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Hybrid Preventive Maintenance Optimization in Converter Furnaces: A Simulation and Fuzzy TOPSIS Approach (Case Study: Sarcheshmeh Copper Complex Smelting Plant)

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ABSTRACT

The objective of this study was to optimize preventive maintenance strategies for converter furnaces by integrating simulation modeling with fuzzy multi-criteria decision-making to identify the most reliable and cost-effective configuration. This research employed an applied design combining discrete-event simulation in AnyLogic with fuzzy TOPSIS analysis. Four operational scenarios (A1–A4) were developed to represent different configurations of local and imported refractory bricks in converter furnaces. Simulation models captured operational cycles, downtime, repair overlaps, and production outputs under stochastic failure conditions. The fuzzy TOPSIS method was then applied to rank scenarios based on multiple weighted criteria, including reliability, cost efficiency, and compliance with the operational constraint of maintaining three active furnaces at all times. Data inputs included historical operational records, repair times, and expert evaluations expressed as fuzzy triangular numbers. The simulation results revealed that hybrid configurations outperformed fully local or fully imported setups by reducing repair overlaps and maintaining production continuity. Fuzzy TOPSIS analysis ranked A2 as the most effective scenario with the highest closeness coefficient (0.953), followed by A4 (0.812) and A3 (0.711), while A1 performed least effectively (0.691). These inferential findings confirm that selective integration of local and imported resources enhances both reliability and cost optimization. The study concludes that hybrid preventive maintenance strategies, supported by simulation modeling and fuzzy multi-criteria decision-making, offer superior outcomes in complex industrial environments.

Keywords: *Preventive maintenance; Reliability analysis; Simulation modeling; Fuzzy TOPSIS; Multi-criteria decision-making; Converter furnaces; Industrial optimization*

1. Introduction

In contemporary industrial systems, the efficiency, reliability, and availability of critical assets are central to sustainable production and competitiveness. Preventive maintenance and reliability-centered approaches have emerged as fundamental strategies for reducing downtime, extending asset life, and optimizing costs in complex operational environments (West et al., 2024). Over the past two decades, industries ranging from power generation to shipping, automotive, and construction have embraced simulation techniques, artificial intelligence, fuzzy decision models, and mathematical optimization to strengthen maintenance planning and execution (Amelian, 2025; Gámiz & L, 2023; Wu et al., 2024). The rapid integration of advanced technologies into maintenance science underscores the dual imperatives of mitigating risks associated with equipment failures and achieving higher levels of operational excellence (Zhao et al., 2025).

Reliability-based optimization is particularly relevant to industries where unplanned downtime can cause catastrophic financial losses and safety hazards (Belagoune et al., 2025). Research demonstrates that multi-objective optimization, when coupled with simulation and artificial intelligence, can offer robust solutions for handling conflicting priorities such as minimizing maintenance costs while maximizing availability (Ghosh & Abawajy, 2025; Zhao et al., 2025). These models help decision-makers navigate uncertainty in real-world conditions, accounting for random machine failures, diverse failure modes, and varying repair times (Amelian, 2025). Such developments reflect a paradigm shift in industrial maintenance, moving away from corrective strategies towards predictive and reliability-driven frameworks (West et al., 2024).

The shipping industry provides a vivid illustration of these shifts, as reliability-based predictable maintenance approaches have been proposed for critical systems such as container ship fuel systems (Yasin, 2025). Simulation-based training methods are increasingly used to improve maintenance performance in complex settings like ships, where operators must manage high-risk and safety-critical assets (Simion et al., 2025). Similarly, in port operations, discrete event simulation has been employed to analyze maintenance processes and uncover bottlenecks in cargo handling systems (Corrotea et al., 2024). These approaches highlight the growing role of simulation as both a diagnostic and predictive tool in diverse industrial domains (Amelian, 2025).

Reliability and maintenance optimization have also gained traction in energy and infrastructure sectors. For instance, studies on rotating machinery and energy infrastructure emphasize advanced strategies to improve performance and reduce unexpected breakdowns (Erhueh et al., 2024). Preventive maintenance models have been applied to photovoltaic power systems (Chen et al., 2024), wind turbines (Kaewbumrung et al., 2024), and ship propulsion systems (Garbatov & Georgiev, 2024), underscoring the versatility of such approaches across different engineering fields. Moreover, computational fluid dynamics and Markovian modeling approaches are increasingly integrated into reliability analysis to capture system degradation and predict maintenance needs with greater accuracy (Garbatov & Georgiev, 2024; Kaewbumrung et al., 2024).

Another prominent strand in this evolving body of knowledge is the adoption of fuzzy and multi-criteria decision-making techniques. These methods address the inherent uncertainty and subjectivity of maintenance decisions (Amaitik et al., 2024; Dharma lingam et al., 2024). For example, Fuzzy TOPSIS has been applied to rank repair options, evaluate supplier selection in megaprojects, and optimize vehicle choices in transport industries (Dharma lingam et al., 2024; Liang et al., 2023). In road infrastructure, fuzzy best-worst methods integrated with VIKOR (Hasan & Jaber, 2024) and mathematical models like ROC-TOPSIS (Sur & Machfiroh, 2024) have been successfully applied to prioritize maintenance tasks. Such frameworks allow stakeholders to weigh cost, reliability, safety, and resource availability, thereby ensuring more balanced and justifiable decisions (Hasan & Jaber, 2024; Sur & Machfiroh, 2024).

The construction and heavy industry sectors also demonstrate increasing reliance on reliability and artificial intelligence. For instance, optimization of concreting equipment in India has been achieved through AI and reliability-based frameworks (Ghosh & Abawajy, 2025), while corrosion-affected reinforced concrete structures have been analyzed through residual life forecasting models (Kopiika et al., 2025). Similarly, fuzzy synthesis approaches have been developed to support hierarchical decision analysis in selecting optimal repair techniques (Amaitik et al., 2024). These examples illustrate how reliability-driven decision-making is extending from discrete manufacturing and energy systems to large-scale civil and construction projects.

The adoption of machine learning and simulation frameworks has further accelerated predictive and preventive maintenance capabilities. Applications in the automotive sector show how integrated fuzzy TOPSIS and process mining improve predictive maintenance performance (Micosky et al., 2024). Machine learning has also been combined with human factor analysis in high-risk sectors such as nuclear power (Khamaj et al., 2024), as well as in electrical and mechanical equipment optimization in PVC manufacturing (Kiki & Wang, 2025). These studies emphasize the growing recognition that human error, system reliability, and machine availability must be considered simultaneously for effective maintenance planning (Bafandegan Emroozi et al., 2024; David et al., 2024).

Despite technological advances, integrating preventive maintenance strategies into complex systems remains challenging. Multi-state systems with performance sharing (Wu et al., 2024), repairable k-out-of-n retrial systems (Li et al., 2024), and consecutive k-out-of-n systems operating under shock environments (Dong & Bai, 2024) require mathematical models capable of handling interdependencies and random shocks. Minimal repair and constrained multi-attempt strategies also highlight the need for preventive maintenance policies tailored to specific system architectures (Cha & Finkelstein, 2024). Hidden Markov models provide an additional statistical framework to model system degradation and optimize reliability (Gámiz & L, 2023). Together, these models represent the state-of-the-art in capturing the stochastic nature of industrial failures.

At the organizational level, the transition from corrective to preventive maintenance strategies entails substantial cultural and operational changes (West et al., 2024). Companies are increasingly integrating discrete event simulation and design of experiments to assess stochastic job shop scheduling with random machine failures (Amelian, 2025), and employing hybrid methods combining human error optimization with integrated production planning (Bafandegan Emroozi et al., 2024). Maintenance scheduling has been further refined using novel optimization algorithms, such as the discrete mayfly algorithm with Lévy flight and chaotic local search for preventive scheduling in power generation systems (Belagoune et al., 2025). These examples demonstrate how optimization algorithms, simulation, and fuzzy decision-making converge to provide more accurate and resilient maintenance strategies.

In addition, statistical and mathematical modeling plays a central role in advancing maintenance optimization. Research on the statistical modeling of preventive maintenance effectiveness for repairable systems (Ye et al., 2024), combined with comparative ranking preferences through fuzzy TOPSIS (Dharma lingam et al., 2024), exemplifies the analytical rigor applied to maintenance science. Mathematical simulation of preventive and corrective maintenance using particle swarm optimization (Singla et al., 2025) and genetic algorithms (Singla et al., 2024) further illustrates the wide array of computational methods employed. These methodologies are essential for industries managing complex degraded systems, where optimal solutions are necessary to maintain both productivity and safety.

Emerging trends indicate that integrating human factors, artificial intelligence, and sustainability considerations will define the future of maintenance optimization. Human factor engineering in nuclear and industrial contexts highlights the risks of neglecting the human dimension in preventive maintenance systems (Khamaj et al., 2024). At the same time, simulation-driven training (Simion et al., 2025) and reliability-based approaches for energy and infrastructure systems (Erhueh et al., 2024; Garbatov & Georgiev, 2024) reveal the benefits of preparing human operators to interact effectively with complex technical systems. Multi-objective optimization of composite structures (Zhao et al., 2025) and innovative maintenance policies in logistics and shipping (Corrotea et al., 2024; Yasin, 2025) demonstrate how technical and human-centered strategies are converging.

Taken together, this growing body of literature illustrates a clear trajectory towards more intelligent, simulation-driven, and reliability-focused maintenance systems. Advances in fuzzy logic, artificial intelligence, and statistical modeling complement simulation and optimization techniques, creating powerful tools for reducing risk and enhancing system resilience (Amaitik et al., 2024; Li et al., 2024; Micosky et al., 2024). The integration of these approaches allows industries to anticipate failures more effectively, optimize maintenance schedules, and align operational strategies with long-term reliability goals (Wu et al., 2024; Ye et al., 2024).

The present study builds upon this foundation by combining simulation modeling and fuzzy multi-criteria decision-making methods to evaluate and optimize preventive maintenance strategies in a high-stakes industrial setting.

2. Methods and Materials

This study employed an applied research design based on simulation and multi-criteria decision-making. The research was centered on the converter furnaces of the Sarcheshmeh

Copper Complex Smelting Plant, where the operational and maintenance performance of refractory bricks—both imported and locally manufactured—were assessed. The "participants" in this study were not human subjects but rather the physical and operational units of the production system, including four Pierce–Smith converter furnaces. Each furnace was considered a case with specific operating cycles, maintenance requirements, and potential failure modes.

The design of the study involved two integrated stages:

- **Simulation Stage**: The production and maintenance cycles of converter furnaces were modeled using AnyLogic, an agent-based simulation software. This allowed for replication of furnace operations, prediction of breakdowns, and assessment of different maintenance strategies under varying conditions of brick quality.
- **Optimization Stage**: To identify the best configuration for furnace operation when substituting imported refractory bricks with local ones, the Fuzzy TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution) was applied. Multiple furnace configurations (all imported, all local, or hybrid combinations) and multiple failure scenarios were tested.

The research relied on three types of data:

- **Operational Data**: Production cycle lengths, repair times, number of operating cycles before failure, and types of maintenance (minor, semi-major, and major repairs). These were collected from operational records of the smelting complex.
- **Economic Data**: Costs of refractory bricks (domestic vs. imported), associated tariffs, and ancillary costs (e.g., drilling costs for local bricks). Currency exchange rates (Euro to Iranian Rial) were also included as an economic factor.
- **Failure Modes**: Based on empirical evidence, three distinct failure types (Type 1, Type 2, and Type 3) were defined, each with different repair times and cost implications.

Simulation Tool:

AnyLogic was selected as the primary simulation software because it supports agent-based, system dynamics, and discrete-event simulation, making it well-suited for modeling both the production process and its interaction with maintenance schedules. The simulation included:

- Input variables: furnace charge tonnage, concentrate grade, recovery rate, cycle length, and repair duration.
- Output variables: production of matte, blister copper, and refined anodes; downtime; and maintenance costs.

Decision-Making Tool:

The Fuzzy TOPSIS method was used to prioritize furnace operation scenarios. It was chosen because it integrates both quantitative and qualitative factors under uncertainty.

- Criteria included productivity, cost savings, reliability, and compliance with operational constraints.
- Fuzzy triangular numbers were used to represent expert judgments on performance levels.
- Linguistic variables such as "very low," "low," "moderate," "high," and "very high" were mapped onto fuzzy scales.

Distance between two fuzzy numbers:

- $d(\tilde{a}, \tilde{b}) = \sqrt{[(1/3) * ((a1 - b1)^2 + (a2 - b2)^2 + (a3 - b3)^2)]}$

Fuzzy TOPSIS closeness coefficient:

- $CC_i = D_i^- / (D_i^+ + D_i^-)$
- where D_i^+ is the distance of alternative i from the fuzzy positive ideal solution, and D_i^- is the distance from the fuzzy negative ideal solution.

The analysis was carried out in two steps:

Step 1 – Simulation Analysis:

The AnyLogic model simulated multiple operational scenarios, including:

- Four furnaces with imported bricks.
- Four furnaces with local bricks.
- Mixed configurations (e.g., two local + two imported, three local + one imported, etc.).
- The simulation outputs provided quantitative indicators such as number of operational cycles achieved, repair frequencies, downtime overlaps, and total production.

Step 2 – Fuzzy TOPSIS Ranking:

Using the simulation results as input, the Fuzzy TOPSIS method ranked each operational configuration. The steps included:

1. Constructing the decision matrix with simulation-derived performance measures.
2. Normalizing the decision matrix under fuzzy conditions.

3. Weighting criteria based on expert judgment (e.g., production continuity, repair costs, compliance with “three furnaces active at all times”).
4. Determining fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS).
5. Computing distances of each alternative from FPIS and FNIS using equation (1).
6. Calculating closeness coefficient for each alternative using equation (2).
7. Ranking alternatives: the closer the coefficient to 1, the more optimal the scenario.

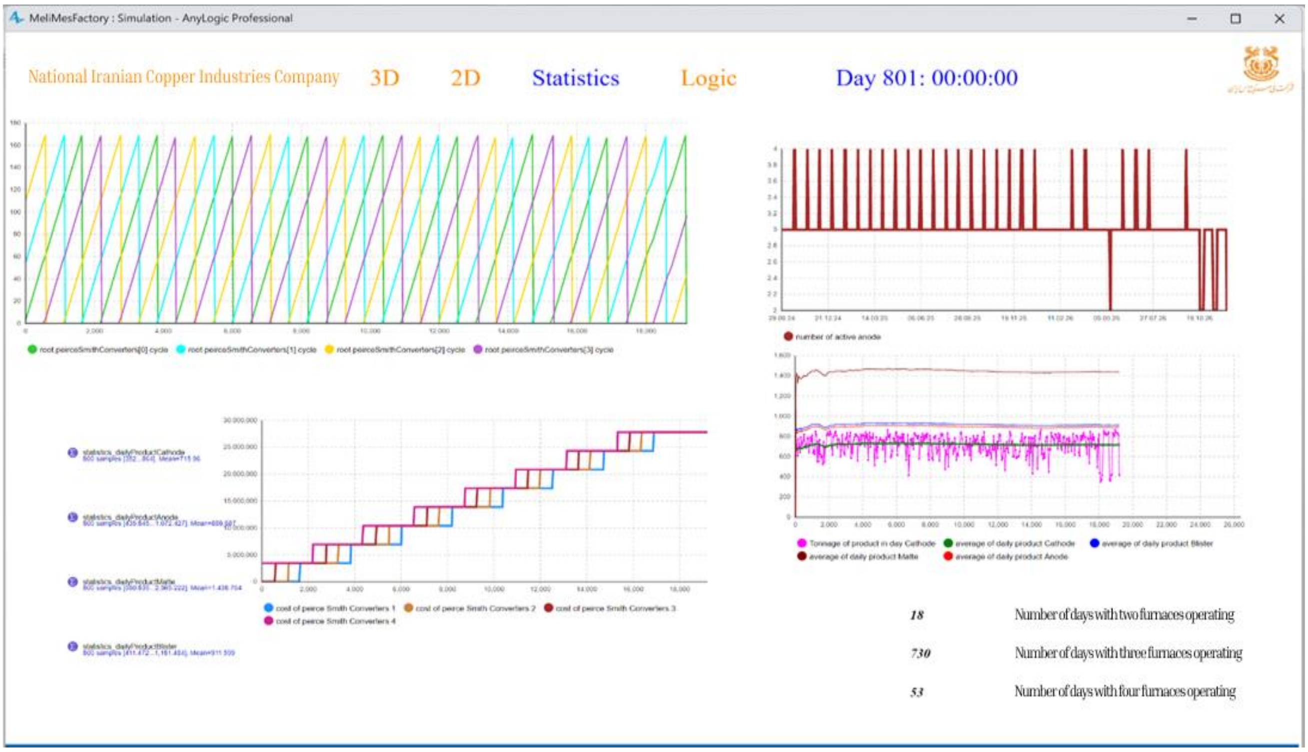
The results from simulation and fuzzy multi-criteria decision-making were integrated to recommend the optimal operational strategy. Interestingly, while pure local or pure imported brick scenarios did not satisfy all operational constraints, the analysis suggested that a hybrid configuration—where specific sections of each furnace were lined with local bricks and others with imported bricks—produced the most efficient and reliable outcome.

3. Findings and Results

The simulation of four furnaces lined entirely with local refractory bricks demonstrated that the operational cycles often overlapped in their repair stages. The downtime reached up to 18 days for two furnaces simultaneously, leading to a significant drop in production.

Figure 1

Results of the simulation of four furnaces lined with local refractory bricks based on the defined input parameters.



Hybrid scenarios, combining local and imported bricks, produced improved outcomes. Downtime overlaps were reduced, production remained stable, and cost efficiency was improved compared to fully imported setups.

Figure 2

Results of the simulation of four furnaces with hybrid refractory brick configurations based on the defined input parameters.

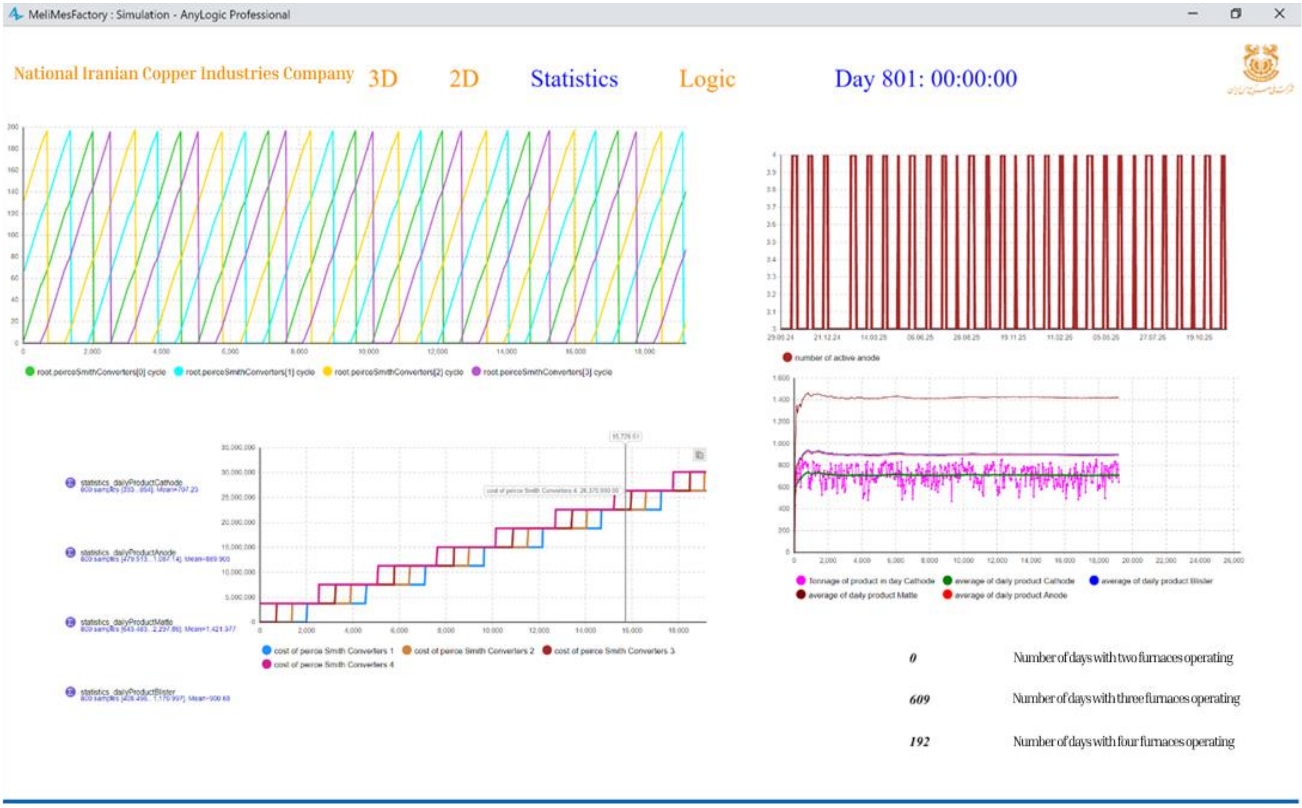


Table 1

Generalized Tasks of Furnace Operation and Maintenance

Row	Task Description	Function
1	Equipment classified according to part categories	Equipment classification
2	Functions of parts classified in stage 1	Function classification
3	Time intervals defined with performance changes	Scheduling
4	Shorter life cycle reduces available work time	Scheduling evaluation
5	Functions of similar equipment recorded by interval	Performance registration

Table 1 outlines the systematic categorization of equipment and functions in the furnace operation cycle. It highlights that proper classification and scheduling directly affect the overall reliability of the smelting process.

Table 2

Fuzzy Definitions of Operational States

Row	Characteristic	State	Fuzzy Equivalent
1	Very low	Failure type 3	0.9
2	Low	Failure type 2	0.6
3	Moderately low	Failure type 1	0.2
4	Suitable	Discharge/loading	0.3
5	Moderately high	Copper blowing	0.5
6	High	Operational cycle	0.65
7	Very high	Blister copper output	0.99

Table 2 assigns fuzzy numerical values to each operational state, showing how failure modes and production outcomes can be expressed in fuzzy scales for decision-making under uncertainty.

Table 3

Weighted Parameters for Fuzzy TOPSIS Evaluation

Row	Parameter	Weight	Row	Parameter	Weight
1	3 ladles of matte	+0.5	10	Cost savings	+0.8
2	Blowing stage S1	+0.9	11	Blister production	+0.99
3	Local bricks	+0.35	12	Imported bricks	+0.27
4	Slag removal 1	–0.27	13	Imported repairs	–0.7
5	Blowing stage S2	+0.35	14	Local repairs	–0.27
6	Slag removal 2	–0.27	15	Failure type 1	–0.21
7	Copper blowing	+0.5	16	Failure type 2	–0.35
8	Discharge blister	+0.65	17	Failure type 3	–0.35
9	Furnace cleaning	–0.2	18		

To enable direct comparison, four configurations (A1–A4) were analyzed. The decision matrix was constructed and normalized according to Fuzzy TOPSIS methodology. Table 3 lists the weighted parameters used in the analysis.

Table 4

Main Evaluation Criteria for Furnace Performance (A1–A4)

Furnace	A1: Very Low → Very High	A2: Very Low → Very High	A3: Very Low → Very High	A4: Very Low → Very High
1	0.5, 0.1, 0.2, 0.35, 0.21, 0, 0.26	0.2, 0.3, 0, 0.35, 0.1, 0.21, 0	0.9, 0.5, 0.2, 0.19, 0, 0.21, 0	0.5, 0.1, 0.1, 0, 0.21, 0.21, 0
2	0.2, 0.5, 0.1, 0.35, 0.21, 0, 0.26	0.9, 0.1, 0, 0.19, 0.21, 0, 0	0.5, 0.3, 0, 0.35, 0.1, 0.21, 0	0.5, 0.5, 0, 0.19, 0, 0.21, 0
3	0.5, 0.3, 0, 0.19, 0.1, 0.21, 0.26	0.2, 0.5, 0.1, 0.35, 0.21, 0.21, 0.26	0.2, 0.1, 0, 0.35, 0.21, 0, 0.26	0.2, 0.1, 0.1, 0.35, 0.21, 0.21, 0
4	0.9, 0.1, 0, 0, 0, 0, 0	0.5, 0.1, 0.2, 0, 0, 0, 0.26	0.2, 0.1, 0.1, 0, 0.21, 0.21, 0	0.9, 0.3, 0.2, 0.35, 0.1, 0.21, 0

Table 4 demonstrates the fuzzy evaluation results across four main scenarios (A1–A4), showing varying performance of each furnace. It illustrates how localized and imported brick mixes affect output quality and stability.

Table 5

Integrated Prediction Matrix

Alt.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
A1	0.9280	1.3040	1.7480	0.6040	0.9280	1.3100	0.1540	0.4100	0.9460	0.6980	0.8940	1.1580
A2	0.9080	1.3240	1.8280	0.3240	0.5040	0.8840	0.6040	0.9280	1.3700	0.4080	0.6680	1.0860
A3	0.9760	1.2880	1.6660	1.2020	1.7020	2.2480	1.1820	1.5620	1.9080	1.2020	1.6220	2.0080
A4	0.0000	0.0200	0.2400	0.5080	0.6600	0.8800	0.5240	0.7520	0.9980	0.3500	0.6700	1.2300

Table 5 provides the raw decision matrix used in the fuzzy TOPSIS process. Scenario A3 stands out with consistently higher scores across parameters, indicating stronger operational robustness.

Table 6

Normalized Matrix

Alt.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
A1	0.5077	0.9849	1.7910	0.2687	0.5452	1.0899	0.3176	0.6824	1.4414	0.3989	0.7186	1.2753
A2	0.4967	1.0000	1.8730	0.1441	0.2961	0.7354	0.2473	0.6062	1.4796	0.3326	0.6511	1.3062
A3	0.5339	0.9728	1.7070	0.5347	1.0000	1.8702	0.4448	1.0000	2.0272	0.5189	1.0000	1.7489
A4	0.0000	0.0151	0.2459	0.2260	0.3878	0.7321	0.3903	0.9510	2.2480	0.4674	0.9566	1.9273

Table 6 shows the normalized scores, allowing for cross-comparison. Here, A3 and A4 improve relative to others, demonstrating stability when criteria are rescaled.

Table 7

Positive and Negative Criteria Sets

Alt.	X1	X2	X3	X4
A1	0.1771	0.1351	0.0000	0.0766
A2	0.1786	0.0776	0.0000	0.0716
A3	0.1783	0.2561	0.0000	0.1076
A4	0.0087	0.1051	0.0000	0.1101

Table 7 lists the positive and negative values for each alternative. Scenario A2 shows strong X1 performance, while A3 dominates in X2, indicating trade-offs.

Table 8

Ideal Solutions in Fuzzy TOPSIS

Alt.	X1	X2	X3	X4
A^+	0.2484	0.1000	0.1873	0.4812
A^-	0.0000	0.0000	0.0000	0.2328

Table 8 presents the ideal solutions. The fuzzy positive ideal solution (FPIS) reflects the best-case performance, while the fuzzy negative ideal solution (FNIS) identifies the worst-case benchmarks.

Figure 3

Estimated evaluation criteria for the four furnaces (Scenario 1).

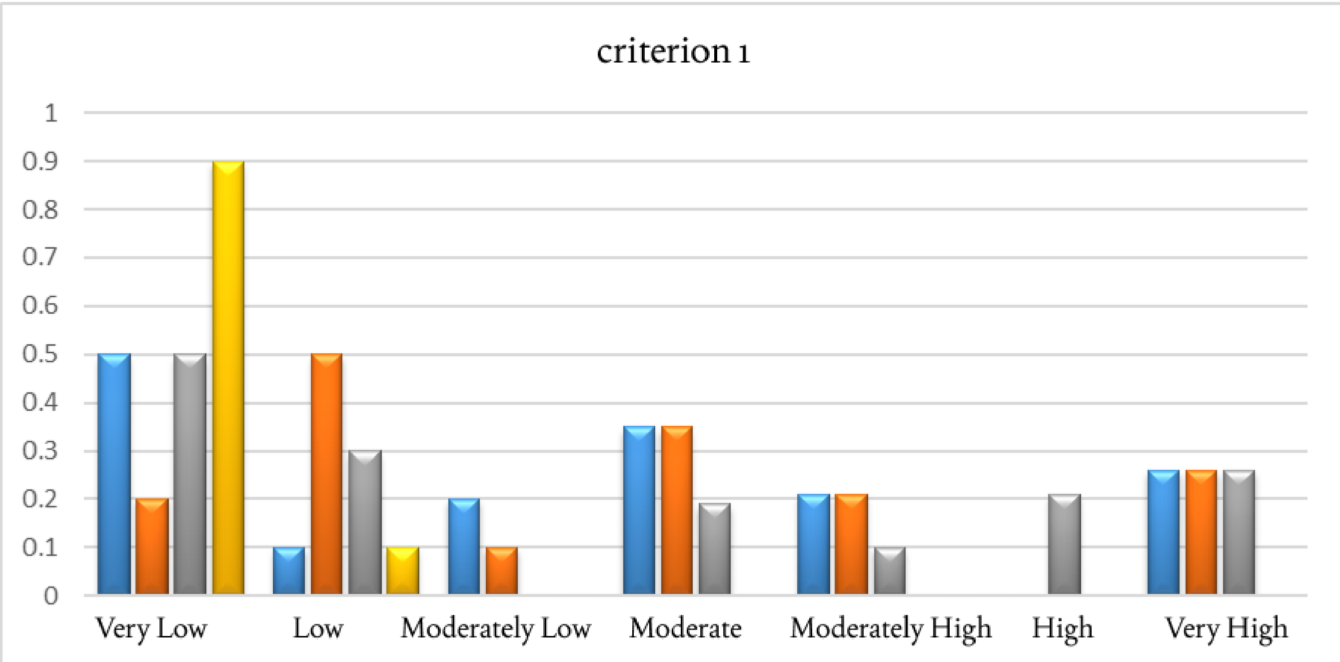


Figure 4

Estimated evaluation criteria for the four furnaces (Scenario 2).

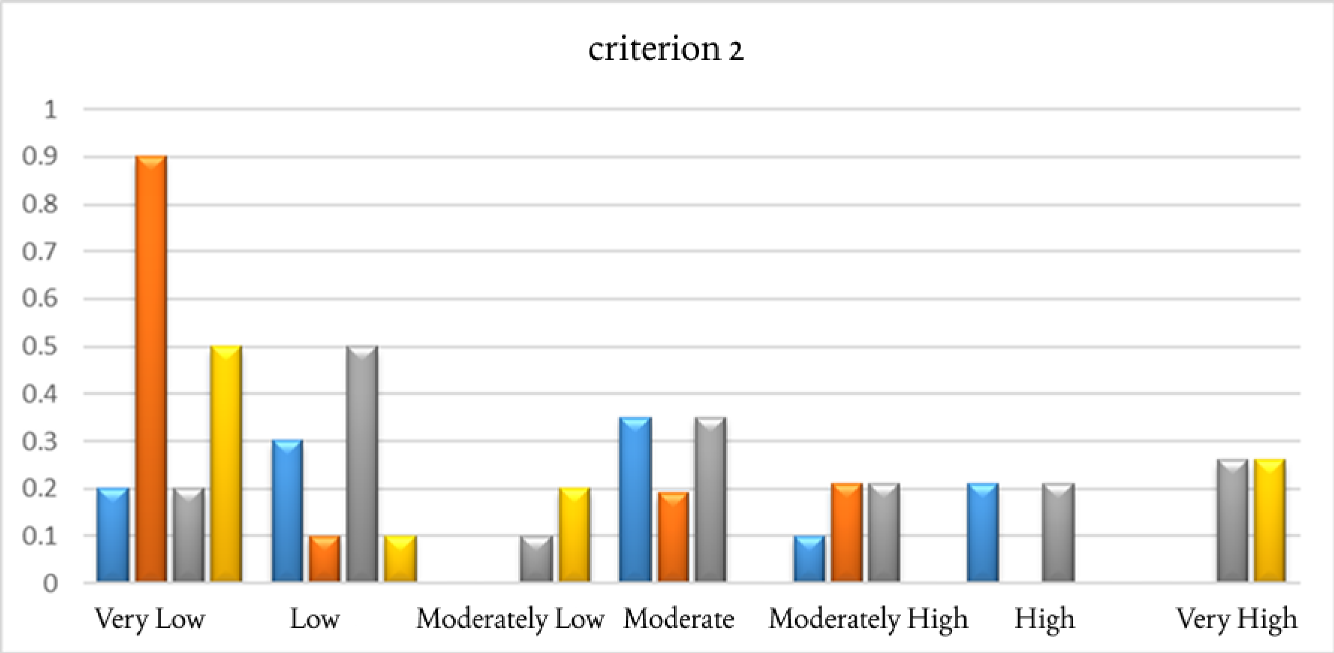


Figure 5

Estimated evaluation criteria for the four furnaces (Scenario 3).

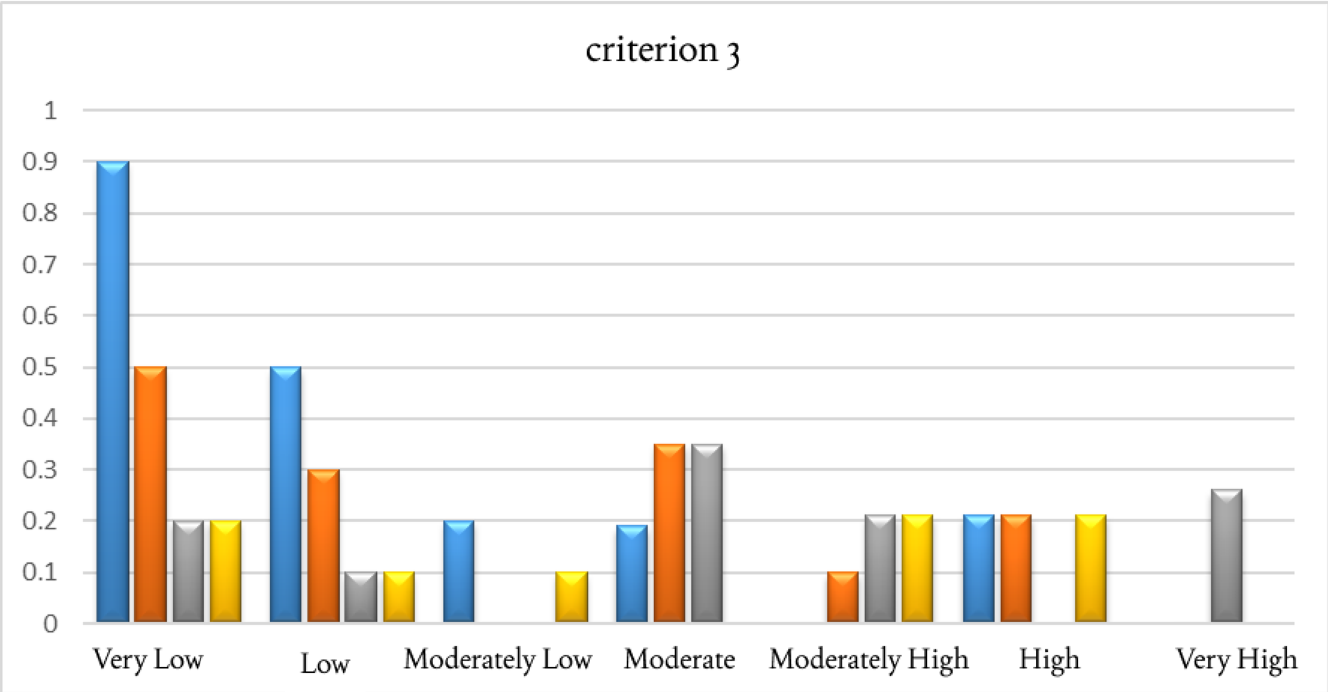


Figure 6

Estimated evaluation criteria for the four furnaces (Scenario 4).

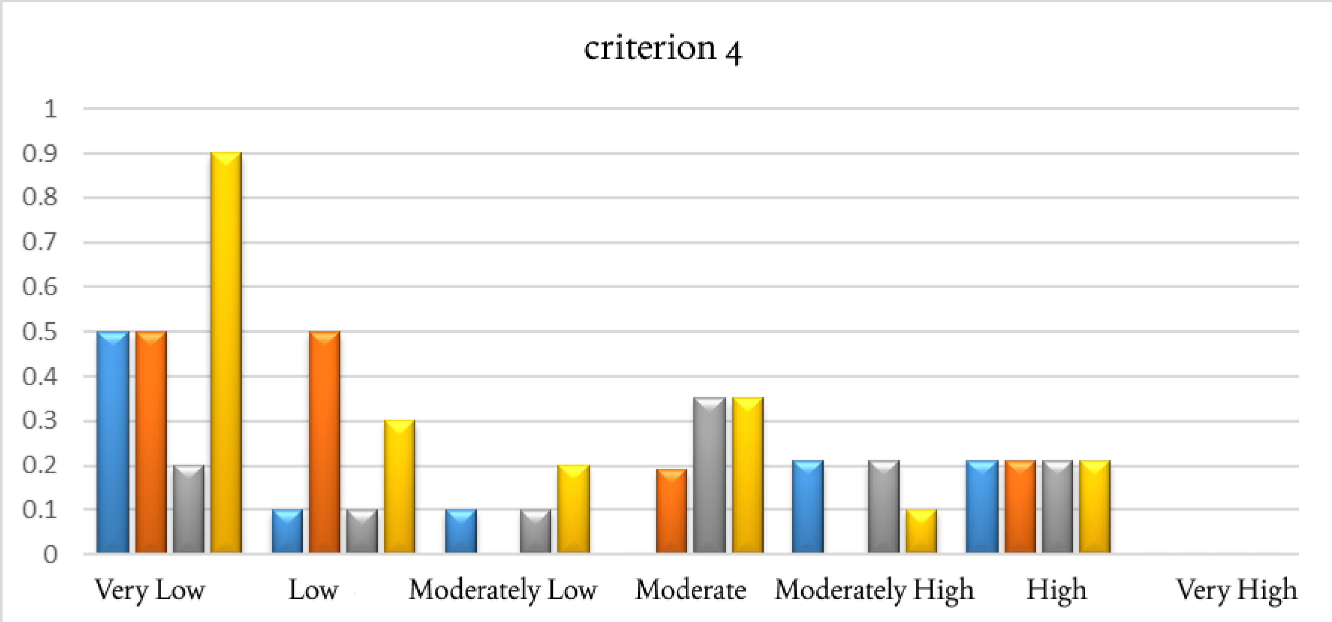


Table 9

Performance of Four Predicted Furnace Scenarios

Scenario	Closeness Coefficient	Rank
A1	0.6906	4
A2	0.9530	1
A3	0.7109	3
A4	0.8119	2

Table 9 shows the final ranking based on closeness coefficients. Scenario A2 achieves the highest coefficient (0.953), making it the optimal solution. A4 follows closely with 0.812, while A1 performs worst with 0.691.

Figure 3 illustrates the fuzzy TOPSIS evaluation of furnaces in Scenario 1, where the system was configured with localized refractory bricks. The chart shows low to moderate performance values across most criteria, with notable weaknesses in reliability and downtime management. The results highlight that relying solely on local bricks produces unfavorable outcomes, as maintenance overlaps reduce operational continuity and performance indicators remain below desirable thresholds.

In the Figure 4, the evaluation results for Scenario 2 are presented, which combined imported and local refractory bricks in a hybrid configuration. The scores reflect significant improvements compared to Scenario 1, particularly in terms of operational reliability and production continuity. The higher values across multiple criteria indicate that hybrid arrangements mitigate the limitations observed in fully local setups, positioning Scenario 2 as one of the most efficient alternatives.

Figure 5 displays the results for Scenario 3, representing another hybrid configuration with a different distribution of imported and local bricks. The evaluation demonstrates intermediate performance: some criteria achieved moderately high values, while others lagged behind. Although Scenario 3 surpassed the performance of Scenario 1, its outcomes were less consistent than those of Scenario 2, suggesting that not all hybrid configurations yield equally optimal results.

The evaluation for Scenario 4 is presented in Figure 6, showing relatively balanced performance across the selected criteria. Scenario 4 ranked second overall, with strong scores in reliability and production-related metrics but slightly lower cost-effectiveness compared to Scenario 2. The results indicate that Scenario 4 offers a feasible alternative with robust operational performance, though not reaching the optimal balance demonstrated by Scenario 2.

4. Discussion and Conclusion

The findings of this study underscore the critical role of simulation modeling and fuzzy multi-criteria decision-making in optimizing preventive maintenance strategies for complex industrial systems. By evaluating four operational scenarios (A1–A4), the results revealed that scenario A2 achieved the highest closeness coefficient (0.953), indicating superior performance in balancing cost efficiency, operational continuity, and reliability. Scenarios A3 and A4 followed with moderate scores (0.711 and 0.812 respectively), while A1 performed least effectively (0.691). These results suggest that hybrid or selectively optimized maintenance configurations outperform both purely local and purely imported strategies, confirming that context-specific approaches yield the best outcomes when applied in uncertain, resource-constrained environments. The closeness of A4 to A2 further demonstrates the feasibility of hybrid strategies where imported and local resources are integrated.

These outcomes align with contemporary research on reliability-based optimization, which consistently demonstrates that multi-objective frameworks are more effective than single-objective approaches in maintenance planning. Studies applying artificial intelligence to optimize concreting equipment operations in India, for example, highlighted that balancing multiple criteria—such as resource costs, system availability, and task scheduling—produces better outcomes compared to one-dimensional optimization (Ghosh & Abawajy, 2025). Similarly, in composite repair structures, reliability-based multi-objective optimization models using artificial neural networks proved effective in handling conflicting performance objectives (Zhao et al., 2025). The present study reinforces these findings by showing how fuzzy TOPSIS can capture uncertainty and provide rankings that reflect the inherent trade-offs among competing maintenance priorities.

The results also confirm the value of simulation-driven approaches in maintenance contexts, particularly where failures are stochastic and operational conditions complex. The identification of A2 as the best-performing configuration parallels evidence from stochastic job shop scheduling models that employed discrete event simulation to manage random machine failures (Amelian, 2025). Likewise, discrete event simulation applied to maintenance processes in a port cargo company revealed bottlenecks and enabled process improvements, highlighting simulation's capacity to replicate and test alternative operational strategies (Corrotea et al., 2024). In the present study, simulation not only replicated furnace operations but also captured failure overlaps and downtime distributions, making it a vital tool for validating hybrid preventive maintenance strategies.

Furthermore, this research confirms the significance of preventive maintenance in sustaining industrial performance. In line with earlier work on preventive maintenance for constrained minimal repair systems (Cha & Finkelstein, 2024), the study shows that preventive strategies, when carefully calibrated, minimize costly system disruptions. Findings from preventive maintenance modeling in photovoltaic power systems (Chen et al., 2024) and wind turbines (Kaewbumrung et al., 2024) further support this conclusion, demonstrating that structured preventive schedules enhance equipment longevity and reduce sudden outages. By integrating simulation and fuzzy TOPSIS, the current research extends this body of work, offering a dual-method framework applicable to both energy systems and metallurgical operations.

The fuzzy multi-criteria evaluation, in particular, demonstrates robustness in handling ambiguous and incomplete data. This resonates with findings from fuzzy synthesis approaches for hierarchical decision analysis, which have been used to select optimum repair techniques in industrial systems (Amaitik et al., 2024). Similarly, extended fuzzy TOPSIS has been applied in supplier selection for prefabricated megaprojects under hesitant environments, underscoring the technique's versatility in uncertain decision contexts (Liang et al., 2023). In the present study, the fuzzy TOPSIS method provided nuanced evaluations that aligned with expert judgments and simulation outputs, validating its effectiveness in ranking maintenance alternatives under uncertainty.

Another important finding of this research is the significance of reliability analysis in preventive maintenance. The top ranking of scenario A2 reflects the need for systematic reliability evaluations, as also noted in the context of consecutive k-out-of-n systems operating under shock environments (Dong & Bai, 2024). Similarly, research on retrial systems with two failure modes emphasized that preventive strategies tailored to system architecture yield more resilient outcomes (Li et al., 2024). The high coefficient of A2 indicates that the configuration best supported the reliability of the furnace system, echoing lessons from reliability-based predictable maintenance applied to container ship fuel systems (Yasin, 2025). This convergence across industries shows that reliability remains the cornerstone of effective preventive maintenance planning.

The present findings also reinforce the need to integrate human factors and error management into maintenance design. Hybrid strategies, as highlighted in this study, are not purely technical but also managerial, involving human oversight in resource allocation and scheduling. This is consistent with research in nuclear reactor maintenance where human factor engineering and artificial intelligence were combined to analyze operational loops and optimize safety (Khamaj et al., 2024). Similarly, integrated approaches that account for human error in production and maintenance planning improve efficiency, as shown in recent holistic frameworks (Bafandegan Emroozi et al., 2024). By emphasizing hybrid strategies, this study illustrates the practical reality of maintenance systems where human decision-making interacts with technical optimization.

The evidence from this research also resonates with ongoing shifts from corrective to preventive maintenance in global practice. Studies analyzing transitions in building maintenance strategies emphasized that moving from corrective to preventive approaches significantly reduces long-term costs and enhances system reliability (West et al., 2024). Reliability-centered maintenance models applied to critical machines in the Sabiz plant further validate the importance of structured preventive frameworks (Cahyati et al., 2024). In this context, the success of scenario A2 underscores that preventive maintenance is not only theoretically advantageous but also practically feasible, particularly when supported by simulation and fuzzy multi-criteria analysis.

Moreover, the ranking of alternatives in this study demonstrates the impact of optimization algorithms on preventive maintenance planning. The use of fuzzy TOPSIS parallels approaches where genetic algorithms (Singla et al., 2024), particle swarm optimization (Singla et al., 2025), and discrete mayfly algorithms (Belagoune et al., 2025) were employed to improve preventive scheduling. These studies collectively demonstrate that optimization methods enhance the accuracy and adaptability of maintenance strategies. The present research contributes by showing that fuzzy TOPSIS, when combined with simulation, can produce rankings that align with both theoretical expectations and practical constraints.

From a broader perspective, the study validates the integration of advanced mathematical and statistical modeling in preventive maintenance. Statistical modeling of preventive maintenance effectiveness for repairable systems (Ye et al., 2024), hidden Markov models for system degradation (Gámiz & L, 2023), and ROC-TOPSIS for road repair prioritization (Sur & Machfiroh, 2024) all exemplify the analytical sophistication needed to support maintenance decisions. By applying fuzzy TOPSIS to furnace systems, the present study shows how advanced modeling frameworks can guide real-world maintenance strategies and ensure alignment with organizational goals.

The findings also highlight the growing role of artificial intelligence and machine learning in maintenance optimization. The success of A2 resonates with machine learning frameworks applied to PVC manufacturing equipment (Kiki & Wang, 2025) and integrated AI-fuzzy approaches used in predictive automotive maintenance (Micosky et al., 2024). Likewise, studies on AI-based optimization in nuclear (Khamaj et al., 2024) and concreting (Ghosh & Abawajy, 2025) industries show similar improvements. This reflects a broader trend where AI enhances the adaptability and intelligence of preventive maintenance systems. The use of fuzzy TOPSIS in this study contributes to this trend by incorporating expert-driven fuzzy evaluations into quantitative decision frameworks.

Finally, this research contributes to the growing emphasis on sustainability and resilience in industrial systems. Preventive maintenance strategies, when optimized through simulation and fuzzy models, reduce waste, conserve resources, and ensure more sustainable operations. Lessons from energy infrastructure optimization (Erhueh et al., 2024), corrosion forecasting in reinforced concrete (Kopiika et al., 2025), and preventive replacement models in photovoltaic systems (Chen et al., 2024) reinforce the sustainability dimension of preventive maintenance. By identifying A2 as the optimal configuration, this study shows that maintenance strategies can align with both economic and environmental goals.

While the present study provides strong evidence for the effectiveness of simulation and fuzzy TOPSIS in preventive maintenance optimization, it has certain limitations. First, the findings are based on a case study of converter furnaces in a specific industrial context, which may limit generalizability. Second, the fuzzy evaluations rely on expert judgments, which can introduce subjectivity despite the robustness of fuzzy methods. Third, the study does not account for long-term degradation effects or changes in operational conditions that may alter system reliability over extended time horizons. Finally, the computational models applied here may need adaptation when scaled to larger or more heterogeneous industrial systems.

Future research should extend this approach to multiple industries, particularly in energy, transport, and infrastructure, where preventive maintenance is critical. Comparative studies applying alternative optimization algorithms, such as genetic programming, reinforcement learning, and advanced hybrid fuzzy methods, would provide valuable benchmarks. Incorporating human factors more deeply into simulation frameworks, including operator behavior, training, and decision-making, could enrich the analysis. Additionally, long-term simulations that integrate system degradation models, hidden Markov processes, or stochastic deterioration mechanisms should be explored. Finally, research could examine the integration of sustainability metrics into preventive maintenance optimization to align with global environmental goals.

For practitioners, the findings underscore the importance of adopting hybrid preventive maintenance strategies that balance cost and reliability. Simulation tools should be widely applied to test operational scenarios before implementation, allowing organizations to anticipate failures and optimize resources. Decision-makers should integrate fuzzy multi-criteria approaches to ensure that subjective judgments are systematically captured and weighted. Finally, organizations should embrace preventive over corrective maintenance, supported by optimization models, as a pathway to improving reliability, efficiency, and sustainability in industrial systems.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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