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Data-Driven Multi-Objective Predictive Maintenance Optimization: Application to Bushings in Fiberglass Manufacturing

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Abstract: Poor maintenance practices in fiberglass manufacturing cause downtimes, quality defects, and increased costs. This study proposes a predictive maintenance (PdM) optimization framework combining a data-driven system, employing a convolutional neural network (CNN) model to predict bushing operational efficiency (OE), and a model-based system that operates a multi-objective optimization approach for scheduling maintenance. The data-driven system identifies critical bushings by predicting OE zones, while the model-based system prioritizes tasks based on criticality levels, minimizing maintenance completion time and servicing costs hierarchically. Results demonstrate criticality-based scheduling where higher-priority bushings are serviced earlier, while lower-priority bushings face longer waiting times. Operator utilization is optimized with balanced task allocation and sequential execution, ensuring efficient resource use and minimized downtime. The integrated framework improves operational efficiency, reduces delays, and addresses urgent tasks, which offers a robust solution for predictive maintenance in fiberglass production.

Keywords: Predictive maintenance, Multi-objective optimization, Glass manufacturing, Operational efficiency.

1. INTRODUCTION

Fiberglass manufacturing is a highly intricate process that relies on the seamless operation of components, such as bushings, to provide efficiency, quality, and cost-effectiveness. However, poor maintenance routines often lead to unplanned downtimes, quality defects, and increased operational costs, all of which can jeopardize the competitiveness of production (de Jonge and Scarf, 2020). With the advent of Industry 4.0 and advanced sensor technologies, the increasing availability of real-time operational data has unlocked new opportunities for implementing predictive maintenance (PdM) strategies. By leveraging this data, manufacturers can transition from reactive or periodic maintenance to predictive maintenance, which proactively prevents failures and minimizes downtime and waste (Florian et al., 2021).

PdM has garnered significant attention across industries for its potential to improve system reliability and operational efficiency. Unlike traditional maintenance strategies, such as preventive or periodic maintenance, that often lead to over-maintenance or insufficient resource allocation, PdM relies on data-driven insights to optimize maintenance schedules. This approach optimizes resource usage, reduces operational interruptions, and enhances the durability of critical components. For instance, PdM has been successfully implemented in power plants and shipbuilding, which demonstrates its versatility and effectiveness (Cipollini et al., 2018; Wu et al., 2017). Despite its potential, PdM faces several persistent challenges, including accurately forecasting the performance of critical components, effectively integrating these insights into maintenance strategies, and optimizing resource-constrained maintenance schedules (Serradilla et al., 2022). Advanced data-driven methods, such as machine learning and deep learning, have made significant strides in enabling precise performance predictions and supporting proactive maintenance decisions (Arena et al., 2022). These approaches are particularly valuable in industries where the performance of key components directly impacts operational efficiency (OE) and product quality.

However, the application of these techniques often falls short in addressing multi-objective optimization challenges in complex industrial systems. In fiberglass manufacturing, for instance, the performance of bushings is characterized as OE and plays a pivotal role in maintaining product quality and minimizing waste (Frederick T. Wallenberger, 2010). Poor bushing performance, indicated by low OE, can not only signal potential failures but also lead to increased glass defects and waste, compounding operational inefficiencies. This highlights the need for a more integrated approach that connects performance predictions with maintenance planning while addressing competing objectives such as cost, downtime, and quality.

The literature showcases numerous PdM models using data-driven techniques. Nguyen and Medjaher (2019) developed a dynamic model for predicting failure probabilities, while Lee and Mitici (2023) applied reinforcement learning to optimize maintenance decisions. In fiberglass manufacturing, such approaches are crucial, especially for bushings, where performance degradation can cascade into broader inefficiencies and waste. Industry 4.0 has further accelerated

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the adoption of machine learning (ML)-based PdM strategies to enhance system efficiency. However, selecting the proper algorithm for specific tasks remains a challenge. Given the sequential nature of furnace sensor data and the complex interactions among operational parameters, convolutional neural networks (CNN) are potential approaches for capturing spatial and temporal dependencies and making them practical for OE prediction (Zhao et al., 2017). Arena et al. (2024) addressed this by proposing a conceptual framework for algorithm selection, offering guidelines based on dataset characteristics and learning objectives, and bridging the gap between theory and practical applications in PdM. Pisacane et al. (2021) proposed bi-objective optimization approaches to maximize system reliability and minimize repair times under resource constraints. These studies show that data-driven predictions and optimization frameworks can be integrated to improve industrial maintenance strategies. Similarly, Wang et al. (2024) integrated remaining useful life predictions with maintenance planning through deep learning and multi-objective MILP models, which achieve cost and time reductions.

To address the limitations in the fiberglass industry, this study employs a multi-objective optimization approach with hierarchical priorities, which stresses the minimization of bushing waiting times for allocation to specific operations while balancing key objectives like reducing downtime and costs. The hierarchical prioritization enables decision-makers to focus on critical aspects, such as minimizing downtime, while still considering secondary objectives like cost reduction. The proposed framework's application to a fiberglass plant serves as a case study, demonstrating its applicability in enhancing operational efficiency, reducing costs, and improving maintenance planning.

The contributions of this study are summarized as follows:

1. A CNN model is developed to predict the OE of bushings based on historical/real-time data (data-driven system) based on key operational parameters, including oxygen (O_2) flow, fuel flow, pressure, and temperature, which are critical indicators of furnace health affecting bushings performance.
2. A multi-objective mixed-integer linear programming (MILP) model is designed to optimize maintenance schedules for multiple bushings, considering costs and downtime (model-based system).
3. The framework is validated using real-world data from a fiberglass manufacturing plant.
4. The study employs multi-objective hierarchical optimization.

By bridging the gap between predictive analytics and optimization, this research contributes to the growing body of knowledge on PdM in manufacturing. It demonstrates that combining machine learning with mathematical optimization can yield improvements in operational efficiency and resource utilization, paving the way for more innovative, data-driven decision-making in industrial environments.

2. PROBLEM DESCRIPTION

Fiberglass production is a sophisticated process that requires precise coordination across multiple stages, from batch preparation to the final product, as depicted in Figure 1. At the core of this process is the furnace, where raw materials are melted into molten glass using heat generated by burners through controlled gas (e.g., natural gas or hydrogen) and O_2 combustion. The molten glass is then channeled into bushings ($b_1 \ldots, b_m$)- specialized components equipped with nozzles/dies. These bushings play a critical role in shaping the molten glass into fine fiber strands. The performance of bushings is influenced by factors such as molten glass temperature, gas and O_2 flows, and pressure inside the furnace observed by sensors. Afterward, the strands are guided over a plate to ensure consistency and uniformity before being cut to specific lengths by choppers. The resulting fibers are grouped into continuous bundles, called rovings, which serve as essential materials for a wide range of applications, including automotive components, construction materials, and reinforcement for composites.

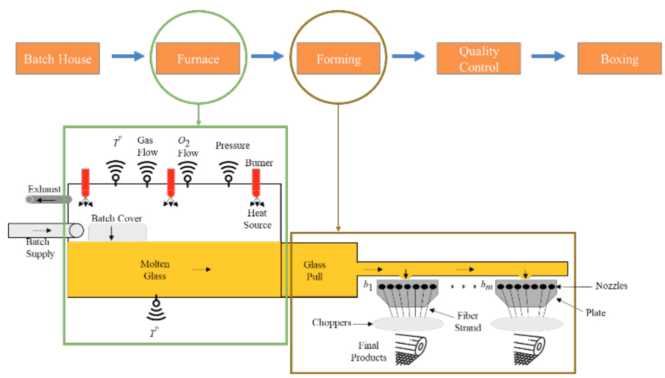

Figure 1. Furnace and bushings at the core of fiberglass production.

Maintaining the OE of bushings (b) is essential to supplying a smooth and cost-effective production process. Poorly performing bushings can lead to nozzle clogging, uneven fiber production, increased glass waste, and product defects. These issues not only affect production quality but also escalate operational costs and environmental impacts, such as increased energy consumption, higher raw material usage, and waste disposal challenges. To address these challenges, bushings occasionally require maintenance, which is carried out by operators (o) stationed at servicing centers within the factory.

The time it takes for an o to begin maintenance on a bushing (t_o^b) depends on workload and scheduling, while the maintenance duration (d_o^b) is influenced by the condition of the bushing. Some bushings are more critical, with assigned criticality levels (θ_b), necessitating faster attention to prevent disruptions in production. Operators perform maintenance tasks sequentially, starting with the most critical bushing based on its assigned θ_b. Each o has a limited capacity. A PdM framework is required to monitor bushing performance using sensor data, predict OE and θ_b, and optimize maintenance schedules. By balancing operator capacity, servicing times, and bushing priorities, this framework aims to reduce waste, improve product quality, and enhance the overall efficiency of fiberglass production.

3. MATHEMATICAL FORMULATION

This section introduces the notations and mathematical optimization model, which integrates CNN-based operational efficiency predictions to optimize maintenance schedules for fiberglass bushings while balancing costs and downtime through a multi-objective MILP framework.

3.1 Notations

In order to describe the mathematical model applied, these notations are introduced:

Sets

B	Set of bushings, b and $b' \in B$
O	Set of operators, $o \in O$

Parameters

t_o^b	Time for operator o to begin maintenance on bushing b (hours)
d_o^b	Maintenance duration for bushing b by operator o (hours)
θ_b	Criticality level of bushing b, with lower values indicating higher priority for maintenance
c_o	Cost associated with assigning operator o to a servicing (€)
ω_o	Maximum number of bushings operator o can handle sequentially within a period.
M	A big positive number

Decision variables

Z_o^b	1 if bushing b is assigned to operator o for maintenance; 0 otherwise.
Y_o^b	1 if bushing b is the first to be maintained by operator o; 0 otherwise.
E_o	1 if operator o is utilized for maintenance tasks; 0 otherwise.
$X^{bb'}$	1 if bushing b' is maintained after bushing b by the same operator; 0 otherwise.
C_b	Maintenance completion time for bushing b (hours)
C_{max}	Total maintenance completion time across all bushings (hours)
W_{max}	Maximum waiting time for any bushing before maintenance starts (hours)
S_b	Maintenance start time for bushing b (hours)
Z_1	Total maintenance time (hours)
Z_2	Total maintenance time (€)

3.2. Mathematical optimization model

The optimization model with a multi-objective approach is described in the following by defining the objective functions and constraints.

3.2.1 Objective functions

$$\text{Min } (Z_1) = C_{max} \tag{1}$$

The first objective (1) minimizes the total maintenance completion time to ensure that all bushings are serviced as quickly as possible to reduce overall downtime.

$$\text{Min } (Z_2) = \sum_{o \in O} c_o \times E_o \tag{2}$$

The second objective (2) minimizes the total cost of utilizing servicing operators to optimize resource allocation.

3.2.2 Constraints

The constraints are defined as follows:

$$\sum_{o \in O} Z_o^b = 1 \quad \forall b \in B \tag{3}$$

Constraint (3) guarantees that each bushing (b) must be assigned to one operator (o) for maintenance.

$$Y_o^b \leq Z_o^b \quad \forall b \in B, o \in O \tag{4}$$

Constraint (4) assures that a bushing (b) can only be the first bushing maintained by an operator (o) if it is assigned to that operator.

$$\sum_{b \in B} Y_o^b = E_o \quad \forall o \in O \tag{5}$$

Constraint (5) specifies that an operator (o) is utilized only if they are assigned at least one bushing (b) as the first maintenance task.

$$Z_o^b \leq E_o \quad \forall b \in B, o \in O \tag{6}$$

Constraint (6) limits that a bushing (b) can only be assigned to an operator (o) if that operator is utilized.

$$\sum_{o \in O} Y_o^b + \sum_{b \text{ and } b' \in B, b \neq b'} X^{bb'} = 1 \quad \forall b \in B \tag{7}$$

Constraint (7) restricts each bushing (b) to either being the first to be maintained by an operator (o) or following another bushing (b') in the maintenance sequence.

$$\sum_{b' \in B} X^{bb'} \leq 1 \quad \forall b \in B, b \neq b' \tag{8}$$

Constraint (8) bounds each bushing (b) can have at most one preceding bushing (b') in the maintenance sequence.

$$X^{bb'} + Z_o^b \leq 1 + Z_o^{b'} \quad \forall b \text{ and } b' \in B, b \neq b', o \in O \tag{9}$$

$$X^{bb'} + Z_o^{b'} \leq 1 + Z_o^b \quad \forall b \text{ and } b' \in B, b \neq b', o \in O \tag{10}$$

Constraints (9-10) ensure that if a bushing (b') is maintained immediately after another bushing (b) in the sequence, bushings must be assigned to the same operator (o). The constraints maintain consistency between maintenance sequences and operator assignments.

$$\sum_{b \in B} \sum_{o \in O} Y_o^b \leq |O| \tag{11}$$

Constraint (11) guarantees that the number of bushings assigned as the first task across all operators (o) must be, at most, the total number of available operators.

$$X^{bb'} = 0 \quad \forall b \text{ and } b' \in B, b \neq b', \text{ if } \theta_b \geq \theta_{b'} \tag{12}$$

Constraint (12) guarantees that a bushing (b') with a lower criticality level cannot be maintained after a bushing (b) with a higher or equal criticality level in the maintenance sequence.

$$C_b \geq \sum_{o \in O} Z_o^b \times (t_o^b + d_o^b) \quad \forall b \in B \tag{13}$$

Constraint (12) states that the maintenance completion time for each bushing (b) must account for the travel time and maintenance duration at the servicing operator (o) to which the bushing is assigned.

$$C_{b'} \geq C_b + \sum_{o \in O} Z_o^{b'} \times d_o^{b'} + M \times (X^{bb'} - 1) \qquad \forall b \text{ and } b' \in B,\ b \neq b' \tag{14}$$

Constraint (14) states that the maintenance completion time for bushing b' must be at least the completion time of the preceding bushing b plus the maintenance duration for b' provided both bushings are maintained sequentially by the same operator. The term $M \times (X^{bb'} - 1)$ ensures the constraint only activates when b' follows b in the sequence.

$$C_{max} \geq C_b \qquad \forall b \in B \tag{15}$$

Constraint (15) states that the total maintenance time must be at least the maintenance completion time for every bushing (b), which guarantees it reflects the maximum completion time among all bushings.

$$\sum_{b \in B} Z_o^b \leq \omega_o \qquad \forall o \in O \tag{16}$$

Constraint (16) states that the number of bushings (b) assigned to any operator (o) must not exceed the operator's maximum capacity.

$$X^{bb'} + X^{b'b} \leq 1 \qquad \forall b \text{ and } b' \in B,\ b \neq b',\ o \in O \tag{17}$$

$$X^{bb'} + X^{b'b} \geq Z_o^b + Z_o^{b'} - 1 \qquad \forall b \text{ and } b' \in B,\ b \neq b',\ o \in O \tag{18}$$

Constraint (17) states that if two bushings are assigned to the same operator, one must be serviced before the other. Both cannot precede each other simultaneously. Constraint (18) states that if two bushings are assigned to the same operator, one must precede the other in the maintenance sequence.

$$W_{max} \geq S_b - t_o^b \qquad \forall b \in B,\ o \in O \tag{19}$$

Constraint (19) remarks that the maximum waiting time must cover the waiting time for every bushing.

$$C_b \geq S_b + (d_o^b \times Z_o^b) \qquad \forall b \in B,\ o \in O \tag{20}$$

Constraint (20) remarks that the maintenance completion time for each bushing must be at least its start time plus the maintenance duration if assigned to the operator.

4. SOLUTION METHODOLOGY

The proposed framework combines a data-driven system for OE prediction with a model-based optimization system for PdM planning, forming the data-driven PdM optimization model (DPdMOM) (Ning and You, 2019).

4.1 Data-driven system: CNN model

A CNN predicts the OE of bushings leveraging features such as O_2 flow, fuel flow, pressure, and temperature (Dehghan Shoorkand et al., 2024). OE is classified into four zones:

1. Green (OE > n_1%): No maintenance required.
2. Yellow (n_2% ≤ OE ≤ n_1%): Maintenance may be scheduled.
3. Orange (n_3% ≤ OE < n_2%): Close monitoring required.
4. Red (OE < n_3%): Immediate maintenance needed (apart from production and shift changes).

Figure 2 illustrates the classification of a bushing OE into four zones based on performance thresholds.

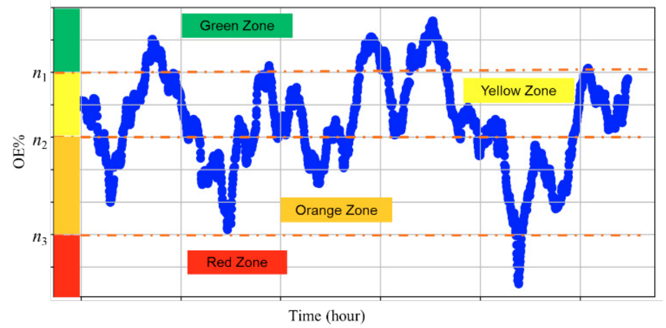

Figure 2. OE zones for a bushing.

The CNN model outputs four probabilities (P_{zone}^b) for each bushing, which indicates its likelihood of falling into each zone. If a bushing's highest probability falls under the red zone, it is flagged for immediate maintenance. Among all flagged bushings in the red zone, the bushing with the highest probability is assigned the highest priority, which is represented by the smallest numerical value. This ranking provides the most critical bushing, which is scheduled first, following standard scheduling and optimization conventions where lower numbers indicate higher priority.

$$P_{zone=red}^b > P_{zone=red}^{b'} \rightarrow \theta_{b'} \geq \theta_b \tag{21}$$

The same logic is applied to bushings in other zones (e.g., yellow and orange), where prioritization is based on probabilities. To optimize the CNN, Optuna (an open-source optimization framework) was utilized for hyperparameter tuning, leveraging two key techniques: the tree-structured Parzen estimator, a Bayesian optimization method that identifies the best hyperparameter configurations by learning from prior trials, and pruning, which halts underperforming trials early to save computational resources (Peivand et al., 2024). Additionally, stratified k-fold cross-validation was applied to ensure robust performance evaluation by splitting the dataset into multiple folds while maintaining a proportional representation of all OE zones. Figure 3 shows the CNN hyperparameter tuning process with Optuna, optimizing convolutional layers, pooling, dropout rate, dense units, and training parameters (optimizer, batch size, epochs).

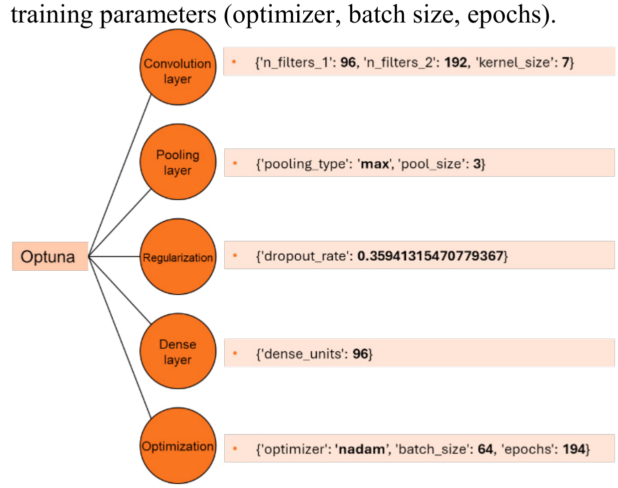

Figure 3. Hyperparameter optimization workflow for CNN using Optuna.

Figure 4 displays the CNN architecture for bushing OE prediction, transforming raw sensor data (e.g., temperature, pressure) through convolution, pooling, and feed-forward layers. The output layer classifies OE into four zones (red, orange, yellow, green) with associated probabilities (P^{b}_{zone}).

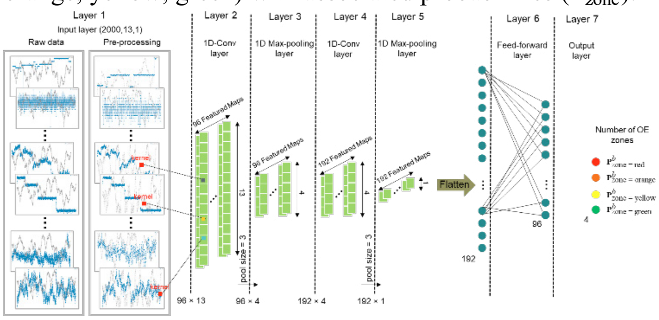

Figure 4. OE prediction framework using CNN.

4.2 Model-based system: Multi-objective optimization model

The probabilities generated by the CNN are incorporated into a multi-objective optimization model, solved using the Gurobi optimization solver, to effectively schedule maintenance activities. The model simultaneously minimizes two objectives, Z_1 and Z_2, while subjecting to operational Constraints (3–21). Gurobi's *model.setObjectiveN* method manages the objectives hierarchically. It prioritizes multiple objectives by assigning each a priority level. The solver first optimizes the highest-priority objective to completion. Once this primary goal is achieved, it proceeds to optimize secondary objectives without compromising the solution to the higher-priority goal (Gurobi Optimization, 2024). Figure 5 depicts the integrated framework combining CNN-based OE prediction with multi-objective optimization to prioritize and schedule maintenance, minimizing downtime and costs.

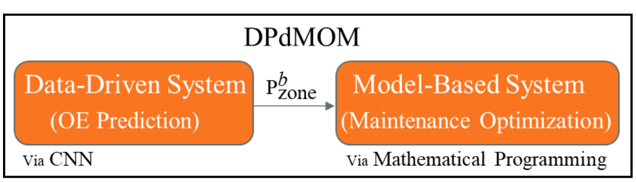

Figure 5. Integrated framework for data-driven PdM optimization.

5. COMPUTATIONAL STUDY

5.1 Case study description

The case study focuses on a fiberglass manufacturing facility producing two products. The production process mirrors the general description in the problem statement, with multiple furnace channels, each containing several positions equipped with bushings. At optimal performance, the facility achieves high daily production volumes. However, a slight reduction in OE results in significant waste, which emphasizes the need to maintain OE. Additionally, the breakage of a single fiber strand compromises the associated final product, further exacerbating production losses. This manufacturer leverages the availability of large-scale sensor data, capturing parameters such as temperature, gas flow (natural gas), O_2 flow, and pressure, which are critical to assessing bushing performance. These data streams enable advanced analytics to evaluate the criticality of each bushing, predict failures, and signal maintenance needs. The current situation highlights the pivotal role of PdM in reducing waste, minimizing defects, and sustaining consistent, high-quality production.

5.2 Computational results

The CNN model predicted the OE zone probabilities for bushing 8 as follows: red ($P^{b_8}_{zone=red}$= 0.0083), orange ($P^{b_8}_{zone=orange}$= 0.3402), yellow ($P^{b_8}_{zone=yellow}$ = 0.4895), and green ($P^{b_8}_{zone=green}$= 0.1620), with fold-wise accuracies ranging from 72% to 80% (average cross-validation accuracy of 75%). It indicates its classification in the yellow zone with a dominant probability of 48.95%. The exact process is applied to all other bushings, generating zone-specific probabilities that guide the prioritization within the optimization framework. By comparing the zone probabilities across bushings, the model-based system assigns criticality levels, which delivers high-priority bushings in critical zones (e.g., red or orange) are scheduled first, while lower-priority bushings, such as bushing 8 (θ_{b_8}= 5), are deferred for maintenance accordingly. Building on the CNN outputs (data-driven system), Figure 6 represents the maintenance schedule of 10 bushings distributed across five operators, with bars representing the start and end times of maintenance tasks. Each bar specifies the corresponding bushing's criticality level, where lower criticality levels indicate higher priority. Waiting times, represented on the left side, highlight the delays before maintenance begins for each bushing. Figure 6 provides several insights into the maintenance scheduling approach. First, the criticality-based scheduling offers that bushings with higher priority (lower criticality levels, represented by smaller θ_b, e.g., bushing 3 with (θ_{b_3} = 1), are scheduled earlier, which demonstrates the model's ability to prioritize tasks based on criticality. Second, there is a correlation between waiting times and θ_b: bushings with higher θ_b (lower priority, e.g., bushing 8 with θ_{b_8}= 5) face longer waiting times, which reflects the scheduling strategy that prioritizes urgent maintenance needs lower θ_b while deferring less critical tasks. Third, operator utilization is well-balanced, with tasks allocated across operators while adhering to capacity constraints, which provides resource management. Finally, the maintenance tasks are executed sequentially for each operator to avoid overlaps and optimize downtime.
The criticality levels (θ_b) are informed by the data-driven model (CNN), which predicts OE and identifies critical bushings requiring attention.

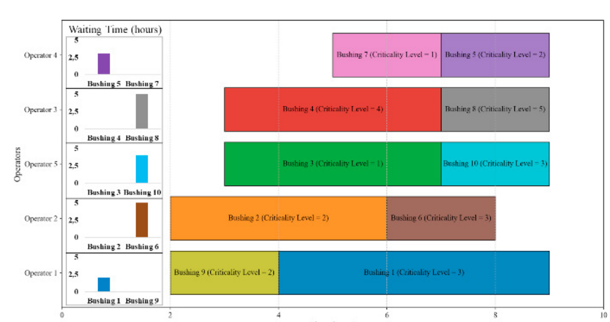

Figure 6. Criticality-aware maintenance scheduling of bushings.

The scheduling is carried out by a multi-objective optimization model, which employs the following objectives: minimizing total maintenance completion time (Z_1) as the primary objective, and minimizing the servicing costs (Z_2) as the secondary objective. This hierarchical objective setting, defined by *model.setObjectiveN*, seamlessly integrates data-driven predictions and optimization techniques to deliver a maintenance plan that minimizes delays and maximizes resource usage (e.g., operator capacity) while addressing urgent tasks.

6. CONCLUSIONS

This study introduces an integrated framework combining a CNN-based predictive model and a multi-objective optimization approach to enhance maintenance scheduling in fiberglass production. The model minimizes downtime and servicing costs while improving resource allocation by leveraging operational data to predict bushing efficiency (OE) and prioritizing tasks based on criticality levels. Limitations include uncertainties in maintenance durations, which could impact scheduling precision, and the effects of transitioning to hydrogen on OE predictions. Furthermore, enhancing CNN model accuracy by incorporating additional data or techniques, such as SMOTE versions, for handling imbalances could improve the accuracy of the data-driven system.

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