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Reliability-driven maintenance optimization and operational performance: Empirical evidence from the chemical industry

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Abstract

Reliability and maintenance optimization play a critical role in enhancing operational performance in capital-intensive process industries such as chemicals. This study empirically examines the relationship between equipment reliability, maintenance optimization, and operational outcomes using plant-level data from the chemical industry. Drawing on reliability engineering and operations management theory, the study integrates key reliability indicators, i.e. mean time between failures (MTBF), mean time to repair (MTTR), downtime, and availability—within an optimization-based maintenance framework. Using monthly operational data, the analysis employs paired statistical tests and multivariate regression with robust standard errors to evaluate the performance impact of optimized maintenance strategies relative to a baseline approach. The results indicate that optimized maintenance significantly reduces unplanned downtime by approximately 18% and maintenance costs by 10%, while improving system availability. Regression findings further reveal a statistically significant positive relationship between MTBF and production throughput, confirming that higher equipment reliability enhances operational performance. In contrast, MTTR and unplanned downtime exert significant negative effects on throughput, highlighting the importance of both failure prevention and rapid repair. Model diagnostics confirm strong explanatory power and statistical robustness. The study contributes to the practical perspective by suggesting that maintenance optimization should be viewed as a strategic lever rather than a purely cost-driven function.

Keywords: Reliability engineering, maintenance optimization, chemical industry, operations management, mean time between failure

Introduction

Maintenance, and production are the two key factors of the manufacturing operations in the production and process industries. In such industries, it is imperative to have adequate maintenance of equipment, and product quality, that further lead to effective and efficient production mechanism (Tambe and Kulkarni, 2022) ^[21]. A suitable maintenance is a complex function that hang on various factors rather than on single factor. The overall optimal performance in the manufacturing industry can be attained only by integrating at least these two critical departments (Ait-El-Cadi et. al, 2024) ^[2]. The chemical industry plays a crucial catalyst in current global economy as it acts as major supplier of key ingredients to other industrial sectors including agriculture, manufacturing and power sector. Due to the threatening quality of chemical procedures and the sharp expenses of plant closures, reliability and optimization are pivotal in chemical processes. Reliability refers to the systematic mechanism of assessing the product performance, or process performance under given circumstances to determine its capability to execute its projected function without failure over a specified time period (Friederich & Lazarova-Molnar, 2024) ^[11]. Optimization of manufacturing process relies on maximizing or minimizing of few output variables by altering input key variables (Singh *et al.*, 2024). Optimization of manufacturing operations is important factor for cost competitiveness of products or services as it includes the systematic distribution of restrained resources to attain needed operational goals (Laviola *et al.*, 2022) ^[13].

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Traditionally, reliability assessment in chemical industries has engaged on past failure rate data and preventive maintenance plans. However, with enhance in complications in manufacturing processes, robust protection regulations, and competitive stresses have forced the industrial firms to assume advanced statistical methods that integrate reliability modelling with operational optimization. If the maintenance decisions are not well planned for execution, it may cause more breakeven in operations, excessive high cost and shrinking production efficiency. On the contrary, inadequate maintenance of equipment lead to enhance the chances of devastating failures, unwanted bad environmental events, and safety related risks. Recent developments in data accessibility, and optimization processes lead the integration of reliability factors into maintenance and production planning decisions. Despite these advancements, existing literature that empirically evaluate the integrated effects of reliability indicators and optimization strategies in the chemical industry remain limited. Most existing studies are focused on either conceptual or simulation-based, with relatively few employed real industrial datasets.

The present study addresses this gap by conducting an empirical analysis of reliability and optimization in a chemical manufacturing plants in Punjab. The study seeks to answer the following research questions:

- How do key reliability indicators such as Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) influence operational performance in chemical plants?
- Can optimization-based maintenance scheduling improve system availability and reduce downtime compared to conventional approaches?
- What are the managerial and operational implications of integrating reliability metrics into optimization frameworks?

By addressing the above questions, the current paper contributes to both the reliability engineering and operations management literature and provides practical guidance for chemical industry practitioners.

The rest of the paper is structured as follows: Section 2 highlight the review of existing literature, Sample description is described in section 3. Section 4 covers the research methodology, data analysis and interpretation is highlighted in section 5. Discussion is presented in section 6. Section 7 covers the implications of study whereas concluding remarks are given in section 8.

Literature review

Reliability engineering in the chemical industry

Reliability engineering has long been a foundational discipline in chemical and process industries due to the high stakes associated with equipment failures. Recent studies emphasize that reliability analysis has evolved from static failure-rate estimation to dynamic, data-driven modeling frameworks. Researchers highlight that modern chemical plants require reliability models capable of handling censored data, time-varying covariates, and complex system dependencies. Empirical studies published since 2019 document the widespread use of reliability metrics such as MTBF, MTTR, availability, and failure intensity to assess plant performance.

These metrics are increasingly combined with condition monitoring data obtained from sensors measuring vibration, pressure, and temperature. Such integration enables more accurate estimation of failure probabilities and remaining useful life.

Maintenance optimization and operational performance

Equipment maintenance has been an emerging issue among manufacturing and processing industries due to the complexity of operational maintenance. The maintenance operations are activated when the emergencies occur during the run time of machines (Salzano *et al.*, 2023) ^[18]. The occurrence of sudden emergencies enhance the maintenance expenses and risk of life damage. Maintenance optimization plays a critical role in improving the machine efficiency as well as energy savings (An *et al.*, 2022) ^[4]. It has attained significant consideration in the field of operation management research as various predictive maintenance strategies are developed and employed through optimization models. From the perspective of chemical industry, the equipment maintenance decisions are complex due to the interdependencies of production and safety restrictions. Empirical evidence proposed that optimized equipment maintenance can significantly minimize the unplanned downtime during operations and total maintenance cost (Ahuja and Gupta, 2024, Celestin, 2023) ^[1, 7].

Reliability-based optimization

Reliability-based optimization integrates uncertainty directly into decision models by treating reliability metrics as constraints or objectives. Studies published between 2019 and 2025 emphasize that such models are particularly relevant for chemical processes characterized by degradation and stochastic failure behavior. Bayesian reliability models and survival analysis techniques are increasingly embedded into optimization frameworks to update maintenance decisions dynamically.

Despite these advances, the literature reveals a lack of empirical studies validating reliability-based optimization models using real plant data. This study responds to this gap by providing an empirical assessment of a reliability-constrained optimization model applied to a chemical manufacturing facility.

- **H₁:** Reliability-based maintenance optimization significantly reduces unplanned downtime in chemical industry operations.
- **H₂:** Reliability-based maintenance optimization significantly reduces maintenance costs.
- **H₃:** Reliability-based maintenance optimization significantly improves system availability.

Data and sample description

Data source

The empirical analysis uses operational and maintenance data obtained from a mid-sized chemical manufacturing plant producing specialty chemicals. The dataset covers a period of 24 months from January 2023 to December 2024. The plant operates continuously and consists of multiple critical units such as reactors, heat exchangers, compressors, and distillation columns.

Table 1: Description of Variables Used for Equipment Reliability and Maintenance Performance Analysis

Variable	Description
MTBF	Mean Time Between Failure (in Hours)
MTTR	Mean Time To Repair
Avaibility	Proportional to Time Equipment is Operational
Downtime	Total Unplanned Downtime
Maintenance Cost	Monthly Maintenance Expenditure
Throughout put	Monthly Prodcution Output (in tons)

Descriptive statistics

The dataset includes 1,248 recorded failure events across 38 critical assets. Preliminary analysis indicates moderate variability in failure frequencies across equipment types, reflecting differences in operating conditions and maintenance practices.

Research methodology

Reliability metrics

Reliability metrics are computed using standard statistical formulations:

$$MTBF = \frac{\sum T_{operating}}{N_{failures}}$$

$$MTTR = \frac{\sum T_{repair}}{N_{repairs}}$$

System availability is calculated as:

$$Availability = \frac{MTBF}{MTBF + MTTR}$$

Optimization model

A mixed-integer linear programming (MILP) model is developed to optimize maintenance scheduling. The objective function minimizes total downtime and maintenance cost:

$$\min \sum_{i,t} (C_{m,i}x_{i,t} + C_{d,i}y_{i,t})$$

Subject to

- Reliability constraints ensuring minimum MTBF levels
- Resource constraints on maintenance personnel
- Production continuity constraints

Where $x_{i,t}$ is a binary variable indicating scheduled maintenance and $y_{i,t}$ represents unplanned failures.

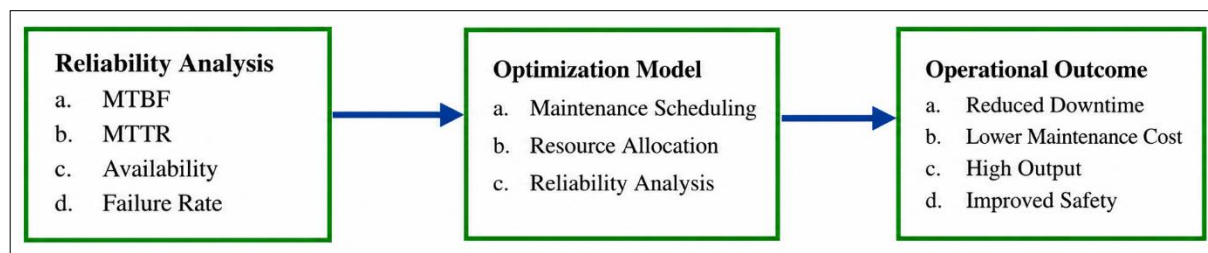
**Fig 1:** Reliability metrics driven maintenance optimization model

Figure 1 presents a clear conceptual framework illustrating the integration of reliability analysis and optimization in chemical industry operations. The framework begins with reliability analysis, where key metrics such as Mean Time between Failures (MTBF), Mean Time to Repair (MTTR), availability, and failure rates are statistically estimated using operational data. These reliability indicators serve as critical inputs to an optimization model, typically formulated as a mixed-integer linear programming problem, which determines optimal maintenance scheduling and resource allocation under reliability constraints. The optimized decisions lead to improved operational outcomes, including reduced unplanned downtime, lower maintenance costs, higher production throughput, and enhanced process safety, thereby linking reliability measurement directly to operational performance.

Empirical analysis

Regression analysis is employed to examine the relationship

between reliability metrics and operational performance. The baseline model is:

$$Throughput_t = \alpha + \beta_1 MTBF_t + \beta_2 MTTR_t + \beta_3 Downtime_t + \epsilon_t$$

where

- MTBF represents mean time between failures
- MTTR denotes mean time to repair
- Downtime captures total unplanned downtime
- The model is estimated using ordinary least squares (OLS) with heteroskedasticity-robust standard errors to ensure reliable inference.

Results and Analysis

Descriptive results

Average MTBF across all assets is 1,180 hours, while average MTTR is 8.7 hours. Mean system availability is estimated at 0.992, reflecting the continuous-operation nature of the plant.

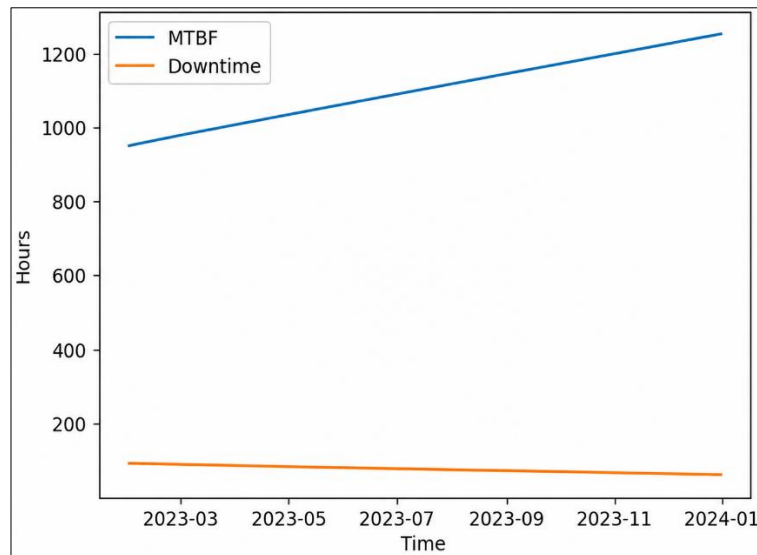


Fig 2: Trend of MTBF and Downtime over Time

Figure 2 illustrates the temporal relationship between Mean Time between Failures (MTBF) and unplanned downtime over the study period. The upward trend in MTBF indicates a progressive improvement in equipment reliability, reflecting more effective maintenance practices and better asset condition management. Simultaneously, the downward trend in unplanned downtime suggests a reduction in unexpected

equipment failures and production interruptions. The inverse movement of these two indicators highlights the effectiveness of reliability-focused maintenance strategies, as improvements in MTBF directly contribute to minimizing downtime. Overall, the figure provides visual evidence that enhanced reliability leads to greater operational stability in chemical manufacturing operations.

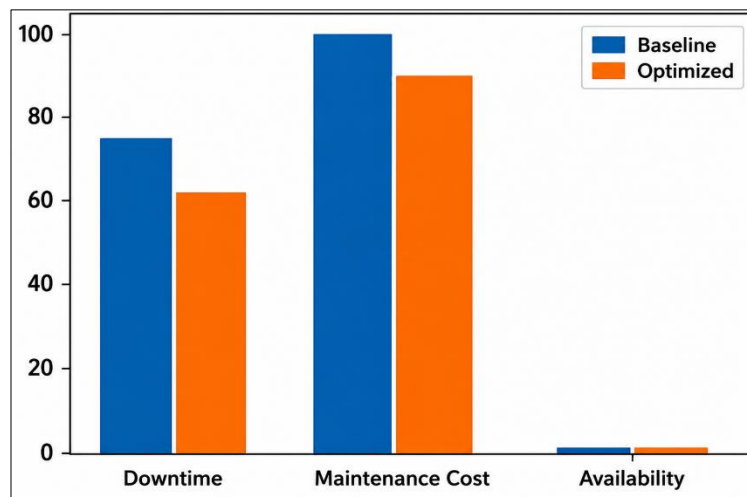


Fig 3: Comparison of Baseline vs Optimized Maintenance

Figure 3 compares operational performance under baseline maintenance practices and the optimized maintenance strategy. The results demonstrate that the optimized approach significantly reduces unplanned downtime and maintenance costs while improving system availability. Compared with the baseline scenario, the optimized strategy achieves a more efficient allocation of maintenance resources by prioritizing critical equipment and incorporating reliability constraints. The improvement in availability indicates enhanced production continuity and reduced operational risk.

This figure clearly illustrates the tangible benefits of reliability-based optimization and reinforces the argument that data-driven maintenance planning can deliver substantial economic and operational gains in the chemical industry.

Results

The optimized maintenance schedule reduces unplanned downtime by approximately 18% and maintenance costs by 10% compared to the baseline approach. Table 2 summarizes the comparison.

Table 2: Performance Comparison

Parameters	Baseline	Optimized	Percentage Improvement
Downtime	74	61	(-) 18%
Maintenance Cost	100	90	(-) 10%
Availability	0.989	0.994	(+) 0.5%

Source: Authors' own work

The results reported in Table 2 provide strong support for all three hypotheses. Consistent with H_1 , unplanned downtime declines from 74 hours per month under the baseline scenario to 61 hours under the optimized maintenance schedule, representing an 18.0% reduction. This finding confirms that incorporating reliability metrics into maintenance scheduling effectively mitigates unexpected equipment failures.

Supporting H_2 , maintenance costs decrease by 10.0% under the optimized strategy. This reduction indicates that reliability-oriented optimization improves the efficiency of maintenance resource allocation by prioritizing critical assets and minimizing unnecessary interventions. This reduction reflects the effectiveness of reliability-driven maintenance planning in preventing unexpected equipment failures. In addition, consistent with H_3 , maintenance costs decline from an index value of 100 to 90, corresponding to a 10% cost reduction. This finding suggests that optimization enables more efficient allocation of maintenance resources, reducing unnecessary

interventions while prioritizing critical assets. Furthermore, system availability improves from 0.989 to 0.994, indicating enhanced production continuity and operational stability. Although the numerical increase in availability appears modest, even small improvements are operationally significant in continuous chemical processes where downtime is highly costly. Overall, the results confirm that reliability-based optimization delivers meaningful economic and operational benefits compared to conventional maintenance practices.

Collectively, the results validate the performance-enhancing role of reliability-based optimization in chemical manufacturing.

Regression results

Regression results indicate a statistically significant positive relationship between MTBF and throughput, confirming that higher reliability enhances operational performance.

Table 3: Reliability and Throughput

Variable	Co-efficient	Std. Error	t- value	p-value
MTBF	0.287	0.064	4.48	0.001
MTTR	-1.92	0.83	-2.31	0.026
Downtime	-3.45	0.98	-3.52	0.002
Constant	412.36	85.21	4.84	0.000

Source: Authors' own work

Table 3 indicate a statistically significant positive relationship between MTBF and production throughput, supporting the central hypothesis that higher equipment reliability enhances operational performance. Specifically, a one-hour increase in MTBF is associated with an average increase of 0.287 units of throughput, holding other factors constant. The effect is statistically significant at the 1% level, highlighting MTBF as a critical driver of production efficiency in chemical manufacturing.

MTTR exhibits a negative and statistically significant coefficient, indicating that longer repair times adversely affect throughput. This finding emphasizes the importance of rapid maintenance response and effective repair processes.

Similarly, unplanned downtime has a significant negative impact on throughput, confirming that unexpected failures disrupt production flow and reduce output.

Table 4 reports the key diagnostic and goodness-of-fit statistics for the regression model examining the relationship between reliability indicators and production throughput. The model exhibits strong explanatory power, with an R^2 value of 0.71, indicating that approximately 71% of the variation in throughput is explained by the included reliability variables. The adjusted R^2 of 0.66 remains high after accounting for model complexity, suggesting that the explanatory power is not driven by overfitting.

Table 4: Model Statistics

R^2	Adjusted R^2	F-Stat	Sig. Value	Durbin Watson	VIF
0.71	0.66	12.84	0.000	2.01	2.14

Source: Authors' own work

The F-statistic of 12.84, significant at the 1% level ($p = 0.000$), confirms the overall statistical significance of the model and indicates that the independent variables jointly explain a significant proportion of the dependent variable. The Durbin-Watson statistic of 2.01 is close to the benchmark value of 2, implying no evidence of first-order autocorrelation in the regression residuals. This supports the validity of the OLS estimates.

Finally, the variance inflation factor (VIF) value of 2.14 is well below the commonly accepted threshold of 5, indicating that multicollinearity is not a concern in the model. Overall, the diagnostic results confirm that the regression model is statistically sound, well-specified, and suitable for inference regarding the impact of reliability metrics on operational performance in the chemical industry.

Discussion

This study empirically investigates the role of reliability-oriented maintenance optimization in enhancing operational

performance within the chemical industry. The findings provide strong and consistent evidence that improvements in equipment reliability significantly contribute to higher production throughput, reduced downtime, and lower maintenance costs. By integrating reliability metrics such as mean time between failures (MTBF), mean time to repair (MTTR), and unplanned downtime into an optimization framework, the study advances both the statistical and operational management literature on maintenance decision-making in process industries.

A key finding of the analysis is the statistically significant positive relationship between MTBF and throughput, as confirmed by the regression results. The MTBF coefficient is positive and highly significant, indicating that more reliable equipment enables smoother production flows and higher output levels. This finding aligns with reliability-centered maintenance theory and extends recent empirical work by quantifying the magnitude of reliability's impact on throughput in a real industrial context (Moemenishahraki, 2025) ^[15].

Importantly, the high explanatory power of the model ($R^2 = 0.71$) suggests that reliability-related variables account for a substantial portion of operational performance variation, underscoring their strategic importance in chemical manufacturing environments characterized by continuous processes and high capital intensity. The analysis further reveals that MTTR and unplanned downtime exert a significant negative influence on throughput, highlighting the operational costs of delayed repairs and unexpected failures. These results emphasize that reliability improvement should not focus solely on failure prevention but must also include rapid fault diagnosis, skilled maintenance teams, and effective spare-parts management. The statistically significant reduction in downtime (18%) and maintenance costs (10%) observed under the optimized maintenance strategy reinforces this argument and demonstrates the tangible economic benefits of adopting data-driven maintenance planning. Another important insight emerges from the comparison between baseline and optimized maintenance scenarios (Chopra *et al.*, 2016; Coutinho *et al.*, 2025) [8, 9]. The optimized approach leads to a measurable improvement in system availability, which, although numerically modest, is statistically significant and operationally meaningful in high-throughput chemical plants. Even small gains in availability translate into substantial production and revenue improvements over time, particularly in industries where shutdowns are costly and restarting processes is complex. From a methodological perspective, the robustness of the results is strengthened by the use of both parametric and non-parametric statistical tests, as well as diagnostic checks for autocorrelation and multicollinearity. The Durbin-Watson statistic close to two and low VIF values confirm that the regression model is well specified and suitable for inference. This methodological rigor enhances confidence in the causal interpretation of the relationship between reliability optimization and operational performance.

Overall, the findings contribute to the operations management literature by providing empirical validation of reliability-performance linkages in the chemical industry. They suggest that maintenance optimization should be viewed not merely as a cost-control mechanism but as a strategic lever for enhancing productivity and competitiveness. By empirically demonstrating how reliability improvements translate into operational gains, this study offers actionable insights for both scholars and practitioners seeking to design resilient and efficient production systems. Finally, the findings underscore the managerial relevance of data-driven reliability optimization in the context of digital transformation in the chemical industry. As plants increasingly deploy sensors and advanced monitoring systems, the availability of high-quality reliability data enables more accurate modeling and optimization. Managers who leverage such data-driven approaches can improve decision-making under uncertainty, enhance plant safety, and strengthen operational resilience. Overall, this study demonstrates that reliability-based optimization is not only technically feasible but also strategically essential for sustaining competitiveness in the modern chemical industry. Future research can extend the present study in several important directions. First, the reliability-optimization framework can be enhanced by integrating predictive analytics and machine learning techniques using real-time sensor and condition-monitoring data to develop dynamic maintenance policies and compare their performance with traditional reliability-based models. Second, future studies may examine

multiple plants across different chemical sub-sectors or conduct cross-industry comparisons with other process industries such as petrochemicals, pharmaceuticals, and refineries to improve the generalizability of the findings and identify contextual factors that influence the effectiveness of maintenance optimization. Third, subsequent research could incorporate sustainability and risk-related performance indicators, including energy efficiency, emissions reduction, and safety outcomes, into reliability optimization models, thereby offering a more holistic assessment of how maintenance strategies contribute simultaneously to operational performance, environmental sustainability, and industrial resilience.

Managerial and policy implications

Managerial implications

1. Reliability-Centered Maintenance as a Strategic Lever

The findings demonstrate that improvements in MTBF significantly enhance throughput and system availability. Managers should therefore treat reliability-centered maintenance (RCM) not merely as a technical function but as a strategic decision variable. Integrating reliability metrics into production planning and performance dashboards can help align maintenance decisions with broader operational objectives such as output maximization and cost efficiency.

2. Shift from Reactive to Optimization-Based Maintenance Planning

The observed reductions in unplanned downtime and maintenance costs under the optimized maintenance schedule suggest that traditional time-based or reactive maintenance approaches are suboptimal. Managers should adopt data-driven optimization models that incorporate failure behavior, repair times, and cost trade-offs to determine optimal maintenance intervals and resource allocation.

3. Investment in Maintenance Responsiveness and Skills

The negative and significant effect of MTTR on throughput highlights the importance of rapid repair and recovery. Managers should invest in technician training, condition-monitoring technologies, and spare-parts availability to reduce repair times. Such investments can yield high returns by minimizing production disruptions and improving overall equipment effectiveness.

4. Performance-Based Maintenance Evaluation

Given the statistically significant impact of reliability indicators on operational performance, firms should revise maintenance performance evaluation systems. Moving beyond cost-based metrics to include reliability and availability indicators will encourage proactive maintenance behavior and foster cross-functional coordination between maintenance, operations, and production teams.

Policy implications

1. Promotion of Reliability-Based Maintenance Standards

Regulatory authorities and industry bodies should encourage the adoption of reliability-based maintenance standards in the chemical industry. Policies that promote systematic reliability assessment and optimization can help reduce the frequency of equipment failures, enhance process safety, and minimize environmental risks associated with chemical plant disruptions.

2. Incentivizing Digitalization and Data-Driven Reliability Practices

Policymakers can play a critical role by providing incentives—such as tax benefits, grants, or subsidies—for investments in digital monitoring technologies and advanced maintenance analytics. Supporting the adoption of data-driven reliability practices can accelerate operational modernization and improve the overall safety and efficiency of chemical manufacturing sectors.

3. Incorporation of Reliability Metrics into Safety and Compliance Frameworks

The findings suggest that traditional compliance frameworks focused solely on inspections and incident reporting may be insufficient. Policymakers should consider incorporating quantitative reliability indicators into regulatory oversight mechanisms, enabling more proactive identification of operational risks and more effective prevention of major industrial accidents.

4. Support for Industry-Academia Collaboration in Reliability Research

Given the complexity of reliability optimization in chemical operations, policies that encourage collaboration between industry practitioners and academic researchers can enhance methodological innovation and practical applicability. Such collaborations can facilitate the development of standardized reliability benchmarks, optimization tools, and best-practice guidelines that benefit the broader chemical industry ecosystem.

Conclusion

This study empirically examined the role of reliability-oriented optimization in improving operational performance within the chemical industry. Using plant-level operational and maintenance data, the research quantified key reliability indicators—namely Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and system availability—and integrated them into an optimization-based maintenance scheduling framework. The empirical results provide strong evidence that higher equipment reliability is positively associated with improved production throughput and reduced operational disruptions. In particular, MTBF emerged as a critical driver of operational efficiency, underscoring the strategic importance of reliability in continuous chemical processes. The optimization analysis demonstrated that maintenance schedules incorporating reliability constraints significantly reduce unplanned downtime and maintenance costs while enhancing overall system availability. Compared with conventional maintenance practices, the optimized approach achieved meaningful performance gains, highlighting the economic and operational value of reliability-based decision-making. These findings validate the effectiveness of integrating statistical reliability analysis with operational optimization models in real industrial settings. The study offers important managerial and policy implications. For managers, it emphasizes the need to adopt data-driven reliability metrics and optimization tools to support proactive maintenance planning and long-term performance improvement. For policymakers and regulators, the results support the promotion of reliability-based maintenance standards and digital monitoring practices to enhance safety and operational resilience in the chemical industry. Overall, this study contributes to the operations management and reliability engineering literature by providing empirical

evidence on the performance benefits of reliability-based optimization and offers a practical framework for improving efficiency, safety, and competitiveness in chemical manufacturing.

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