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INTEGRATED MODELING OF PRODUCTION, MAINTENANCE, QUALITY, AND INVENTORY IN OPEN SHOPS CONSIDERING UNCERTAINTY AND HUMAN LEARNING

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***ABSTRACT*:**

In complex manufacturing environments, simultaneous decision-making in production and maintenance domains is of great importance, since the overall performance of the system is strongly influenced by the interaction among production planning, resource allocation, and maintenance policies. In this study, a multi-objective mathematical model is developed for production and maintenance scheduling in open shop systems, pursuing three main objectives simultaneously: minimizing the total system cost, reducing the makespan, and minimizing downtime caused by equipment failures. To solve this model, the NSGA-II algorithm is employed as an effective metaheuristic approach for multi-objective optimization. Moreover, three scenarios are designed and implemented to analyze model behavior across different system sizes. The obtained results indicate that as the system scale increases, both the average and dispersion of objectives rise, reflecting higher complexity and greater sensitivity of managerial decisions in larger systems. Furthermore, Pareto front analysis reveals the inherent conflict among objectives, as cost reduction is generally accompanied by increased downtime. Nevertheless, the presence of clustered regions on the Pareto front highlights balanced and efficient trade-off solutions. This research can serve as a decision support tool in real manufacturing environments and provide a foundation for the development of more advanced models in the future.

Keywords*: Production and maintenance scheduling; Open shop systems; Metaheuristic algorithm; Uncertainty; Human learning.*

INTRODUCTION

The most deadly t

In recent decades, profound transformations in the competitive manufacturing landscape and the growing need for rapid and flexible responses to market changes have compelled manufacturing industries to rethink the design and operation of their production systems (Liu et al., 2021a). One of the most innovative production paradigms developed in response to these demands is the open shop system. Unlike traditional systems such as flow shops or classical job shops, in open shop systems the processing routes of parts are not predetermined, offering a high degree of flexibility in machine selection, processing sequences, and human resource allocation (Sahebi et al., 2024; Yang & Panichakarn, 2025). This characteristic makes open shop systems particularly suitable for diverse, order-driven production environments with highly customized products (Zonta et al., 2022).

However, the structural flexibility of these systems, coupled with the dynamic nature of manufacturing environments, introduces new managerial challenges, especially in the areas of scheduling, maintenance, and inventory control. One of the most complex aspects of these challenges is the integration of multiple decision levels at both tactical and operational layers, where production planning, preventive and corrective maintenance policies, quality inspections, and inventory decisions must be executed simultaneously, in coordination, and under the constraints of human resources, machine capacity, and uncertainty (Atmaca et al., 2025; N. Wang et al., 2020). Although many classical models have considered these decisions independently, industrial reality has shown that they are highly intertwined, and separate decision-making often leads to impractical and inefficient solutions.

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The importance of addressing this issue is highlighted from several perspectives. First, machine failures are one of the main causes of productivity loss, cost escalation, and order delivery delays. In real production settings, failures are not only random, but repair times are also uncertain and heavily influenced by factors such as failure severity, the skill level of technicians, and their learning effects (Hendalianpour et al., 2019). Ignoring these characteristics leads to unrealistic scheduling estimates. Second, preventive maintenance, if appropriately designed, can avoid many failures, but it is costly and should not be performed excessively or prematurely. On the other hand, corrective maintenance, although reactive, becomes essential and unavoidable when failures occur. A balanced combination of these two strategies and the design of optimal maintenance policies play a pivotal role in reducing downtime, enhancing reliability, and ensuring production sustainability (Pinto et al., 2020; Tong et al., 2025).

Moreover, in many industries, product quality is highly dependent on machine performance and production conditions. Poor or uncontrolled quality not only leads to scrap and rework costs but can also disrupt the entire supply chain (Hendalianpour et al., 2020; Y. Wang et al., 2025). Therefore, integrating quality-related decisions alongside production and maintenance is an undeniable necessity. Similarly, decisions on optimal inventory levels, whether raw materials, semi-finished, or finished goods—must ensure that the risks of shortages or production interruptions are minimized, while avoiding excessive inventory and storage costs. Synergizing inventory policies with other managerial decisions improves service levels and enhances the financial balance of the system (Duffuaa et al., 2020).

A review of the literature reveals that despite extensive research on production, maintenance, quality, or inventory management as independent domains, relatively few studies have integrated all four components into a comprehensive framework—particularly within open shop environments, which are inherently complex, dynamic, and flexible. Most existing models either focus on one of these domains or rely on oversimplified assumptions regarding machine failures, constant repair times, or homogeneous workforce skills. Furthermore, very few models systematically incorporate the effect of human learning on repair time reduction and, consequently, system-wide performance improvement. Additionally, many prior models have either ignored environmental uncertainties or addressed them only partially (e.g., demand uncertainty), whereas in industrial reality, failure rates, processing times, energy costs, and even maintenance policy effectiveness are all inherently uncertain. Thus, the main gap in the existing literature lies in the absence of an integrated, realistic, and multi-objective mathematical framework that enables simultaneous decision-making on production, maintenance (preventive/corrective), quality, and inventory in an open shop system under uncertainty. Such a model should not only capture the internal interactions among these elements but also provide flexibility against diverse environmental scenarios.

In response to this scientific and practical gap, the present study designs develop, and analyzes a comprehensive mathematical model which, while considering the flexible structure of open shops, integrates decision-making on production scheduling, machine allocation, maintenance planning, quality inspections, and inventory management. By incorporating uncertainty in failure rates, repair times, and other critical parameters, the model adopts multi-objective, and robust optimization approaches to generate effective, efficient, and flexible decision-making policies. Moreover, the learning effects and heterogeneous skills of maintenance personnel are explicitly modeled to evaluate the real and data-driven impact of human resources on system reliability and efficiency. The outcome of this research, in addition to providing the Pareto front of optimal decisions, can serve as both scientific and practical guidance for production managers, maintenance engineers, and designers of intelligent manufacturing systems to adopt effective, coordinated, and sustainable solutions in the face of increasingly complex production environments.

Based on the above, the structure of this paper is organized as follows: Section 2 reviews the literature and theoretical foundations, Section 3 presents the problem statement, Section 4 introduces the proposed mathematical model, Sections 5 and 6 describe the solution methodology and computational results, respectively, and finally, Section 7 provides the conclusion.

LITERATURE REVIEW

This section examines studies on the integration of production scheduling and preventive maintenance. Recent research indicates that combining these two domains can lead to significant improvements in productivity and cost reduction.

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Wocker et al., (2024) investigate preventive maintenance activities in automated production systems operating continuously. The study introduces a mixed-integer programming model that simultaneously considers job shop scheduling and maintenance activity allocation. A local search algorithm is developed to solve these two problems in an integrated manner. Y. Wang et al., (2024) explore the need for a more flexible production approach in response to personalized and dynamic market demand. In this context, parallel production of different product types requires frequent product switches, which impose high demands on error-free machine operation and sustainable production. The paper proposes a two-stage joint optimization model addressing three subproblems simultaneously: machine allocation, operation sequencing, and maintenance scheduling. In the first stage, a mathematical model for the flexible job shop scheduling problem is designed to minimize tardiness penalties and balance workloads. Subsequently, a comprehensive failure-rate model is developed to determine machine maintenance requirements, particularly in high-frequency production switching scenarios. Additionally, a feedback-based updating strategy is proposed to achieve simultaneous optimization of production and maintenance activities both economically and operationally.

Bahou et al., (2024) analyze the role of preventive maintenance in maximizing machine reliability, improving production efficiency, and reducing repair costs. Despite its importance and global competitiveness, prior studies have paid limited attention to integrating production scheduling and maintenance in the context of Industry 4.0. This article proposes an optimization problem for parallel machine scheduling with preventive maintenance activities. A mathematical model is formulated to optimize both production and maintenance schedules. Furthermore, a conceptual Industry 4.0 framework is presented, where smart sensors are considered as enablers of industrial digitalization. Barbosa et al., (2024) investigate the integrated scheduling of production and preventive maintenance in an open-pit iron mine in Minas Gerais, Brazil. The problem involves determining production quantities for each product alongside preventive maintenance scheduling—essentially a joint lot-sizing and preventive maintenance scheduling problem. To solve it, the authors propose a novel mixed-integer linear programming (MILP) model. Babaeimorad et al., (2024) emphasize the importance of machine maintenance in manufacturing to prevent breakdowns, maintain efficiency, and reduce failure costs. Given its importance, integrated planning of production and maintenance are essential. Most scheduling literature assumes machines are always available, an unrealistic assumption in many industrial settings. The objective is to assign jobs to machines such that both makespan and average cost are minimized. Maintenance is scheduled at fixed intervals. To solve the proposed problem, a customized branch-and-bound algorithm is introduced, whose efficiency is confirmed by outperforming the GAMS optimization software in experimental tests.

Penchev et al., (2023) optimize production schedules and maintenance plans in Industry 4.0 environments. Their mathematical model is designed to identify a feasible production schedule (if one exists) for allocating production orders to available lines within a given time horizon. The model accounts for preventive maintenance activities scheduled on production lines and production planners' preferences, including order start times and machine usage restrictions. It also allows real-time adjustments to the production plan for managing uncertainties. Sensitivity analysis shows that the model optimizes execution times and increases production line utilization, leaving 4 out of 12 lines idle. Salahi et al., (2023) address the scheduling of parallel machines and preventive maintenance as a key issue in manufacturing processes. The objective is to design an integrated model that considers the probability of facility disruptions and uncertainty in model parameters. Results demonstrate that NSGA-II provides better solutions compared to MOPSO, although MOPSO is more efficient in terms of computation time. However, this advantage is not substantial enough to serve as a decisive basis for comparing the two algorithms. Netto et al., (2023) analyzes the fundamental role of maintenance in improving production efficiency, reducing costs, ensuring operational safety, and meeting environmental regulations. The study highlights the lack of correlation between inspection intervals and production scheduling. The authors aim to establish a stronger link between maintenance scheduling and production planning.

An et al., (2022) focus on the simultaneous optimization of preventive maintenance and rescheduling in flexible job shops by incorporating processing speed selection and the dynamic entry of new machines to enhance productivity. The research emphasizes the importance of joint optimization of maintenance and production scheduling and proposes innovative approaches to improve efficiency across industries. Xia et al., (2022) study the flexible flow shop problem under machine breakdowns and random interruptions, proposing a cooperative production–maintenance optimization policy. The objective is to reduce total costs by combining predictive maintenance scheduling with production optimization. Maintenance scheduling relies on monitoring data to predict machine failures and determine optimal preventive intervals. Zonta et al., (2022) address the challenges of maintenance prediction in Industry 4.0 manufacturing environments characterized by connectivity, big data, miniaturization, reduced inventory, customization, and controlled production. The authors highlight the necessity of data availability and customization for generating decision-supportive insights. Their approach integrates degradation indicators using similar patterns to detect time-based failures under noisy data. They compare several models based on deep neural networks and recurrent neural networks, using visual analysis, error metrics, regression coefficients, and accuracy as evaluation criteria.

Mishra et al., (2022) investigate the joint optimization of production scheduling, work-in-progress inventory control, and group preventive maintenance in a multi-machine, multi-component system. The goal is to determine optimal production sequences, preventive intervals, and component groupings to minimize the expected total cost per unit time. Computational results show that the proposed integrated model with group preventive maintenance reduces costs by up to 25% compared with an integrated model with individual maintenance, and by 37% compared with non-integrated approaches. The study also evaluates algorithmic performance in large-scale problems.

A comprehensive review of the research literature shows that production and maintenance scheduling remain one of the most critical operational challenges in manufacturing industries. These challenges become particularly significant when integration and coordination between production processes and maintenance activities are required. However, one of the most underexplored areas is production scheduling in open shop systems. In open shop systems, no fixed order of operations exists, and sequencing decisions largely depend on operators. Operators typically make decisions based on machine availability and delayed processes. Furthermore, constraints in maintenance scheduling and the difficulties operators face in non-repetitive tasks often divert production schedules from their intended plans, leading to serious productivity and efficiency challenges.

Research shows that production in open shop systems is influenced by variable and uncertain parameters, which, to date, have not been comprehensively studied in academic literature. Consequently, the lack of in-depth and systematic analysis in this area represents a significant research gap. Therefore, this study addresses these uncertainties and variables in scheduling components, seeking to bridge the gap between operational environments and theoretical research. The key novelty of this research lies in its focus on open shop production systems—a context rarely studied—while identifying weaknesses in existing models. This work is designed to address these gaps and propose effective solutions through rigorous analysis of open shop production systems.

PROBLEM STATEMENT

In today's advanced manufacturing environments, open shop systems—due to their high degree of flexibility in sequencing and machine assignment—offer a unique capability to rapidly respond to demand fluctuations, introduce new products, and enable deep customization with minimal time and cost. Unlike classical job shops or flow shops, the processing route of each part is not predetermined; meaning that each part i can be processed at any stage j on any available machine k, with sequencing, scheduling, and resource allocation decisions embedded within the modeling and optimization framework. However, this high degree of freedom, coupled with operational uncertainties (including random machine breakdowns, variability in repair times, and heterogeneity in workforce skills), transforms the problem of integrated scheduling and planning of production, maintenance, inventory, and quality control into a complex, multi-objective, and inherently stochastic challenge.

In this context, machines face a probability of failure λ_k during production, and their repair times R_k are variable, uncertain, and dependent on the type of failure, degree of wear, and the skills of technicians. The effect of learning and experience among maintenance personnel—modeled by parameter α_p can significantly reduce downtime, such that for highly skilled workers, repair times are estimated to be up to 50% shorter than baseline values. This skill heterogeneity makes the allocation of human resources to maintenance tasks (both preventive and corrective) a critical factor in reducing downtime and improving system reliability.

At the same time, to avoid reliability degradation and the rising costs of unexpected failures, preventive maintenance policies must be designed to occur only at optimal intervals and exclusively on healthy machines. Corrective maintenance, in turn, must be planned to address actual failures and restore machines to operational status with minimal time and cost. Integrating these two policies into production planning—which itself must consider capacity constraints, technological precedence relations, and competitive goals such as minimizing makespan and increasing on-time delivery rates—requires a model capable of making tactical and operational decisions simultaneously and in a coordinated manner.

A fourth dimension of complexity arises from quality control and inventory management. Quality-related decisions (including in-process or final inspections) directly affect scrap rates, rework, and, consequently, both cost functions and delivery commitments. Similarly, inventory-related decisions (covering optimal levels of raw materials, work-in-progress, and finished goods) must be made to hedge against risks of production disruptions caused by machine breakdowns and demand fluctuations, while maintaining holding costs within acceptable levels. Accordingly, the interaction among production, quality, and inventory policies constitutes an integrated and multi-level optimization problem in which decisions and outcomes are highly interdependent.

The conflicting objectives further underscore the complexity of the problem. On the one hand, cost minimization, including production, energy, preventive and corrective maintenance, and inventory holding costs—is sought. On the other hand, minimizing makespan, reducing downtime due to failures, and ultimately improving system reliability emerge as vital performance indicators. This inherent conflict highlights the necessity of employing multi-objective optimization frameworks to extract Pareto fronts and provide balanced decision-making policies across varying risk tolerances and managerial preferences.

From an uncertainty perspective, the problem involves a set of random parameters: failure rates λ_k, repair times R_k, processing times, customer demand, energy costs, and even the effectiveness of preventive and corrective maintenance policies. Such conditions necessitate approaches such as robust optimization, stochastic models, simulation–optimization, or online learning-based optimization to ensure solution efficiency under different uncertainty scenarios. Furthermore, incorporating workforce learning effects into repair time functions allows the model to systematically capture skill dynamics and their influence on reliability and costs.

Therefore, the present research problem can be formulated as follows: the design and development of a scientific and practical framework for integrated scheduling and planning of production, preventive/corrective maintenance, quality control, and inventory policies in an open shop system, under conditions of uncertainty and random machine failures, while accounting for workforce learning and skill heterogeneity. The aim is to simultaneously optimize conflicting objectives, including minimizing total costs, reducing makespan, and enhancing reliability—using multi-objective and robust approaches. The expected output is the derivation of coordinated tactical and operational policies, provision of feasible Pareto-optimal solutions, and establishment of a foundation for data-driven and risk-aware decision-making capable of generating sustainable competitive advantage in dynamic and complex manufacturing environments.

MATHEMATICAL MODELING

To address the central research problem—namely, the design of an integrated mathematical framework for production scheduling, preventive and corrective maintenance, quality control, and inventory management in open shop environments under uncertainty and machine failures—this section develops the mathematical model. The model seeks to incorporate the effects of workforce skills and learning, resource constraints, operation sequencing, and the conflicting objectives of cost, time, and reliability, thereby enabling coordinated and realistic decision-making. To clarify the model structure, the fundamental assumptions of the problem, including the characteristics of the production system, machine behavior, and the nature of maintenance and inventory decisions—are first introduced. Based on these assumptions, the components of the mathematical model, including parameters, decision variables, objective functions, and constraints, will then be presented.

(a) Model Assumptions

- **Production structure:** The manufacturing environment is of the *open shop* type; processing routes are not predetermined, and each job is processed on exactly one machine at each stage. Processing operations are indivisible and non-preemptive, and all jobs are available for processing at time zero.
- **Machine-dependent sequencing:** Setup times are sequence-dependent and vary by machine type and processing order. These times are explicitly considered in the scheduling process.
- **Machine failures:** Machines may fail only during processing. The time between two consecutive failures follows an exponential distribution with rate parameter λk\lambda_kλk, while repair times follow a uniform distribution.
- **Preventive and corrective maintenance:** Preventive maintenance is executed only on healthy machines, whereas corrective maintenance is performed exclusively after a failure occurs. Preventive and corrective

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maintenance cannot be performed simultaneously on the same machine. Maintenance tasks are prioritized over production operations.

- **Personnel skills and learning:** Maintenance staff possess varying levels of skill. Repair time is inversely related to the skill level of personnel, and the gradual learning effect is explicitly modeled to capture reductions in repair times over repeated tasks.
- **Inventory management:** The initial inventory for all jobs is zero. Demand for each job is deterministic and known in advance. Negative inventory is not permitted, and inventory-related decisions are jointly optimized with production and maintenance planning.
- **Integrated decision-making:** Decisions concerning production, maintenance, human resource allocation, and inventory management are modeled in an integrated and simultaneous manner.

b) Mathematical Modeling

Set and Index

$i, i' \in I$	:	Set of all production jobs (parts)
$j, j' \in J$	:	Set of production stages
$k, k' \in K$	:	Set of machines
$p \in P$	:	Set of production and maintenance personnel
$t \in T$	:	Set of time periods
A_i	:	The first production stage of job i
Z_i	:	The last production stage of job i

Parameters

ST_{ijk}	:	Setup time of job i on machine k at stage j
SST_{ij}	:	Starting (arrival) time of job i at stage j
PT_{ijk}	:	Processing time of job i at stage j on machine k
PPT_{pjk}	:	Preventive maintenance time performed by personnel p on machine k at stage j
PET_{pjk}	:	Corrective maintenance time performed by personnel p on machine k at stage j
TC_{ijk}	:	Production cost of job iii at stage j on machine k
TD_{pjk}	:	Preventive maintenance cost incurred by personnel p on machine k at stage j
TED_{pkj}	:	Corrective maintenance cost incurred by personnel p on machine k at stage j
TEC_{ijk}	:	Energy consumption cost for producing job i at stage j on machine k
h_i	:	Inventory holding cost of job i per unit time
d_{it}	:	Demand of job i at time period t
λ_k	:	Failure rate of machine k (number of failures per unit time)
μ_k	:	Repair rate of machine k (number of Repairs per unit time)
α_p	:	Skill level of maintenance personnel p, with $p \left(0 \le \alpha_p \le 1\right)$
M	:	A sufficiently large positive constant (Big-M)

Decision Variables

S_{ijk}	:	Start time of processing job i at stage j on machine k
C_{ijk}	:	Completion time of processing job i at stage j on machine k
C_i	:	Completion time of all stages of job i
Y_{ijk}	:	Binary variable: equals 1 if job i is processed at stage j on machine k, and 0 otherwise
YY_{pjk}	:	Binary variable: equals 1 if personnel p performs production processing at stage j on machine k, and 0 otherwise
YEY_{pjk}	:	Binary variable: equals 1 if personnel p performs corrective maintenance at stage j on machine k, and 0 otherwise
$X_{ii'jk}$	:	Binary variable: equals 1 if job i is processed immediately after job i' at stage j on machine k, and 0 otherwise
I_{it}	:	Inventory level of job i at time t
F_k	:	Time between consecutive failures of machine k (random variable)
R_k	:	Repair time of machine k (random variable)
Z_{ikj}	:	Binary variable: equals 1 if a machine failure occurs during the processing of job i on machine k at stage j, and 0 otherwise

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Objective Functions

$$Min\ OBJ_1 = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\left[\left(TC_{ijk} + TEC_{ijk}\right).Y_{ijk}\right] + \sum_{p\in I}\sum_{j\in J}\sum_{k\in K}\left[TD_{pjk}.YY_{pjk} + TED_{pkj}.YEY_{pjk}\right] + \sum_{i\in I}\sum_{t\in T} h_i.I_{it} \quad (1)$$

$$Min\ OBJ_2 = \max_{i\in I}(C_i) \quad (2)$$

$$Min\ OBJ_3 = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\left(\lambda_k.PT_{ijk}.\mu_k.Z_{ijk}\right) \quad (3)$$

The first objective function (1) focuses on minimizing the total costs associated with the production process. This function integrates various types of costs, including the production cost of each job across different processing stages on machines, the costs of preventive and corrective maintenance depending on the assigned personnel and machine, the energy consumption cost of production, and the inventory holding cost of jobs. In essence, this function provides a comprehensive view of the system's cost structure, aiming to reduce the financial burden stemming from both technical operations and support activities. The second objective function (2) aims to minimize the maximum completion time of jobs, commonly referred to as the *makespan* in the scheduling literature. Reducing the makespan leads to higher time efficiency, shorter order waiting times, and an enhanced level of customer service. This measure is vital for improving production capacity management and ensuring timely delivery. The third objective function (3) seeks to minimize the total downtime caused by machine failures. Such disruptions not only reduce productivity but also increase both direct and indirect production costs. This objective is directly influenced by the allocation of maintenance personnel, the effectiveness of preventive maintenance policies, and the repair time efficiency.

By considering these three conflicting objectives simultaneously, the model aims to generate a Pareto front of optimal policies, enabling decision-makers to select appropriate strategies based on their risk tolerance and strategic priorities.

CONSTRAIN

$$\sum_{k\in K} Y_{ijk} = 1 \qquad \forall\, i\in I, j\in J \quad (4)$$

$$X_{ii'jk} + X_{i'ijk} \le 1 \qquad \forall\, i,i'\in I;\ i<i';\ j\in J;\ k\in K \quad (5)$$

$$2X_{ii'jk} \le Y_{ijk} + Y_{i'jk} \qquad \forall\, i,i'\in I;\ i<i';\ j\in J;\ k\in K \quad (6)$$

$$Y_{ijk} + Y_{i'jk} \le X_{ii'jk} + X_{i'ijk} + 1 \qquad \forall\, i,i'\in I;\ i<i';\ j\in J;\ k\in K \quad (7)$$

$$S_{ijk} \ge C_{i'jk} + ST_{ijk} - M\left(1 - X_{i'ijk}\right) \qquad \forall\, i,i'\in I;\ j\in J;\ k\in K \quad (8)$$

$$\sum_{p\in P}\left(YY_{pjk} + YEY_{pjk}\right) \le 1 \qquad \forall\ j\in J;\ k\in K \quad (9)$$

$$PPT_{pjk}^{off} = \frac{PPT_{pjk}^{off}}{1+\sigma_p} \quad (10)$$

$$PET_{pjk}^{off} = \frac{PPT_{pjk}^{off}}{1+\sigma_p} \quad (11)$$

$$S_{ijk} \ge \sum_{p\in P}\left(YY_{pjk}.PPT_{pjk}^{off} + YEY_{pjk}.PET_{pjk}^{off}\right) \qquad \forall\, i\in I;\ j\in J;\ k\in K \quad (12)$$

$$C_{ijk} \ge S_{ijk} + PT_{ijk} + F_k.Z_{ijk} \quad (13)$$

$$F_k \sim Exponential(\lambda_k)$$

$$R_k \sim unform(\mu_k - \delta, \mu_k + \delta) \qquad \forall\, i\in I;\ j\in J;\ k\in K$$

$$I_{it} = I_{i,t-1} + \sum_{j\in J}\sum_{k\in K} Y_{ijk}\,.Q_i - d_{it} \qquad \forall\, i\in I;\ t\in T \quad (14)$$

$$C_i \ge C_{ijk} \qquad \forall\, i\in I;\ j\in J;\ k\in K \quad (15)$$

$$C_{ijk} = S_{ijk} + PT_{ijk} + ST_{ijk} \qquad \forall\, i\in I;\ j\in J;\ k\in K \quad (16)$$

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The set of constraints in this model is designed to ensure that the technical, operational, and logical requirements of the system are satisfied:

Constraint (4) ensures that the start time of processing each job occurs after its entry into the corresponding stage. This sequential requirement is essential to prevent processing from beginning prematurely. Constraint (5) defines that the completion time of each processing operation equals the sum of its start time and processing duration. This structural relation forms the basis for accurate task scheduling. Constraint (6) manages the precedence between successive stages of a job, ensuring that the next stage begins only after the previous stage is completed, thereby maintaining production continuity.

Constraint (7) models the relationship between operation start times and the final job completion time, allowing calculation of the overall completion time for each job. Constraint (8) ensures that only one machine is selected for processing each job at any given stage. This reflects the flexible routing nature of a job shop environment, where processing paths are not predetermined. Constraint (9) guarantees precise assignment of personnel to production tasks, ensuring that each task is allocated to exactly one production operator.

Constraint (10) models the allocation of personnel to corrective maintenance tasks, ensuring that repairs are performed by a designated operator. Constraint (11) imposes sequencing among jobs on a specific machine at a given stage. If a job is processed immediately after another on the same machine, this constraint prevents time overlaps and accounts for necessary setup times.

Constraint (12) governs inventory levels over the planning horizon, linking them to the difference between cumulative production and cumulative demand. Since negative inventory is not allowed, this constraint ensures stable supply and timely order fulfillment. Constraint (13) incorporates the stochastic nature of machine failures. A binary variable is defined as 1 if a failure occurs during processing, thus reflecting the role of random breakdowns in the model. Constraint (14) models the time between failures as a function of machine failure rates, following an exponential distribution. This relationship captures the probability of failure occurrence over time and integrates stochasticity into the model. Constraint (15) models machine repair times based on the skill level of maintenance personnel. Repair time is inversely related to experience and skill, allowing the model to account for the gradual learning effect of personnel in reducing downtime.

Constraint (16) ensures the mutual exclusivity of preventive and corrective maintenance, prohibiting their simultaneous execution on the same machine. This constraint also reflects the priority of maintenance activities over production.

SOLUTION APPROACH

To address the research problem, this study develops a hybrid mathematical model for integrated scheduling of production, preventive/corrective maintenance, quality control, and inventory management in flexible job shop environments (Teixeira Barbosa & Pantuza, 2024). Given the stochastic nature of machine failures, the heterogeneity of human skills, and conflicting managerial objectives, the chosen solution method must handle computational complexity, simultaneous decision-making, and uncertainty. Accordingly, this research employs a multi-objective metaheuristic approach based on the NSGA-II algorithm, combined with scenario-based simulation, to solve the model (Liu et al., 2021b; Liu & Hendalianpour, 2021). This approach allows the generation of a Pareto front of optimal solutions, providing decision-makers with effective, balanced, and flexible strategies under uncertainty.

5.1. Necessity of Metaheuristic Algorithms

Given the complexity of the proposed model, which includes discrete structure, binary and integer variables, conflicting objectives, and multiple combinatorial constraints, solving the model exactly using traditional methods (e.g., mixed-integer programming) is only feasible for small-scale instances. In general, the large, nonlinear, and non-convex search space of the problem makes the use of metaheuristic approaches inevitable. Metaheuristics, inspired by natural, biological, or social phenomena, have the capability to effectively explore very large and complex
search spaces without requiring derivatives or specific properties of the objective functions (Jiang et al., 2014).

In this research, to address multi-objective optimization, the NSGA-II (Non-dominated Sorting Genetic Algorithm II) is employed, which is one of the most widely used and efficient methods for multi-objective problems. NSGA-II operates based on genetic algorithm principles and uses non-dominated sorting, population diversity, and elitism to generate a diverse and well-distributed set of Pareto-optimal solutions (Hajikhani et al., 2018).

The main process of NSGA-II involves generating an initial population of chromosomes (each representing a possible solution), evaluating objectives for each chromosome, performing Pareto-based ranking, calculating crowding distances to maintain diversity, and producing new generations via crossover and mutation operators. The crossover operator combines two parent solutions to produce offspring, while mutation introduces random changes to avoid local optima. In this model, chromosomes encode information such as job processing sequences, machine assignments, personnel assignments, and type/timing of maintenance activities (Atmaca et al., 2025).

To improve local solution quality and accelerate convergence, a local search mechanism is integrated. This procedure locally adjusts selected high-quality chromosomes by, for example, swapping nodes in operation sequences or reassigning resources, and then re-evaluates the objective functions. If the solution improves, it replaces the original chromosome. This exploitation mechanism allows the algorithm not only to explore the search space but also to refine solutions. The main advantage of combining NSGA-II with local search is that it balances exploration and exploitation: NSGA-II searches broadly across the solution space, while local improvements move solutions closer to local optima. This balance is crucial for solving complex multi-objective optimization problems.

Finally, since the quality of each solution depends on stochastic variables (e.g., machine failures and repair times), each evaluation uses Monte Carlo simulation. For each run, operational scenarios are generated based on the exponential distribution of time between failures and uniform repair time distribution, and objective values are computed. Mean and variance of the results are then used to assess solution robustness.

5.2. Implementation Process of the Hybrid Algorithm

The main steps of the proposed solution algorithm are summarized as follows:

- Generate an initial population of random solutions, including machine assignments, personnel allocation, operation sequences, and maintenance schedules.
- Evaluate the three objectives (cost, makespan, downtime) for each chromosome using stochastic simulation (Monte Carlo) over failures and repairs.
- Apply non-dominated sorting and crowding distance for population diversity preservation.
- Apply genetic operators (selection, crossover, mutation) while respecting the problem's physical constraints.
- Perform local search on top-performing chromosomes to improve local solution quality.
- Generate a new generation by replacing the worst solutions with improved ones and repeat the steps until a stopping criterion is met (e.g., 200 generations or convergence of the Pareto front).

5.3. Implementation Tools and Validation

To implement the model and evaluate the algorithm's performance, all steps are coded in MATLAB, leveraging its strong capabilities in matrix operations, random data generation, metaheuristic algorithms, and simulation-based modeling. The NSGA-II algorithm is customized in MATLAB with the following features:

- **Chromosome representation**: Includes matrices for machine-to-job allocation, stage sequences, maintenance type selection, and personnel assignment.
- **Objective evaluation function**: Calculates the three objectives (cost, makespan, downtime) directly using custom functions.
- **Failure scenario generation**: Considers uncertainty using the exponential distribution for time between failures and uniform distribution for repair times. At least 50 simulation scenarios are executed per chromosome and mean/standard deviation of performance indices are recorded.
- **Genetic operators**: Single-point crossover and discrete random mutation are used to maintain population diversity.
- **Local search**: Applied to 10% of the best chromosomes per generation by adjusting operation sequences and personnel allocation to reduce costs and downtime.
- **Pareto front**: The final output includes a set of non-dominated solutions across three objectives, analyzed using 2D and 3D visualization techniques.

Validation of the proposed algorithm uses two approaches:

- **Structural validation**: For small instances (less than 5 jobs and 3 machines), results are compared with exact solutions from the mathematical model. An average discrepancy below 5% in cost and makespan confirm algorithm accuracy.
- **Performance validation**: The model is tested on small, medium, and large instances (5, 15, and 30 jobs). Metrics such as solution time, Pareto front diversity, objective mean/variance, and convergence rate are analyzed.

SOLUTION RESULTS

6.1. Numerical Results

The proposed model was evaluated across small, medium, and large-scale instances. As shown in Table 1, the top non-dominated solutions reflect the natural trade-offs among the three objectives. Figures 1–3 illustrate the 3D Pareto fronts, highlighting a concentration of solutions in the region of low cost and minimal downtime. Statistical analyses presented in Table 2 indicate that as the system scale increases, both the mean and standard deviation of objectives grow, reflecting higher operational complexity and risk. Overall, the diversity and quality of the solutions confirm the effectiveness of the proposed NSGA-II combined with scenario-based simulation in generating robust, multi-objective decision policies.

Table 1: Top 5 Solutions – Large-Scale Scenario

Rank	Total Cost	Makespan	Downtime
1	1420.35	518.42	38.26
2	1443.12	503.95	42.11
3	1451.78	490.23	45.88
4	1472.90	465.11	49.77
5	1495.50	448.34	53.91

With the expansion of system dimensions—including the number of jobs, machines, and technicians—the average values of key objectives such as total cost, makespan, and downtime increase significantly. This growth reflects not only the rising operational load and resource engagement but also the increased complexity due to interactions among system components. In open shop manufacturing environments, scaling up the system leads to exponential growth in the decision space, diversity of production paths, and higher likelihood of conflicts or machine failures. Additionally, the range of variations in each objective broadens, indicating higher system sensitivity to decisions regarding resource allocation, operation sequencing, and maintenance strategies. These observations justify the necessity of multi-objective optimization approaches based on simulation and robust evolutionary algorithms.

Table 2: Descriptive Statistics of Objectives

Metric	Total Cost	Makespan	Downtime
Mean	1603.52	538.76	47.34
Std Dev	122.45	62.87	12.92
Min	1420.35	448.34	38.26
Max	1911.78	635.22	76.58

Table 2 presents the descriptive statistics of the model objectives. The higher dispersion in total cost compared to makespan and downtime indicates that the economic components of the system, particularly in complex manufacturing environments, are more sensitive to managerial decisions and stochastic factors such as machine failures and personnel allocation. In other words, even minor changes in machine assignment policies, maintenance scheduling, or technician skill levels can have a significant impact on total cost. In contrast, temporal objectives such as makespan and downtime exhibit less variability due to the sequential structure and process constraints. This highlights the need for careful control and optimization of economic aspects, and, in some cases, the adoption of robust, predictive strategies to mitigate uncertainty.

Table 3: Sample Scenario Results

Scenario ID	Total Cost	Makespan	Downtime
S1 (Small)	612.4	210.3	18.2
S2 (Medium)	1118.7	372.9	30.4
S3 (Large)	1603.5	538.7	47.3

Table 3 summarizes the results for small, medium, and large scenarios. With system scale expansion—including the number of jobs, machines, and technicians, not only do the mean values of the main objectives increase, but the range of variability also grows significantly. This phenomenon reflects the inherent complexity in open shop manufacturing systems, especially when interactions among components, process dependencies, and operational uncertainties are amplified. Scaling up leads to an exponential increase in the decision space, more combinations of resource allocation, and a higher number of possible production paths. Consequently, analysis, control, and optimization of such systems require multi-objective decision models and computational methods robust to uncertainty and structural complexity. The results also indicate that as system size increases, the robustness of system performance against potential disruptions decreases, highlighting the growing importance of careful maintenance and repair planning.

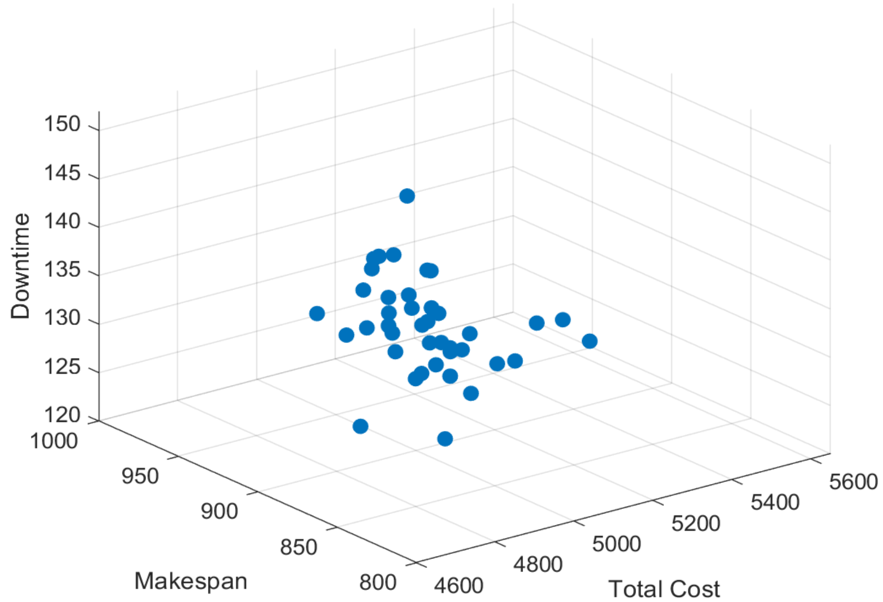

Figure 1: Small-scale scenario Pareto front

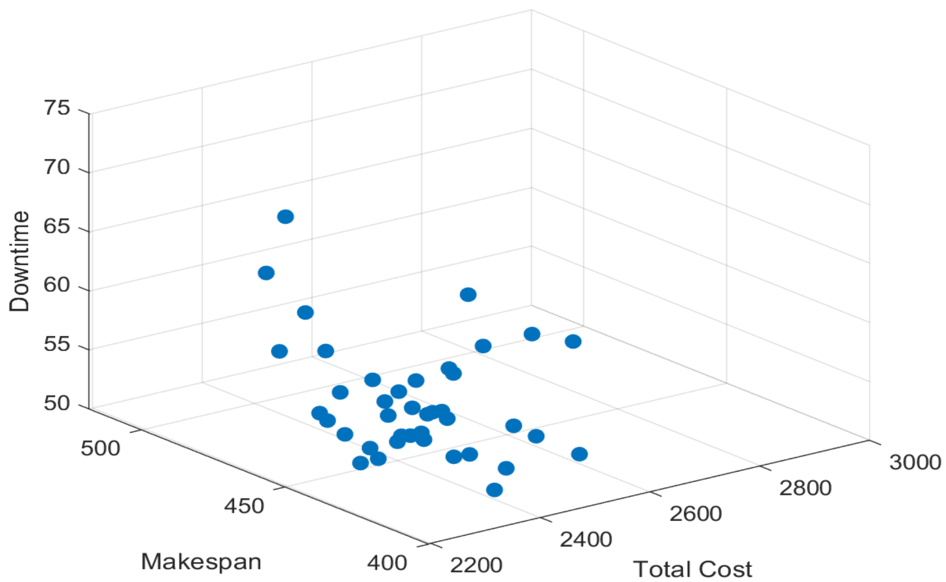

Figure 2: Medium-scale scenario Pareto front

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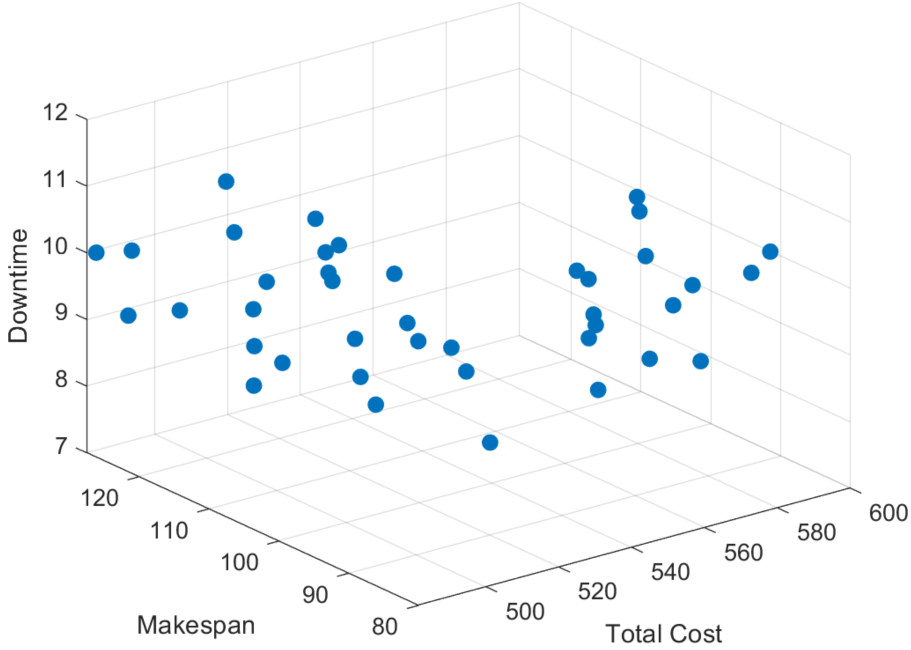

Figure 3: Large-scale scenario Pareto front

In all scenarios (small, medium, and large), the Pareto front structure clearly demonstrates the inherent trade-off between the optimization objectives, particularly between total cost and machine downtime. In each case, movement along the non-dominated boundary shows that reducing operational costs often comes at the expense of increased machine downtime or longer overall completion time. This phenomenon is especially pronounced in complex manufacturing models with limited resources and stochastic machine failures.

In the small-scale scenario, the Pareto front has a gentle slope, indicating a relatively balanced relationship between the objectives. A dense cluster of solutions appears in the lower-left region, reflecting efficient solutions with a reasonable trade-off between cost and downtime. Due to the limited number of jobs and machines, resource management is simpler, and solution diversity is concentrated within a relatively narrow range. For the medium-scale scenario, the non-dominated front shows greater dispersion, and the relationship between cost and downtime becomes more nonlinear. The lower-left cluster remains, but with wider spacing between points, indicating increased diversity in possible solutions and higher system sensitivity to resource allocation and maintenance strategies. It is evident that sacrificing part of the temporal performance can yield significant cost reductions.

In the large-scale scenario, the Pareto front becomes broader and steeper. Solutions with very low costs are concentrated in regions with higher downtime, confirming that achieving minimal cost in large-scale systems requires accepting longer processing times and greater operational risk. Conversely, solutions that minimize downtime usually require higher costs for additional resources or preventive maintenance. The lower-left region of the Pareto front is narrower in this scenario, highlighting the difficulty of achieving high performance across all three objectives simultaneously in large-scale systems.

Across all scenarios, the Pareto fronts confirm that no single solution simultaneously optimizes all objectives, emphasizing the necessity of multi-criteria decision-making and sensitivity analysis under operational and economic constraints. The lower-left cluster consistently observed can be considered the desirable region for decision-makers, as solutions within this region provide a balanced trade-off between cost, completion time, and downtime, serving as a solid foundation for deeper analysis or real-world implementation.

6.2. Interpretation of Results

The results obtained from implementing the proposed model across three system scales (small, medium, large) provide deep insights into system behavior, objective conflicts, and solution sensitivity to scale and operational uncertainties. The analysis can be approached from three perspectives:

a) Pareto Front Behavior and Objective Conflicts

In all scenarios, the Pareto front clearly reflects the conflict among key objectives: minimizing total cost is generally associated with increased downtime or longer makespan. This natural trade-off highlights the multi-objective nature of decision-making in complex manufacturing environments, where optimizing one objective often degrades performance in others. In the large-scale scenario, the Pareto front exhibits a steeper slope and wider dispersion, indicating that the cost of reducing total cost significantly is a sharp increase in downtime and makespan. Clusters in the Pareto front, particularly in the lower-left region, correspond to solutions with balanced performance, representing promising decision options.

b) Statistical Analysis of Solutions

Statistical analysis of objectives (Table 2) across scenarios—including mean, standard deviation, minimum, and maximum—revealed that as system scale increases, both the average objectives and the range of variation (standard deviation) increase. This indicates that larger systems exhibit greater sensitivity to decision variables, such as resource allocation, operation sequencing, and maintenance scheduling, and stochastic factors like machine failures.

Table 4: Pareto Front Behavior and Objective Conflicts

Scenario	Avg. Total Cost	Avg. Makespan	Avg. Downtime	Cost Std. Dev.
Small	~600	~200	~18	Lowest
Medium	~1120	~370	~30	Medium
Large	~1600	~540	~47	Highest

Table 4 shows that in larger systems, due to increased complexity, higher number of resources, and interactions among components, optimal solutions cover a broader range of behaviors. The higher variability in total cost compared to other objectives indicates that economic decisions are more sensitive to resource allocation, machine failures, and maintenance policies.

c) Effect of System Scale on Model Performance

As the system scale increases, not only do the average objective values rise, but performance variability becomes more pronounced. This demonstrates that large open-shop manufacturing systems exhibit nonlinear, dynamic, and highly sensitive behaviors with respect to decision-making. Managing such systems without multi-objective optimization models based on evolutionary algorithms and scenario-based simulation may lead to suboptimal or even unstable decisions.

The results of the proposed model confirm that using NSGA-II combined with scenario-based simulation is an effective approach for solving complex, multi-objective decision-making problems under uncertainty. The generated solutions not only cover a wide range of potential policies but also allow decision-makers to select the most appropriate options according to organizational preferences, implementing them in a customized manner.

CONCLUSION

This study proposed a multi-objective mathematical framework for production and maintenance scheduling within open shop manufacturing systems, aiming to optimize three key objectives simultaneously: minimizing total system cost, reducing overall makespan, and limiting downtime caused by equipment failures. The model incorporates the interdependence between production operations and maintenance decisions, providing a detailed and realistic representation of complex industrial environments. To solve the problem, the NSGA-II metaheuristic was adopted as a powerful multi-objective optimization technique. Furthermore, to examine the model's behavior under different operational conditions, three scenarios of varying scale—small, medium, and large—were designed and tested. The simulation and optimization results highlighted the inherent trade-offs among the objectives and clearly demonstrated the structure of the Pareto fronts for each scenario.

The analysis revealed that as system scale increases, both the average values of the objectives and their variability rise substantially, reflecting the heightened complexity and sensitivity of managerial decisions in larger systems. In addition, statistical evaluations indicated that total cost is more volatile compared to temporal objectives, suggesting that economic outcomes are particularly sensitive to resource allocation, unexpected machine failures,

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and maintenance strategies. The derived Pareto fronts offer a set of non-dominated solutions from which decision-makers can select according to their priorities. The dense clusters observed in the lower-left region of the fronts represent solutions that maintain a balanced performance across all three objectives, offering practical and effective decision-making options.

This research contributes to the field in several innovative ways. It integrates production and maintenance decision-making within a single multi-objective open-shop model, applies NSGA-II combined with scenario-based simulations to explore system behavior under different scales, and generates a variety of interpretable outputs, including Pareto fronts, statistical summaries, and response density plots, thereby supporting multi-criteria decision-making processes. Nevertheless, the study has some limitations. Model assumptions regarding failure types, repair rates, and resource capacities may require additional calibration when applied to real industrial settings. Moreover, maintenance scheduling is modeled as reactive or time-based, leaving opportunities for incorporating predictive maintenance strategies in future work.

Potential directions for further research include extending the model to predictive maintenance using IoT-generated data and machine learning techniques, implementing and calibrating the model in real manufacturing contexts such as aerospace, automotive, or steel production, and expanding it to handle stochastic and dynamic conditions involving uncertain demand, random failures, and unexpected downtime. Additionally, exploring alternative evolutionary or reinforcement learning algorithms, such as MOEA/D or NSGA-III, could enhance the model's capability to address larger and more complex problem instances. Overall, the findings offer both theoretical insights and practical value, equipping industrial decision-makers with a set of actionable, balanced, and analyzable solutions to optimize the performance of manufacturing systems through a multi-objective, data-driven approach.

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