Integrating Condition-Based Preventive Maintenance into Passenger Rescheduling at Airport Check-In Counters

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***Abstract*— This paper addresses a passenger rescheduling problem at airport check-in counters equipped with weighing conveyor belts subject to degradation. Passengers are dynamically assigned to counters with the objective of minimizing service inefficiency while controlling the degradation level of the conveyors. Building on previous work that incorporates degradation-aware rescheduling, we extend the problem by integrating a condition-based preventive maintenance policy. In the proposed approach, a preventive maintenance action is triggered whenever the degradation rate of a conveyor belt reaches a predefined threshold, restoring the system to an as-good-as-new state. The rescheduling process is embedded within a predictive–reactive framework, allowing passenger assignments and maintenance decisions to be jointly managed in real time. Computational experiments are conducted to analyze the impact of the maintenance threshold on system behavior. The results highlight the trade-offs between passenger service level, conveyor degradation, and the number of preventive maintenance actions. In particular, the analysis shows how appropriate combinations of weighting strategies and maintenance thresholds can significantly reduce degradation while limiting maintenance interventions. The proposed model provides decision support for airport operators seeking to balance operational efficiency and maintenance effort in dynamic passenger handling systems.**

Keywords: *rescheduling, failure rate, preventive maintenance, predictive-reactive strategy, MILP optimization*

I. Introduction and Literature Review

The continuous growth of air transportation, particularly following the post-COVID-19 recovery, has significantly increased the operational pressure on airport terminal infrastructures. Passenger check-in systems, which constitute a critical interface between passengers and airport operations, must handle growing passenger volumes while maintaining high service quality and operational reliability. Long waiting times at check-in counters negatively impact passenger satisfaction, whereas excessive or unbalanced use of handling equipment, such as weighing conveyor belts, accelerates degradation and increases maintenance costs and failure risks.

In most airports, passengers are free to choose among several check-in counters assigned to their flight. This decentralized and self-organized behaviour often leads to uneven queue distributions and unbalanced equipment usage. While some counters may remain lightly loaded, others may experience excessive congestion and accelerated mechanical wear. Consequently, passenger assignment decisions have a direct impact not only on service performance but also on the long-term sustainability of airport handling equipment. This observation motivates the need for decision-support tools capable of jointly addressing passenger service efficiency and equipment degradation.

From an operational research perspective, passenger assignment to check-in counters can be naturally modelled as a scheduling problem on parallel machines. Passengers or groups of passengers correspond to jobs, while check-in counters represent machines. Processing times depend on passenger group sizes and operational procedures, whereas equipment degradation depends on baggage characteristics, such as weight and handling duration. Moreover, passenger arrivals are dynamic and uncertain, requiring real-time rescheduling decisions. These characteristics make the problem particularly challenging and representative of real-world service systems with degrading resources.

A. *Passenger scheduling and rescheduling in transportation systems*

Passenger scheduling and rescheduling problems have been extensively studied in transportation systems, particularly in rail and public transit networks. In these contexts, rescheduling is often required to mitigate disruptions, delays, or demand fluctuations, with the objective of minimizing passenger inconvenience. Several studies have proposed mathematical programming models and heuristics to reassign passengers, retime services, or reallocate capacities in real time. Mixed-integer linear programming formulations have been widely used to model passenger flows, timetables, and capacity constraints, often combined with heuristic or decomposition approaches to ensure computational tractability. For example, Cao et al. (2024) [1] investigate the reassignment of passengers to predefined security screening time slots in order to reduce operational inefficiencies. The problem is modelled as a Minimum Cost Network Flow formulation, which admits an exact polynomial-time solution thanks to its underlying linear programming structure.

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In air transportation, most existing works related to check-in operations focus on determining the number of counters to open or staffing levels in order to balance service quality and operating costs (Bruno et al. 2019 [2]). These approaches typically rely on queueing theory or simulation-based optimization and primarily aim to minimize passenger waiting times or staffing costs. However, they generally do not address the explicit assignment of passengers to specific counters, nor do they consider the operational consequences of passenger assignment decisions on equipment usage and degradation.

Compared to rail transportation (Zhu and Goverde (2020) [3], Hong et al. (2021) [4]), passenger rescheduling at airport terminals remains relatively underexplored. One reason lies in the decentralized nature of passenger behaviour and the difficulty of enforcing assignments without negatively affecting passenger acceptance. Nevertheless, the increasing availability of digital interfaces and real-time information systems makes guided passenger assignment increasingly feasible. This opens new perspectives for optimization-based approaches capable of improving both service performance and infrastructure sustainability.

B. Parallel machine scheduling and predictive–reactive strategies

Parallel machine scheduling problems constitute a well-established class of problems in scheduling theory. They have been widely applied in manufacturing, logistics, and service systems to model the allocation of jobs to multiple identical or unrelated machines. In dynamic environments, where new jobs arrive over time or disruptions occur, rescheduling becomes necessary to maintain system performance.

Predictive–reactive strategies have emerged as a dominant paradigm for handling such dynamic scheduling problems. In this framework, an initial schedule is generated in a predictive phase based on the information available at the beginning of the planning horizon. Subsequently, the schedule is updated in a reactive phase whenever disruptions or new arrivals occur. This approach offers a good compromise between solution quality and computational efficiency and has been successfully applied to various parallel machine rescheduling problems (Tighazoui et al. 2021a [5]).

Several studies have proposed mixed-integer linear programming models to generate initial schedules, followed by heuristic or rule-based methods to repair schedules in real time. These approaches are particularly relevant for service systems, where decisions must be taken quickly and repeatedly. However, most parallel machine rescheduling models focus on traditional performance criteria such as Makespan, flow time, or tardiness, without explicitly accounting for machine degradation or maintenance considerations. For example, Tighazoui et al. 2021b [6] investigated a rescheduling problem across different machine environments. To simultaneously evaluate schedule efficiency (using total weighted waiting time) and stability (using weighted completion time deviation), they introduced a new performance measure. The authors developed a predictive-reactive strategy based on MILP formulation. The predictive phase generates an initial schedule optimized for the waiting time criterion, which the reactive phase then updates upon the arrival of new tasks.

C. Integration of degradation and maintenance in scheduling problems

The integration of maintenance considerations into scheduling and rescheduling problems has attracted increasing attention in recent years. In many industrial systems, machine degradation depends on usage rather than on operating time alone. As machines process jobs, their condition deteriorates, increasing the likelihood of failures and unplanned downtime. Ignoring this interaction may lead to short-term optimal schedules that are detrimental to long-term system performance.

Existing works on integrated production and maintenance planning often assume predefined preventive maintenance intervals or consider maintenance as a decision variable to be optimized jointly with production scheduling (Tighazoui et al 2024 [7]). Some studies model maintenance as machine unavailability periods triggered by failures, while others consider imperfect maintenance actions that partially restore machine condition. Condition-based maintenance policies, where maintenance actions are triggered when degradation reaches a given threshold, are particularly relevant for systems subject to usage-dependent wear. For instance, Tijjani et al. (2025) [8] propose a hybrid maintenance optimisation framework for solar–wind energy systems that combines reliability-based preventive maintenance with predictive strategies based on Remaining Useful Life (RUL) estimation. The authors model component degradation using a Cox Proportional Hazards approach and employ artificial neural networks to forecast RUL.

Despite these advances, most contributions focus on manufacturing environments and static or semi-dynamic scheduling settings. Moreover, degradation is often modelled in an aggregated manner, without explicitly linking job characteristics to machine wear. In service systems, and especially in passenger-oriented applications, the explicit consideration of usage-dependent degradation remains scarce.

D. Passenger rescheduling with degradation-aware assignment

Only a limited number of studies have addressed scheduling decisions that explicitly account for the impact of individual jobs on machine degradation. In the context of airport check-in systems, baggage weight and handling duration play a critical role in the wear of weighing conveyors. Assigning heavy baggage repeatedly to the same conveyor may significantly accelerate degradation and increase the risk of failure.

The work of Schmitt et al. 2025 [9] introduced a passenger rescheduling problem that jointly minimizes total check-in time and conveyor belt degradation. In this approach, conveyor degradation is modelled using a Weibull failure rate, where each passenger's baggage contributes incrementally to equipment wear. A predictive–reactive strategy combining a mixed-integer linear programming model and a dynamic heuristic was proposed to balance service efficiency and degradation. Computational results demonstrated that intelligent passenger assignments can significantly reduce conveyor degradation without excessively increasing passenger waiting times.

However, this degradation-aware rescheduling framework assumes that conveyors continuously degrade over time without any maintenance intervention. In practice, airport operators rely on preventive maintenance actions to restore equipment condition and avoid unexpected breakdowns. Ignoring maintenance decisions may lead to overly conservative assignment strategies or unrealistic degradation trajectories, limiting the practical applicability of the model.

E. Contribution and scope of the present work

Motivated by this limitation, the present paper extends the passenger rescheduling problem by explicitly integrating a condition-based preventive maintenance policy. When the degradation level of a conveyor reaches a predefined threshold, a preventive maintenance action is triggered, restoring the conveyor to an as-good-as-new condition. This extension introduces a new decision dimension, as passenger assignment decisions now influence not only service performance and degradation but also the frequency of maintenance actions.

The resulting problem combines passenger rescheduling, degradation dynamics, and maintenance triggering in a unified framework. A predictive–reactive strategy is adopted, in which an initial schedule is generated and dynamically updated as passengers arrive. The rescheduling heuristic is extended to handle maintenance triggering in real time, resetting the degradation level when the threshold is reached. In addition to traditional performance indicators such as Makespan and maximum degradation level, the number of preventive maintenance actions is explicitly analyzed.

The main contributions of this paper are threefold. First, it introduces a threshold-based preventive maintenance policy into a dynamic passenger rescheduling problem with usage-dependent degradation. Second, it extends a predictive–reactive rescheduling heuristic to jointly manage passenger assignment and maintenance decisions. Third, it provides a detailed sensitivity analysis showing how the number of maintenance actions varies with the weighting between service efficiency and degradation objectives, as well as with the choice of the maintenance threshold.

By explicitly linking passenger assignment decisions, equipment degradation, and preventive maintenance, this work provides airport operators with practical decision-support tools to balance passenger service quality, equipment reliability, and maintenance effort. The proposed framework also contributes to the broader literature on integrated scheduling and maintenance in service systems with degrading resources.

II. PROBLEM DESCRIPTION

This paper investigates the operation of an airport check-in system composed of several parallel counters, each equipped with a weighing conveyor belt. Let $\mathcal{M} = \{1, 2, \ldots, M\}$ denote the set of available check-in counters, where the number of counters remains fixed during the check-in period. Passengers are grouped into reservations according to their flights and arrival patterns. Let $\mathcal{J} = \{1, 2, \ldots, J\}$ represent the set of reservations considered during the planning horizon. Each reservation $j \in \mathcal{J}$ corresponds to an individual passenger or a group of passengers waiting to be processed. Each reservation is characterized by a deterministic processing time DUR_j, which represents the duration of the check-in procedure, and by a baggage weight W_j, reflecting the load applied to the conveyor belt. In this study, each reservation is modelled as an independent job. Once the processing of job j starts at time S_j, it continues without interruption until completion at time $C_j = S_j + DUR_j$ All job characteristics are assumed to be known in advance at the beginning of the planning horizon. For each counter $m \in M$, a set of processing positions is defined as $P = \{1, 2, \ldots, P\}$, where each position represents the order in which jobs are processed in the queue. The assignment of job j to position p on counter m is described by the binary variable

$$X_{jpm} = \begin{cases} 1 \; if\; job\; j\; is\; assigned\; to\; p\; on\; machine\; m \\ 0\; otherwise \end{cases}$$

This formulation enables simultaneous determination of both machine assignment and processing sequence. The problem is addressed through a two-phase framework. In the first phase, all reservations present at the airport before the opening of check-in are scheduled. The objective is to determine an initial assignment and sequencing of jobs on the available counters. In the second phase, passengers arriving after the start of check-in are dynamically inserted into the existing schedules and are assigned to the end of the corresponding queues.

The degradation of conveyor belts is modelled using a two-parameter Weibull distribution, which is commonly used for analyzing mechanical wear and failure behavior. The failure rate function is given by

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}$$

Where β and η respectively denote the shape and scale parameters, and t represents the cumulative operating time of the conveyor. In the considered system, conveyor degradation depends not only on operating time but also on the characteristics of processed baggage. Each job contributes to equipment wear according to its processing duration and its associated weight. To account for this effect, the failure rate is evaluated at each processing position. The degradation level at position p on counter m is computed recursively as

$$\lambda_{pm} = \lambda_{p-1,m} + \sum_{j=1}^{J} \frac{\beta}{\eta}\left(\frac{DUR_j}{\eta}\right)^{\beta-1} \frac{W_j}{W_{max}} X_{j,p,m}$$

Where W_{max} denotes the maximum admissible baggage weight. This formulation captures the cumulative impact of successive jobs on conveyor deterioration. The maximum degradation level over all counters and positions is defined as $\lambda_{max} = \max_{p \in P \; m \in M} \lambda_{p,m}$

Reducing this value contributes to improving conveyor availability and limiting failure risks. To reflect maintenance practices in real airport operations, a condition-based preventive maintenance policy is incorporated into the model. Let $\bar{\lambda}$ represent a predefined degradation threshold. Whenever $\lambda_{max} \geq \bar{\lambda}$ a preventive maintenance intervention is initiated on the affected conveyor. This action restores the equipment to an as-good-as-new condition and resets its degradation level according to $\lambda_{pm} \leftarrow 0;\ \forall p \in P$ After maintenance completion, degradation starts accumulating again following the same Weibull-based mechanism.

System performance is evaluated using two main criteria. Service quality is measured through Makespan $C_{max} = \max_{j \in J} C_j$ which represents the total time required to process all reservations. Equipment reliability is assessed through the maximum failure rate $\lambda_{\max}$. These two conflicting objectives are combined using a weighting parameter $\alpha \in [0,1]$, leading to the following objective function:

$$f = \alpha\, \lambda_{max} + (1\text{-}\alpha)\, C_{max}$$

The proposed formulation allows decision-makers to adjust the relative importance of service efficiency and equipment preservation. Moreover, the integration of preventive maintenance introduces an additional performance dimension related to maintenance frequency. The problem is finally solved within a predictive–reactive framework, in which initial schedules are generated in the first phase and continuously adapted in the second phase to account for new arrivals and maintenance actions

III. MATHEMATICAL MODEL

The implemented model is inspired by Tighazoui et al. (2023) [10] and has been adapted to the studied problem variables and constraints. The model implementation is given below:

Indexes:
J: number of jobs
P: number of positions
M: number of machines
$j = 1, \ldots, J$: job index
$p = 1, \ldots, P$: position index
$m = 1, \ldots, M$: machine index
Job parameters:
DUR_j: processing time of job j
W_j: baggage weight of job j
W_{max}: maximum admissible weight
Weibull parameters:
β: shape parameter
η: scale parameter
Maintenance parameters:
$\bar{\lambda}$: degradation threshold
T^{PM}: preventive maintenance duration
U: large constant (Big-M)
Assignment:
$X_{jpm} \in \{0,1\}$ if job j is assigned to position p on machine m
Timing:
$SP_{pm} \geq 0$ start time of position p on machine m
$CP_{pm} \geq 0$ start time of position p on machine m
$S_j \geq 0$ start time of job j
$C_j \geq 0$ start time of job j
Degradation
$\lambda_{pm} \geq 0$ failure rate at position p on machine m
$y_{pm} \in \{0,1\}$ if maintenance is triggered before position p on machine m
$N^{PM} \in \mathbb{N}$ total number of maintenances
Objective function
$C_{max} = max\ C_j\ \forall j \in \mathcal{J}$ Makespan
$\lambda_{max} = max\ \lambda_{pm}\ \forall p \in P,\ \forall m \in M$ Maximum failure rate

$$Minimize\ f = \alpha\, \lambda_{max} + (1\text{-}\alpha)\, C_{max} \quad (1)$$

Constraints

$$\textstyle\sum_{p=1}^{P} \sum_{m=1}^{M} X_{jpm} = 1\ \forall j \in \mathcal{J} \quad (2)$$
$$\textstyle\sum_{j=1}^{J} X_{jpm} \leq 1\ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (3)$$
$$\textstyle\sum_{j=1}^{J} X_{jpm} \geq \sum_{j=1}^{J} X_{jp+1m}\ \ \forall m \in \mathcal{M},\ \ \forall p \in \{1,2,\ldots,P-1\} \quad (4)$$
$$SP_{p+1m} = CP_{pm} + y_{p+1m} * T^{PM}\ \forall m \in \mathcal{M},\ \ \forall p \in \{1,2,\ldots,P-1\} \quad (5)$$
$$CP_{pm} = SP_{pm} + \textstyle\sum_{j=1}^{J} X_{jpm} * DUR_j\ \ \forall m \in \mathcal{M},\ \ \forall p \in \mathcal{P} \quad (6)$$
$$C_j \geq CP_{pm} - U(1 - X_{jpm})\ \forall j \in \mathcal{J},\ \ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (7)$$
$$C_j \leq CP_{pm} + U(1 - X_{jpm}) \forall j \in \mathcal{J},\ \ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (8)$$
$$C_j = S_j + DUR_j\ \forall j \in \mathcal{J} \quad (9)$$
$$SP_{1m} = 0\ \forall m \in \mathcal{M} \quad (10)$$
$$\lambda_{0m} = 0\ \ \forall m \in \mathcal{M} \quad (11)$$
$$\lambda_{pm} \geq \lambda_{p-1m} + \textstyle\sum_{j=1}^{J} \frac{\beta}{\eta}\left(\frac{DUR_j}{\eta}\right)^{\beta-1} \frac{W_j}{W_{max}} X_{jpm} - U y_{pm}\ \ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (12a)$$
$$\lambda_{pm} \leq \lambda_{p-1m} + \textstyle\sum_{j=1}^{J} \frac{\beta}{\eta}\left(\frac{DUR_j}{\eta}\right)^{\beta-1} \frac{W_j}{W_{max}} X_{jpm} + U y_{pm}\ \ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (12b)$$
$$\lambda_{pm} \leq \textstyle\sum_{j=1}^{J} \frac{\beta}{\eta}\left(\frac{DUR_j}{\eta}\right)^{\beta-1} \frac{W_j}{W_{max}} X_{jpm} + U(1 - y_{pm})\ \ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (12c)$$
$$\lambda_{pm} \geq \textstyle\sum_{j=1}^{J} \frac{\beta}{\eta}\left(\frac{DUR_j}{\eta}\right)^{\beta-1} \frac{W_j}{W_{max}} X_{jpm}\ \ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (12d)$$

$$\lambda_{p-1m} \leq \bar{\lambda} + U y_{pm}\ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (13)$$
$$\lambda_{p-1m} \geq \bar{\lambda} - U(1 - y_{pm})\ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (14)$$
$$N^{PM} = \textstyle\sum_{pm} y_{pm} \quad (15)$$
$$y_{pm} \leq \textstyle\sum_{j=1}^{J} X_{jpm}\ \ \forall p \in \mathcal{P}, \forall m \in \mathcal{M} \quad (16)$$
$$C_{max} \geq C_j\ \forall j \in \mathcal{J} \quad (17)$$
$$\lambda_{max} \geq \lambda_{P,m}\ \forall m \in \mathcal{M} \quad (18)$$
$$X_{jpm}, y_{pm} \in \{0,1\}\ \forall j \in \mathcal{J},\ \ \forall p \in \mathcal{P},\ \ \forall m \in \mathcal{M} \quad (19)$$
$$SP_{pm},\ CP_{pm},\ S_j,\ C_j \geq 0\ \forall p \in \mathcal{P},\ \ \forall j \in \mathcal{J}\ \ \forall m \in \mathcal{M} \quad (20)$$
$$N^{PM} \in \mathbb{N} \quad (21)$$

Constraint (2) ensures that each job is assigned to exactly one position on one check-in counter, while Constraint (3) guarantees that each position can process at most one job. Constraint (4) enforces the continuity of queues by imposing that if a position on a counter is empty, all subsequent positions on the same counter remain empty. Constraint (5) defines the temporal relationship between successive positions on each counter by incorporating possible preventive maintenance durations. Constraint (6) determines the completion time of each position as a function of its start time and the processing duration of the assigned job. Constraints (7) and (8) link job completion and start times to the corresponding position times through linearization techniques. Constraint (9) establishes the relationship between the start and completion times of each job.

Constraint (10) initializes the processing time on each counter. Constraint (11) sets the initial degradation level of all conveyors at the beginning of the planning horizon. Constraints (12a), (12b), (12c) and (12d) models the recursive evolution of the failure rate by integrating the cumulative impact of baggage handling and the possible reset induced by preventive maintenance actions. Constraints (13) and (14) implement the threshold-based maintenance policy by activating a maintenance intervention whenever the degradation level exceeds the predefined limit. Constraint (15) computes the total number of preventive maintenance actions. Constraint (16) ensures that preventive maintenance action can only be triggered at a position if this position is effectively occupied by a job on the corresponding check-in counter. Constraints (17) and (18) define the Makespan and the maximum degradation level, which are used to evaluate service quality and equipment reliability, respectively. Finally, Constraints (19) – (21) specify the domains of the decision variables, ensuring the consistency and feasibility of the proposed mathematical formulation.

IV. HEURISTIC RESCHEDULING METHOD

To handle the dynamic arrival of passenger groups after the start of the check-in process, a heuristic rescheduling procedure is developed. This method aims to efficiently integrate newly arriving jobs into the existing schedule while preserving service quality and controlling conveyor degradation. The proposed approach follows a predictive–reactive framework, in which an initial schedule is generated before check-in and subsequently updated in real time.

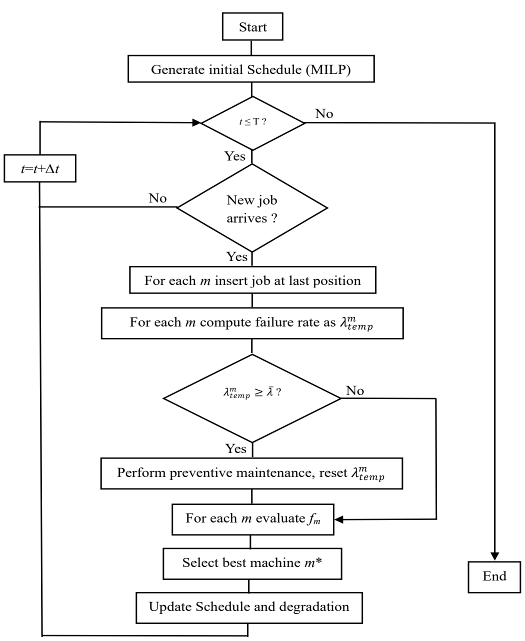


Fig. 1 Flowchart of the proposed heuristic

When a new job arrives, the algorithm evaluates all feasible insertion positions at the end of the queues of the available counters. For each feasible position, the corresponding impact on completion times, conveyor degradation, and maintenance triggering is estimated. The weighted objective function is then computed for each candidate insertion. The job is finally assigned to the position that minimizes the objective value. If the degradation threshold is reached after insertion, a preventive maintenance action is automatically scheduled, and the degradation level is reset. This procedure is repeated for each arriving job, enabling continuous adaptation to evolving operational conditions.

V. ILLUSTRATIVE EXAMPLE

In this section, we present an illustrative example involving 10 jobs. The data used for this example are reported in Table 1, with the following parameter settings: $\beta = 1.6$, $M = 2$, $\bar{\lambda} = 1\ 10^{-6}$, and $\alpha = 0.5$. The corresponding results are shown in Figure 2.

Table. 1 Data of the illustrative example

j	1	2	3	4	5	6	7	8	9	10
DUR_j	3	9	8	3	8	7	4	6	7	6
W_j	39	20	35	17	36	20	38	22	45	13

At time instant 1, jobs arrive sequentially in a random manner. For each arrival, Algorithm 1 determines the most appropriate machine assignment so as to minimize the objective function f. Whenever the failure rate of a machine reaches the predefined threshold, a preventive maintenance intervention is immediately initiated to restore the system condition.

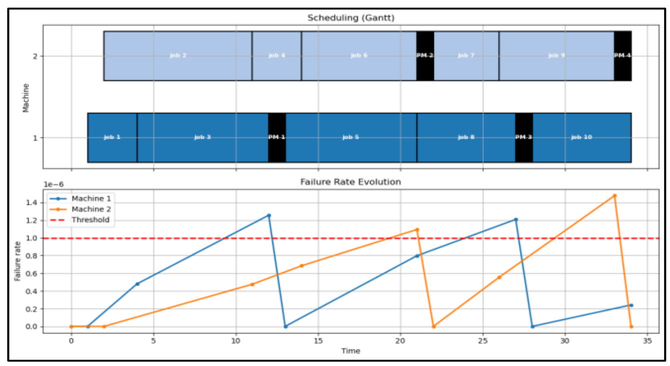


Fig. 2 Gantt diagram and Failure rate evolution

Figure 2 illustrates both the dynamic schedule and the corresponding failure rate evolution for the two machines. The Gantt chart shows how jobs are sequentially assigned according to Algorithm 1, while preventive maintenance actions (in black) are inserted whenever the degradation threshold is reached. The lower graph highlights the typical saw-tooth behavior of the failure rate: it increases progressively as jobs are processed and drops sharply after each maintenance intervention, reflecting the reset of the degradation level. As shown in the lower graph, the failure rate of Machine 1 increases progressively until it reaches approximately $1.2\ 10^{-6}$around time 12, triggering a preventive maintenance action and causing an immediate reset of the degradation level. A similar behavior is observed for Machine 2, whose failure rate reaches about $1.1\ 10^{-6}$near time 22 before dropping sharply after maintenance. The resulting saw-tooth pattern confirms that degradation accumulates gradually due to successive job processing and is effectively controlled by the threshold-based policy.

VI. NUMERICAL RESULTS

The proposed heuristic algorithm was implemented and solved in Python. All computational experiments were performed on a laptop equipped with an Intel® Core™ i7-13800H processor running at 2.50 GHz.

The computational experiments were conducted using synthetically generated test instances designed to reflect realistic operational conditions. Job processing times were randomly drawn from a discrete uniform distribution ranging from 1 to 10 time units (t.u.), i.e., $\mathrm{DUR}_j \sim U(1{,}10)$. In practical terms, this interval may correspond to service durations between 1 and 10 minutes, depending on the number of passengers included in a reservation.

Similarly, baggage weights were generated according to a discrete uniform distribution between 10 and 50 kg, i.e., $W_j \sim U(0{,}50)$. A weight equal to zero indicates that no baggage is checked in, whereas 50 kg represents the upper bound of the tested range. The parameter $W_{\max}$ was set to 100 kg for normalization purposes in the degradation function.

A. Analysis of the Number of Maintenance Actions

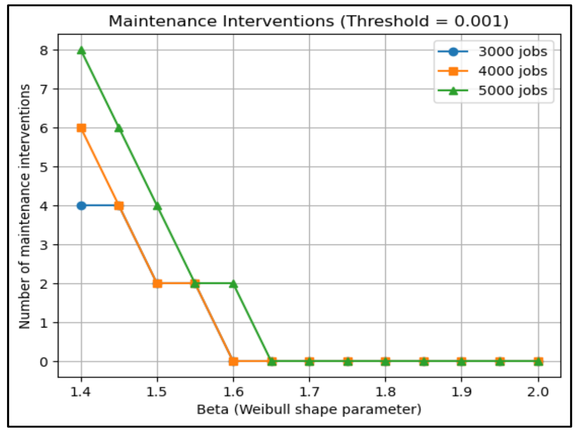
In this study, we analyze the variation in the number of preventive maintenance actions as a function of three key factors: the number of processed jobs, the shape parameter β, and the baggage weight levels. The experiments were conducted under fixed parameter settings with $\alpha = 0.5$, $\eta = 10000$ minutes, and $W_{\max} = 100$kg. The parameter αensures a balanced trade-off between makespan and maximum degradation in the objective function, while η and $W_{\max}$ are used to normalize the degradation dynamics. This analysis allows us to evaluate how workload intensity and degradation sensitivity jointly influence the frequency of maintenance interventions.

Table. 2 Number of maintenance actions for $\bar{\lambda} = 0.001$

β	Number of maintenance interventions 3000 jobs	4000 jobs	5000 jobs
1,4	4	6	8
1,45	4	4	6
1,5	2	2	4
1,55	2	2	2
1,6	0	0	2
1,65	0	0	0
1,7	0	0	0
1,75	0	0	0
1,8	0	0	0
1,85	0	0	0
1,9	0	0	0
1,95	0	0	0
2	0	0	0

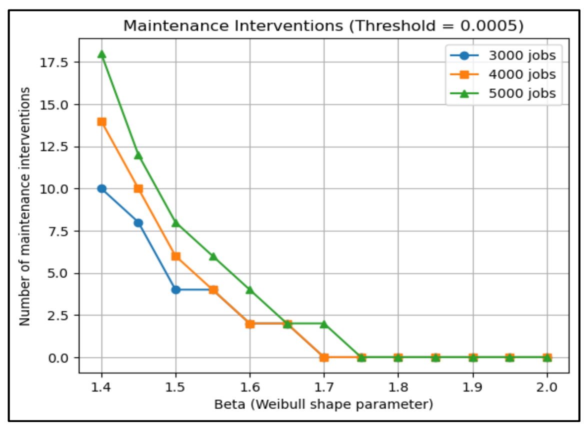
The numerical results clearly show the combined influence of the shape parameter β, the workload size, and the maintenance threshold on the number of preventive actions. For a maintenance threshold equal to 0.001 failure/minute, the number of maintenance operations remains moderate. For instance, when $\beta = 1.4$, the number of interventions increases from 4 for 3000 jobs to 8 for 5000 jobs. However, as βincreases, the number of maintenance actions decreases significantly, reaching zero for $\beta \geq 1.65$, regardless of the number of jobs. This behavior is illustrated in Figure 3.

Fig. 3 Impact of β on the Number of Maintenance Interventions (Threshold = 0.001)



When the threshold is reduced to 0.0005 failure/minute, the system becomes much more sensitive to degradation. In this case, for $\beta = 1.4$, the number of preventive actions rises to 10, 14, and 18 for 3000, 4000, and 5000 jobs, respectively. Even for intermediate values such as $\beta = 1.5$, maintenance actions range from 4 to 8 depending on the workload.

Fig. 4 Impact of β on the Number of Maintenance



Interventions (Threshold = 0.0005)

These results confirm that a lower threshold and smaller values of βlead to more frequent preventive interventions, while higher βvalues significantly delay or even eliminate maintenance triggering under the tested conditions.

Physically, increasing β shifts the degradation mechanism toward a long-term wear-out behavior. Since the processing times remain very small compared to the scale parameter η, the incremental degradation per job decreases as β increases. Consequently, the failure rate accumulates more slowly, leading to fewer threshold crossings and a reduced number of preventive maintenance actions.

To further analyze the influence of baggage weight on maintenance frequency, we conducted additional experiments where baggage weights were generated according to $W_j \sim U(50,80)$. This heavier load configuration represents a more demanding operational scenario compared to the previous range $U(0,50)$. The objective is to evaluate how increased load intensity affects degradation accumulation and the number of preventive maintenance actions.

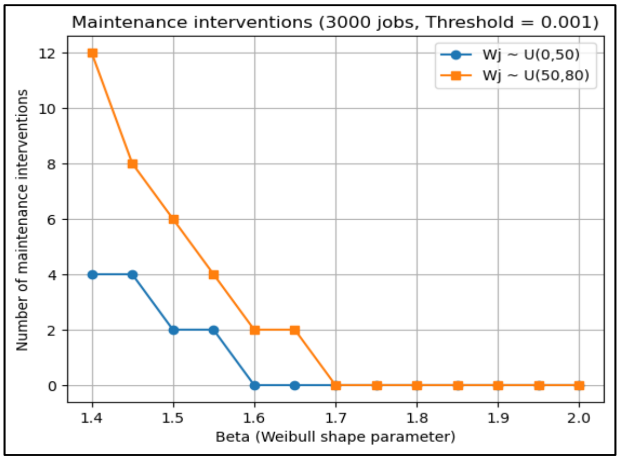


Fig. 5 Effect of baggage weight on maintenance interventions

As illustrated in the corresponding figure (3000 jobs, threshold = 0.001), increasing the baggage weight significantly raises the number of preventive maintenance actions. For instance, when $\beta = 1.4$, the number of interventions increases from 4 under $W_j \sim U(0,50)$to 12 under $W_j \sim U(50,80)$. A similar amplification effect is observed for intermediate values such as $\beta = 1.5$, where maintenance actions rise from 2 to 6. Physically, heavier baggage imposes greater mechanical stress on the weighing conveyor through higher belt tension and increased load on rollers thereby accelerating degradation accumulation and causing the maintenance threshold to be reached more frequently.

VII. CONCLUSION AND PERSPECTIVES

This paper proposed a dynamic integrated scheduling and maintenance approach for parallel check-in counters subject to degradation effects. The problem was formulated as a mixed-integer linear programming (MILP) model that jointly determines job assignment, sequencing decisions, and preventive maintenance actions while minimizing a weighted objective function combining makespan and maximum failure rate. To address the dynamic arrival of jobs and the computational complexity of real-time decision-making, a heuristic re-scheduling algorithm was also developed.

Computational experiments demonstrated the strong interdependence between operational decisions and system degradation. The results showed that the shape parameter β plays a key role in the degradation dynamics: lower values of β lead to faster accumulation of failure intensity and, consequently, a higher number of maintenance interventions, whereas higher values significantly reduce maintenance frequency. Furthermore, the analysis highlighted the direct influence of baggage weight on system deterioration, confirming that heavier loads accelerate conveyor wear and increase the number of required maintenance actions. The sensitivity analysis with respect to the maintenance threshold further illustrated the trade-off between operational continuity and reliability preservation.

Overall, the proposed framework contributes to bridging production scheduling and condition-based maintenance in service systems with degradation-dependent performance. Future research could extend this work by considering stochastic arrivals, variable maintenance durations, multi-component degradation models, or real-world industrial data validation.

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