Design of a Fuzzy Multi-Objective Mathematical Model for Short-Term Preventive Maintenance Scheduling Using a Total Productive Maintenance Approach

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Received: 2026-02-03 **Revised:** 2026-06-24 **Accepted:** 2026-07-01 **Initial Publish:** 2026-07-24 **Final Publish:** 2027-07-01

Abstract

This study aimed to design a fuzzy multi-objective mathematical model for short-term preventive maintenance scheduling based on the Total Productive Maintenance approach to optimize production completion time, total cost, greenhouse gas emissions, and product quality under uncertainty. This applied quantitative study was conducted using mathematical modeling and computational optimization. The proposed model integrated production scheduling and preventive maintenance decisions within a short-term planning horizon and formulated four objective functions: minimization of completion time, total cost, and greenhouse gas emissions, and maximization of product quality. Uncertain parameters were modeled using a fuzzy approach to increase the realism of the scheduling environment. Five small-scale numerical instances with increasing complexity were generated and solved using GAMS as an exact optimization benchmark. The NSGA-II metaheuristic algorithm was implemented in MATLAB to solve the same instances and evaluate the model's computational efficiency, accuracy, and stability. The inferential comparison between GAMS and NSGA-II indicated that the proposed algorithm generated near-optimal solutions across all objective functions. For the quality objective, deviations ranged from 0.39% to 2.78%, and for completion time, deviations ranged from 0.97% to 2.87%. For the cost objective, deviations ranged from 0.57% to 2.65%, while greenhouse gas emission deviations ranged from 0.36% to 2.93%. Repeated executions of the algorithm showed low dispersion between best, worst, and mean solutions, confirming acceptable convergence and stability. The best–worst deviation for the cost objective reached 3.02% only in the largest instance, while the quality objective remained below 1% across all instances. The proposed fuzzy multi-objective model provides an effective decision-support framework for short-term preventive maintenance scheduling in TPM-based production systems. The results confirm that NSGA-II can generate accurate, stable, and computationally efficient solutions close to exact optimization results while balancing economic, environmental, operational, and quality-related objectives.

Keywords: *Fuzzy mathematical model; multi-objective optimization; preventive maintenance; short-term scheduling; Total Productive Maintenance; NSGA-II.*

How to cite this article:

Rajabpour, F., Zeinalnezhad, M., & Hajipour, V. (2027). Design of a Fuzzy Multi-Objective Mathematical Model for Short-Term Preventive Maintenance Scheduling Using a Total Productive Maintenance Approach. Management Strategies and Engineering Sciences, 9(4), 1-14.

1. Introduction

Industrial production systems are increasingly required to operate under simultaneous pressures of productivity, cost efficiency, quality assurance, energy control, and environmental responsibility. In contemporary manufacturing environments, operational decisions can no longer be limited to the narrow objective of increasing output or reducing direct production costs, because the reliability of equipment, the timing of maintenance interventions, the consumption of energy, and the environmental consequences of production all influence organizational performance. This issue is especially important in short-term scheduling, where decisions about the sequencing of activities, allocation of resources, machine availability, and preventive maintenance timing must be made within limited planning periods and under operational uncertainty. The shift toward sustainable and efficient production has therefore created a need for integrated decision-support models capable of coordinating production scheduling with preventive maintenance while simultaneously considering economic, operational, environmental, and quality-related criteria. The relevance of this issue has intensified as industrial systems face growing concern about energy use and carbon emissions, and recent studies have emphasized that manufacturing and scheduling decisions are directly associated with greenhouse gas emissions, energy consumption, and sustainability outcomes [1]. Accordingly, the design of mathematical models that integrate preventive maintenance with production scheduling is a critical step toward improving the short-term performance of manufacturing systems.

Preventive maintenance is one of the most important pillars of equipment reliability and operational continuity. Unlike corrective maintenance, which is performed after equipment failure, preventive maintenance is implemented before breakdowns occur and seeks to reduce failure probability, unexpected downtime, quality loss, and emergency repair costs. Early maintenance optimization studies emphasized the importance of determining appropriate thresholds and intervention policies for condition-based and preventive maintenance programs [2]. More recent research has further shown that preventive maintenance planning can improve system performance by reducing unplanned interruptions and supporting more reliable production schedules [3]. In short-term production settings, the timing of preventive maintenance is especially sensitive because maintenance actions occupy machine capacity and may delay production activities if not coordinated with the schedule. However, when maintenance is scheduled intelligently, it can prevent breakdowns, stabilize production flow, improve equipment efficiency, and support quality objectives. Therefore, preventive maintenance should not be considered a separate technical function but an integrated decision variable within the production scheduling model.

Total Productive Maintenance provides an appropriate managerial and operational framework for this integration. TPM emphasizes the involvement of production and maintenance functions in improving equipment effectiveness, reducing losses, minimizing downtime, and increasing the reliability of production systems. In a TPM-oriented environment, preventive maintenance is not merely a mechanical repair activity; rather, it is a proactive approach to protecting productivity, quality, safety, and resource efficiency. The logic of TPM is consistent with modern optimization-based production management because it requires coordinated decisions about maintenance timing, machine utilization, workforce capability, and production priorities. In this regard, mathematical programming can operationalize the principles of TPM by translating them into objective functions and constraints. Such a model can determine when maintenance should be performed, which activities should be assigned to available machines, how resources should be allocated, and how competing goals should be balanced during a short-term planning horizon. Recent studies have shown that maintenance decisions can be modeled dynamically in multi-component systems, where grouping and scheduling maintenance activities can improve operational performance [4]. This supports the idea that TPM-based preventive maintenance scheduling requires integrated and systematic modeling rather than fragmented decision-making.

The integration of production scheduling and preventive maintenance has received increasing attention because production and maintenance decisions are structurally interdependent. Machine maintenance affects availability, production capacity, processing stability, and completion time, while production schedules influence equipment workload, deterioration patterns, and the feasible timing of maintenance activities. If production scheduling and preventive maintenance are planned independently, the resulting decisions may be locally efficient but globally suboptimal. For example, a production schedule that ignores maintenance may appear feasible but may lead to higher breakdown risk, quality defects, or excessive energy consumption. Conversely, a maintenance plan that ignores production priorities may cause unnecessary delays or resource conflicts. Studies on scheduling problems with periodic maintenance have shown that the inclusion of maintenance constraints changes the structure of optimal schedules and requires specialized solution approaches [5]. Similarly, hybrid production scheduling models with resource constraints and preventive maintenance considerations demonstrate that maintenance integration is necessary for realistic and efficient production planning [6]. Therefore, an effective short-term model must simultaneously coordinate production activities and preventive maintenance interventions.

Sustainability considerations have further complicated production and maintenance scheduling. Traditional scheduling models usually focused on minimizing makespan, tardiness, or production cost, but contemporary manufacturing systems must also address environmental objectives. Energy consumption and carbon emissions are increasingly recognized as essential criteria in operational decision-making. Research on sustainable manufacturing has shown that real-time energy control can improve system efficiency and reduce unnecessary energy use [7]. In addition, scheduling under time-of-use electricity prices has demonstrated that production timing can significantly affect energy cost and environmental outcomes [8]. Energy-efficient flow shop scheduling studies have also shown that optimization algorithms can reduce energy consumption while preserving production performance [9]. More recent research on heterogeneous multi-stage hybrid flow shops confirms that energy-efficient collaborative scheduling is necessary in complex manufacturing environments [10]. These findings indicate that production schedules and maintenance policies should be designed not only to meet operational objectives but also to reduce energy-related environmental impacts.

Carbon emission reduction has become a central objective in green scheduling models. Flexible job shop and flow shop scheduling studies have shown that carbon reduction policies, machine allocation decisions, sequencing rules, and energy-aware production plans can substantially affect total emissions [11]. Research on flexible job shop scheduling has also demonstrated that multi-objective genetic algorithms can minimize total carbon footprint while considering production criteria such as late work [12]. Low-carbon flexible job shop scheduling further confirms that emission management must be embedded directly into production planning rather than treated as an external evaluation criterion [13]. In addition, disruption management and scheduling models designed to reduce carbon emissions show that operational disturbances and rescheduling decisions can influence environmental performance [14]. Recent scheduling studies involving non-identical parallel machines, due dates, carbon emissions, and multiple energy sources demonstrate that emission-aware scheduling is a current and practical concern in modern production systems [15]. These studies collectively justify the inclusion of greenhouse gas emissions as a formal objective in a fuzzy multi-objective short-term preventive maintenance scheduling model.

Cost reduction remains a fundamental concern in production and maintenance planning. Preventive maintenance can reduce long-term and short-term operational costs by preventing breakdowns, reducing emergency repairs, limiting idle time, and improving equipment availability. However, maintenance itself also consumes resources, time, labor, and spare parts, which makes the timing and frequency of maintenance interventions critical. Simultaneous planning of maintenance and spare parts inventory has shown that maintenance decisions are linked to inventory control and operational cost structures [16]. Reliability-based maintenance approaches in failure-prone production systems also demonstrate that maintenance decisions influence revenue, system availability, and production losses [17]. Inspection and preventive maintenance planning under machine deterioration further shows that maintenance policies must account for uncertain deterioration processes and demand conditions [18]. Similarly, inspection and preventive maintenance planning for deteriorating systems has highlighted the importance of Markovian deterioration modeling in determining effective maintenance timing [19]. These studies indicate that maintenance scheduling must be included in short-term cost optimization models to avoid both excessive maintenance and costly failure-related disruptions.

Quality is another key dimension that connects preventive maintenance to production scheduling. Poorly maintained machines are more likely to produce defective items, deviate from technical tolerances, increase rework, and reduce process stability. TPM explicitly emphasizes quality improvement through equipment effectiveness, and preventive maintenance plays a central role in maintaining stable operating conditions. In production systems where activity quality depends on machine condition, maintenance interventions can directly influence the quality objective. This makes quality maximization a necessary component of integrated short-term maintenance scheduling. Sustainable supply chain studies have also shown that imperfect items and withdrawal policies must be considered in operational planning because product quality affects inventory, production, and supply chain performance [20]. Consumer environmental awareness and channel coordination studies further indicate that quality, environmental responsibility, and market competitiveness are increasingly interconnected [21]. Thus, a comprehensive preventive maintenance scheduling model should not focus only on cost and time but should also include product quality as a strategic objective.

A major methodological challenge in this field is the existence of multiple conflicting objectives. Minimizing cost may conflict with maximizing quality, reducing completion time may increase energy consumption, and performing preventive maintenance may temporarily reduce machine availability while improving long-term reliability. Because these objectives cannot usually be optimized simultaneously by a single solution, multi-objective optimization provides a suitable framework for identifying trade-offs among competing criteria. Integrated machine scheduling and vehicle routing models have shown that total carbon emissions can be minimized through coordinated decisions across production and transportation functions [22]. Pollution-routing studies under uncertainty also demonstrate that environmental objectives can be integrated into operational models with uncertain demand and travel time [23]. Research on air emissions assessment in transportation highlights the broader importance of quantifying and reducing emissions across operational systems [24]. Although these studies focus on related operational domains, they support the broader argument that environmental, economic, and operational objectives must be optimized together rather than separately.

The need for integration extends beyond production and maintenance alone. Modern operational systems are interconnected, and decisions at one level can influence routing, inventory, supply, delivery, and service performance. Reviews of integrated production scheduling and vehicle routing have emphasized that operational-level integration can reduce cost, improve responsiveness, and enhance resource utilization [25]. Coordinated algorithms for integrated production scheduling and vehicle routing also confirm that joint optimization can outperform isolated planning approaches [26]. Although the present study focuses on short-term production and preventive maintenance, this wider literature supports the conceptual necessity of integrated decision-making. It also suggests that models capable of coordinating multiple operational dimensions are better aligned with real industrial conditions than models that optimize a single function in isolation.

Uncertainty is another essential characteristic of real-world preventive maintenance scheduling. Processing times, machine deterioration, maintenance durations, resource availability, energy consumption, environmental emissions, and quality levels are often imprecise rather than fully deterministic. In short-term scheduling, even small uncertainties can affect feasibility and performance because the planning horizon is limited and operational flexibility is constrained. Fuzzy set theory provides a suitable method for representing ambiguous or imprecise parameters when exact probability distributions are unavailable. Fuzzy decision-making approaches have been applied to select preventive maintenance periods for single-purpose equipment, showing that fuzzy methods can support more realistic maintenance planning under uncertainty [27]. Risk-based preventive maintenance models have also emphasized that intangible and uncertain risk indicators must be included in maintenance planning to improve practical applicability [28]. These findings justify the use of fuzzy modeling in short-term preventive maintenance scheduling, especially when the model must reflect uncertain operating conditions and imperfect information.

The computational complexity of fuzzy multi-objective preventive maintenance scheduling requires efficient solution methods. Exact optimization methods are useful for validating small-scale instances and producing benchmark solutions, but they may become computationally expensive as the number of activities, projects, skills, machines, periods, and constraints increases. Metaheuristic algorithms are therefore widely used to solve complex scheduling and maintenance problems. Hybrid multi-objective metaheuristic algorithms have shown strong performance in distributed re-entrant permutation flow shop scheduling under preventive maintenance and uncertainty [29]. The NSGA-II algorithm is particularly suitable for multi-objective problems because it can generate a diverse set of non-dominated solutions, maintain solution diversity, and approximate Pareto fronts efficiently. Computational research using NSGA-II has demonstrated its usefulness in optimization problems involving sustainability, comfort, and complex system performance [30]. In the context of preventive maintenance scheduling, NSGA-II can provide decision-makers with alternative trade-off solutions rather than forcing selection of a single deterministic optimum.

Despite the expansion of research on green scheduling, preventive maintenance, fuzzy decision-making, and multi-objective optimization, there remains a need for a unified short-term model that simultaneously integrates TPM-based preventive maintenance with production scheduling under uncertainty. Many previous studies have focused on only one dimension, such as energy-aware scheduling, carbon emission reduction, machine maintenance, inspection planning, or routing integration. However, short-term industrial decision-making requires simultaneous consideration of maintenance timing, production completion time, cost, emissions, and quality within one coherent mathematical structure. A fuzzy multi-objective model can address this gap by incorporating uncertainty, representing competing objectives, and producing practical trade-off solutions. Such a model can help managers move from reactive or isolated maintenance decisions toward proactive TPM-based coordination of maintenance and production, thereby improving equipment reliability, reducing costs, controlling emissions, shortening completion time, and enhancing product quality.

Therefore, the aim of this study is to design a fuzzy multi-objective mathematical model for short-term preventive maintenance scheduling using a Total Productive Maintenance approach in order to minimize production completion time, total cost, and greenhouse gas emissions while maximizing product quality under uncertain operating conditions.

2. Methodology

This applied study employed a quantitative operations-research design to develop a fuzzy multi-objective mathematical model for short-term preventive maintenance scheduling within the framework of Total Productive Maintenance. The unit of analysis was the manufacturing and maintenance scheduling problem rather than human participants; therefore, the study did not involve patients, employees, or survey respondents. The proposed model was designed to coordinate production activities and preventive maintenance interventions over a finite short-term planning horizon while accounting for machine availability, activity sequencing, resource and skill requirements, maintenance timing, operational constraints, and uncertain system parameters. In accordance with the principles of Total Productive Maintenance, preventive maintenance was treated as an integral component of production planning rather than as an independent support activity. The model simultaneously pursued four conflicting objectives: minimizing production completion time, minimizing total operational and maintenance costs, minimizing greenhouse gas emissions, and maximizing the quality of completed production activities. To assess the behavior of the model under different levels of computational complexity, a set of randomly generated numerical instances was constructed. The small-scale validation set comprised five instances ranging from 6 activities, 2 projects, 2 skills, and 2 time periods to 15 activities, 6 projects, 6 skills, and 4 time periods. These instances represented progressively more complex short-term production and preventive maintenance environments and were used to examine the feasibility, accuracy, convergence, and computational efficiency of the proposed solution procedure.

The data required for model development were obtained through a structured library-based review and the generation of numerical test data. Scientific articles, technical studies, and methodological sources concerning preventive maintenance, Total Productive Maintenance, production scheduling, fuzzy mathematical programming, sustainable manufacturing, multi-objective optimization, and evolutionary algorithms were reviewed to identify the principal decision variables, objective functions, constraints, assumptions, and solution methods required for constructing the model. The literature review provided the conceptual and analytical foundation for defining the relationships among production scheduling, machine maintenance, cost, processing time, environmental emissions, and product quality. Based on this foundation, numerical values were randomly generated for the parameters of the computational instances, including the number of activities and projects, required skills, planning periods, processing requirements, operational and maintenance costs, quality coefficients, and greenhouse gas emission values. Parameters characterized by ambiguity or imprecision were represented through fuzzy values so that the mathematical formulation would more realistically reflect uncertainty in short-term industrial planning. The principal computational tools were the General Algebraic Modeling System and MATLAB. GAMS was used to formulate and solve small-scale instances through an exact optimization approach and thereby establish reference solutions, whereas MATLAB was used to implement the Non-dominated Sorting Genetic Algorithm II. The outputs generated by these tools included objective-function values, computational solution times, Pareto-optimal solutions, and repeated-run performance measures required to evaluate the reliability of the algorithm.

Data analysis was conducted through mathematical optimization, fuzzy modeling, and comparative computational experimentation. Initially, the conceptual structure of the short-term preventive maintenance scheduling problem was translated into a mathematical formulation consisting of indices, parameters, decision variables, four objective functions, and operational constraints. The objective functions were defined to minimize total cost, greenhouse gas emissions, and production completion time while maximizing production quality. Constraints were incorporated to ensure feasible activity assignment, compliance with precedence relationships, availability of machines and required skills, observance of the planning horizon, and proper coordination of preventive maintenance with production operations.

Fuzzy programming techniques were then applied to parameters whose exact values could not be determined with certainty, allowing the model to incorporate the ambiguity inherent in processing conditions, maintenance requirements, operational costs, quality levels, and environmental effects. Small-scale instances were solved in GAMS to obtain exact or benchmark solutions. The NSGA-II procedure was subsequently implemented in MATLAB using population initialization, fitness evaluation, non-dominated sorting, crowding-distance calculation, parent selection, crossover, mutation, feasibility control, and iterative population updating to generate a diverse set of Pareto-efficient solutions.

The accuracy of the metaheuristic procedure was evaluated by comparing the objective-function values obtained from NSGA-II with those generated by GAMS for the five benchmark instances. Percentage deviation was calculated separately for the cost, greenhouse gas emission, quality, and completion-time objectives. Computational efficiency was also assessed by comparing the solution times of the two methods. To evaluate the stability and repeatability of NSGA-II, each numerical instance was executed repeatedly, and the best, worst, and mean solutions were recorded. The percentage difference between the best and worst solutions, the deviation of the mean solution from the reference value, and the variance of repeated solutions were calculated for each objective function. Small deviations and low variance were interpreted as evidence of algorithmic convergence and robustness. Finally, the quality of the generated Pareto set was examined in terms of solution diversity, proximity to desirable objective values, and the algorithm’s ability to maintain balanced trade-offs among cost reduction, emission minimization, quality maximization, and shorter production completion times.

3. Findings and Results

Because the present study was based on mathematical modeling and computational experimentation, no human participants were included and conventional demographic characteristics such as age, sex, educational level, or occupational status were not applicable. Accordingly, the initial descriptive information concerned the structural characteristics of the numerical problem instances used to evaluate the proposed fuzzy multi-objective model. Five small-scale instances with progressively increasing complexity were generated. The first instance included 6 activities, 2 projects, 2 skill categories, and 2 short-term planning periods. The second instance consisted of 8 activities, 3 projects, 3 skill categories, and 2 planning periods. The third instance included 10 activities, 4 projects, 4 skill categories, and 3 planning periods, whereas the fourth instance comprised 12 activities, 5 projects, 5 skill categories, and 3 planning periods. The largest benchmark instance included 15 activities, 6 projects, 6 skill categories, and 4 planning periods. This progressive structure made it possible to evaluate the proposed solution procedure under different levels of problem dimensionality and to determine whether increasing the number of activities, projects, skills, and planning periods affected solution accuracy, stability, and computational performance. The exact GAMS solutions were used as benchmark values, and the results obtained from the NSGA-II algorithm were compared with these values for all four objective functions, namely product quality, production completion time, total cost, and greenhouse gas emissions.

Table 1. Evaluation of the Efficiency of the NSGA-II Algorithm for the Quality and Time Objective Functions in Small-Scale Instances

Example No.	Activities	Projects	Skills	Time Periods	Quality Objective: GAMS	Quality Objective: NSGA-II	Quality Deviation	Time Objective: GAMS	Time Objective: NSGA-II	Time Deviation
1	6	2	2	2	103.6	103.2	0.39%	41.2	41.6	0.97%
2	8	3	3	2	170.0	167.9	1.24%	69.4	70.1	1.01%
3	10	4	4	3	236.2	231.4	2.03%	96.4	98.0	1.66%
4	12	5	5	3	378.1	368.7	2.49%	110.2	113.0	2.54%
5	15	6	6	4	478.4	465.1	2.78%	125.3	128.9	2.87%

As shown in Table 1, the NSGA-II algorithm generated quality and completion-time values that were consistently close to the exact benchmark values obtained through GAMS. For the quality-maximization objective, the deviation between the two methods was only 0.39% in the first instance, where GAMS produced a quality value of 103.6 and NSGA-II produced a value of 103.2. In the second instance, the quality values were 170.0 and 167.9, respectively, corresponding to a deviation of 1.24%. With the increase in the number of activities, projects, skills, and planning periods, the quality deviation rose gradually to 2.03% in the third instance, 2.49% in the fourth instance, and 2.78% in the fifth instance. Nevertheless, even in the largest small-scale instance, the difference between the exact and metaheuristic solutions remained below 3%, indicating that NSGA-II retained a high level of accuracy despite the increasing complexity of the search space. A similar pattern was observed for the time-minimization objective. The exact completion time for the first instance was 41.2, compared with 41.6 obtained by NSGA-II, resulting in a deviation of 0.97%. In the second instance, the corresponding values were 69.4 and 70.1, with a deviation of 1.01%. The deviations increased to 1.66%, 2.54%, and 2.87% in the third, fourth, and fifth instances, respectively. These findings demonstrate that the proposed algorithm was capable of generating near-optimal schedules for both quality maximization and completion-time minimization. The gradual increase in deviation was expected because the addition of activities, projects, skill requirements, and periods expanded the number of feasible scheduling combinations and complicated the simultaneous coordination of production and preventive maintenance decisions. However, the limited magnitude of the deviations confirms that NSGA-II preserved acceptable solution quality throughout the tested problem sizes.

Table 2. Evaluation of the Efficiency of the NSGA-II Algorithm for the Cost and Greenhouse Gas Emission Objective Functions in Small-Scale Instances

Example No.	Activities	Projects	Skills	Time Periods	Cost Objective: GAMS	Cost Objective: NSGA-II	Cost Deviation	Greenhouse Gas Objective: GAMS	Greenhouse Gas Objective: NSGA-II	Greenhouse Gas Deviation
1	6	2	2	2	210.6	211.8	0.57%	56.3	56.5	0.36%
2	8	3	3	2	224.3	226.8	1.11%	69.7	70.4	1.00%
3	10	4	4	3	256.7	260.1	1.32%	96.2	98.0	1.87%
4	12	5	5	3	289.4	296.9	2.59%	121.1	124.1	2.48%
5	15	6	6	4	321.2	329.7	2.65%	136.3	140.3	2.93%

Table 2 presents the comparative results of GAMS and NSGA-II for the total-cost and greenhouse gas emission objectives. For the first instance, the exact total cost generated by GAMS was 210.6, whereas the NSGA-II value was 211.8, indicating a deviation of only 0.57%. The cost deviation remained limited in the second and third instances, at 1.11% and 1.32%, respectively. In the fourth instance, GAMS produced a cost value of 289.4 and NSGA-II produced 296.9, resulting in a deviation of 2.59%. In the fifth and most complex instance, the exact and metaheuristic cost values were 321.2 and 329.7, respectively, and the deviation reached 2.65%. Therefore, although the difference between the two methods increased with the expansion of the problem dimensions, the maximum cost deviation remained below 3%. This result indicates that the proposed algorithm was able to identify solutions with total costs closely approximating the exact optimum while simultaneously considering the other conflicting objectives of the model. The greenhouse gas emission results followed a comparable pattern. In the first instance, the emission values obtained through GAMS and NSGA-II were 56.3 and 56.5, respectively, corresponding to a deviation of only 0.36%. The deviation increased to 1.00% in the second instance and 1.87% in the third instance. For the fourth instance, GAMS generated an emission value of 121.1 and NSGA-II generated 124.1, resulting in a deviation of 2.48%. The highest deviation, 2.93%, occurred in the fifth instance, where the respective emission values were 136.3 and 140.3. The consistently small differences between the two approaches demonstrate that NSGA-II was effective in minimizing both the economic and environmental consequences of the integrated production and maintenance schedule. More importantly, the findings show that the algorithm did not achieve cost efficiency at the expense of environmental performance; rather, it maintained close correspondence with the exact solutions for both objectives concurrently. This pattern supports the suitability of the proposed fuzzy multi-objective model for short-term preventive maintenance decisions in which cost control and emission reduction must be pursued simultaneously.

Table 3. Stability and Repeatability of the NSGA-II Algorithm for the Cost Objective Function

No.	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Best Solution	Worst Solution	Mean Solution	B-W Deviation	Mean–Worst Deviation	Variance
1	52.2	52.2	52.3	52.2	52.2	52.2	52.3	52.2	52.2	52.3	52.23	0.19%	0.05%	0.002
2	69.7	69.8	69.6	69.7	69.7	69.8	69.9	69.7	69.6	69.9	69.74	0.43%	0.20%	0.008
3	85.7	85.8	86.2	86.7	86.5	85.7	86.9	85.9	85.7	86.9	86.18	1.40%	0.55%	0.225
4	85.9	86.3	85.9	87.4	86.9	87.2	85.9	85.9	85.9	87.4	86.43	1.75%	0.61%	0.414
5	278.4	278.2	278.6	278.1	286.3	281.3	277.9	278.4	277.9	286.3	279.65	3.02%	0.63%	8.391

The repeated-run results reported in Table 3 demonstrate the stability and reproducibility of the NSGA-II algorithm for the total-cost objective. In the first instance, the eight cost values ranged only from 52.2 to 52.3. The best and worst solutions were therefore 52.2 and 52.3, respectively, while the mean was 52.23. The deviation between the best and worst solutions was only 0.19%, the deviation of the mean from the worst solution was 0.05%, and the variance was 0.002. This extremely limited dispersion indicates that the algorithm converged almost identically across independent executions. In the second instance, the observed values ranged from 69.6 to 69.9, with a mean of 69.74, a best–worst deviation of 0.43%, a mean–worst deviation of 0.20%, and a variance of 0.008. The third instance showed a slightly broader range, from 85.7 to 86.9, but the best–worst deviation was still limited to 1.40%, the mean–worst deviation was 0.55%, and the variance was 0.225. In the fourth instance, the eight solutions varied between 85.9 and 87.4, producing a mean of 86.43, a best–worst deviation of 1.75%, a mean–worst deviation of 0.61%, and a variance of 0.414. The fifth instance exhibited the largest dispersion because of its greater dimensionality. In this instance, the best solution was 277.9, the worst solution was 286.3, and the mean solution was 279.65. Even under this more complex condition, the best–worst deviation was only 3.02%, and the mean–worst deviation was 0.63%. Although the variance increased to 8.391, this increase should be interpreted in relation to the substantially larger magnitude of the objective-function values in the fifth instance. Overall, the proximity of the repeated solutions, particularly the small differences between the mean and best-performing values, indicates that the algorithm was not excessively sensitive to stochastic initialization, crossover, or mutation. The results therefore confirm that NSGA-II provided stable and repeatable cost-minimization solutions and that its performance remained reliable as the number of scheduling components increased.

Table 4. Stability and Repeatability of the NSGA-II Algorithm for the Quality Objective Function

No.	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Best Solution	Worst Solution	Mean Solution	B-W Deviation	Mean–Worst Deviation	Variance
1	246	247	246	247	246	247	246	246	246.4	246.6	246.48	0.08%	0.03%	0.011
2	334	335	335	334	335	335	335	335	334.4	335.0	334.68	0.18%	0.08%	0.045
3	406	406	407	407	406	406	407	407	406.2	407.0	406.60	0.20%	0.10%	0.091
4	495	495	495	494	495	495	495	495	493.8	495.4	494.83	0.32%	0.21%	0.256
5	533	534	535	532	534	535	534	537	531.9	536.5	534.06	0.86%	0.41%	2.083

Table 4 shows that the NSGA-II algorithm also displayed strong convergence and low run-to-run variability for the quality-maximization objective. In the first instance, the repeated quality values were concentrated between 246 and 247, while the calculated best and worst solutions were 246.4 and 246.6 and the mean solution was 246.48. The best–worst deviation was only 0.08%, the mean–worst deviation was 0.03%, and the variance was 0.011. These values indicate almost complete consistency across the eight independent executions. In the second instance, the repeated values remained within a similarly narrow interval, and the best, worst, and mean values were 334.4, 335.0, and 334.68, respectively. The best–worst deviation was 0.18%, the mean–worst deviation was 0.08%, and the variance was 0.045. For the third instance, the quality values ranged between 406 and 407, producing a mean of 406.60, a best–worst deviation of 0.20%, and a variance of 0.091. In the fourth instance, despite the increase in the number of activities and resource requirements, the deviation between the best and worst solutions was only 0.32%, the mean–

worst deviation was 0.21%, and the variance was 0.256. The fifth instance produced values ranging from 532 to 537 across the eight executions. Its best, worst, and mean solutions were 531.9, 536.5, and 534.06, respectively. Nevertheless, the best–worst deviation remained below 1%, at 0.86%, while the mean–worst deviation was 0.41% and the variance was 2.083. The low dispersion observed across all five instances confirms that the algorithm consistently identified similar high-quality regions of the search space. This finding is especially important in a multi-objective maintenance-scheduling problem because the quality objective must be optimized in parallel with completion time, total cost, and environmental emissions. The results indicate that the stochastic search process did not produce unstable or widely divergent quality outcomes and that the proposed algorithm maintained reliable quality performance even when the problem dimensions increased.

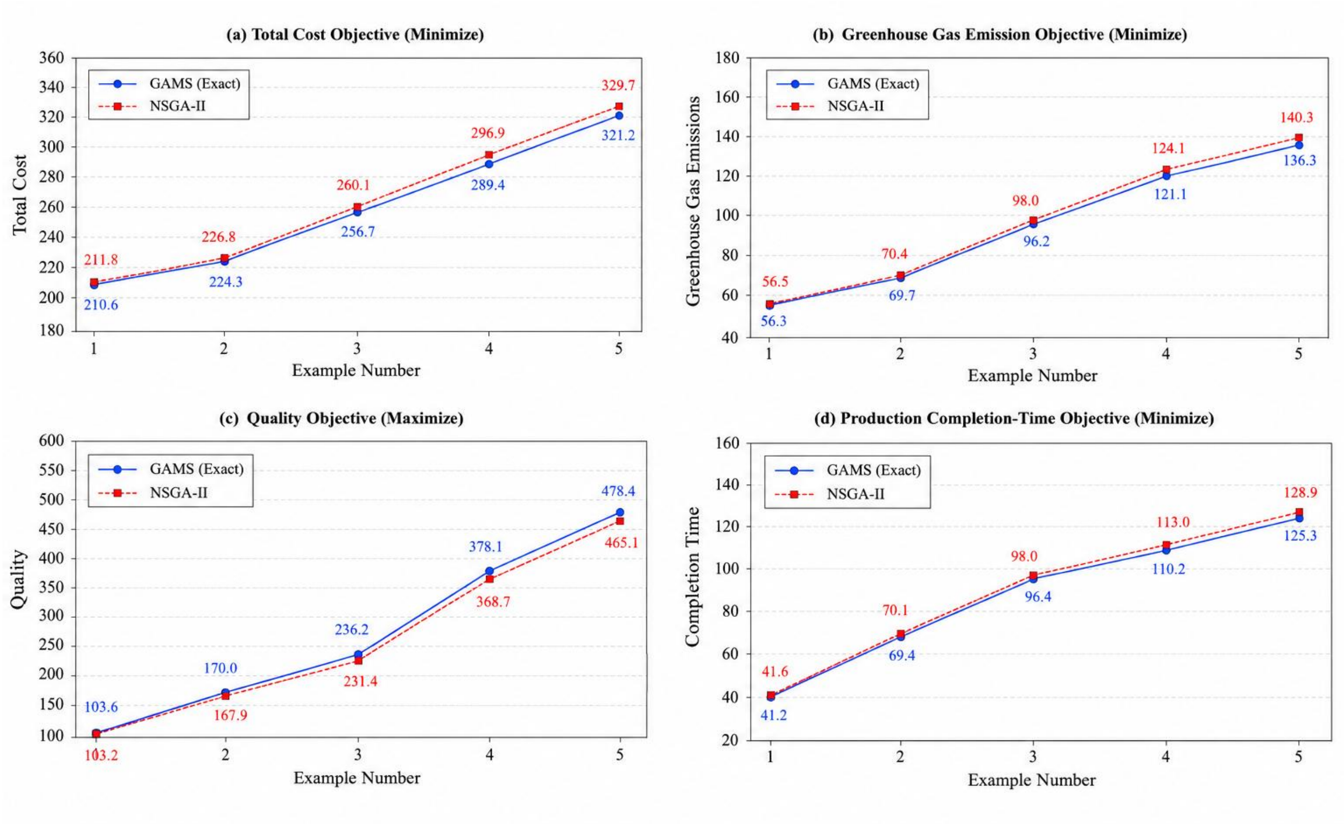

Figure 1. Comparative Evaluation of GAMS and NSGA-II Performance Across the Cost, Greenhouse Gas Emission, Quality, and Production Completion-Time Objective Functions

The comparative pattern presented in Figure 1 indicates that the solution trajectories obtained through NSGA-II closely followed the corresponding GAMS benchmark values across all five computational instances and all four objective functions. For the cost, greenhouse gas emission, and completion-time objectives, both methods showed increasing objective values as the number of activities, projects, skill requirements, and planning periods increased. This upward trend reflected the greater resource consumption, longer scheduling horizon, and higher operational burden associated with more complex instances rather than deterioration in the model's performance. For the quality objective, the values also increased with problem size because larger instances included more activities and production opportunities contributing to the aggregated quality measure. Across the four panels, the GAMS and NSGA-II lines remained close and approximately parallel, with only modest separation in the more complex instances. The proximity of the two methods visually confirms the numerical deviations reported in Tables 1 and 2. In particular, the differences were minimal in the first and second instances and increased gradually in the fourth and fifth instances, yet no abrupt divergence or unstable behavior was observed. Consequently, the graphical comparison supports the conclusion that NSGA-II reproduced the general direction and magnitude of the exact solutions with acceptable accuracy. Taken together, the tabular and graphical findings indicate that the proposed fuzzy multi-objective model was computationally feasible, that the NSGA-II algorithm generated stable and near-optimal solutions, and that the algorithm successfully balanced quality improvement with reductions in completion time, total cost, and greenhouse gas emissions in short-term preventive maintenance scheduling.

4. Discussion and Conclusion

The findings of the present study demonstrated that the proposed fuzzy multi-objective mathematical model can provide an effective framework for short-term preventive maintenance scheduling based on the Total Productive Maintenance approach. The model was able to coordinate preventive maintenance with production scheduling while simultaneously considering four major objective functions: minimizing production completion time, minimizing total cost, minimizing greenhouse gas emissions, and maximizing product quality. The comparison between the exact GAMS solutions and the NSGA-II algorithm showed that the proposed metaheuristic approach produced results very close to the benchmark values in small-scale instances. For the quality objective, the deviation between GAMS and NSGA-II ranged from 0.39% in the smallest instance to 2.78% in the largest tested instance. For the production completion-time objective, the deviation ranged from 0.97% to 2.87%. Similarly, for the cost objective, deviations increased from 0.57% to 2.65%, and for the greenhouse gas emission objective, deviations ranged from 0.36% to 2.93%. These results indicate that although the complexity of the problem increased with the number of activities, projects, skills, and planning periods, the NSGA-II algorithm preserved high accuracy and generated near-optimal solutions. This finding is consistent with previous studies showing that multi-objective metaheuristic algorithms are efficient tools for solving complex scheduling problems involving preventive maintenance, uncertainty, and multiple conflicting objectives [5, 29].

One of the most important findings of the study was that the model successfully integrated production scheduling and preventive maintenance decisions within a unified optimization structure. This result is significant because traditional production planning often treats maintenance as an external or secondary activity, while in real manufacturing systems, machine availability, equipment deterioration, maintenance timing, and production sequencing are closely interdependent. The results showed that when preventive maintenance is considered as part of short-term scheduling, the model can reduce completion time and cost while maintaining quality and controlling emissions. This finding is aligned with previous research emphasizing the importance of combining maintenance planning with production scheduling to improve operational performance. Sharifzadegan et al. showed that hybrid production scheduling models with resource constraints can benefit from the inclusion of preventive maintenance decisions, particularly when the objective is to balance production efficiency with maintenance feasibility [6]. Similarly, Qamhan et al. demonstrated that scheduling problems with release dates, sequence-dependent setup times, and periodic maintenance require integrated mathematical modeling because maintenance constraints directly affect the feasibility and quality of production schedules [5]. The present study extends these findings by incorporating uncertainty and environmental objectives into a TPM-oriented short-term preventive maintenance model.

The reduction of production completion time in the proposed model can be explained by the coordinated timing of maintenance activities and production operations. When preventive maintenance is scheduled without coordination, it may interrupt production flow, occupy critical machines at inappropriate times, and increase idle periods. Conversely, when maintenance interventions are optimized jointly with production scheduling, machine downtime can be placed in less disruptive periods, production activities can be assigned more efficiently, and unexpected failures can be reduced. This interpretation is supported by studies on integrated maintenance and scheduling models, which show that coordinated planning improves resource utilization and reduces makespan or completion time [2, 3]. The findings are also compatible with research on maintenance planning under machine deterioration, where appropriate inspection and preventive maintenance policies reduce operational disruption and improve system reliability [18, 19]. Therefore, the observed improvement in completion-time performance is not only an algorithmic result but also a consequence of embedding preventive maintenance into the short-term structure of production planning.

The findings also indicated that the proposed model was effective in reducing total cost. The cost values generated by NSGA-II remained close to the exact values obtained by GAMS across all five instances, and the maximum deviation remained below 3%. This result suggests that the algorithm was able to locate economically efficient schedules while also considering quality, time, and environmental performance. Preventive maintenance can reduce costs by preventing unexpected failures, reducing emergency repair costs, decreasing production stoppages, and improving the predictability of resource allocation. Previous studies have similarly emphasized that optimal preventive maintenance policies can reduce total maintenance and production-related costs by identifying appropriate intervention periods [3]. Research on simultaneous maintenance and spare parts inventory planning further confirms that maintenance decisions are strongly connected to cost control, because inappropriate maintenance timing can increase spare parts consumption, downtime costs, and operational inefficiencies [16]. In the same direction, reliability-based production system models have shown that maintenance strategies influence not only technical reliability but also revenue and economic performance [17]. The present study supports this body of evidence by showing that a fuzzy multi-objective TPM-based model can reduce cost in short-term scheduling without isolating cost from other important objectives.

Another major result was the model's ability to control greenhouse gas emissions. The greenhouse gas emission values obtained by NSGA-II were very close to those generated by GAMS, with deviations ranging from 0.36% to 2.93%. This finding demonstrates that emission minimization can be integrated into preventive maintenance scheduling without making the model computationally impractical. The result is consistent with the growing literature on green and sustainable scheduling, which has shown that production sequencing, machine assignment, processing time, energy use, and operational disruptions are closely related to carbon emissions [11, 12]. Low-carbon flexible job shop scheduling studies have also demonstrated that environmental objectives can be incorporated into operational models to reduce emissions while preserving production efficiency [13]. Moreover, research on disruption management and manufacturing scheduling has shown that reducing operational instability can contribute to lower carbon emissions [14]. The present findings are therefore consistent with previous research, but they add an important maintenance-oriented dimension by showing that preventive maintenance can contribute to environmental performance through improved equipment condition and more stable machine operation.

The environmental performance of the model can also be explained through the relationship between maintenance, energy efficiency, and machine reliability. Deteriorated equipment may consume more energy, require longer processing times, generate more defective output, and produce higher emissions. Preventive maintenance helps machines operate closer to their intended technical condition, thereby reducing unnecessary energy consumption and emission intensity. This explanation is aligned with studies on energy-efficient manufacturing, which indicate that scheduling decisions can significantly affect energy consumption and sustainable production outcomes [7, 8]. Energy-efficient flow shop and hybrid flow shop scheduling studies have also shown that optimization-based scheduling can reduce energy-related environmental impacts in complex production environments [9, 10]. Furthermore, recent research on carbon-aware production scheduling with non-identical parallel machines and multiple energy sources confirms the importance of considering carbon emissions directly in scheduling models [15]. Accordingly, the present study supports the argument that preventive maintenance should be considered an environmental management tool as well as an operational reliability strategy.

The improvement and preservation of product quality constituted another important result of the study. The comparison between GAMS and NSGA-II showed that the quality objective was approximated with high accuracy, and the repeated-run results indicated low dispersion in quality solutions. In a TPM framework, maintenance has a direct relationship with quality because machine condition influences process precision, defect rates, rework, and output consistency. Well-maintained machines are more likely to operate within technical tolerances, while poorly maintained equipment can increase variability and reduce the quality of production activities. This interpretation is consistent with studies on reliability-based maintenance and failure-prone production systems, where maintenance decisions influence production performance and output reliability [17]. The importance of quality also aligns with sustainable supply chain research, which shows that imperfect items affect operational decisions and must be considered in planning models [20]. In addition, studies on consumer environmental awareness suggest that quality and sustainability are increasingly linked to organizational competitiveness and market coordination [21]. Therefore, the inclusion of quality maximization in the proposed model is theoretically and practically justified.

The repeated execution of the NSGA-II algorithm showed that the algorithm was stable and reliable. For the cost objective, the best–worst deviation remained very small in the first four instances and reached 3.02% only in the largest tested instance. For the quality objective, the best–worst deviation remained below 1% in all instances, indicating strong convergence and limited sensitivity to stochastic variation. These findings show that NSGA-II did not produce highly unstable results across independent runs and that the algorithm was able to consistently identify high-quality areas of the solution space. This is particularly important in fuzzy multi-objective optimization, where uncertainty and competing objectives can make the search space complex. Previous studies have emphasized that metaheuristic algorithms are valuable for multi-objective scheduling because they can provide high-quality solutions within reasonable computational time when exact methods become expensive or infeasible [29, 30]. The stability observed in the present study therefore supports the use of NSGA-II as an appropriate solution method for short-term preventive maintenance scheduling.

The use of fuzzy modeling was also supported by the results. In real production systems, many parameters cannot be estimated with complete precision, including processing times, maintenance requirements, equipment condition, cost values, environmental impacts, and quality coefficients. A deterministic model may generate solutions that appear optimal mathematically but perform poorly under actual uncertainty. By incorporating fuzzy logic, the proposed model represented ambiguous and imprecise operational information more realistically. This approach is consistent with fuzzy preventive maintenance studies that show fuzzy decision-making can support the selection of appropriate maintenance periods when precise data are unavailable [27]. It is also aligned with risk-based preventive maintenance research, which emphasizes that intangible and uncertain risk indicators should be included in maintenance planning [28]. The successful application of fuzzy modeling in the present study indicates that uncertainty-aware models are more suitable for TPM-based short-term maintenance scheduling than purely deterministic approaches.

From a broader perspective, the findings support the growing movement toward integrated and sustainable operational planning. Manufacturing decisions increasingly extend beyond the factory floor and interact with inventory, routing, transportation, supply chain coordination, and environmental policy. Studies on integrated production scheduling and vehicle routing have shown that joint decision-making can improve cost, service, and resource utilization [25, 26]. Integrated machine scheduling and vehicle routing research has also shown that carbon emissions can be reduced through coordinated operational planning [22]. Pollution-routing studies under demand and travel-time uncertainty further demonstrate the importance of robust environmental optimization under uncertain conditions [23]. In addition, air emissions assessment research confirms that emissions must be treated as measurable operational consequences rather than abstract environmental concerns [24]. The present study contributes to this integrated research stream by focusing on the short-term coordination of production and preventive maintenance while incorporating cost, emissions, time, quality, and uncertainty in one model.

The findings also show that environmental and economic objectives do not necessarily have to be treated as fully incompatible. Although reducing emissions may sometimes require additional investment or operational adjustment, the proposed model demonstrated that coordinated scheduling and preventive maintenance can reduce emissions while also controlling costs and completion time. This supports the sustainable manufacturing argument that operational optimization can create simultaneous economic and environmental value [11, 14]. The increasing attention to climate-related operational challenges further reinforces the need for decision models that reduce environmental burdens while preserving system performance [1]. Therefore, the present study offers evidence that TPM-based preventive maintenance scheduling can serve both productivity and sustainability objectives, particularly when supported by fuzzy multi-objective optimization.

The present study has several limitations. First, the model was evaluated using randomly generated numerical instances rather than empirical data from a specific manufacturing organization, which may limit the immediate generalizability of the findings to all industrial settings. Second, the analysis focused on short-term preventive maintenance scheduling and did not incorporate corrective, predictive, or condition-based maintenance strategies in a comprehensive comparative structure. Third, although uncertainty was modeled through fuzzy parameters, the study did not include real-time disruptions such as sudden machine failure, workforce absence, urgent customer orders, or supply shortages. Fourth, the computational evaluation was mainly based on comparison between GAMS and NSGA-II, while other metaheuristic, hybrid, or machine-learning-based optimization algorithms were not examined. Finally, the model considered selected operational, economic, environmental, and quality objectives, but did not include all possible organizational factors such as safety, operator workload, spare parts lead time, or dynamic energy pricing.

Future research should extend the proposed model by validating it with real industrial data from manufacturing systems that implement Total Productive Maintenance. Future studies can incorporate predictive maintenance using sensor data, machine health indicators, and Industry 4.0 technologies to make maintenance scheduling more dynamic and responsive. Researchers may also compare NSGA-II with other advanced optimization algorithms, including hybrid evolutionary algorithms, swarm intelligence methods, decomposition-based multi-objective algorithms, and machine-learning-assisted optimization procedures. Another useful direction would be to develop stochastic, robust, or simulation-based versions of the model to examine the effects of unexpected disruptions, demand fluctuations, machine deterioration, and resource unavailability. Future research can also expand the model by integrating spare parts inventory, workforce scheduling, transportation planning, and energy pricing mechanisms into the same decision framework.

From a practical perspective, manufacturing managers should consider preventive maintenance as a strategic component of short-term production scheduling rather than as a separate technical function. The findings suggest that coordinated planning can help organizations reduce production completion time, control total cost, improve product quality, and decrease greenhouse gas emissions at the same time. Managers should therefore develop decision-support systems that combine maintenance data, production requirements, machine availability, and environmental indicators in one integrated platform. Organizations can also benefit from adopting TPM principles more systematically by improving coordination between production operators, maintenance teams, planners, and quality-control personnel. In addition, companies should invest in accurate data collection, equipment monitoring, maintenance history documentation, and staff training so that optimization-based scheduling models can be implemented effectively in real operational environments.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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