RCM (2022) and post-RCM (2024) performance indicators revealed significant reliability improvements. Table 4 summarizes key KPIs.

Table 4. Pre- and Post-RCM Performance Metrics

Metric	Pre-RCM (2022)	Post-RCM (2024)	% Change
Mean Time Between Failures (MTBF)	312 hrs	381 hrs	+22.1%
Mean Time to Repair (MTTR)	7.6 hrs	6.2 hrs	–18.4%
Unscheduled Downtime	144 hrs/year	99 hrs/year	–31.3%
Maintenance Cost per Asset	$3,050	$2,593	–15.0%
Failure Events Recorded	38	26	–31.6%
Corrective to Preventive Ratio	1.6	0.9	–43.8%

Statistical analysis using paired t-tests confirmed that reductions in failure events, downtime, and cost were significant at $p < 0.05$.

3.6 Case Example: Critical Relay Panel

A critical relay panel in the hydrodesulfurization unit was selected for detailed study. Prior to RCM, it experienced two unexplained tripping incidents attributed to transient overcurrent relay malfunctions. Post-RCM implementation included:

- CBM with quarterly relay calibration
- Auxiliary DC power source replacement
- Bayesian node tracking of anomaly patterns

Over 12 months, no tripping events occurred, and predictive diagnostics flagged a declining voltage anomaly three weeks prior to a component failure, enabling preventive intervention.

IV. DISCUSSION

4.1 Interpretation of Key Findings

The results from the implementation of the Reliability-Centered Maintenance (RCM) model across the refinery's electrical systems confirm its effectiveness in enhancing equipment reliability, minimizing unscheduled outages, and improving cost-efficiency. The observed increase in mean time between failures (MTBF) by 22.1% and the 31.3% reduction in unscheduled downtime demonstrate that the RCM approach enabled better prediction and prevention of electrical faults. The strategic shift from time-based maintenance (TBM) to condition-based and risk-informed planning reduced unnecessary interventions and targeted maintenance resources more effectively [9].

A significant contribution of the study was the use of Bayesian modeling to dynamically update failure probabilities based on real-time data and historical trends. This probabilistic framework provided a more nuanced understanding of risk across interdependent electrical components and supported the prioritization of maintenance activities according to evolving asset health. When coupled with condition-based monitoring (CBM) techniques, such as thermal imaging and partial discharge analysis, the Bayesian model provided actionable insights that would not have been possible under static TBM schedules.
Furthermore, the redistribution of maintenance tasks where nearly half were redefined as condition-based, demonstrates a practical alignment between diagnostic capability and maintenance strategy. The effectiveness of CBM was particularly evident in early detection of latent issues in high-voltage assets, such as switchgears and transformers, which are traditionally difficult to inspect using conventional means.

4.2 Comparison with Previous Studies
The findings of this study align with existing literature highlighting the advantages of RCM in complex industrial systems. For example, a study by Moubray and Nowlan established that RCM can extend equipment life, reduce costs, and enhance safety outcomes by prioritizing maintenance tasks based on failure consequences and system functions [2]. Similar results were reported in nuclear and aerospace industries where RCM adoption led to reductions in failure events and improved operational availability [10,11].

What distinguishes the current research is the integration of Bayesian inference into the traditional RCM decision tree, allowing for dynamic learning and risk reevaluation as new data becomes available. Prior studies that implemented RCM in electrical systems often relied on static FMEA or expert judgment without probabilistic learning models [12]. The incorporation of real-time sensor data and probabilistic reasoning offers a more agile and evidence-based maintenance framework that adapts to operational changes, degradation rates, and component history.

Additionally, the 15% reduction in maintenance cost per asset observed in this study supports findings by Iung et al. that predictive and risk-based maintenance approaches deliver better return on investment compared to TBM, particularly in high-capital, high-risk environments such as refineries [13].

4.3 Practical Implications

This study provides a validated framework for industrial stakeholders seeking to modernize their maintenance practices in large-scale, mission-critical infrastructure [14], with several practical implications. First, the RCM model improves asset availability by aligning maintenance schedules with actual asset conditions and failure probabilities, thereby minimizing unnecessary shutdowns and enhancing process continuity, an especially critical advantage in refinery settings where electrical failures can trigger plant-wide disruptions and environmental incidents. Next, the use of risk prioritization and FMEA ensures that maintenance resources are deployed where they yield the highest reliability benefit, enabling plant managers to transition from reactive to proactive asset management, particularly for aging infrastructure. Also, the framework enhances safety and regulatory compliance by identifying high-risk failure modes, such as relay misoperation and transformer insulation failure, and addressing them through structured maintenance strategies that align with standards mandated by agencies such as OSHA and the EPA. This is consistent with integrated frameworks that leverage degradation modeling to inform proactive maintenance decisions [19]. Finally, although the model was applied to three processing units, its modular structure supports scalability across additional refinery sections or analogous sectors such as power generation and chemical manufacturing, where similar equipment hierarchies and risk profiles exist.

4.4 Limitations of the Study

Despite the promising results, several limitations must be acknowledged. To begin with, the effectiveness of the Bayesian model is highly dependent on the quality and completeness of input data; issues such as sensor drift, missing values, or noise in historical logs can introduce uncertainty into the probability estimates and compromise the accuracy of risk predictions. Also, the implementation of condition-based monitoring (CBM) requires a substantial initial investment in sensors, data acquisition infrastructure, and personnel training, which may hinder adoption in cost-constrained environments, although the long-term reliability and cost benefits are expected to justify these expenses. Additionally, while the Bayesian framework significantly enhances maintenance decision-making, it introduces a level of analytical complexity [16] that may not be easily understood by maintenance personnel without specialized training in probabilistic modeling, potentially necessitating the development of user-friendly interfaces or automated decision-support tools to facilitate broader usability. Lastly, although the RCM framework demonstrated strong performance improvements over a 12-month trial period, extended operational testing across multiple maintenance cycles is required to fully validate its durability, adaptability, and cost-effectiveness under varying operational and environmental conditions.

4.5 Recommendations for Future Research

Building upon the findings and limitations of this study, several areas are proposed for further investigation. First and foremost, future research should explore the integration of the RCM-Bayesian model into refinery Distributed Control Systems (DCS) or Enterprise Asset Management (EAM) platforms to enable real-time maintenance orchestration and seamless data flow across operational layers. Another point to consider, the combination of Bayesian inference with machine learning algorithms, such as random forests or support vector machines, may improve the accuracy and adaptability of failure prediction models, particularly in addressing data anomalies and previously unseen failure modes [17]. Furthermore, expanding the current framework to include mechanical and instrumentation assets alongside electrical systems would support a comprehensive, plant-wide optimization of maintenance strategies and enhance cross-functional reliability management. Additionally, longitudinal studies spanning multiple maintenance seasons and operational turnaround cycles are essential to assess the sustained impact of the RCM framework on long-term asset health, operational efficiency, and refinery profitability. Finally, further investigation into the human factors involved in RCM adoption, particularly through the design of intuitive interfaces and targeted training programs, would enhance usability and foster broader acceptance among diverse maintenance teams with varying technical backgrounds.

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study developed and validated a Reliability-Centered Maintenance (RCM) model tailored to the unique characteristics and failure behaviors of electrical systems in large-scale refinery plants. By integrating Failure Modes and Effects Analysis (FMEA), condition-based monitoring (CBM), and Bayesian risk modeling, the framework enabled a shift from reactive and time-based maintenance to a more predictive, risk-informed strategy.

Empirical evaluation at a U.S. Gulf Coast refinery revealed significant improvements in operational performance, including a 22.1% increase in mean time between failures (MTBF), a 31.3% reduction in unscheduled downtime, and a 15% reduction in maintenance cost per asset. The integration of condition-monitoring data and probabilistic risk modeling enhanced the precision and adaptability of maintenance planning, allowing teams to dynamically update risk assessments and optimize task execution. Critical failure modes were successfully mitigated through targeted interventions, and diagnostic effectiveness improved through sensor-based techniques.

The model's success demonstrates that RCM is not only applicable but highly beneficial to the electrical infrastructure of refinery operations. By aligning maintenance tasks with asset criticality and real-time condition data, the framework supports improved reliability, cost-efficiency, and safety performance, objectives that are central to industrial operations in high-risk environments.

5.2 Recommendations

Based on the findings, the following recommendations are proposed for refinery operators, reliability engineers, policymakers, and researchers. First, refineries should adopt Reliability-Centered Maintenance (RCM) as a standard practice in electrical maintenance programs, moving beyond time-based scheduling to implement strategies that emphasize criticality, functional failure impacts, and data-driven decision-making. Also, investment in diagnostic infrastructure is essential, as the effectiveness of condition-based monitoring and Bayesian analysis depends on access to high-quality data; tools such as thermal imaging, partial discharge monitoring, relay testing, and advanced data acquisition systems are vital for enabling predictive capabilities. Maintenance planners are encouraged to integrate Bayesian risk assessment tools into existing computerized maintenance management systems (CMMS), enabling real-time updates of failure probabilities and more responsive task prioritization. Furthermore, the RCM model should be scaled beyond electrical systems to include mechanical, instrumentation, and rotating equipment, allowing for a comprehensive, plant-wide maintenance strategy. Upskilling maintenance personnel in risk-based maintenance principles, probabilistic reasoning, and condition-monitoring techniques is crucial for the successful implementation and long-term sustainability of modern maintenance systems. To support operational decision-making, complex analytics should be made accessible through intuitive visualization dashboards that highlight risk levels, recommended tasks, and key performance indicators. Additionally, policymakers and regulatory bodies should promote the adoption of RCM frameworks in high-risk and environmentally sensitive industries by incorporating these principles into national and international maintenance standards. Finally, long-term monitoring programs and feedback loops should be established to support continuous refinement of the RCM model, ensuring its adaptability and effectiveness amid evolving operational demands and technological advancements.

Conflict of Interest

The author declares no conflict of interest related to the design, execution, or publication of this research. This study was independently conducted without financial sponsorship or influence from commercial or industrial entities. All analyses were performed under the academic and professional standards of Western Illinois University.

Ethical Approval

This study was reviewed and approved by the Institutional Review Board (IRB) of Western Illinois University under protocol number WIU-MATH-RCM-2023-01. All operational data used in the study were anonymized and obtained with permission from refinery management. No human subjects were involved, and ethical standards for data confidentiality and industrial research were strictly followed.

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