OmniaScience

Journal of Industrial Engineering and Management
JIEM, 2026 – 19(3): 568-584 – Online ISSN: 2013-0953 – Print ISSN: 2013-8423
https://doi.org/10.3926/jiem.9388

Decision-Oriented Opportunistic Maintenance Optimization under Uncertain Idle Windows: An Integrated MILP and System Dynamics Approach

Andry Jitro*, Suharjito Suharjito

Industrial Engineering Department, BINUS Graduate Program – Master of Industrial Engineering, Bina Nusantara University (Indonesia)

*Corresponding author: andry.jitro@binus.ac.id
suharjito@binus.ac.id

Received: February 2026
Accepted: October 2026

Abstract:

Purpose: The present research intends to develop a decision-based model to determine the scheduling of Opportunistic Maintenance in continuous production lines, dealing with uncertain idle periods, in an effort to bridge the model-practice maintenance decision gap.

Design/methodology/approach: This paper provides a structured framework for opportunistic maintenance scheduling under idle window availability uncertainty and execution constraints. A Mixed-Integer Linear Programming (MILP) model optimizes task selection within each idle window, and its outputs are integrated into a System Dynamics (SD) simulation to evaluate long-term reliability implications. A case study of a continuous steel coating production line is provided.

Findings: Simulation results show that the proposed framework maintains a higher system reliability trajectory and slows reliability degradation compared to the baseline maintenance condition. It also increases completed maintenance tasks by 114%, enhances man-hour utilization from 83% to 100%, and increases avoided maintenance risk by over 80%.

Research limitations/implications: The research is based on a single case of continuous production lines, which might affect the applicability of this research. Further research should consider incorporating idle window prediction using data-driven, stochastic, or even digital twin technologies into this framework.

Practical implications: This framework is expected to offer a useful tool for Maintenance Planners and Maintenance Supervisors in deciding maintenance activities under uncertain idle time, enabling better utilization of idle time in continuous production systems.

Social implications: Better maintenance planning within continuous production systems can help create a stable environment, reduce waste materials, and indirectly help create a sustainable environment through efficient use of resources.

Originality/value: This work contributes to the field of Opportunistic Maintenance by proposing a decision-oriented framework for scheduling maintenance in continuous production lines with uncertain idle opportunities, taking into account execution constraints and decision-making.

Keywords: opportunistic maintenance, maintenance scheduling, continuous production line, idle window uncertainty, decision-oriented framework, industrial case study

To cite this article:

Jitro, A., & Suharjito, S. (2026). Decision-oriented opportunistic maintenance optimization under uncertain idle windows: An integrated MILP and system dynamics approach. *Journal of Industrial Engineering and Management*, *19*(3), 568–584. https://doi.org/10.3926/jiem.9388

1. Introduction

Continuous Process Manufacturing Systems (CPMSs), which include sectors such as steel coating, chemical processing, and pharmaceuticals, are specifically designed to ensure the achievement of maximum production efficiency and system stability. However, due to the close integration of the equipment and the low buffering capacity of the system, along with the demand for the smooth running of the system, unplanned outages of critical equipment can easily cascade throughout the production system, leading to significant losses. Thus, the maintenance of maximum system reliability becomes a major managerial and operational problem in the CPMS system (Battesini et al., 2021; Bergenhenegouwen et al., 2023).

On the other hand, the maintenance planning in the Continuous Process Manufacturing System (CPMS) is considered to have inherent complexities due to the inadmissibility of interruptions in the continuous process. The implementation of the traditional time-based and condition-based maintenance approaches is considered to have largely assumed the availability of maintenance windows. However, the determination of the maintenance windows in the continuous process has been considered challenging. In the actual scenario, the maintenance activities are performed during the irregular, unavoidable, and uncertain idle periods, which are caused due to various disturbances in the production system, including the cancellation of orders, and so forth. It is observed that the occurrence of the idle period is considered dependent on the nature of the production system, which is considered to have added more complexity in the determination of the maintenance activities in the CPMS (Ab-Samat & Kamaruddin, 2014; Lu et al., 2024; Yang et al., 2018).

Opportunistic Maintenance (OM) has been extensively investigated and recognized as an efficient method to benefit from the certainty of machine idle time, utilizing this time to coordinate maintenance with production downtime (Ab-Samat & Kamaruddin, 2014; Mena et al., 2021; Yang et al., 2018). As opposed to traditional maintenance methods, opportunistic maintenance aims at reducing machine stoppages and thereby eliminating losses due to these stoppages. Previous research has confirmed the benefits of opportunistic maintenance with regard to increasing reliability and performance of the system, particularly when maintenance at the system level is considered rather than focusing on machines separately (Ab-Samat & Kamaruddin, 2014; Chen et al., 2023; Yang et al., 2018). Considering maintenance at the system level within the context of opportunistic maintenance involves utilizing the combined condition of multiple machines and their operational relationships.

In spite of this, many of the OM models that have been developed, particularly in support of CPMSs, have often been built on assumptions that have limited their application in an industrial scenario. One of the assumptions that is often used in many of these models is that there is an opportunity that is considered to be deterministic or periodic in nature, and that it is possible to carry out all planned maintenance during this opportunity. Besides, a number of OM models assume perfect maintenance, where the machine or equipment can be brought back to its "as-good-as-new" condition after maintenance. However, it is important to note that the execution of maintenance activities within a CPMSs is subject to various limitations, while maintenance effectiveness is also imperfect (Budiono et al., 2021; Liu et al., 2021; Wei et al., 2023; Xiao et al., 2020).

Recent studies aimed to ease some of these restrictions by adding imperfect maintenance and more realistic system behaviors into the OM models. These studies acknowledged the fact that maintenance operations do not always bring the machine back to a condition "as good as new," or, on the other hand, "as bad as old." Additionally, it was acknowledged that uncertainty may exist in maintenance operations. Even though it makes the model more realistic, its extension for CPMSs, particularly where maintenance opportunities may be irregular, uncertain, and subject to varying production demands, is still limited (Allaham & Dalalah, 2022; Wei et al., 2023; Xiao et al., 2020).

In addition, there are still two issues left unsolved regarding the application of OM to continuous production systems. First, a large percentage of OM research works have mostly focused on machine-level performance and optimization objectives, failing to sufficiently consider system-level operating constraints and the relationship between maintenance and production decisions within a CPMSs environment. In such systems, machine condition, product quality, and production objectives are highly interrelated, and ignoring such interrelations can cause suboptimal maintenance decisions (Ab-Samat & Kamaruddin, 2019). Second, although OM models have proven efficiency improvement, they have also been criticized for providing little support for maintenance decision-making, as they are uncertain regarding idle opportunity execution and decision logic (Aiello et al., 2021).

In order to bridge this research gap, this research article contributes an Opportunistic Maintenance Scheduling model using Mixed Integer Linear Programming (MILP), particularly in continuous production systems where there is an element of uncertainty in terms of available idle time. Unlike other research articles that only treat opportunistic maintenance as an optimization problem, this research article organizes its mixed integer linear programming model in a way that it is useful in decision-making, considering that opportunistic maintenance must always be feasible in terms of available idle time.

The validity of the proposed method, based on the application of the MILP model, is verified through the application of the proposed method to the case of a continuous steel coating production line, where the performance of the proposed method is evaluated through simulation, comparing it with the performance of the non-optimized strategy. The major contributions of this work are summarized as follows:

1. This study explicitly embeds execution feasibility constraints, including idle window duration and manpower limitations, into opportunistic maintenance optimization for continuous production systems.
2. It establishes a systematic linkage between short-term opportunistic maintenance decisions and long-term system reliability dynamics by integrating a Mixed-Integer Linear Programming (MILP) model with System Dynamics simulation.
3. It proposes a decision-oriented opportunistic maintenance framework, validated through an industrial case study of a continuous steel coating production line.

The rest of this paper is structured such that, in Section 2, the problem context, characteristics, and decision environment related to OM within continuous production systems are described. In Section 3, the formulation of the MILP model related to the opportunistic selection of maintenance tasks, based on idle-window constraints, is discussed. In Section 4, the simulation model that integrates the opportunistic decision model, based on the MILP model, within the System Dynamics (SD) simulation environment, the simulation scenarios, and the simulation model's parameterization are discussed. In Section 5, the simulation model's results are presented, with particular emphasis on the reliability-related performance. Finally, in Section 6 the conclusions drawn, along with the potential directions for further research, are discussed.

2. Problem Statements

2.1. System Overview

The research focuses on the analysis of the continuous line production system, where several dependent machines are connected in serial processing. The unidirectional movement of materials, together with the absence of intermediate buffer storages, leads to the occurrence of performance degradation throughout the system due to disturbances at any of the key machines (Chen et al., 2023; Colledani et al., 2018; Yang et al., 2018). The dependency structure of the machines in the system shows that the continuity of the production system is very sensitive to the availability of machines, where even small losses in availability lead to substantial losses in production.

In the real world of industry, the maintenance operations of the continuous production system are often subject to very strong constraints of production continuity. Planned outages are often infrequent and limited, which makes it very complex to schedule specific windows of time for the maintenance of the system independent of production schedules (Li et al., 2021; Mena et al., 2021). This suggests that system operations often require maintenance to be done in an opportunistic manner, as opposed to scheduled.

The interruptions caused by the factors mentioned above may be viewed as idle windows, where there are no specific patterns governing their occurrence. The idle windows are absent or are not integrated into the production plans. Rather, idle windows may arise due to the dynamic nature of the problems that may arise, such as machine downtime, changes in orders, or temporary unavailability of material, etc (Bergenhenegouwen et al., 2023; Pastore et al., 2023). Therefore, the knowledge of the characteristics of continuous-line systems, along with the idle windows that arise due to the factors related to the production process, can be considered an essential prerequisite for the development of opportunistic-based strategies related to the scheduling of the maintenance activities. A brief overview of the major characteristics related to the continuous-line production system considered in the current study can be found in the Table 1.

Aspect	Description
Production type	Continuous line production
System configuration	Serially connected process stages
Product flow	Single-directional, uninterrupted material flow
Maintenance strategy	Preventive and corrective maintenance
Production stoppage impact	Line-wide impact due to process dependency
Idle time characteristics	Irregular, short-duration idle windows
Decision environment	Time- and resource-constrained

Table 1. Overview of the continuous line production system

2.2. Idle Window Characteristic

In continuous production systems, maintenance opportunities generally arise in the course of unavoidable idle periods, and these idle periods are herein referred to as idle windows. As shown in Figure 1(a), idle windows emerge in production systems owing to fluctuations from standard continuous-line production behavior, which might arise owing to production system disruptions such as system failure, order cancellation, and temporary unavailability of raw materials in production systems (Bergenhenegouwen et al., 2023; Pastore et al., 2023). As shown in Figure 1(a), idle windows are neither scheduled in production systems nor are their start and end times predictable and constant in nature (Lee et al., 2020; Yang et al., 2018), making them difficult to anticipate and systematically exploit. Every idle window has a specific time interval within which maintenance activities can be carried out without creating more production losses, as shown in Fig. 1(b), where idle windows are shown to exist between successive periods of operation. Nevertheless, it is to be noted that the time period of an idle window is usually insufficient to complete all the maintenance jobs, and hence several maintenance job candidates emerge for the same limited time period. Moreover, the presence of idle windows creates process uncertainties since the timing and duration of idle windows depend on the changing production environment rather than deterministic timing. As a result, the maintenance decision is formulated under time-constrained opportunity windows where only some tasks out of the set of possible tasks can be selected within the given idle window duration, thus complicating the maintenance decision process in the production environment.

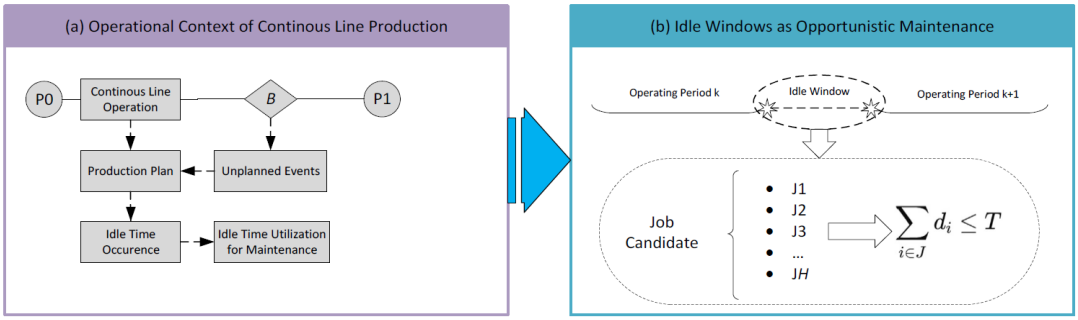


Figure 1. Operational context and idle window characteristics in continuous line production

2.3. Maintenance Task Characteristic

A group of candidate maintenance tasks is assessed and evaluated to be carried out within the idle windows. Each maintenance task is characterized by a particular execution time, required personnel, and maintenance benefit, which is a measure of the contribution of the maintenance task to the reliability or the operating performance of the system (Aiello et al., 2021; Li et al., 2021). Maintenance tasks may have varying urgency, operating significance, and execution ease depending on the equipment status and production needs, making the maintenance task prioritization a nontrivial decision problem (Chen et al., 2023). In view of the limited and variable lengths of idle windows, it is not possible to carry out all the candidate maintenance tasks within one idle window, which constitutes the initial opportunity (Mena et al., 2021; Yang et al., 2018). The maintenance planning problem, therefore, becomes the selection of a feasible subset of maintenance tasks that are schedulable within the idle window, with the aim of optimizing the overall maintenance benefit based on the criteria developed in the prioritization phase. In the case study, the candidate maintenance tasks include inspection, alignment, cleaning, lubrication, component replacement, and corrective follow-up activities identified from maintenance abnormality records.

2.4. Resource and Feasibility Constraints

The execution of maintenance activities within continuous production systems is limited by the availability of certain resources, i.e., the maintenance personnel and their skill sets. During a certain system's idle window, only a certain number of maintenance personnel may be available to execute the activity. Moreover, the availability of the activity to be executed and the existing operational constraints may limit the execution of the activity. However, it must be noted that the feasibility of executing a certain activity does not lie merely within the existence of an idle window; rather, it depends upon the availability of certain resources and the alignment of the activity with existing constraints. Hence, it must be noted that an activity may be theoretically feasible to be executed, yet it may not be feasible within a certain idle window (Aiello et al., 2021; Neto et al., 2021). This distinction between theoretical optimization and actual feasibility becomes a major point of consideration while certain decisions regarding maintenance activities are to be taken.

2.5. Decision Problem Statement

The specific problem under consideration in the context of maintenance scheduling, as considered in this particular study, is related to the selection of suitable maintenance activities to be carried out during different idle window opportunities within a continuous production system (Chen et al., 2023; Yang et al., 2018). The selection of these activities is to be made while considering the availability of idle window opportunities, the time required to execute different activities, and other system-level constraints due to the continuous nature of the production system (Bergenhenegouwen et al., 2023; Pastore et al., 2023). The selection is to be made in such a manner that not only is the feasibility of these activities within the selected set guaranteed, but at the same time, the maximum potential benefit that can be obtained from such a selection is maximized. Hence, the specific problem is to be formulated as an MILP model, as discussed in the following sections.

3. MILP Model Formulation

In this context, and following from the problem defined in the previous section, a mixed-integer linear programming formulation is developed to support the application of Opportunistic Maintenance schedules in continuous production systems. In this context, the model identifies which maintenance activities should be carried out within a given idle time period in order to maximize the overall maintenance benefit.

3.1. Model Assumptions

To make the problem tractable and implementable, the following assumptions are stated:

1. The production system acts like a continuous production line, where all the machines are closely coupled, and maintenance can be done only during the time when there is an idle window.
2. The idle windows are specified exogenously and are available only in finite duration.
3. The number of maintenance tasks offered at any given idle period is finite.

4. Each maintenance task is associated with a predefined duration of execution, resource needs, and maintenance benefit.
5. Resources for maintenance, in terms of manpower, are limited and fixed in each of the idle windows.
6. The maintenance tasks are non-preemptive, meaning they have to be completed within the same idle window.
7. There is no idle time creation when carrying out a maintenance task.

These assumptions represent the practical operational constraints that have been observed in the continuous production environment and that ensure the feasibility of the execution of the decision related to the maintenance (Akl et al., 2022; Allaham & Dalalah, 2022; Xiao et al., 2020).

3.2. Model Notation

Category	Symbol	Description
Sets	I	Set of candidate maintenance tasks available for execution during an idle window
	$I_m \subset I$	Subset of mandatory maintenance tasks that must be executed
Parameters	c_i	Criticality score (maintenance benefit) associated with task
	p_i	Execution duration required to complete task (hours)
	m_i	Manpower requirement for executing task (number of personnel)
	W	Duration of the available idle window (hours)
	M	Number of available internal maintenance personnel during the idle window
	H_{max}	Maximum allowable average working hours per maintenance personnel during an idle window
Decision Variables	x_i	Binary variable indicating whether maintenance task is selected (1) or not selected (0)

Table 2. Model notation for opportunistic maintenance task selection

3.3. Objective Function

The major aim is to maximize the net benefit accrued from the execution of the maintenance activities during the idle windows:

$$\max Z = \sum_{i \in I} c_i x_i \tag{1}$$

This objective captures a decision-based approach to the prioritization of different activities in terms of their relative contributions to the overall benefit. The benefit coefficient represents the expected maintenance impact considered in the selection process, whereas the subsequent effects in terms of system reliability and performance are determined using simulation analysis.

3.4. Constraints

3.4.1. Internal Man-Hour Capacity Constraint

Maintenance execution during an idle window is limited in terms of its internal man-hour capacity. Also, the combined man-hour demand of selected maintenance tasks must not exceed the product of the duration of the idle window and available maintenance personnel. This can be expressed as:

$$\sum_{i \in I} p_i \cdot m_i \cdot x_i \leq W \cdot M \tag{2}$$

The constraint specifically links the length of the task and the personnel needs to the execution capacity provided in the idle window. This ensures that the maintenance tasks are completed well within the specified time without

exceeding the workforce capabilities. Since the maintenance tasks are non-preemptive in nature, the selected task needs to be completed totally within one idle window.

3.4.2. Average Working Hour Constraint

In addition to total man-hour capacity, the maintenance execution is limited in terms of permissible workload allocated to each of the maintenance personnel. To ensure that there is no overworking and that there is an efficient distribution of tasks, the mean working hours of each personnel is limited by a certain predefined upper bound, which is expressed as:

$$\frac{\sum_{i \in I} p_i \cdot m_i \cdot x_i}{M} \leq H_{max} \tag{3}$$

This constraint will make the model more realistic by preventing solutions in which a large part of the workload is assigned to a few personnel. It follows a practical scenario in which working hour constraints are implemented for safe and sustainable working conditions.

3.4.3. Mandatory Task Constraint

Some of the maintenance tasks are specified as being of a mandatory nature due to safety reasons or regulatory requirements. These types of maintenance should be performed whenever the idle window becomes available, independent of the criticality score of the maintenance task. The implementation of the mandatory requirement of the maintenance task is as follows:

$$x_i = 1 \quad \forall i \in I_m \tag{4}$$

By satisfying this constraint, the model ensures that the execution plan will include the execution of non-negotiable activities.

3.4.4. External Vendor Task Consideration

The external vendor activities are considered not to require any man-hours from the internal population. Therefore, the activities do not influence the man-hour capacity constraints. This model assumption facilitates the integration of the external vendor activities into the model, yet still within the constraints imposed by the idle window duration.

$$m_i = 0 \text{ if task } i \text{ is performed by an external vendor} \tag{5}$$

3.4.5. Binary Task Selection Constraint

Selection of maintenance tasks for maintenance can be formulated as a binary decision problem, where each selected maintenance task either performs immediately or waits until the next opportunity window becomes available. The decision problem can be formulated as follows:

$$x_i \in \{0,1\} \quad \forall i \in I \tag{6}$$

This constraint prevents maintenance tasks from being performed partially and makes the optimization model similar to the real world, where maintenance tasks must be performed completely after they have started.

3.5. Model Interpretation

The suggested MILP formulation identifies the feasible region of the maintenance actions that are to be performed during the idle periods by considering the idle window, the availability of resources, and the expected benefits of the maintenance activities. By considering the feasibility of executing the selected maintenance activities, the suggested formulation ensures that the selected activities are practically executable under the existing constraints. Thus, the suggested MILP formulation is a decision-support tool for the planners, which helps them schedule the opportunistic maintenance activities optimally under the existing continuous production environment (Aiello et al., 2021; Zhang & Tang, 2022).

4. Integration of MILP-Based Maintenance Decisions with System Dynamics Simulation

The MILP model determines the set of feasible maintenance activities to be performed within a given idle window, subject to temporal and resource constraints. However, the optimization model does not directly capture the dynamic effects of maintenance actions on equipment condition over time. To evaluate how the selected maintenance activities affect long-term system reliability, the MILP results are incorporated into a System Dynamics (SD) simulation model. Several simulation approaches can be applied to maintenance and production systems, each serving different analytical purposes. Discrete Event Simulation is commonly used to represent detailed event sequencing and operational-level scheduling, making it suitable for machine-level analysis but less effective for capturing long-term policy feedback (Budiono et al., 2021). Monte Carlo simulation primarily focuses on uncertainty propagation and probabilistic outcome estimation, which limits its ability to represent endogenous feedback and decision-driven dynamics (Alrabghi & Tiwari, 2015). Agent-Based Simulation emphasizes bottom-up modeling of individual agent behavior and interactions, making it suitable for decentralized decision-making contexts rather than system-level policy analysis in continuous production systems (Nazabadi et al., 2024). In contrast, System Dynamics explicitly represents feedback loops and stock–flow structures, enabling policy-level evaluation of opportunistic maintenance decisions and their long-term reliability implications (Yıldız & Soylu, 2023).

4.1. System Dynamics Model Structure

The SD model was developed to evaluate the reliability impact of opportunistic maintenance decisions derived from the MILP model. The model transforms static, period-specific maintenance task selection decisions into dynamic system-level reliability responses in a continuously operating production environment. It describes system responses to the interactions among idle time availability, maintenance resource utilization, and system reliability changes over time (Chen et al., 2023; Yang et al., 2018). Conceptually, a reinforcing loop represents reliability improvement through feasible opportunistic maintenance execution, while a balancing loop captures natural system degradation. The full architecture of the SD model is represented in a stock-flow diagram, as shown in Figure 2.

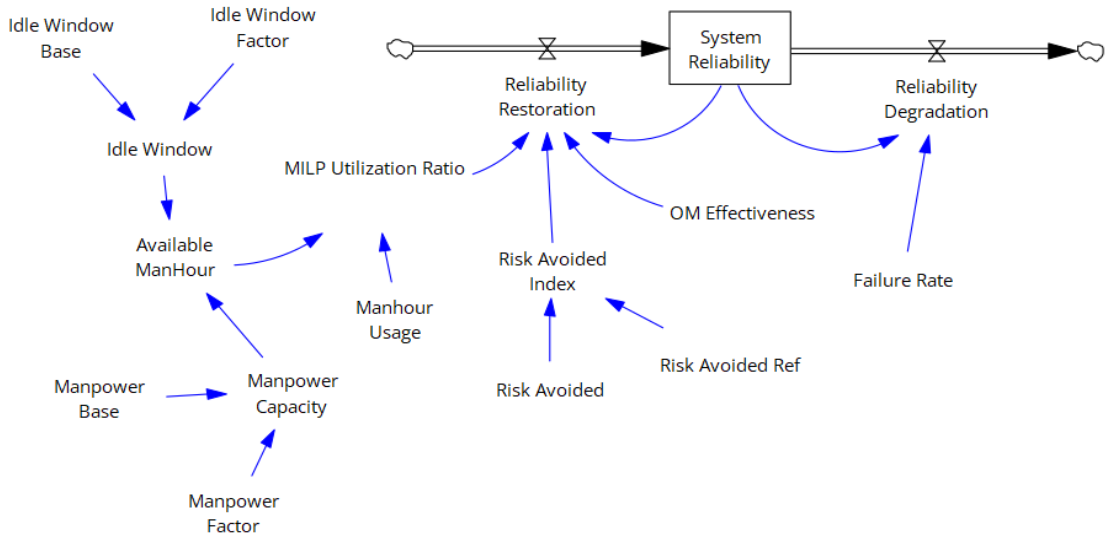


Figure 2. SFD of the system dynamics model for evaluating opportunistic maintenance execution under idle window and manpower constraints

The model structure is built around a single stock variable — System Reliability — representing the aggregate reliability level of the production system. Changes in System Reliability are governed by two opposing flows: (1) Reliability Degradation, an outflow representing natural deterioration driven by an aggregate failure rate; and (2) Reliability Restoration, an inflow representing the recovery in system reliability achieved through the execution of opportunistic maintenance activities.

System reliability degradation represents the natural deterioration of the system condition and is modeled as a function of the current system reliability level and a constant failure rate, consistent with standard reliability

modeling practices (Colledani et al., 2018). If the maintenance intervention does not suffice, the system reliability will degrade gradually.

Reliability restoration, in turn, refers to the recovery achieved through the execution of maintenance activities during the available idle windows. The percentage of available resources that can be harnessed is determined by the MILP Utilization Ratio, which represents the feasibility of execution based on the MILP task selection result (Zhang & Tang, 2022). In addition, the quality of the maintenance activities is incorporated through the Risk Avoided Index, derived from the objective function of the MILP model.

To clarify the computation mechanism within the stock-flow diagram, each variable of the System Dynamics model is specified in terms of its equation, unit, and the basis for its value. This specification is necessary so that the relationships among variables are not only understood conceptually but can also be traced mathematically, and it shows how the MILP outputs are integrated into the dynamic simulation through parameters representing the intensity of opportunistic maintenance execution. Table 3 provides the complete formal specification of the SD model, including equations, units, initial values, and the basis for each parameter. All equations were verified for dimensional consistency as part of the model validation procedure.

Variable	Type	Equation	Unit	Basis / Notes
System Reliability	Stock (Level)	INTEG (Reliability Restoration − Reliability Degradation, 0.85)	dimensionless	Initial value 0.85 derived from historical downtime data at start of observation period
Reliability Restoration	Auxiliary (Inflow)	MILP Utilization Ratio × OM Effectiveness × Risk Avoided Index × (1 − System Reliability)	dimensionless/ month	(1 − System Reliability) term creates diminishing returns: restoration slows as system approaches full reliability
Reliability Degradation	Auxiliary (Outflow)	Failure Rate × System Reliability	dimensionless/ month	First-order degradation model proportional to current reliability; consistent with standard reliability modeling
MILP Utilization Ratio	Auxiliary	Total selected man-hour / Available man-hours during Idle Window	dimensionless	Proportion of available capacity utilized; driven directly by MILP optimization outputs
Available ManHour	Auxiliary	Idle Window × Manpower Capacity	man-hours	Total maintenance capacity available during idle window
Risk Avoided Index	Auxiliary	MIN(1, MAX(0, Risk Avoided / Risk Avoided Ref))	dimensionless	Normalizes MILP objective value to [0,1]; prevents over-restoration. Risk Avoided Ref = 47.0 (max achievable under case study conditions)
OM Effectiveness	Constant	0.001	1/month	Calibration coefficient; converts maintenance activity intensity into reliability recovery; validated through expert review
Failure Rate	Constant	0.08	1/month	Aggregate system failure rate; derived from historical unplanned downtime data of the case study facility
Idle Window	Auxiliary	Idle Window Base × Idle Window Factor	hours	Represents available maintenance opportunity. Base value = 12 hours (median from historical operational log, FY25)
Manpower Capacity	Auxiliary	Manpower Base × Manpower Factor	persons	Effective manpower available. Base value = 10 persons (internal crew, from operational records)

Table 3. System Dynamics Model Equations, Units, and Parameter Basis

4.2. MILP – System Dynamics Integration Mechanism

The integration between the MILP model and the SD simulation operates through two key linking indicators that translate short-term optimization decisions into dynamic system inputs:

MILP Utilization Ratio quantifies the proportion of available maintenance capacity (in man-hours) successfully allocated to selected maintenance tasks by the MILP model:

$$U(t) = \frac{\sum_{i \in I} p_i \, m_i x_i}{W(t) M(t)} \tag{7}$$

Where p_i is the execution duration of task i, m_i is the internal manpower requirement of task i, x_i is the binary decision variable, $W(t)$ is the idle window duration, and $M(t)$ is the number of available internal maintenance personnel. In the baseline scenario, this ratio is 0.83, reflecting partial utilization due to suboptimal task selection. In the OM scenario, the ratio reaches 1.00, indicating full utilization through optimized scheduling.

Risk Avoided Index quantifies the quality of selected maintenance tasks in terms of risk mitigation impact, normalized to a reference value:

$$Q(t) = \min\left(1, \max\left(0, \frac{\sum_{i \in I} c_i \, x_i}{RA^{ref}}\right)\right) \tag{8}$$

where $\sum_{i \in I} c_i \, x_i$ is the MILP objective function value, representing the total criticality-weighted benefit of selected tasks, and $RA^{ref} = 47.0$ is the maximum achievable avoided risk value under the case study conditions. This normalization ensures that the index remains within the range of 0 to 1 and prevents over-restoration in the SD model.

These two indicators are passed as exogenous inputs to the SD model, jointly governing the Reliability Restoration rate according to the equation in Table 3:

$$Reliability\ Restoration(t) = \theta \times U(t) \times Q(t) \times [1 - R(t)] \tag{9}$$

Where θ is the OM effectiveness coefficient, $U(t)$ is the MILP Utilization Ratio, $Q(t)$ is the Risk Avoided Index, and $R(t)$ is the System Reliability. This linkage ensures that the dynamic system behavior simulated in the SD model directly reflects both the quantity of maintenance execution, represented by $U(t)$, and the quality of selected maintenance decisions, represented by $Q(t)$. Table 4 provides a full mapping of MILP outputs to SD input variables.

MILP Output	Symbol	SD Variable Influenced	Role in SD Simulation
Volume of OM tasks executed	$\sum x_i$	OM Activity Rate	Determines restoration intensity per simulation period
Idle time utilization level	$U(t)$	Idle Window Available / Used	Represents effectiveness of opportunity window exploitation
Total internal man-hours required	$MH^{int}(t)$	Manpower Utilization	Reflects resource consumption intensity
Risk Avoided (objective function value)	$\sum_{i \in I} c_i \, x_i$	Risk Avoided Index	Input to Reliability Restoration rate; captures maintenance quality
Mandatory task execution status	$x_i = 1 \ \forall \ i \in I_m$	Minimum OM Activity	Guarantees minimum reliability restoration even under constrained idle windows

Table 4. Mapping of MILP Outputs to System Dynamics Input Variables

4.3. Simulation Scenarios and Parameter Setting

The SD simulation assesses the long-term reliability performance of different maintenance decision strategies under controlled conditions. Five scenarios were defined to systematically evaluate the contribution of each operational policy layer. The scenarios are cumulative: each subsequent scenario retains all constraints from the previous one and adds a new operational constraint or flexibility.

Scenario	Description	Distinguishing Feature
0 – Baseline	Existing maintenance practice without OM Task Selection; idle time utilization based on ad hoc criticality-driven decisions without optimization	Non-optimized; partial utilization (83%) of idle window capacity
1 – OM Basic	OM Task Selection with idle time duration constraint and internal manpower capacity constraint	Represents the basic MILP-based OM scheduling form
2 – OM + Work Hour Limit	Scenario 1 + maximum average working hours per internal manpower ≤ 12 hours	Introduces individual workload distribution constraint
3 – OM + Mandatory Jobs	Scenario 2 + mandatory tasks that must always be executed when idle window is available	Reflects regulatory/safety-driven maintenance requirements
4 – OM + External Vendor	Scenario 3 + flexibility for external vendor tasks (vendor tasks do not consume internal manpower capacity)	Most complete and practically realistic policy configuration; primary comparison with Baseline

Table 5. Simulation Scenarios

The primary comparison reported in this paper is between Scenario 0 (Baseline) and Scenario 4 (full OM framework), as Scenario 4 represents the complete decision-support framework as deployed in practice. Results from intermediate scenarios confirm the incremental contribution of each policy constraint.

In the baseline scenario, the maintenance strategy represents existing practice in accordance with criticality-driven task selection without optimization of idle window utilization. The baseline utilization ratio of 0.83 reflects the partial utilization of available capacity attributable to inefficiencies in non-optimized task selection. In the OM scenario, the utilization ratio reaches 1.00, reflecting high utilization through optimized task scheduling.

Table 6 provides all key parameter values and explicitly identifies their source, distinguishing between industrial operational data, MILP optimization results, and literature-based calibration.

Parameter	Value	Unit	Source
Simulation horizon	12	months	Aligned with historical data availability (FY25)
Time step	1	month	Consistent with data resolution and monthly operational reporting
Initial System Reliability	0.85	dimensionless	Derived from historical downtime records at start of observation period (FY25)
Failure Rate	0.08	1/month	Estimated from historical unplanned downtime frequency on the continuous coating line
OM Effectiveness coefficient	0.001	1/month	Calibrated to reproduce reliability behavior consistent with historical maintenance patterns; verified through expert review
Idle Window (representative case)	12	hours	Median idle window duration from historical operational log (FY25)
Internal Manpower available	10	persons	Actual internal crew size documented in operational records
Max avg. working hours per person	12	hours/person	Internal operational policy (labor regulation constraint)
Risk Avoided Ref	47.0	dimensionless	Maximum achievable risk avoided value from MILP optimal solution under full resource availability (Scenario 4)
Baseline utilization ratio	0.83	dimensionless	Calculated from historical idle window usage data under non-optimized practice
OM utilization ratio	1.00	dimensionless	MILP optimization result for the representative idle window case (Scenario 4)

Table 6. Key Parameter Values and Sources

4.4. Model Validation

Model validation was conducted following the multi-step evaluation framework recommended by Sterman (2000), encompassing structure verification, extreme condition testing, behavioral validation, face validity assessment, and sensitivity analysis.

(1) Structure Verification. The dimensional consistency of all model equations was verified systematically. Each equation in the stock-flow structure was checked to ensure that units on both sides are consistent (e.g., Reliability Degradation in dimensionless/month = [1/month] × [dimensionless]). No dimensional inconsistencies were identified. The logical ordering of causal relationships in the reinforcing and balancing loops was also verified against physical expectations.

(2) Extreme Condition Test. The model was tested under boundary conditions to verify logical behavior. When the MILP Utilization Ratio is set to zero (no maintenance executed), System Reliability degrades continuously at a rate governed by the Failure Rate, as expected. When the Risk Avoided Index is set to zero, Reliability Restoration becomes zero and the system reliability progressively degrades — consistent with physical expectations. These boundary tests confirm that the model structure produces logically consistent behavior under degenerate inputs.

(3) Behavioral Validation. The baseline scenario (Scenario 0) was evaluated by comparing the simulated reliability trajectory qualitatively with observed trends in historical unplanned downtime and reliability data from the case study facility (FY25). The direction and general rate of reliability degradation in the baseline simulation were found to be consistent with the observed trend of increasing downtime frequency over the observation period. Exact numerical reproduction was not targeted, as the objective of the SD model is policy evaluation rather than precise point prediction (Law, 2022).

(4) Face Validity. The model structure, causal relationships, and simulation outputs were reviewed with a Maintenance Supervisor and a Production Planning representative from the case study facility. Both confirmed that the direction of relationships between variables — higher OM activity leads to slower reliability degradation; constrained idle windows limit restoration rate — is consistent with their operational experience and judgment.

(5) Sensitivity Analysis. A sensitivity analysis was conducted by varying the two principal operational parameters — idle window duration and available internal manpower — across a range of ±30% from baseline values. The results show that variations in these parameters affect the absolute level of reliability restoration but do not alter the direction or qualitative pattern of the comparison between the baseline and OM scenarios. In all tested configurations, the OM scenario consistently outperforms the baseline, confirming the robustness of the proposed framework's decision logic across different operational conditions.

5. Results and Discussion

5.1. System Reliability Performance

This section focuses on assessing the system reliability performance of the baseline maintenance strategy compared with the MILP-based OM strategy, through the system dynamics simulation approach. The focus is on the influence of changes in the maintenance decision-making approach on system reliability performance under the same operating conditions. Figure 3 shows the reliability performance of the two approaches obtained through the system dynamics simulation.

In the baseline scenario, system reliability continues to decrease during the simulation period, indicating the poor effectiveness of criticality-based maintenance approaches in which optimal use of idle windows is not considered. In contrast, the OM scenario maintains a higher reliability trajectory and exhibits a slower degradation rate over time due to optimized maintenance task selection, improved resource utilization, and more effective risk mitigation. The results suggest that the improvement in system reliability is caused by more effective maintenance decision-making rather than changes in system structure or resource availability, supporting the conclusion that opportunistic system maintenance using MILP can maintain a higher reliability trajectory in continuous production systems.

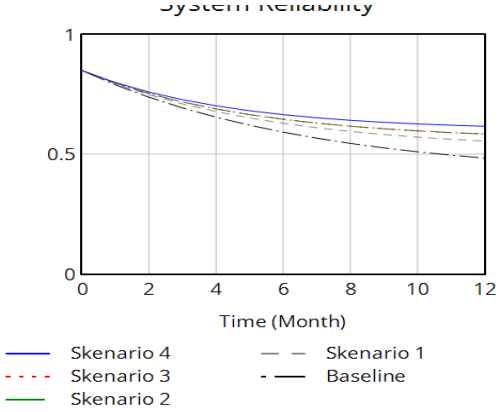


Figure 3. Comparison of system reliability trajectories under baseline and MILP-based opportunistic maintenance scenarios

5.2. Impact of Optimized Maintenance Decisions

Table 7 presents a comparative evaluation of the baseline criticality-based approach (Scenario 0) and the full OM approach (Scenario 4). The results show a considerable difference in maintenance task execution efficiency, which contributed to the higher reliability trajectory observed in Section 5.1.

Indicator	Baseline (Criticality Based)	OM Task Selection	Change
Total executed maintenance duration (hours)	40	72	+80%
Total internal man-hour	100	120	+20%
Man-hour Utilization (%)	83%	100%	+17%
Completed Tasks	7	15	+114%
Uncompleted Task	9	1	-88.9%
Risk Avoided	25.8	47.0	+82.2%
Risk Not Done	24	2.8	-88.3%
Avg MH per crew	10	12	+20%

Table 7. Comparative Maintenance Performance Between Baseline and OM Task Selection Scenarios

In the OM Task Selection scenario (Scenario 4), the total duration of maintenance activities increases by 80%, from 40 hours to 72 hours, while total internal man-hours show a moderate increase of 20%. The increase is attributable to effective utilization of idle time rather than an increase in total manpower. The OM scenario achieves 100% man-hour utilization versus 83% in the baseline.

The number of completed tasks increases by 114% from 7 to 15, while uncompleted tasks are reduced by approximately 89%. Most significantly, the OM strategy results in an 82.2% increase in risk avoided and an 88.3% decrease in risks not addressed. These observations confirm that the OM strategy based on the MILP model not only improves workload but also strategically addresses maintenance tasks within the available idle time.

5.3. Discussion of MILP – System Dynamics Integration

The integration between the MILP model and the SD simulation creates a transparent and traceable linkage between short-term maintenance decision quality and long-term system reliability behavior. As described in Section 4.2, this integration operates through two key indicators — the MILP Utilization Ratio and the Risk Avoided Index — which together translate optimization outputs into dynamic system inputs.

The MILP Utilization Ratio directly governs the intensity of maintenance execution in the SD model: a higher utilization ratio produces a stronger Reliability Restoration rate. The Risk Avoided Index scales the restoration effect by the quality of selected tasks: tasks with higher criticality scores contribute more to reliability recovery per

unit of man-hour consumed. This dual mechanism ensures that the SD model captures both the quantity (how much maintenance was done) and the quality (which tasks were prioritized) of the maintenance decisions.

In the SD model, the Reliability Restoration rate has an important structural property: as System Reliability approaches 1.0, the restoration rate diminishes, representing diminishing returns — it becomes increasingly difficult to further improve an already highly reliable system. Conversely, as System Reliability falls (as in the baseline scenario), the potential for restoration increases, reflecting the greater margin for improvement in a degraded system.

Compared with recent studies, this work extends opportunistic maintenance research from task-selection optimization to decision evaluation under dynamic reliability behavior. Chen et al. (2023) model opportunistic maintenance optimization under imperfect maintenance and epistemic uncertainty, while Mena et al. (2021) and Liu et al. (2021) propose optimization-based OM scheduling frameworks that mainly emphasize optimal policies within predefined modelling assumptions. In contrast, the present study explicitly links MILP-based feasible execution decisions to long-term reliability dynamics using System Dynamics, enabling direct interpretation of how short-term opportunistic decisions translate into sustained reliability trajectories under limited idle windows and manpower constraints.

The sensitivity analysis results (Section 4.4) confirm that the relative improvement delivered by the integrated MILP –SD framework over the baseline is preserved across a range of operational parameter variations. This robustness supports the use of analytical generalization: the decision logic captures a pattern applicable to continuous production systems with similar structural characteristics.

6. Conclusions

In this study, a new framework for Opportunistic Maintenance is developed based on the integration of a Mixed Integer Linear Programming (MILP) model and a System Dynamics (SD) model for a continuous production system. The MILP model is applied to optimize opportunistic maintenance decisions by maximizing total avoided risk under idle window and manpower constraints, while the SD model evaluates the long-term reliability impact of these optimized decisions. The results show that the MILP-based OM strategy consistently maintains a higher system reliability level, ending at approximately 0.6 compared to about 0.5 under the criticality-based strategy, indicating a noticeably slower reliability degradation under the proposed approach.

The connection between the MILP Utilization Ratio and the Risk Avoided Index provides a transparent mechanism for transferring optimization output into reliability dynamics. Specifically, the utilization ratio determines the feasibility of execution during constrained idle windows, while the risk avoidance index provides a measure of the effectiveness of the determined maintenance actions.

6.1. Practical and Managerial Implications

From a practical and policy-oriented perspective, the proposed framework provides useful guidelines for maintenance planning in continuous production industries. Instead of relying on time schedules or criticality-based approaches, maintenance policies should focus on opportunistic execution considering idle window availability, with decisions guided by the MILP-based selection framework.

The proposed framework is primarily intended for use by Maintenance Planners and Maintenance Supervisors at the operational level — practitioners who must make rapid maintenance scheduling decisions within a tightly constrained time window when an idle opportunity arises. The framework is most valuable in settings where: (1) idle windows are irregular and difficult to predict in advance; (2) the number of candidate maintenance tasks exceeds what can be completed in a single idle window; and (3) maintenance decisions must be made quickly — often within minutes — to avoid wasting available production downtime. These conditions are characteristic of continuous steel coating, chemical processing, pharmaceutical manufacturing, and similar continuous process industries.

In practice, the framework requires four types of input data typically available in facilities with a functioning Computerized Maintenance Management System (CMMS): (1) a list of pending maintenance tasks with duration,

manpower requirements, and criticality scores; (2) the duration of the current idle window; (3) the number of internal maintenance personnel available; and (4) the status of task readiness (spare parts, tools, and access). For the case-study scale considered in this research, the MILP model was implemented using Microsoft Excel Solver, making it accessible for daily maintenance planning without requiring specialized optimization software. For larger-scale applications with a higher number of candidate tasks or multiple simultaneous idle windows, the model can also be migrated to commercial or open-source optimization solvers. This makes the proposed framework both practical for simple daily use and scalable for future digital decision-support development.

Integration with existing plant systems is feasible as follows. CMMS can export the pending work order list and import MILP-selected tasks as execution instructions. ERP systems can provide spare part availability status to support the ready-to-execute filter. Manufacturing Execution Systems (MES) can detect idle window occurrences and trigger the decision-support process automatically. The SD simulation component, while not required for every idle window decision, provides strategic insight for maintenance policy evaluation over longer planning horizons and is intended for use by maintenance managers and reliability engineers in periodic performance reviews.

The framework is not designed to replace the professional judgment of maintenance practitioners, but to accelerate and discipline the prioritization process — transforming what is currently a manual, experience-dependent discussion into a structured, data-driven, and reproducible decision process.

6.2. Research Limitations and Future Directions

This research has several limitations. The model assumes a constant failure rate and does not explicitly include probabilistic deterioration processes or condition-based maintenance. The study is based on a single continuous production case, which may affect generalizability. The SD model represents reliability at the system aggregate level, not at the individual component level, which is a consequence of the focus on policy-level evaluation.

Future research may extend this model to include probabilistic models, cost-based approaches, rolling-horizon approaches, and integration with idle window prediction using data-driven or digital twin technologies. The framework can also be adapted for other continuous process industries (chemical, power generation, metals processing) by adjusting the model parameters and operational constraints to match the specific system context.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Authors' contributions

Andry Jitro: Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, Software, Visualization, Writing – Original Draft.

Suharjito Suharjito: Supervision, Conceptualization, Methodology, Formal Analysis, Validation, Writing – Review & Editing.

Data availability

Data supporting this study cannot currently be made publicly available because the dataset was obtained from operational records of a third-party organization, and authorization for public disclosure has not yet been obtained from the data-owning organization.

Use of Artificial Intelligence

Artificial Intelligence (AI)-assisted tools were used solely to support English-language writing and editing, including grammar correction, sentence clarity, and improvement of manuscript readability. These tools were not used to

generate or modify research data, perform data analysis, or produce scientific results. The authors take full responsibility for the accuracy, originality, and integrity of the manuscript.

References

Ab-Samat, H., & Kamaruddin, S. (2014). Opportunistic maintenance (OM) as a new advancement in maintenance approaches: A review. *Journal of Quality in Maintenance Engineering*, *20*(2), 98–121. https://doi.org/10.1108/JQME-04-2013-0018

Ab-Samat, H., & Kamaruddin, S. (2019). Development of opportunistic maintenance policy towards optimal maintenance system (OPTOMS) model. *Journal of Quality in Maintenance Engineering*, *26*(1), 129–165. https://doi.org/10.1108/JQME-07-2018-0057

Aiello, G., Benítez, J., Carpitella, S., Certa, A., Enea, M., Izquierdo, J., & La Cascia, M. (2021). A decision support system to assure high-performance maintenance service. *Journal of Quality in Maintenance Engineering*, *27*(4), 651–670.

Akl, A. M., El Sawah, S., Chakrabortty, R. K., & Turan, H. H. (2022). A Joint Optimization of Strategic Workforce Planning and Preventive Maintenance Scheduling: A Simulation–Optimization Approach. *Reliability Engineering and System Safety, 219*. https://doi.org/10.1016/j.ress.2021.108175

Allaham, H., & Dalalah, D. (2022). MILP of multitask scheduling of geographically distributed maintenance tasks. *International Journal of Industrial Engineering Computations*, *13*(1), 119–134.

Alrabghi, A., & Tiwari, A. (2015). State of the art in simulation-based optimisation for maintenance systems. *Computers & Industrial Engineering*, *82*, 167–182. https://doi.org/10.1016/J.CIE.2014.12.022

Battesini, M., ten Caten, C. S., & Pacheco, D. A. de J. (2021). Key factors for operational performance in manufacturing systems: Conceptual model, systematic literature review and implications. *Journal of Manufacturing Systems, 60,* 265–282. https://doi.org/10.1016/j.jmsy.2021.06.005

Bergenhenegouwen, T., Kasper, T. A. A., Bokhorst, J. A. C., & Land, M. J. (2023). Managing premature idleness in high-variety manufacturing. *Flexible Services and Manufacturing Journal, 36,* 1399-1421. https://doi.org/10.1007/s10696-023-09521-x

Budiono, A. L., Siswanto, N., & Kurniati, N. (2021). Modeling opportunistic maintenance using discrete event simulation. *IOP Conference Series: Materials Science and Engineering*, *1072*(1). https://doi.org/10.1088/1757-899x/1072/1/012045

Chen, Z., Chen, Z., Zhou, D., Xia, T., & Pan, E. (2023). Opportunistic maintenance optimization of continuous process manufacturing systems considering imperfect maintenance with epistemic uncertainty. *Journal of Manufacturing Systems, 71*. https://doi.org/10.1016/j.jmsy.2023.10.001

Colledani, M., Magnanini, M. C., & Tolio, T. (2018). Impact of opportunistic maintenance on manufacturing system performance. *CIRP Annals*, *67*(1), 499–502. https://doi.org/10.1016/j.cirp.2018.04.078

Law, A. M. (2022). How to build valid and credible simulation models. *2022 Winter Simulation Conference (WSC)* (pp. 1283–1295).

Lee, S., Issabakhsh, M., Jeon, H. W., Hwang, S. W., & Do Chung, B. (2020). Idle time and capacity control for a single machine scheduling problem with dynamic electricity pricing. *Operations Management Research*, *13*(3–4). https://doi.org/10.1007/s12063-020-00156-x

Li, L., Wang, Y., & Lin, K.-Y. (2021). Preventive maintenance scheduling optimization based on opportunistic production-maintenance synchronization. *Journal of Intelligent Manufacturing*, *32*(2), 545–558.

Liu, G., Chen, S., Jin, H., & Liu, S. (2021). Optimum opportunistic maintenance schedule incorporating delay time theory with imperfect maintenance. *Reliability Engineering & System Safety*, *213*, 107668. https://doi.org/10.1016/j.ress.2021.107668

Lu, Y., Wang, S., Zhang, C., Chen, R., Dui, H., & Mu, R. (2024). Adaptive maintenance window-based opportunistic maintenance optimization considering operational reliability and cost. *Reliability Engineering & System Safety*, *250*, 110292. https://doi.org/10.1016/J.RESS.2024.110292

Mena, R., Viveros, P., Zio, E., & Campos, S. (2021). An optimization framework for opportunistic planning of preventive maintenance activities. *Reliability Engineering & System Safety*, *215*, 107801. https://doi.org/10.1016/j.ress.2021.107801

Nazabadi, M. R., Najafi, S. E., & Rasinojehdehi, R. (2024). Integrated decision-making in production, maintenance, repair, and quality planning using an agent-based simulation. *Risk Assessment and Management Decisions*, *1*(1), 12–21.

Neto, A. A., Carrijo, B. S., Romanzini Brock, J. G., Deschamps, F., & de Lima, E. P. (2021). Digital twin-driven decision support system for opportunistic preventive maintenance scheduling in manufacturing. *Procedia Manufacturing*, *55*(C), 439–446. https://doi.org/10.1016/j.promfg.2021.10.060

Pastore, E., Alfieri, A., & Castiglione, C. (2023). Addressing idle and waiting time in short term production planning. *Materials Research Proceedings*, *35*.

Sterman, J. D. (2000). *Business Dynamics: Systems thinking and modeling for a complex world.* McGraw-Hill Company.

Wei, F., Wang, J., Ma, X., Yang, L., & Qiu, Q. (2023). An Optimal Opportunistic Maintenance Planning Integrating Discrete- and Continuous-State Information. *Mathematics*, *11*(15). https://doi.org/10.3390/math11153322

Xiao, L., Zhang, X., Tang, J., & Zhou, Y. (2020). Joint optimization of opportunistic maintenance and production scheduling considering batch production mode and varying operational conditions. *Reliability Engineering & System Safety*, *202*, 107047. https://doi.org/10.1016/j.ress.2020.107047

Yang, L., Zhao, Y., Peng, R., & Ma, X. (2018). Opportunistic maintenance of production systems subject to random wait time and multiple control limits. *Journal of Manufacturing Systems, 47,* 12–34. https://doi.org/10.1016/j.jmsy.2018.02.003

Yıldız, G. B., & Soylu, B. (2023). Integrating preventive and predictive maintenance policies with system dynamics: A decision table approach. *Advanced Engineering Informatics, 56,* 101952.

Zhang, Z., & Tang, Q. (2022). Integrating preventive maintenance to two-stage assembly flow shop scheduling: MILP model, constructive heuristics and meta-heuristics. *Flexible Services and Manufacturing Journal, 34*(1), 156–203. https://doi.org/10.1007/s10696-021-09403-0

Article's contents are provided on an Attribution-Non Commercial 4.0 Creative commons International License. Readers are allowed to copy, distribute and communicate article's contents, provided the author's and Journal of Industrial Engineering and Management's names are included. It must not be used for commercial purposes. To see the complete license contents, please visit https://creativecommons.org/licenses/by-nc/4.0/.