Optimized maintenance of production systems via hierarchical and multi-criteria methods

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Abstract: In the context of complex industrial systems, effective maintenance strategies play a critical role in ensuring equipment availability,minimizing production downtime, and controlling operational costs. Although preventive and corrective maintenance approaches have been extensively studied, the dynamic selection of the most appropriate maintenance strategy remains a challenging issue, particularly under uncertain and disruptive operating conditions. This paper introduces PHADEM (Analytical Hierarchy Process for Maintenance Decision), an interactive multi-criteria decision-Making approach aimed at optimizing maintenance strategies. The proposed method simultaneously considers economic, technical, and environmental criteria, enabling real-time adaptation of maintenance policies to operational contexts. The model is implemented using a simulation framework that incorporates detailed representations of production stations, material flows, resources, and failure modes. The results demonstrate that the proposed hierarchical approach significantly enhances overall system performance while ensuring optimal resource allocation.

Keywords: Preventive maintenance, Corrective maintenance, Maintenance strategy optimization, Decision Making, PHADEM algorithm, Industrial simulation, Operational performance, Reliability, Availability.

1. INTRODUCTION

In an increasingly competitive industrial environment, the performance and availability of equipment have become important. Breakdowns, unplanned shutdowns and technical failures can lead to significant economic losses, disrupt production and affect the quality of finished products. Implementing a good maintenance strategy is therefore crucial to ensure the continuity of service and the profitability of the industrial system. Maintenance, whether corrective (repairs after failure) or preventive (planned maintenance) (Taous et al., 2024), has a direct impact on reliability, availability, operating costs and even environmental impacts (Barlow and Proschan, 1996). Much research has been conducted to optimize these policies, ranging from probabilistic models to artificial intelligence to improve real-time decision making (Zonta et al., 2022).

However, several limitations persist. Many works focus on a single strategy (preventive or corrective) without considering the interactions between the two (Wang et al., 2006). Moreover, few studies take into account the changes in the production environment and the real disturbances. In this context, we propose a global model named PHADEM (Analytical Hierarchical Process for Maintenance Decision). This model combines both types of maintenance, preventive and corrective, according to several criteria: cost minimization, availability improvement, and reduction of the environmental impact.

Our approach is based on the simulation of the production system using Alosurf, which allows to model failures, flows and dynamic interactions. The originality of this work lies in the integration of a decision algorithm, based on performance indicators, to adapt the maintenance policy to each critical situation (Lee et al., 2015).

This article introduces PHADEM, a hierarchical and multicriteria decision support framework that extends the classic AHP approach by integrating a filtering mechanism based on machine criticality. Rather than evaluating all the possible maintenance scenarios, PHADEM focuses only on the most critical machines, which allows for a significant reduction in the calculation load while preserving the relevance of decisions. This work provides a concrete response to industrial needs by proposing a flexible decision support tool, capable of adapting to complex environments.

2. STATE OF THE ART

2.1 Manufacturing Systems

Manufacturing systems are necessary in industry because they transform raw materials into finished products through organized and optimized operations. They are constantly evolving with the addition of new technologies, improving their flexibility, efficiency and ability to meet current challenges. In the field of manufacturing industry, some work focuses on the sizing of storage areas or even the organization of processing stations to improve productivity (El-Khalil, 2015).
A manufacturing system is an organized set of resources such as machines, operators and software that work together to manufacture industrial products or parts. These systems can be classified according to several criteria:

Depending on the degree of automation

- Traditional systems: manual or semi-automated production
- Automated systems: robotization of processes
- Intelligent systems: integration of AI and IoT for process optimization.

Depending on the organization of work

- Production in blocks: grouping of machines by functions
- Online production: sequential flow
- Flexible production: dynamic adaptation to needs Groover (2016)

Components and organization of a manufacturing system
A manufacturing system is based on several interdependent components, which ensure the transformation of inputs into finished products (Askin and Standridge, 1993):

Material resources

- Machine tools and production equipment
- Transport and storage systems (conveyors, AGVs)
- Sensors and quality control systems

Human resources

- Operators and maintenance technicians
- Engineers and production managers

Production flows

- Physical flows: movement of materials and products
- Information flow: planning and monitoring of operations Wiendahl et al. (2007)

Management and control systems

- ERP (Enterprise Resource Planning) for integrated management
- MES (Manufacturing Execution System) for production tracking
- Supervisory Control and Data Acquisition (SCADA) for real-time control

Performance criteria and issues

Evaluation of the performance of a manufacturing system is based on several key indicators (Koren et al., 2018):

- Efficiency and productivity: machine utilization rate, overall performance
- Flexibility: ability to adapt to changes in demand
- Reliability and maintainability: availability of equipment, frequency of failures
- Product quality: defect rate, compliance with standards
- Cost of production: inventory management, resource optimization

2.2 Overview of Industrial Maintenance

Industrial maintenance is very important for production. It helps to keep machines in good condition, prevents breakdowns and facilitates repairs. It also improves product quality, worker safety and productivity. This requires technical skills, a good knowledge of machines and well-organized interventions.
Historically, since antiquity, maintenance was done only after a breakdown, which was often expensive. But over time, it became clear that regular and planned maintenance can reduce costs, prevent unplanned downtimes and limit errors.
Maintenance covers all the technical and administrative actions to maintain or restore equipment in good condition, so that it can function properly, according to NF-EN 13306.

Maintenance policies
A maintenance strategy is a plan that organizes the different ways in which equipment can be repaired or maintained. These interventions can be carried out on site, in a workshop or at the manufacturer's. They also apply to different parts of the equipment, such as printed circuit boards. Each type of intervention depends on the skills of the staff, the tools available and where it takes place. The choice of intervention also takes into account the difficulty in repairing the part, its accessibility, the necessary tools and safety rules (Simeu-Abazi and Sassine, 2001).
The literature (Sassine et al., 1996) define several maintenance policies, which are grouped into three main categories: corrective maintenance, preventive maintenance and mixed maintenance, see Fig. 1.

Corrective maintenance (CM)

Corrective maintenance is the intervention after a failure to restore equipment to working order. In production systems, it aims to limit the consequences of failures by quickly repairing machines or finding solutions to reduce losses during shutdown.
Corrective maintenance actions follow the following steps, in order:

- Test: Comparison of measurements with a reference.
- Detection: Identification of the appearance of a defect.
- Location: Identification of the items affected by the failure.

- Diagnosis: Analysis of causes of failure.
- Repair: Put equipment back into operation.
- Possible improvement: Put in place measures to prevent the recurrence of failures.
- History: Record actions for future follow-up.

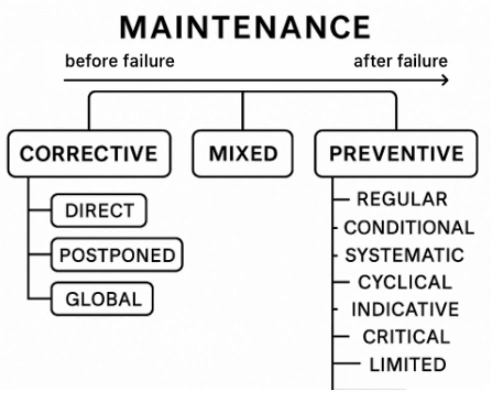

Fig. 1. Maintenance policies

The maintenance operation can be an emergency repair or a full repair. In both cases, the corrective maintenance (CM) policies are as follows:

- Direct CM: When a machine breaks down, a repair service is immediately called in to restore it to working order.
- Postponed CM: The repair is not performed immediately after failure, but postponed according to certain maintenance rules, such as waiting for several machines to fail.
- Global CM: When all of the machines fail in the production system, then, repair service is employed to restore them to working order.

Preventive maintenance (PM)

Preventive maintenance is the maintenance of equipment at scheduled times or according to certain criteria, in order to avoid breakdowns and maintain good performance. It allows for the detection of problems before they occur and for necessary repairs. Its main objectives are:

- Reduce the frequency of equipment failures,
- Reduce the cost of outages,
- Improve production system availability,
- Increase the reliability of machines,
- Optimize equipment life cycle efficiency,
- Improve task planning,
- Simplify inventory management

Preventive maintenance (PM) policies are presented below:

- Regular PM: Maintenance tasks are scheduled after a certain period of regular operation.
- Conditional PM: Maintenance is performed when a sign of wear or problem is detected, as the average time between failures is unknown.
- Systematic PM: Maintenance is performed at regular intervals after a number of operating periods.
- Cyclical PM: A maintenance cycle (for example, every 30 days) is defined. Each machine undergoes maintenance at each cycle.
- Indicative PM: An optimal interval is defined for each machine, and maintenance is performed after this period.
- Critical PM: Maintenance is performed when a critical signal is received, for example, when the level of an upstream buffer reaches a threshold. Maintenance is also performed on all other machines in the same group.
- Limited PM: This maintenance policy is applied according to specific criteria limited to certain machines or situations.

If a failure occurs before planned preventive maintenance, the machine will wait for this intervention to be repaired. Although preventive maintenance is often preferred, corrective maintenance remains vital. Unplanned outages can always happen and must be dealt with quickly.

Mixed maintenance (MM)

Mixed maintenance combines corrective and preventive maintenance policies. If a failure occurs prior to preventive maintenance, corrective maintenance can be performed.

- Permissive MM, Cyclical MM, or Indicative MM: Similar to systematic preventive maintenance, but in the event of a failure before preventive maintenance, the machine is repaired and the next preventive maintenance is scheduled after a certain operating time.
- Functional MM: In case of failure, regular repair is carried out and preventive maintenance is applied to other machines of the same type (assembly, series, disassembly).
- Cellular MM: When a machine breaks down, it is repaired and preventive maintenance is performed on all other machines in the same group.

2.3 Manufacturing systems modelling tools

Petri-net modelling

To model a system, you need a clear model that shows how it works. The tool used must be able to explain coordination, resource sharing and measure performance. Petri nets (RdP) are often chosen because they have many advantages Florin and Natkin (1985).

They help to better understand the system (qualitative benefits) and also allow for precise calculations (quantitative benefits). For example, they show the structure of the system well, facilitate communication, manage resources, and adapt easily. They can also take failures into account, help plan maintenance, and measure reliability and performance.

Petri nets are very useful for production systems because they can represent actions that happen at the same time and conflicts between these actions. This helps to better organize and improve manufacturing systems.

Markov chain modelling

Markov chains are used to model stochastic transitions between different states of a system, such as operating or failure states in manufacturing systems. They are suitable for analyzing the reliability and performance of systems where events are probabilistic. These models are particularly used to assess equipment life and predict potential failures (Simeu-Abazi et al. (1997)).

Hybrid and multi-agent approaches

Hybrid approaches combine different models (such as Petri nets and Markov chains) to better represent the complex dynamics of a manufacturing system. Multi-agent systems, where each machine or component of the system is modelled as a stand-alone agent, allow processes to be optimized by taking into account cooperation and competition between agents Ferber and Weiss (1999). These models are useful for simulating distributed production environments and to optimize decision-making in manufacturing systems.

2.4 Simulation tools

Simulation of production flows

Production flow simulation is used to reproduce manufacturing processes in a virtual environment. It allows to analyze the performance of the system under different scenarios and to identify bottlenecks, inefficiencies, or opportunities for improvement (Banks, 2005). The simulation allows to test maintenance policies before their actual implementation, reducing risks and associated costs.

Simulation software (Arena and Alosurf)

In this study, we use two simulation software: Arena and Alosurf. These tools allow modeling and analyzing production systems to evaluate their performance and optimize their operation.
Arena is a discrete event software that facilitates the modeling of production flows and interactions between different machines and operations.
Alosurf focuses on inventory management and the impact of maintenance policies on overall performance. It was chosen here for its ability to directly integrate inventory and maintenance into the simulation, which complements Arena's more general approach and allows accurate results for decision making.

2.5 Decision support methods

Multi-criteria methods (AHP and TOPSIS)

Multi-criteria methods are decision support tools that allow several alternatives to be evaluated by simultaneously considering several criteria. They are particularly suitable for the selection of maintenance strategies, where it is key to balance various factors such as costs, equipment availability, failure risks and overall system performance.
Among these methods, the Analytic Hierarchy Process (AHP), developed by saaty (Saaty, 1980), relies on a hierarchical decomposition of the problem and the use of pairs comparisons to assign weights to criteria and alternatives. This approach is frequently used to structure and streamline complex decisions in maintenance management.
On the other hand, the TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution), is based on the principle that the best alternative is the one which is closest to an ideal solution and furthest from a negative solution. It allows to classify the maintenance strategies according to their overall effectiveness.

Artificial intelligence approaches

Artificial intelligence based approaches such as machine learning and neural networks are used to optimize maintenance decisions by processing large amounts of equipment data. These methods make it possible to predict failures in real time and propose appropriate maintenance interventions.

Optimization and decision making in maintenance Maintenance optimization and decision-making focuses on reducing costs while maximizing equipment reliability and availability. Optimization techniques such as genetic algorithms and linear programming are used to determine the most cost-effective maintenance policy (Rao, 2019).

2.6 Existing works and limits

In recent years, industrial maintenance has evolved with predictive maintenance, Industry 4.0, digital twins and artificial intelligence, while existing work focuses mainly on two types of approaches. A first category studies the optimization and reliability of an isolated machine or equipment, exploiting single-element modelling or simulation techniques, which limits their applicability to complex multi-machine systems. For example, predictive maintenance frameworks driven by digital twins have been proposed to improve multi-level maintenance decision making but remain focused on hierarchical decision structures or sub-sets of components rather than the entire global production system(multi-scale management via digital twin) (Feng et al., 2023).
Another category uses hierarchical decision-making methods, such as multicriteria analysis or AHP, to select maintenance strategies or prioritize actions, but these approaches are often applied to a limited number of machines and do not effectively manage the combinatorial explosion of possible alternatives in larger systems (multicriteria approaches applied to individual or small-scale maintenance cases) (Torres-Sainz et al., 2024).
On the other hand, few works fully and simultaneously integrate system simulation, criticality analysis, and a hierarchical decision-making approach to address the challenges specific to complex multi-machine systems, where interactions between machines, dependencies of failure and maintenance decisions must be considered globally. Recent publications certainly indicate a move towards dynamic decision frameworks or advanced predictive models (notably via machine learning or reinforcement) but not yet a systemic integration with stochastic simulation and multidimensional criticality in a robust hierarchical approach adapted to complex industrial environments (Qiu, 2025).
In this section, we show how our work compares to existing works. We propose an integrated approach that combines simulation, criticality analysis and hierarchical decision-making.

3. METHODOLOGY

3.1 The RDP models of different cells in a production system

In a production system, Petri nets (RdP) are used to model different manufacturing cells according to their organization and mode of operation. The main configurations include:

- Serial cell

This cell represents a production line where tasks are performed sequentially. Each station depends on the completion of the previous operation before it can start. RdP modeling allows to analyze the synchronization between machines, waiting times and flow management.

- Assembly cell

This type of cell is a process where several components are combined to form a final product. The modeling with Petri nets makes it possible to represent the constraints of synchronization between the different supply lines, the management of resources and the scheduling of tasks.

- Disassembly cell

Unlike the assembly, this cell concerns the dismantling of a product into several sub-components. The use of RdP allows to manage the different stages of disassembly, the allocation of resources and the optimization of output flows.

3.2 Taking into account maintenance

Maintenance is about keeping a machine in good working order to minimize breakdowns. It must allow continuous monitoring of each machine in the workshop, including repairs and preventive actions. Therefore, one or more maintenance policies can be assigned to each machine. Thus, an C_i elementary cell is defined as an assembly comprising a M_i machine, the associated maintenance policies, and its input and output inventories, as shown in Fig. 2.

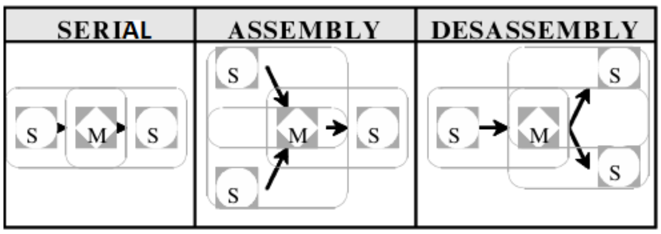

Fig. 2. Principal elementary cells including maintenance

- Corrective Maintenance Modeling

In a manufacturing environment, corrective maintenance is intended to occur after an equipment failure. The optimization of this policy consists in reducing costs and impacts on production, relying on simulation models to evaluate the most effective moments to intervene.

- Preventive maintenance modelling

Preventive maintenance, on the other hand, aims to prevent failures before they occur. Optimizing this policy involves determining the best response frequencies, taking into account maintenance costs and failure risks. The simulation tool makes it possible to test different strategies to maximize equipment availability while minimizing costs.

Before initiating a maintenance procedure, whether corrective or preventive, it is necessary to prepare, organize, and mobilize the operators, spare parts, and tools required. For simplicity, this process can be modeled using an exponential rate, which varies depending on the maintenance policy. Specifically, for corrective maintenance (CM), this rate represents the total duration of corrective maintenance tasks such as testing, detection, localization, diagnostics, and the preparation of operators and tools. In the case of preventive maintenance (PM), this rate only refers to the preparation phase, and the planning of preventive actions can be determined based on various PM policies. For random planning, this rate (β) may follow an exponential distribution.

- Modeling Maintenance in a Production Line

To evaluate the effectiveness of modular modeling, this section focuses on a basic series line. The example presented involves a machine (M), the maintenance policy applied to it (such as corrective maintenance, CM), and its associated input and output stocks. The input (S1) and output (S2) stocks for the machine each have a limited capacity of 1. This series cell can be broken down into three smaller subcells.

3.3 PHADEM methodology

The PHADEM methodology is a structured decision support procedure, and is not limited to a classic application of the AHP method. It aims to integrate simulation, performance analysis and multi-criteria decision-making into a coherent and operational framework for the choice of maintenance strategies.
The PHADEM approach takes place in several successive stages:
1) Simulation of the production system: The industrial system is modeled and simulated in order to represent the actual behavior of machines, production flows and random events such as breakdowns and shutdowns.
2) Calculation of performance indicators: From the simulation results, several indicators are evaluated, including cost, availability, reliability, productivity, maintainability and energy consumption.
3) Machine criticality analysis: The machines of the system are classified according to their degree of criticality, taking into account their impact on the overall performance of the production system.
4) Filtering of machines and maintenance scenarios: Only the most critical machines and maintenance scenarios deemed relevant are retained for in-depth analysis, which reduces the complexity of the problem and the computational effort.
5) Application of the AHP method on relevant cases: The AHP method is then applied only to the filtered scenarios in order to select the most appropriate maintenance strategy for each critical machine.
This approach allows to efficiently combine simulation and multicriteria decision, while avoiding the exhaustive evaluation of all possible combinations of maintenance policies.

4. SIMULATION TOOLS

4.1 Introduction to ALOSURF

ALOSURF (Functional Safety and Reliability Software Workshop) is an advanced software based on stochastic Petri nets (RdP), an efficient method for modelling complex and dynamic systems. With this approach, ALOSURF clearly shows the interactions between different parts of a production system, taking into account random events such as outages, maintenance delays and production variations (Santos et al., 2019).

The software allows to create detailed models that reflect the reality of a production line, including machines, processes and maintenance policies, whether corrective or preventive. It can analyze how failures affect overall performance, which helps to test and optimize different maintenance strategies before they are implemented (SIMEU-ABAZI et al., 1996).

In this study, ALOSURF was used to simulate several maintenance scenarios, model failures and interventions, and analyze related costs. The results identified the best policies to reduce downtime, increase machine availability and decrease costs. Thus, ALOSURF is a valuable tool for improving the management and efficiency of maintenance in production systems.

Performance indicators in ALOSURF

ALOSURF creates several indicators to measure the effectiveness of the simulated production system, especially when integrating maintenance policies. These indicators show the overall system performance and the effect of maintenance strategies (preventive and corrective). The main indicators calculated in ALOSURF with their formulas are as follows:

Cost: This indicator calculates the total operating cost of the production system, taking into account the costs associated with maintenance (preventive and corrective), breakdowns, repairs, and energy consumption. The calculation of total cost allows to determine the economic impact of different maintenance policies.

$$C = C_{Maintenance} + C_{Production} + C_{Outages} \qquad (1)$$

Availability: Availability is the proportion of time that each machine or system as a whole is operational. It is directly dependent on the effectiveness of maintenance policies and unplanned outages. A high availability rate is core to ensure smooth and continuous production. Availability measures the proportion of time that the production system is operational in relation to the total expected time.

$$A = \frac{\mathrm{MTBF}}{(\mathrm{MTBF} + \mathrm{MTTR})} \qquad (2)$$

Reliability: Reliability measures the ability of a machine to operate without failure for a given period. This indicator is directly influenced by the frequency of failures and the success of preventive maintenance. A reliable machine has a low failure rate, which optimizes production.

$$R(t) = \exp(-\lambda t) \qquad (3)$$

with λ: Machine failure rate and t: Operating time.

Productivity: Productivity shows how much the system produces over a period of time. ALOSURF calculates it taking into account the efficiency of machines, unplanned shutdowns and maintenance. This is an important indicator of whether the system is cost-effective. It is calculated by dividing production by resources used, such as operating time or number of operators.

$$\mathrm{P} = \frac{\text{Production}}{\text{Total Operating Time}} \qquad (4)$$

Ratios: Several ratios can be calculated to analyze the performance of the system, such as the machine performance ratio, which compares the actual output with the expected theoretical output. These ratios help identify system inefficiencies and identify areas for improvement.

Maintainability: Maintainability measures the ability of a system to be repaired within a reasonable time.

$$\mathrm{M} = \frac{1}{\mathrm{MTTR}} \qquad (5)$$

Failure rate: The failure rate indicates the frequency of failures within a given period. A high failure rate is often a sign of an inappropriate maintenance strategy, requiring adjustments.

Mean Time to Repair (MTTR) and Mean Time Between Failures (MTBF): These two indicators are used to assess the average time required to repair equipment after a failure (MTTR) and the average time between two successive failures (MTBF). These measurements are necessary to assess the performance of equipment and maintenance processes.

Reliability-based models: Models like Markov's allow to predict failures and choose the right maintenance strategy. They help to know when a machine is likely to break down.

The indicators used in ALOSURF are used to measure system performance. Thanks to them, we can improve maintenance, production and management.

In the production lines simulated with ALOSURF, the effect of preventive and corrective maintenance is measured. An indicator on energy consumption is also added.

Environment: When optimizing maintenance strategies, it is important to include environmental criteria such as energy consumption. This often overlooked parameter plays a crucial role in the sustainability of production systems and their compliance with environmental standards. The energy consumption of machine i is calculated taking into account all its periods of operation (we do not take into account its period of maintenance and shutdown) and we consider that each machine i has a particular usage rate. It can be expressed as follows:

$$\mathrm{E}_i = (\mathrm{Power}_i \times \mathrm{Duration}_i) \times \mathrm{Usage}_i \qquad (6)$$

with:

- E_i is the energy consumption of machine i (in kWh).
- Power_i is the power consumed by machine i (in kW).
- $\mathrm{Duration}_i$ is the total operating time of machine i (in hours).
- Usage_i is the usage rate of machine i.

A Dashboard, why ?
The dashboard (Fig. 3) and Table 1, from management to operators, allow four types of indicators to be monitored: productivity, costs, reliability and availability. These indicators help to measure the performance of the production system at all levels of the enterprise. Maintenance ratios provide accurate data to monitor and improve these points, quickly identifying what needs to be corrected. Each level can make appropriate decisions to produce better, reduce costs, or make machines more reliable and available. The dashboard then serves as a management and communication tool for everyone to work together to improve overall performance.

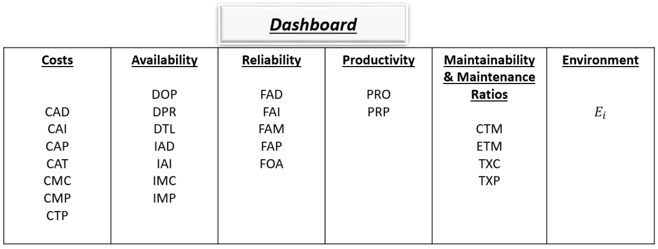

Fig. 3. The indicators dashboard

Table 1. list of indicators used

Sigle	Signification
CAD	Cost of Downtime due to Failure
CAI	Cost of Induced Downtime
CAP	Cost of Own Downtime
CAT	Total Downtime Cost
CDP	Direct Production Cost
CMC	Downtime Cost for Corrective Maintenance
CMP	Downtime Cost for Preventive Maintenance
CMS	Cost of Maintenance in Operating Condition
CTM	Total Maintenance Cost
CTP	Total Production Cost
DOP	Operational Availability
DPR	Proper Availability
DTL	Total Availability
ETM	Technical Efficiency of Maintenance
FAD	Frequency of Downtime due to Failure
FAI	Frequency of Induced Downtime
FAM	Frequency of Downtime due to Maintenance
FAP	Frequency of Own Downtime
FOA	Operational Downtime Frequency
IAD	Unavailability due to Failures
IAI	Unavailability due to Induced Downtime
IMC	Unavailability due to Corrective Maintenance
IMP	Unavailability due to Preventive Maintenance
PRO	Operational Productivity
PRP	Own Productivity
THA	Hourly Rate
TRQ	Required Time
TXC	Corrective Rate
TXP	Preventive Rate

4.2 Example of results obtained for a serial cell

To illustrate the configuration of the series cell modelled in ALOSURF, we will use the following Fig 4. It is a production line in series configuration, composed of two machines separated by a stock capacity 3 pieces. The system's input and output stocks are considered to be of infinite capacity.

In this case, a preventive maintenance policy is applied to the first machine, while a corrective maintenance policy is associated with the second machine. This approach allows to explore the effects of these different maintenance policies on system performance.

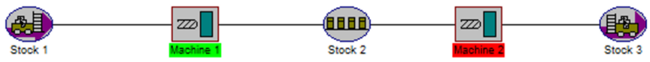

Fig. 4. Series cell modelled in ALOSURF with preventive and corrective maintenance

The simulation results obtained via ALOSURF for this configuration are summarized in a table. They include key indicators such as the overall system availability rate, total maintenance cost and production rate. These results will then be used as a basis for applying the AHP method to compare different maintenance strategies.

The technical parameters used to model machine behaviour are:

- ϵ: average loading rate
- δ: average service rate
- λ: average failure rate
- μ: average repair rate

These parameters have been entered for each machine according to their respective configuration (preventive or corrective), as summarized in Table 2. They form the basis of the simulation model.

Table 2. Production system parameters for Machines 1 and 2 (Duration = 5000h)

Known data	Machine M1	Machine M2
Component parameters	$\varepsilon_1 = 10$ $\delta_1 = 1$ $\lambda_1 = 0.015$ $\mu_1 = 0.3$	$\varepsilon_2 = 20$ $\delta_2 = 1.5$ $\lambda_2 = 0.01$ $\mu_2 = 0.25$
Probabilities of component states *(Based on 4 simulations)*	$Pr_{R1} = 0.18464$ $Pr_{M1} = 0.7486425$ $Pr_{P1} = 0.0000$ $Pr_{A1} = 0.0667175$	$Pr_{R2} = 0.4294325$ $Pr_{M2} = 0.4294325$ $Pr_{P2} = 0.492595$ $Pr_{A2} = 0.05763$
External data	TRQ(M1)=5000h THA(M1)=100€/h CDP(M1)=100,000€ CMS(M1)=20,000€	TRQ(M2)=5000h THA(M2)=100€/h CDP(M2)=100,000€ CMS(M2)=20,000€

The simulation results with ALOSURF are presented in Table 3 and show key indicators such as availability, maintenance cost and production rate. As the breakdowns are random, several simulations are necessary to obtain a representative average, which will then be used to compare the maintenance strategies with the AHP method.

4.3 Application of the AHP method for the serial cell

The results obtained from the ALOSURF simulation are analyzed through several key indicators: availability, maintenance cost and productivity. These indicators serve as the basis for applying the AHP (Analytic Hierarchy Process), a multi-criteria decision support method that allows several alternatives to be compared according to prioritized and weighted criteria.
The AHP begins by organizing criteria into a hierarchical structure, ranging from the overall objective (choosing the best maintenance strategy) to evaluation criteria, up

Table 3. Indicator calculations for Machine 1 and Machine 2

Indicators	Machine M1	Machine M2	Unity
CAD	0	5027.91	€
CAI	14563.98	32818.41	€
CAP	8574.47	9826.22	€
CAT	23124.41	24596.13	€
CMC	0	4793.21	€
CMP	8574.47	0	€
CTP	38833.73	57883.01	€
DOP	73.6245	48.045	%
DPR	91.0425	84.3725	%
DTL	80.8975	56.935	%
IAD	0	12.08	%
IMC	0	4.5375	%
IAI	20.5975	47.28	%
IMP	8.9575	0	%
FAD	0	0.0164925	Arrêt/h
FAI	1.9105475	8.61316	Arrêt/h
FAM	1	0	Arrêt/h
FAP	1	0.0164925	Arrêt/h
FOA	2.9105475	8.826525	Arrêt/h
PRO	0.73649	0.7206975	p/h
PRP	0.910541	1.2656325	p/h
CTM	22.3375	8.29	%
ETM	0	50.695	%
TXC	0	100	%
TXP	100	0	%
Ei	2670452.5	1533235.25	kWh

to possible scenarios. Each criterion is then weighted according to its relative importance, and each alternative is evaluated against these criteria. This approach helps to determine the most balanced solution.

In our case, we have developed a dedicated algorithm, called PHADEM (Analytical Hierarchical Process for Maintenance Decision), which applies the principles of the AHP to identify the optimal maintenance policy for each machine.

The PHADEM algorithm (Fig 5) consists of three main steps:

- Evaluation of the performance and safety of each machine based on measured or simulated indicators,
- Classification of machines according to their criticality,
- Selection of the most appropriate maintenance strategy for the machine deemed to be the most critical.

The objective is to optimize overall performance and operating safety (PSdF) by finding a compromise between different technical and environmental criteria.

To simplify the model, we have reduced the initial hierarchy by keeping only, three cost indicators, three reliability indicators, and the indicator "energy consumption" for environmental impact. The final hierarchy used in our approach is shown in Fig 6.

To rank machines by importance, we compared performance indicators using matrices, where each element represents the relationship between machine values for a given indicator. Then, for each line, we calculated the geometric mean of the elements, according to the formula:

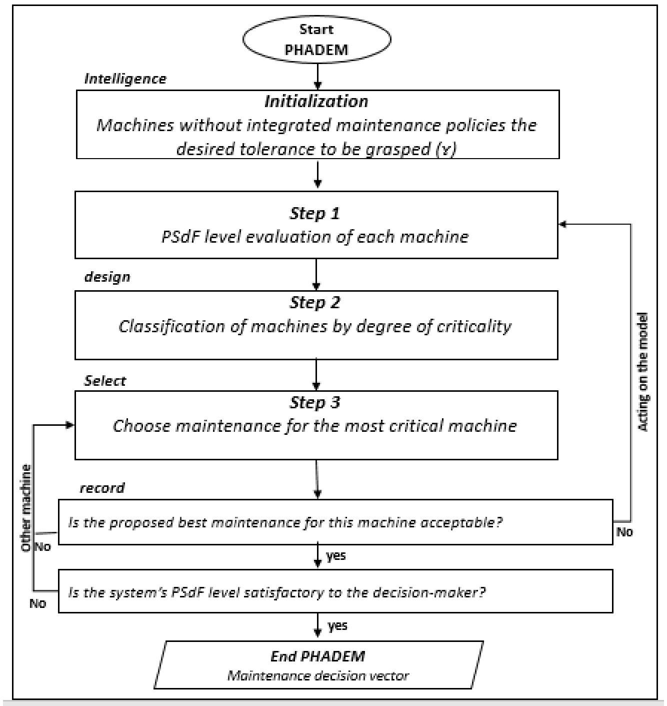

Fig. 5. PHADEM algorithm for the maintenance decision

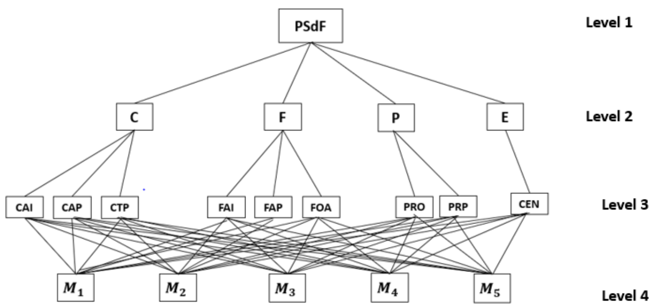

Fig. 6. Simplified hierarchy

$$W_i = \left(\prod_{j=1}^{n} Z_{ij} \right)^{1/n} \tag{7}$$

where i is the priority of the i machine and Z_{ij} is the element of the matrix. These values are then normalized between 0 and 1 to obtain a ranking, and to determine the relative importance of the different criteria, we use the comparison matrix (Example Fig. 7) using the table with a scale from 1 to 9 for pairs comparisons Table 4.

[Q]=

(PSdF)	C	F	P	E
C	1	2	3	6
F	1/2	1	2	4
P	1/3	1/2	1	3
E	1/6	1/4	1/3	1

Fig. 7. Comparison Matrix

Table 4. 1-9 scale of pairs comparisons

Intensity of Importance	Definition
1	Equal importance
3	Weak importance of one over another
5	Moderate importance
7	High importance
9	Absolute importance
2, 4, 6, 8	Intermediate values between the two adjacent judgments when a compromise is needed

This approach allows us to compare the criteria between them and assign a weight to them according to their impact on overall performance. Thanks to this method, we were able to identify the most critical machines and demonstrate that the M1 machine is more efficient when it benefits from preventive maintenance.

5. APPLICATION TO THE CAR PRODUCTION WORKSHOP

5.1 Presentation of the workshop and its different cells

The production workshop studied corresponds to an automobile assembly line organized in several functional cells. These cells include, but are not limited to, the painting, disassembly and other intermediate steps necessary for the complete manufacture of a vehicle. Each item plays a key role and is interconnected through a sequential production flow.

The simulation diagram used is a model of an automotive production process Fig 8, structured around five machines (or workstations) separated by eight storage areas (stocks). The S1, S2 stocks are assumed to be of infinite capacity, allowing an entry/exit without restriction of parts. On the other hand, other stocks have a limited capacity of 5 pieces, which can lead to blockages or expectations in the flow if these areas are saturated.

This model allows to analyze the effects of different maintenance scenarios and detect critical points in the production line. The objective is to optimize flow continuity and minimize time losses due to machine downtime or congestion of storage areas.

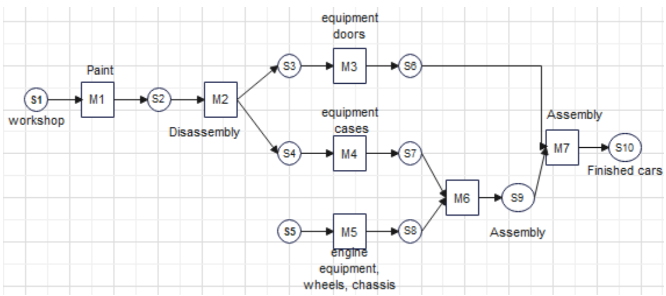

Fig. 8. Diagram of the production system

5.2 Table of data for each cell

For each cell in the production workshop, a known data set was identified upstream. These data mainly concern the structure of the cell (Average load rate (ε), Average service rate, Average failure rate (λ), Average repair rate (μ)) and the basic assumptions used for the simulation. Other

Known data	M1	M2	M3	M4	M5
Component parameters					
ε	10	20	20	20	10
δ	1	1.5	1.5	1.5	1
λ	0.015	0.01	0.01	0.01	0.015
μ	0.3	0.25	0.25	0.25	0.3
State probabilities					
Pr_R	0.08762	0.64737	0.64294	0.65092	0.47163
Pr_H	0.86552	0.33259	0.33579	0.33946	0.49858
Pr_P	0.04686	0.02006	0.02128	0.00961	0.02979
Pr_A	0	0	0	0	0
External data					
TRQ (h)	5000				
THA (FF/h)	100				
CDP (FF)	100 000				
CMS (FF)	20 000				

Fig. 9. Technical data and state probabilities for system components (Duration = 5000h)

information required for modeling, such as component parameters, probabilities of states or some external data, is generated or calculated automatically via the ALOSURF tool during the simulation phase, see Fig 9.

The simulation was performed over 5000 hours with 10 repetitions to ensure reliable results. The time between failures and repair times follow an exponential law, while service durations are considered deterministic.

The simulation results for the M1 machine reveal several points of concern. Although it is running (Pr_R) 86.5% of the time, which seems acceptable at first glance, it still spends about 9% of the time in the assumed state (Pr_M), which may indicate poor synchronization with the rest of the line or unnecessary waiting times. In addition, the machine is down about 4.7% of the time (Pr_P), which is not negligible and could significantly impact production if these failures are frequent or long. The absence of a prolonged shutdown (Pr_A) is positive, but current levels of availability and outages suggest that the maintenance strategy in place is not optimal. Improvement is needed to reduce unproductive downtime and improve overall system performance.

The state probability curves (Probabilities of machines condition (rest, on, off, failure) represented in Fig 10 are also used to visualize the dynamics of machines and identify potential sources of performance degradation.

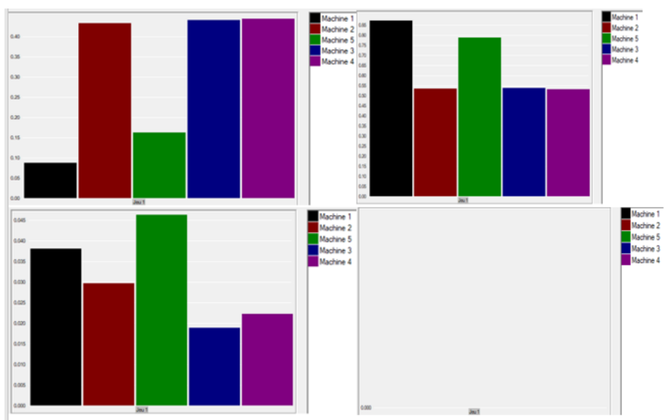

Fig. 10. Probabilities of machines condition (rest, on, off, failure)

5.3 Simulation results without maintenance integration

Initially, a simulation was performed without integrating a maintenance policy. This phase aims to evaluate the natural behavior of the system in the face of failure hazards, without any preventive or corrective maintenance. It allows identifying the intrinsic weaknesses of the system and measuring its basic performance level. For this, several key performance indicators (availability, cost, production rate, etc), were calculated from the simulation results, such as machine availability, production rate, and overall cost of operating the system. The values obtained for each of these criteria are summarized are presented in Table 5 , providing an overview of the performance of each production cell in the absence of a maintenance strategy. This table is an crucial reference point for evaluating the impact of the different maintenance policies tested.

Table 5. Calculation of indicators for the five machines

Indicators	**M1**	**M2**	**M3**	**M4**	**M5**	**Unity**
CAD	3572.13	1528.75	1622.90	732.59	2270.48	€
CAI	6678.77	49030.68	49614.47	35912.88	0	€
CAP	3572.13	1528.75	1622.90	732.59	2270.48	€
CAT	10250.89	50848.96	50598.67	50314.14	38182.12	€
CMC	0	0	0	0	0	€
CMP	0	0	0	0	0	€
CTP	25495.79	66126.45	65912.94	65521.21	53426.43	€
DOP	86.55	33.26	33.58	33.95	49.86	%
DPR	94.86	94.31	94.04	97.25	94.36	%
DTL	91.24	35.27	35.71	34.91	52.84	%
IAD	5.14	5.69	5.96	2.75	5.64	%
IAI	9.19	66.06	65.69	65.72	48.61	%
IMC	0	0	0	0	0	%
IMP	0	0	0	0	0	%
FAD	0.01406	0.00502	0.00532	0.00240	0.00894	stop/h
FAI	0.87620	12.94699	12.85873	13.01848	4.71633	stop/h
FAM	0	0	0	0	0	stop/h
FAP	0.01406	0.00502	0.00532	0.00240	0.00894	stop/h
FOA	0.89026	12.95200	12.86405	13.02088	4.72527	stop/h
PRO	0.86552	0.49888	0.50368	0.50919	0.49858	p/h
PRP	0.94864	1.41467	1.41062	1.45869	0.94362	p/h
CTM	0	0	0	0	0	%
ETM	0	0	0	0	0	%
TXC	0	0	0	0	0	%
TXP	0	0	0	0	0	%
E_i	3089906.4	1187346.3	1198770.3	1211872.2	1779930.6	kWh

To assess the performance and criticality of each machine in the system, it is also fundamental to calculate the reliability of each component as well as its importance factor. The reliability of a machine is determined by its failure rate and average time between failures (MTBF - Mean Time Between Failures). This calculation estimates the probability that a machine will function properly over a given period of time without failure. The reliability expressed according to equation (3).
The significance factor, on the other hand, is an indicator that measures the impact of a machine failure on the overall system. It takes into account not only the reliability of the machine, but also its contribution to the production line and its role in the production flow. The more critical a machine is for the proper functioning of the system, the higher its importance factor will be. The importance factor for each machine ii is calculated taking into account the reliability of the machine in operation and the machine out of service. The significance factor is given by the difference between these two values as follows:
Equation:

$$\mathrm{F}_i = \mathrm{R_i}(\text{machine on}) - \mathrm{R_i}(\text{broken machine}) \quad (8)$$

The reliability R_i of a running machine is calculated from its failure rate λ and observation time t, according to the following equation:

$$R_i(\text{MachineOn}) = e^{-\lambda t} \quad (9)$$

In contrast, the reliability of a machine in failure is zero, which gives:

$$\mathrm{R_i}(\text{Broken Machine}) = 0 \quad (10)$$

Thus, the factor of importance F_i is simply equivalent to the reliability of the machine when it is running. This calculation makes it possible to identify the most sensitive machines, which require special attention in terms of maintenance strategy.
Machines with the highest importance factor, calculated from their reliability, are considered the most critical and should be prioritized for maintenance to reduce downtime and optimize system performance.
After all the calculations made and summarized in Fig 11, it is found that M1 and M5 machines are the most critical, having the highest degree of criticality, which means they have a more significant influence on the system. This analysis highlights the importance of integrating appropriate maintenance policies for these machines. It is therefore key to integrate corrective maintenance (MC) and then preventive maintenance (MP) in ALOSURF for M1 and M5 to optimize system availability and productivity.

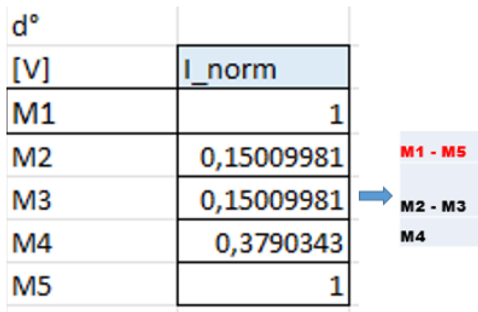

Fig. 11. Classification of machines according to their degree of criticality

5.4 Maintenance policy integration

In this section, we integrate different maintenance policies into the ALOSURF model to illustrate the impact of corrective and preventive maintenance on machine M1. we use the same parameter values for components (known data).
In this scenario (Fig 12), we associate a corrective maintenance policy with the M1 machine. This policy occurs when the machine fails, and the system triggers a corrective maintenance to restore it. Downtime and costs associated with these outages are simulated in the model.

In another scenario, we add a second maintenance policy, namely systematic preventive maintenance. This policy consists of performing planned maintenance on M1, regardless of the condition of the machine, to prevent failures before they occur. This approach maximizes machine performance and reliability while reducing the risk of unplanned downtime.

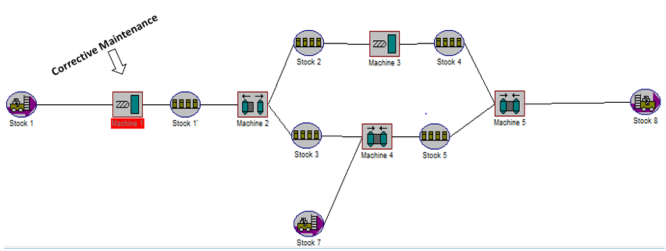

Fig. 12. Machine 1 corrective maintenance scenario in ALOSURF

By combining these two maintenance policies, we can observe and analyze the interactions between corrective and preventive maintenance in the ALOSURF model and study their impact on the overall performance of the production system.

5.5 Application of the AHP method for decision support

The AHP method, as well as how our PHADEM algorithm works, were detailed in the previous section. In this part, we apply them concretely to evaluate two maintenance scenarios: Scenario 1: corrective maintenance on M1; Scenario 2: systematic preventive maintenance on M1. The performance indicators obtained from the ALOSURF simulation (availability, cost, productivity etc.) are used as evaluation criteria. These values are integrated into a series of comparison matrices, in which each criterion is related to the others according to the defined priorities. Each alternative is then compared according to these matrices, which makes it possible to calculate an overall score for each scenario. We compared the simulation results with theoretical values from known formulas. This validates the reliability of the simulation results. The results show that the M1 machine performs better when preventive maintenance is performed (Scenario 2). In contrast, in the corrective maintenance scenario (Scenario 1), the M1 machine is less efficient, but the other machines (M2, M3, M4 and M5) become more significant to maintain production. In comparison between the two scenarios (Fig 13), we see that the best performance of M1 is obtained with preventive maintenance. However, the M2, M3, M4 and M5 machines perform less well in this scenario, but are still more important for the overall balance of the system. Thus, the scenario with systematic preventive maintenance for M1 is more advantageous for this machine, while highlighting the importance of managing other machines.

Perf Cor			Perf Prev	
[U]	PSdF		[U]	PSdF
M1	3,0613658	<	M1	2,2793405
M2	1,9815482		M2	1,7293246
M3	2,0436202		M3	1,7839391
M4	2,0819165		M4	1,8185428
M5	1,8467221	>	M5	1,4671452

Fig. 13. Performance Comparison between Preventive and Corrective Maintenance for the M1 Machine

5.6 Discussion on the Results

The results obtained from the corrective and preventive maintenance simulations offer an interesting perspective on the impact of these strategies on the overall performance of the production system. After comparing the two scenarios, several important points emerge.

M1 Machine Performance: The analysis shows that the M1 machine performs better when preventive maintenance is applied. Indeed, in the preventive maintenance scenario (Scenario 2), the machine remains operational longer, which allows for better availability and a reduction in the number of unexpected failures. However, in the corrective maintenance scenario (Scenario 1), although the M1 machine is less efficient due to the need for frequent repairs after failures, it does allow for better management of other machines in the system.

Impact on other machines: When applying corrective maintenance, M2, M3, M4, and M5 machines play a more important role in maintaining production as failures on M1 cause adjustments to the overall system. However, when preventive maintenance is used for M1, these machines become less efficient because the focus is on keeping M1 in good working order.

Maintenance cost and strategy feasibility: Although preventive maintenance for M1 offers better performance in terms of availability and productivity, it results in higher maintenance costs. This cost increase must be balanced against the gains achieved in terms of reduced downtime and production optimisation. Corrective maintenance, while potentially involving lower costs in the short term, can result in more frequent production shutdowns affecting overall productivity.

Towards integration in Industry 4.0: This modeling approach can be used as a basis for future integration with Industry 4.0 technologies. The ALOSURF model, combined with IoT sensors and a digital twin, would allow for real-time monitoring of machine status and failure anticipation to improve decision making and production system performance.

Choosing the optimal strategy: In summary, although preventive maintenance is the best option to ensure the high performance of the M1 machine, corrective maintenance may be more appropriate in situations where costs need to be minimized. The hybrid approach, combining both strategies depending on the state of the machines, could offer an optimized solution, balancing performance and maintenance costs. The results obtained highlight the importance of adapting maintenance strategies to the specific characteristics of the production system, in order to maximize overall performance while minimizing associated costs.

6. CONCLUSION

6.1 Synthesis of this work

In this work, we developed a multi-criteria decision support model for the optimization of maintenance policies in a manufacturing production system. The approach is based on key criteria such as cost, reliability, availability, maintainability and environmental impact. Through the Alosurf simulation tool, we modelled several maintenance scenarios applied to different critical machines in the workshop.

The analysis compared the effect of corrective maintenance and systematic preventive maintenance on overall system performance.It was conducted using simulated data, as real-world industrial values were not accessible for this study. The results show that preventive maintenance applied to the M1 machine leads to a significant improvement in the availability and stability of the process, while corrective maintenance, although less expensive, exposes the system more to disturbances.

The proposed model, based on a hierarchy of criteria via the AHP method coupled with the PHADEM algorithm, has proven its effectiveness in guiding decision-makers to choose the most appropriate maintenance strategy according to the production context.

6.2 Development prospects

In the light of these results, several avenues of research can be explored:

(1) Extension of the model to the entire production chain, integrating several critical positions and taking into account their interdependence.
(2) Integration of machine learning to develop a predictive system capable of dynamically adapting maintenance strategies based on data collected in real time.
(3) Addition of new evaluation criteria, such as energy constraints or carbon emissions, to propose more sustainable and responsible maintenance policies.
(4) Experimental field validation of the proposed model using real industrial data, in order to strengthen its robustness and transferability.
(5) Development of an interactive user interface for maintenance managers, facilitating the visualization of scenarios and decision-making in a dynamic industrial environment.

This work thus paves the way for a more intelligent maintenance management in industrial systems, reconciling technical, economic and environmental performance.

REFERENCES

Askin, R.G. and Standridge, C.R. (1993). Modeling and analysis of manufacturing systems. *(No Title)*.

Banks, J. (2005). *Discrete event system simulation*. Pearson Education India.

Barlow, R.E. and Proschan, F. (1996). *Mathematical theory of reliability*. SIAM.

El-Khalil, R. (2015). Simulation analysis for managing and improving productivity: A case study of an automotive company. *Journal of Manufacturing Technology Management*, 26(1), 36–56.

Feng, Q., Zhang, Y., Sun, B., Guo, X., Fan, D., Ren, Y., Song, Y., and Wang, Z. (2023). Multi-level predictive maintenance of smart manufacturing systems driven by digital twin: A matheuristics approach. *Journal of Manufacturing Systems*, 68, 443–454.

Ferber, J. and Weiss, G. (1999). *Multi-agent systems: an introduction to distributed artificial intelligence*, volume 1. Addison-wesley Reading.

Florin, G. and Natkin, S. (1985). Les réseaux de petri stochastiques, technique et science informatiques, vol.

Groover, M.P. (2016). *Automation, production systems, and computer-integrated manufacturing*. Pearson Education India.

Koren, Y., Gu, X., and Guo, W. (2018). Reconfigurable manufacturing systems: Principles, design, and future trends. *Frontiers of Mechanical Engineering*, 13, 121–136.

Lee, J., Bagheri, B., and Kao, H.A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing letters*, 3, 18–23.

Qiu, S. (2025). Optimizing predictive maintenance in intelligent manufacturing: An integrated fno-dae-gnn-ppo mdp framework. *arXiv preprint arXiv:2511.05594*.

Rao, S.S. (2019). *Engineering optimization: theory and practice*. John Wiley & Sons.

Saaty, T.L. (1980). The analytic hierarchy process (ahp). *The Journal of the Operational Research Society*, 41(11), 1073–1076.

Santos, F.P., Teixeira, Â.P., and Soares, C.G. (2019). Modeling, simulation and optimization of maintenance cost aspects on multi-unit systems by stochastic petri nets with predicates. *Simulation*, 95(5), 461–478.

Sassine, C., Simeu-Abazi, Z., and Descotes-Genon, B. (1996). Modelling of maintenance policies by petri nets: Application to series production line. In *Symposium on discrete events and manufacturing systems (Lille, July 9-12, 1996)*, 752–757.

SIMEU-ABAZI, Z., SASSINE, C., DANIEL, O., and JUTTET, P. (1996). Alosurf pour l'évaluation des paramètres caractéristiques de la sûreté de fonctionnement des systèmes de production. In *10e colloque national de fiabilité & maintenabilité (Saint Malo, 1-3 octobre 1996)*, 751–760.

Simeu-Abazi, Z., Daniel, O., and Descotes-Genon, B. (1997). Analytical method to evaluate the dependability of manufacturing systems. *Reliability Engineering & System Safety*, 55(2), 125–130.

Simeu-Abazi, Z. and Sassine, C. (2001). Maintenance integration in manufacturing systems: from the modeling tool to evaluation. *International Journal of Flexible Manufacturing Systems*, 13(3), 267–285.

Taous, H., Gascard, E., Simeu-Abazi, Z., and Njima, C.B. (2024). Joint modeling of preventive and corrective maintenance in production workshop simulation: a literature review. In *International Conference on Control, Automation and Diagnosis (ICCAD 2024)*. IEEE.

Torres-Sainz, R., Sánchez-Aguilera, L., Trinchet-Varela, C.A., Pérez-Vallejo, L.M., and Pérez-Rodríguez, R. (2024). Maintenance strategy selection using bayesian networks. *Production*, 34, e20240010.

Wang, H., Pham, H., et al. (2006). *Reliability and optimal maintenance*, volume 14197. Springer.

Wiendahl, H.P., ElMaraghy, H.A., Nyhuis, P., Zäh, M.F., Wiendahl, H.H., Duffie, N., and Brieke, M. (2007). Changeable manufacturing-classification, design and operation. *CIRP annals*, 56(2), 783–809.

Zonta, T., Da Costa, C.A., Zeiser, F.A., de Oliveira Ramos, G., Kunst, R., and da Rosa Righi, R. (2022). A predictive maintenance model for optimizing production schedule using deep neural networks. *Journal of Manufacturing Systems*, 62, 450–462.