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Advancing Sustainable Glass Manufacturing through Optimized Predictive Maintenance Planning of Critical Forming Components

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Abstract: The glass manufacturing industry is a key contributor to various sectors, including construction, automotive, and packaging. However, it is also energy-intensive and contributes significantly to global carbon emissions. Decarbonizing glass production is essential for aligning industrial practices with global climate goals. This study focuses on advancing sustainability in glass manufacturing through a predictive maintenance planning framework adapted to critical forming components, including Gob Delivery System, Blank Moulds, and Blow Moulds. By optimizing maintenance schedules and minimizing unplanned downtimes, the framework reduces resource wastage, energy inefficiencies, and associated carbon emissions, thereby aligning operational practices with sustainability objectives. The proposed framework integrates reliability analysis, cost evaluation, and advanced optimization techniques to dynamically generate maintenance schedules. A computational tool developed for this purpose simulates degradation and maintenance processes, offering actionable insights into component reliability and cost efficiency. While validated using simulated data, the methodology is adaptable for broader industrial applications, promising significant contributions to the sustainability of glass manufacturing.

Keywords: Predictive maintenance, Glass manufacturing, Reliability analysis, Maintenance optimization, Forming processes, Sustainability, Maintenance scheduling.

1. INTRODUCTION

Glass manufacturing plays a crucial role in modern industries, providing essential materials for sectors such as construction, automotive, packaging, and electronics. Its widespread use is attributed to the unique properties of glass, including its durability, versatility, and sustainability compared to alternative materials. However, the production process is highly energy-intensive, requiring temperatures above 1500°C to melt raw materials and refine molten glass into products. This dependency on energy-intensive processes makes glass manufacturing a notable contributor to carbon emissions, highlighting the need for measures to reduce its environmental impact (Collina et al., 2023).

Decarbonizing glass manufacturing is pivotal in achieving global climate goals, including those set by the Paris Agreement (United Nations, 2024; Rio et al., 2022). While the integration of hydrogen as an alternative energy source in furnaces is a promising development, as highlighted by initiatives like (H2GLASS, 2023), decarbonization also depends on reliable operations of infrastructure, minimizing energy waste, and reducing material losses across the value chain. Achieving these objectives requires innovations not only in energy supply but also in manufacturing processes. Predictive maintenance can potentially support energy and resource efficiency, particularly when maintenance actions are precisely timed to prevent unnecessary resource consumption and operational inefficiencies (Colangelo, 2024). However, achieving these benefits depends on effective implementation and integration within the manufacturing system.

Predictive maintenance departs from traditional reactive and preventive strategies by employing real-time condition monitoring, historical data, and predictive models to assess the health of components and anticipate their degradation (Sang, 2021). However, predictive maintenance planning goes beyond prediction by integrating these insights into a structured, cost-optimized maintenance strategy (Amaitik et al., 2023). For the glass industry, where precision in shaping and dimensional accuracy, as well as operational reliability, are essential, predictive maintenance planning involves not only predicting when equipment will degrade but also determining the most cost-effective and operationally efficient schedule for performing maintenance. This proactive approach ensures maintenance actions are performed only when necessary, reducing unplanned downtimes and extending the lifetime of critical equipment (Cachada, 2018; Collina et al., 2023). Incorporating predictive maintenance planning into glass manufacturing process directly aligns with the goals of decarbonization by improving reliability and reducing operational inefficiencies.

This paper introduces an innovative predictive maintenance planning framework adapted to the forming process in glass manufacturing. It focuses on three critical components: Gob Delivery System, which ensures precise molten glass transfer; Blank Moulds, responsible for initial shaping; and Blow Moulds, which finalize product quality. The proposed framework aims to minimize downtime, enhance efficiency, and support sustainability objectives. Through these advancements, predictive maintenance planning can complement broader industry efforts, such as hydrogen adoption for glass furnaces, and contribute to the modernization and decarbonization of glass manufacturing.

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2. PREDICTIVE MAINTENANCE PLANNING FOR GLASS MANUFACTURING

Glass manufacturing is a complex process that transforms raw materials such as silica, soda ash, and limestone into a variety of products. This process starts with melting the raw materials in furnaces, followed by forming, annealing, and finishing stages. Each stage demands precision and control to ensure product quality. The forming stage is critical, as it shapes molten glass into final products with desired specifications and dimensions (Hubert, 2019).

The forming process involves three key components: Gob Delivery System, Blank Moulds, and Blow Moulds, which work in synchrony to create the glass product. The Gob Delivery System plays a crucial role in transferring molten glass from the forehearth to the forming machine. The system precisely cuts the molten glass into uniform gobs and delivers them to moulds for shaping, as shown in Figure 1, while the Blank and Blow Moulds are responsible for shaping and refining the product. Several forming methods are employed in the glass industry, including blow-and-blow, press-and-blow, and narrow-neck press-and-blow techniques. These methods are selected based on the product type and desired characteristics. For instance, the blow-and-blow method is commonly used for producing hollow glass containers like bottles. As depicted in Figure 2, this method involves an initial shaping phase in the blank mould, followed by a final shaping phase in the blow mould, where compressed air is used to refine the product. This process highlights the need for precise coordination and reliability of the forming components to ensure high-quality output (Miller & Sullivan, 1984).

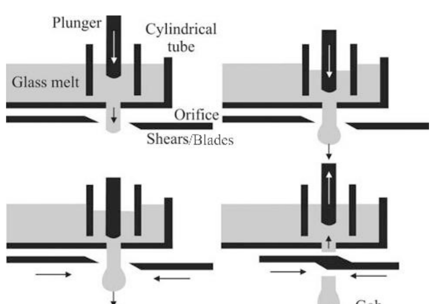


Figure 1. Gob delivery process (Le Bourhis, 2008)

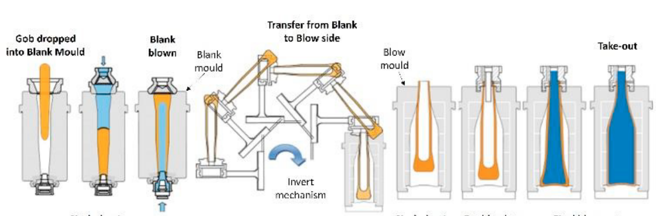


Figure 2. Blown glass forming process (Miller & Sullivan, 1984)

Ensuring the reliability of these components is essential, as it directly impacts the precision required to maintain product quality in glass forming processes. Traditional maintenance methods, such as reactive and preventive maintenance, have limitations. Reactive maintenance often results in costly unplanned downtimes, while preventive maintenance can lead to over-maintenance and unnecessary resource expenditure (Alsaif et al., 2024). Predictive maintenance offers a more cost-effective alternative, using real-time condition monitoring data to predict equipment degradation and optimize maintenance actions.

Predictive maintenance approaches have shown increasing applicability in glass manufacturing, addressing the reliability and efficiency of critical components. A study by Okwuobi et al. (2018) explored the use of Reliability-Centered Maintenance (RCM) in individual section-forming machines, demonstrating its potential to reduce downtime and improve system availability through a structured failure analysis. Similarly, Alsaif et al. (2024) highlighted the role of multi-objective optimization in preventive maintenance planning in a Saudi glass production plant. Furthermore, Collina et al. (2023) emphasized the importance of Risk-Based Maintenance (RBM) in managing the unique operational challenges of the glass industry, particularly with evolving decarbonization efforts. These methodologies collectively illustrate the benefits of predictive maintenance while highlighting the need for integrated solutions to address the specific demands of glass forming processes.

Recent advancements in predictive maintenance utilize condition monitoring data, machine learning, and real-time analytics to predict component degradation before failures occur. Machine learning-based approaches, such as Deep Reinforcement Learning, Random Forest Classifiers and Support Vector Machines, have demonstrated efficacy in identifying patterns and predicting failures, as seen in applications for machinery like laminated glass cutters and manufacturing systems (Ornati, 2019; Zhang et al., 2022a). Intelligent predictive maintenance frameworks now combine condition-based monitoring with decision-support systems to provide actionable insights, improving operational reliability and reducing costs (Cachada, 2018; Zhang et al., 2022b).

Despite these advancements, existing methodologies often lack seamless integration between predictive insights and maintenance planning. Current approaches focus on failure prediction or risk prioritization but have limited integration of cost analysis and dynamic scheduling to optimize maintenance actions. The proposed framework addresses this gap by combining reliability analysis, cost evaluation, and advanced artificial intelligence optimization techniques. It focuses on developing degradation curves for critical components in the glass forming process, including Gob Delivery System, Blank Moulds, and Blow Moulds, and integrates these with maintenance cost models and scheduling algorithms. This holistic approach ensures that maintenance actions are not only timely and accurate but also cost-effective and operationally efficient, addressing the unique demands of high-precision, high-temperature environments like glass manufacturing.

3. PROPOSED FRAMEWORK FOR PREDICTIVE MAINTENANCE PLANNING

In this section, we present the proposed framework for predictive maintenance planning applied to glass forming process.

3.1 Framework Overview

The proposed framework contributes to predictive maintenance planning research by integrating degradation modelling, cost evaluation, repair impact model and dynamic scheduling in a structured optimization approach to establish an optimized predictive maintenance schedule for the three key components of glass forming process: Gob Delivery System, Blank Moulds, and Blow Moulds. This framework enables real-time decision-making adapted to high-precision, energy-intensive environments such as glass manufacturing.

The degradation model uses Weibull reliability function to predict the condition of each component over time through generated degradation curves. They are dynamically updated as new data is collected, enhancing prediction accuracy, and ensuring maintenance decisions reflect current equipment conditions. The repair impact model evaluates the effects of different maintenance actions on component reliability and system performance. The maintenance cost model complements this by calculating the financial implications of various maintenance strategies, including costs associated with repairs, replacements, and potential downtimes. The scheduling model integrates outputs from other models to create optimized maintenance plans. It employs Genetic Algorithms techniques to generate schedules that balance reliability, cost, and operational efficiency. The goal is to ensure maintenance activities are performed at the most cost-effective times while minimizing disruptions to production.

3.2 Computational Approach and Problem Formulation

This comprehensive framework offers a structured approach to predictive maintenance planning, as presented in Figure 3. By dynamically integrating degradation analysis, cost evaluation, and scheduling, the framework ensures that maintenance decisions are data-driven, cost-effective, and adapted to the specific requirements of high-precision manufacturing environments.

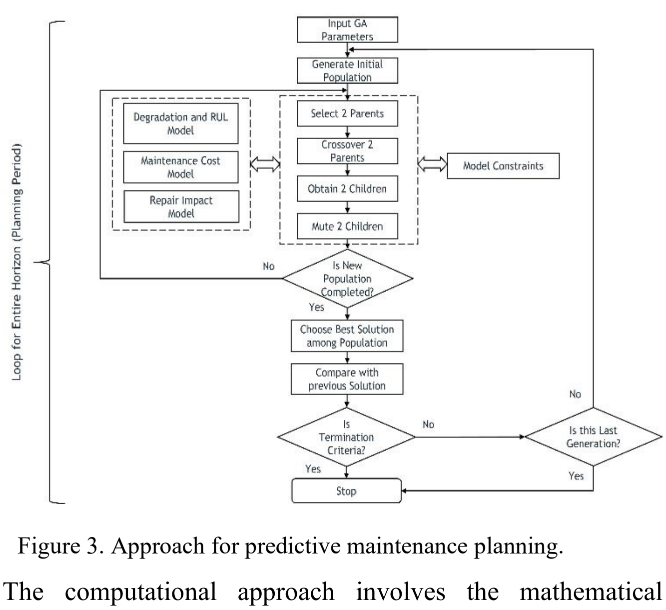


Figure 3. Approach for predictive maintenance planning.

The computational approach involves the mathematical formulation of the predictive maintenance planning problem. The problem is modelled to balancing the goals of maximizing component reliability and minimizing maintenance costs. Given a machine with known initial conditions for its components, and if a repair or no-repair action is taken, the degradation and impact models can predict the components' conditions over any time interval. Each repair strategy has an associated repair cost. Therefore, it is possible to construct an optimization problem to determine the best set of repairs that achieve the maximum reliability/cost ratio.

The objective function and constraints for the machine *i* at time interval *t* to maximize reliability/cost ratio are formulated in Equations (1) through (6).

<u>Objective function:</u>

$$Maximize \; {RT(i,t)}\Big/{PV(MC(i,t))} \tag{1}$$

<u>Subject to:</u>

$$RT(i,t) \geq Threshold_i \; (min\ reliability\ for\ machine\ i) \tag{2}$$

$$RT(c,t) \geq Threshold_c \; (min\ reliability\ for\ component\ c) \tag{3}$$

$$\sum_{t=1}^{T}\sum_{c=1}^{C} PV(MC(c,t)) \leq Threshold_t \; (max\ repair\ budget\ per\ t) \tag{4}$$

$$RT(c,t) = \begin{cases} RT(c,t)^{new} & if\ c\ is\ selected\ for\ repair \\ RT(c,t) & otherwise \end{cases} \tag{5}$$

$$RT(i,t) = \prod_{c=1}^{C} RT(c,t)\,, \quad \text{at any time } t \tag{6}$$

Where, *i* denotes to machine, *t* denotes to time interval (e.g., hours, days, years), *C* is the number of components to be analyzed for the machine, *T* is the number of time interval in planning horizon, *RT(i,t)* is the overall reliability of the machine *i* at the end of time *t*, *RT(c,t)* is the reliability of the component *c* at the end of time *t*, *MC(i,t)* is total maintenance cost of the machine *i* at the end of time *t, MC(c,t)* is the maintenance cost of component *c* at the end of time *t*, $RT(c,t)^{new}$ is the new reliability of a component *c* after maintenance at the end of time *t,* and *PV* is costs present value.

The decision variables in this optimization include timing and type of maintenance actions recommended by the predictive model based on estimated component reliability. Separate optimizations are carried out for each time interval in the planning horizon. A solution for the problem is structured as a string of three elements, as shown in Figure 4. Each variable can be assigned an integer value from 0 to 2, corresponding to one of the predictive maintenance actions: (0 = no action when reliability is high; 1 = repair when moderate degradation is detected; 2 = replace when severe degradation is predicted).

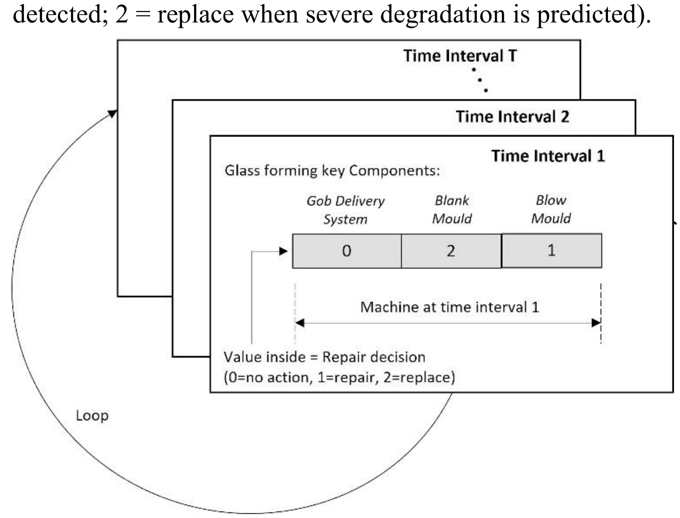


Figure 4. Solution structure for the schedule algorithm.

4. IMPLEMENTATION TO GLASS FORMING PROCESS

In this section, we present the implementation of proposed predictive maintenance planning framework to glass forming process and results obtained.

4.1 Case Study Setup

The framework is validated through a simulation-based approach, utilizing reliability parameters and maintenance cost models. The computational tool developed for this study simulates degradation patterns and optimizes maintenance schedules, demonstrating the feasibility and effectiveness of the model. While real-world implementation is a future step, the simulated results provide actionable insights for manufacturing applications. We use expert judgment supported by literature conducted in section (2). We estimate the model parameters, as summarized in Tables 1 through 4, to experiment our framework. These parameters include components lifetime, Weibull reliability parameters (η-Eta and β-Beta) for degradation estimation, maintenance cost data, and percentages of reliability restored for each component.

4.1.1 Critical Components and Maintenance Strategies

The three-tier maintenance strategy employed consists of: *No Action*, *Repair*, and *Replace*. These strategies reflect increasing levels of intervention, with corresponding impacts on cost and reliability. Table 1 summarizes the critical components, their functions, and the defined maintenance actions, inlight of Figures 1 & 2.

Table 1. Components and predictive maintenance actions

Component	Function	Predictive Maintenance Actions
Gob Delivery System	Transfers molten glass to moulds	• No Action (high reliability) • Repair (moderate degradation) • Replace (severe degradation)
Blank Mould	Initial shaping of molten glass	• No Action (high reliability) • Repair (moderate degradation) • Replace (severe degradation)
Blow Mould	Final shaping of glass products	• No Action (high reliability) • Repair (moderate degradation) • Replace (severe degradation)

4.1.2 Weibull Reliability Parameters

To simulate degradation behaviour, hypothetical Weibull parameters (scale parameter η and shape parameter β) were assumed for each component. These parameters reflect the reliability characteristics, with η representing the time to failure and β indicating the failure rate trend (increasing, constant, or decreasing). Table 2 provides the assumed values.

Table 2. Weibull parameters (η, β)

Component	η	β
Gob Delivery System	2000 hours	1.5
Blank Mould	1500 hours	2.0
Blow Mould	1800 hours	2.2

For experimentation, η and β were assumed to vary across components to reflect realistic degradation patterns. The Gob Delivery System, was assigned a β=1.5, indicating an increasing failure rate due to blade wear over time. The Blank Moulds and Blow Moulds, with β ≥ 2.0, were modelled with a sharper failure rate trend, representing surface fatigue from repeated exposure to high temperatures and mechanical stress.

The scale parameter η represents the expected operating lifetime under normal conditions and was assigned based on relative usage patterns and criticality. These parameters enable the simulation of reliability degradation curves, essential for optimizing maintenance schedules.

4.1.3 Repair Impact on Reliability

The repair impact model assumes that repairs restore a percentage of the component's reliability. These percentages were hypothesized based on the severity of the degradation and the type of repair action, as shown in Table 3.

Table 3. Repair impact parameters

Component	Repair Impact (% Reliability Restored)		
	No action	Repair	Replace
Gob Delivery System	0	70	100
Blank Mould	0	60	100
Blow Mould	0	60	100

4.1.4 Maintenance Costs

Maintenance costs were assigned for each component and repair action to evaluate cost optimization. Table 4 lists the hypothetical cost values.

Table 4. Maintenance cost parameters

Component	Cost (€)		
	No action	Repair	Replace
Gob Delivery System	0	300	1800
Blank Mould	0	400	1300
Blow Mould	0	400	1400

4.2 Results and Discussions

To implement the proposed predictive maintenance planning framework, a computational tool based on VBA programming language has been developed, utilizing algorithms to simulate the degradation, repair, and maintenance processes for the critical forming components over a predefined planning horizon. The tool integrates the estimated parameters for the Gob Delivery System, Blank Moulds, and Blow Moulds, as presented in the case study setup (Tables 1–4). For this analysis, a 5000-hours is considered as the planning horizon, assuming all components are brand new at the start. The tool dynamically updates the degradation of components based on simulated reliability parameters. In real-world scenario, the tool dynamically leans and updates reliability parameters based on condition monitoring data collected on the compnent. The tool subsequently generates optimized maintenance schedules that effectively balance cost considerations with reliability requirements. Key outputs include predicted degradation curves, the reliability impact of different maintenance strategies, and cost analyses for repair and replacement actions, providing actionable insights for sustainable maintenance planning in the glass forming process.

Degradation Analysis: The tool provides degradation curves for components and the whole machine system throughout the analysis period (Figures 5–8). These curves show the performance over time and analyze the impact of different repair and replacement strategies on component reliability. The Gob Delivery System, for example, has experienced 4 interventions (3 repairs and 1 replacement of the blades) throughout the planning horizon. The first repair occurred on hour 1567. This resulted in an improvement in the Gob Delivery System's reliability to 0.892. This demonstrates the value of predictive maintenance interventions, as opposed to allowing components to run to failure and then replacing them.

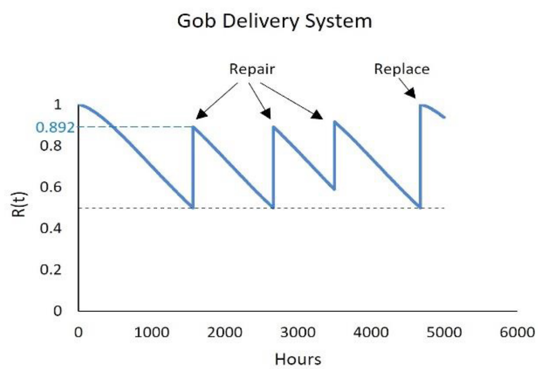


Figure 5. Degradation curve for Gob Delivery System.

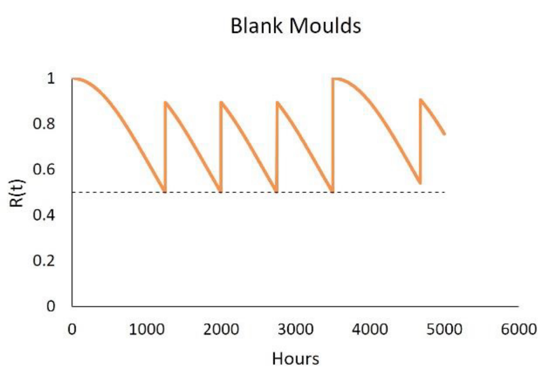


Figure 6. Degradation curve for Blank Moulds.

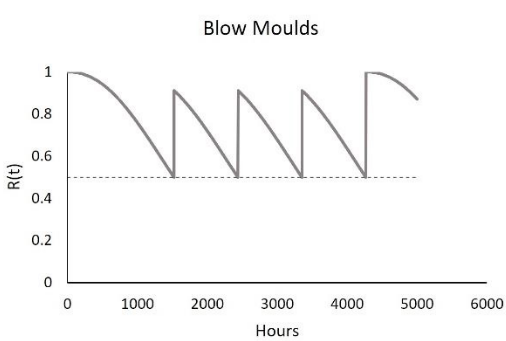


Figure 7. Degradation curve for Blow Moulds.

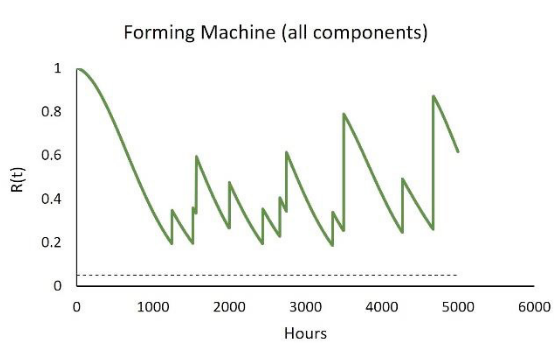
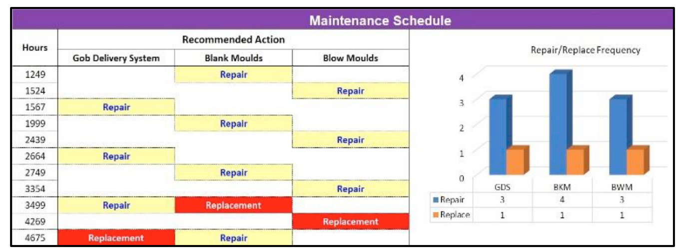


Figure 8. Degradation curve for Forming Machine.

Maintenance Schedule**:** The tool presents a predictive maintenance schedule for each component based on degradation and cost analysis so that manufacturers are informed in advance for taking the necessary arrangements for maintenance activities. Additionally, it shows statistics on repair and replacement implemented for each component (Figure 9). For example, during the 5000-hours planning horizon, 13 repair/replacement interventions are expected to be occurred (10 repairs and 3 replacements).


Maintenance Schedule

Hours	Recommended Action: Gob Delivery System	Blank Moulds	Blow Moulds
1249		Repair	
1524			Repair
1567	Repair		
1999		Repair	
2439			Repair
2664	Repair		
2749		Repair	
3354			Repair
3499	Repair	Replacement	
4269			Replacement
4675	Replacement	Repair	

Figure 9. Maintenance schedule and statistics.

Maintenance Cost Analysis**:** The tool provides detailed analysis and insights into the maintenance cost of the machine. It shows cumulative costs, costs per intervention, and cost breakdown per component. For example, during the 5000-hours planning horizon, a cumulative cost analysis is conducted (Figure 10-a) to provide manufacturers with insights into the intervals where higher costs are expected, enabling them to plan the required budget for maintenance activities accordingly. Additionally, the cost incurred for each component is calculated (Figure 10-b), highlighting the components that require the most expenditure. In our example, the Blank Moulds component demands the highest cost followed by Gob Delivery System.

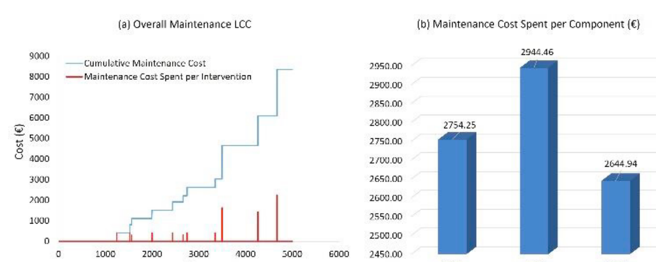


Figure 10. Maintenance cost analysis.

5. CONCLUSION

The proposed predictive maintenance planning framework integrates reliability analysis, cost evaluation, and advanced optimization techniques to generate dynamic and efficient maintenance schedules. By utilizing real-time condition monitoring data and dynamically updating reliability parameters, the framework ensures timely interventions, reducing downtime and extending component lifetime. This approach addresses the specific challenges posed by the high-temperature and precision-driven environment of glass forming processes, particularly for the Gob Delivery System, Blank Moulds, and Blow Moulds.

The framework represents a significant advancement in predictive maintenance planning for the glass industry, offering a tailored solution that balances operational reliability, cost-efficiency, and sustainability. While this study focuses on the forming stage of glass manufacturing, the methodology demonstrates adaptability, providing potential for extension to other stages of production. This adaptability enhances its relevance for broader industrial applications, particularly in high-precision, energy-intensive sectors.

Despite the feasibility demonstrated, the reliance on simulated data in this study introduces limitations. When applied to real-world industrial environments, the framework may require adjustments such as incorporating industry-specific operational constraints, integrating diverse condition monitoring systems, and refining reliability parameters based on empirical data to account for variability and complexity. Future research should emphasize validating the model with empirical data to improve its accuracy and adaptability. Additionally, integrating this framework with advanced digital tools, such as digital twins, could enhance real-time simulation and optimization for predictive maintenance. Further research could also focus on multi-objective optimization, incorporating sustainability metrics alongside cost and reliability, and AI-driven adaptive maintenance scheduling. Extending this approach to other high-precision manufacturing sectors would provide broader insights into predictive maintenance strategies, strengthening its industrial applicability.

Ultimately, this framework underscores the potential of predictive maintenance planning in fostering more sustainable and efficient manufacturing practices. This approach contributes to the decarbonization of glass manufacturing, advancing the industry's commitment to sustainability by aligning maintenance strategies with operational and environmental goals.

ACKNOWLEDGEMENTS

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