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Designing a Fuzzy Multi-Objective Mathematical Model for Long-Term Preventive Maintenance Scheduling Based on the Total Productive Maintenance Approach

Foroud. Rajabpour[1], Masoomeh. Zeinalnezhad[2*], Vahid. Hajipour[2]

[1] Department of Industrial Engineering, Ki.C., Islamic Azad University, Kish, Iran
[2] Department of Industrial Engineering, WT.C., Islamic Azad University, Tehran, Iran

*** Corresponding author email address**: m.zeinalnezhad@gmail.com

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A B S T R A C T

This study aimed to design and validate a fuzzy multi-objective mathematical model for long-term preventive maintenance scheduling based on Total Productive Maintenance principles to minimize total cost, completion time, and greenhouse-gas emissions while maximizing quality under uncertain operating conditions. This applied operations-research study employed mathematical modeling and computational experimentation. A fuzzy multi-objective model was formulated to coordinate preventive maintenance activities across multiple projects, technical skill categories, resources, and long-term planning periods. Uncertain parameters related to maintenance duration, equipment condition, costs, resource requirements, and environmental impacts were represented using fuzzy logic. The model included four objective functions: minimization of total cost, maintenance completion time, and greenhouse-gas emissions and maximization of quality. Five progressively complex benchmark instances were generated. Exact solutions for validation instances were obtained using GAMS, whereas the Non-dominated Sorting Genetic Algorithm II was implemented in MATLAB to solve larger and more complex instances. Algorithmic performance was evaluated through percentage deviation from exact solutions, repeated independent runs, best and worst solutions, mean performance, variance, convergence, and stability. The NSGA-II solutions closely approximated the exact GAMS results across all objective functions. Mean deviations were 1.96% for quality, 2.32% for completion time, 2.23% for total cost, and 2.42% for greenhouse-gas emissions, while the maximum observed deviation remained below 4%. Repeated-run analyses demonstrated strong convergence and computational stability. In the largest instance, the mean total-cost solution differed from the best solution by only 0.65%, and the mean quality solution differed from the best result by 0.40%. The limited best-to-worst deviations and low relative variability confirmed the robustness of the proposed solution procedure under increasing problem complexity. The proposed fuzzy multi-objective model provides an effective and computationally reliable framework for integrating long-term preventive maintenance scheduling with economic, operational, quality, and environmental objectives, while NSGA-II offers a practical solution method for large-scale industrial applications.

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

1. Introduction

Industrial organizations are increasingly required to maintain high levels of productivity, quality, responsiveness, and equipment availability while simultaneously controlling costs, reducing environmental impacts, and complying with sustainability requirements. This pressure has intensified as industrial energy consumption, greenhouse-gas emissions, resource depletion, and climate-related disruptions have become central concerns in operations management. Climate change affects not only natural and agricultural systems but also the continuity, resilience, and energy requirements of industrial operations, making long-term adaptation and resource-efficient planning increasingly important (Fanourakis, 2025). At the same time, the development of computational approaches for balancing environmental performance, energy efficiency, and operational objectives demonstrates the growing value of multi-objective optimization in complex planning environments (Lotfinejad et al., 2025). Manufacturing firms must therefore move beyond short-horizon, single-objective decision-making and adopt integrated planning models capable of coordinating production and maintenance decisions across extended periods. Long-term maintenance scheduling is especially important because equipment deterioration, resource constraints, replacement decisions, environmental consequences, and production commitments accumulate over time. A maintenance plan that appears economical within a limited period may generate higher failure rates, excessive energy consumption, declining product quality, and substantial operational losses in subsequent periods. Consequently, long-term preventive maintenance planning should be treated as a strategic component of sustainable production management rather than merely as a technical response to equipment failure.

Maintenance management has traditionally been classified into corrective, preventive, condition-based, predictive, and reliability-centered strategies. Corrective maintenance is performed after a failure occurs and may therefore lead to unplanned downtime, emergency repair costs, production delays, safety risks, and quality losses. Preventive maintenance, by contrast, involves performing maintenance interventions at predetermined times or usage thresholds to reduce the likelihood of failure and preserve equipment functionality. The effectiveness of preventive maintenance depends heavily on the determination of appropriate intervention thresholds, because excessively frequent maintenance increases direct costs and interrupts production, whereas delayed intervention increases the probability of failure and the associated operational consequences. Dynamic programming approaches have shown that optimizing preventive-maintenance thresholds can improve the effectiveness of condition-based maintenance programs and reduce the total consequences of equipment deterioration (Shahanaghi et al., 2010). Similarly, optimization-based preventive maintenance models have demonstrated that maintenance timing should be selected by considering the interactions among failure probability, repair cost, downtime, and system performance rather than relying solely on fixed technical recommendations (Molaverdi et al., 2020). These considerations become more complex in a long-term planning horizon, where the maintenance decisions made in one period influence machine condition, capacity, resource availability, and risk exposure in later periods.

The Total Productive Maintenance approach provides a comprehensive managerial framework for addressing these challenges. Total Productive Maintenance seeks to maximize overall equipment effectiveness through the participation of production personnel, maintenance specialists, managers, and other organizational units. Rather than treating maintenance as an isolated engineering activity, this approach integrates maintenance with production, quality management, employee involvement, safety, continuous improvement, and waste reduction. Its central logic is that equipment losses, including breakdowns, minor stoppages, reduced speed, defects, and start-up losses, should be systematically identified and minimized. In this context, preventive maintenance supports the broader objectives of Total Productive Maintenance by maintaining equipment in a reliable condition, reducing unplanned stoppages, and improving process stability. A reliability-based maintenance perspective is particularly relevant because the performance of a production system depends not only on individual machines but also on the propagation of failures and capacity losses throughout the production network. Simulation-optimization research on failure-prone production systems has shown that maintenance policies influence reliability, revenue, operational coordination, and the distribution of benefits among interconnected units (Sajjadi, 2022). Accordingly, a long-term preventive-maintenance model based on Total Productive Maintenance should reflect the strategic relationship among equipment reliability, production continuity, quality preservation, cost control, and collective organizational performance.

The integration of production scheduling and preventive-maintenance planning is essential because both functions compete for the same machines, labor, time, and financial resources. Production schedules determine when machines are expected to operate, while maintenance schedules determine when those machines must be removed from service. If these decisions are developed independently, maintenance interventions may interrupt critical production activities, and production plans may prevent maintenance from being conducted at the appropriate time. Integrated scheduling models have therefore been proposed to coordinate production and periodic maintenance while considering release dates, sequence-dependent setup times, and machine availability (Qamhan et al., 2019). Bi-objective production-scheduling models with preventive-maintenance considerations have also demonstrated that simultaneously optimizing resource allocation and maintenance timing can reduce completion-related losses and improve system utilization (Sharifzadegan et al., 2022). In addition, dynamic grouping models for maintenance activities indicate that combining compatible interventions can reduce repeated shutdowns and improve the use of maintenance resources, particularly in multi-component systems with intermittent operations (Moazzam Jozi et al., 2023). These findings suggest that long-term planning requires not only the timing of individual maintenance actions but also the coordination, grouping, and sequencing of activities across multiple machines, projects, skills, and periods.

Long-term maintenance planning is also strongly affected by resource constraints. Preventive-maintenance activities may require specialized technicians, spare parts, inspection equipment, service tools, and access to specific machines. These resources are often limited and must be allocated among several competing maintenance projects. Maintenance planning is therefore closely related to workforce planning, project scheduling, and spare-parts management. The simultaneous planning of maintenance and spare-parts inventory can reduce both equipment downtime and excessive inventory investment by ensuring that critical components are available when maintenance is scheduled (Raeisi, 2019). Furthermore, integrated inspection and preventive-maintenance models demonstrate that inspection decisions can provide essential information about machine deterioration and help determine whether maintenance should be advanced, postponed, or combined with other interventions (Lotfi, 2020). Mathematical models that jointly optimize inspection and preventive maintenance under deterioration and demand uncertainty also show that maintenance policies should respond to both technical conditions and changes in operational requirements (Nouri et al., 2020). In a long-term environment, these interdependencies become more pronounced because resource availability, deterioration states, inspection results, and production requirements change across successive periods.

Uncertainty constitutes another major challenge in long-term preventive-maintenance scheduling. Parameters such as maintenance duration, failure probability, machine deterioration, labor availability, cost coefficients, production demand, energy prices, and environmental impacts cannot be predicted with complete accuracy over an extended planning horizon. Deterministic models may generate mathematically optimal schedules that become infeasible or inefficient when actual conditions differ from expected values. Risk-based preventive-maintenance models have therefore incorporated both tangible and intangible risk indicators to improve the realism of maintenance decisions (Damchi & Saebi, 2023). Fuzzy decision-making approaches have likewise been used to select appropriate preventive-maintenance periods when equipment condition, expert assessments, and operational consequences are expressed through imprecise or linguistic information (Azimian et al., 2021). Fuzzy modeling is especially suitable for long-term maintenance planning because it allows uncertain parameters to be represented as ranges or membership functions rather than exact values. This capability is important when historical data are limited, expert judgments differ, or future operating conditions are inherently ambiguous. A fuzzy mathematical model can therefore provide more flexible and robust maintenance schedules than a purely deterministic formulation.

Environmental sustainability further increases the complexity of maintenance and production decisions. Industrial equipment consumes energy during operation, idling, setup, shutdown, and restart, while inefficient or deteriorated machinery may require more energy to produce the same output. Preventive maintenance can improve energy efficiency by reducing friction, misalignment, wear, leakage, and other technical conditions associated with excessive consumption. Real-time energy-control research has shown that manufacturing systems can identify opportunities to reduce energy use by coordinating operating states and production decisions (Sun & Li, 2013). Energy-efficient scheduling models have also demonstrated that production sequences and machine assignments can substantially affect electricity consumption and environmental performance (Lu et al., 2017). In heterogeneous and multi-stage production systems, collaborative scheduling can improve energy efficiency by coordinating operations across different machines and processing stages (Duan et al., 2022). These findings indicate that maintenance scheduling and energy management should not be treated as independent domains. Over a long-term horizon, the energy implications of machine deterioration and maintenance timing accumulate, making environmental criteria essential components of preventive-maintenance optimization.

Greenhouse-gas emissions have consequently become an important objective in industrial scheduling. Production schedules influence machine utilization, idle time, energy-source selection, and the timing of electricity consumption. Scheduling problems involving non-identical parallel machines have shown that carbon emissions may vary considerably according to machine assignments, due dates, and the types of energy sources used (Bok et al., 2024). Low-carbon flexible job-shop scheduling similarly demonstrates that environmental performance can be improved through appropriate job sequencing and resource allocation (Ning & Huang, 2021). Disruption-management models further indicate that rescheduling after unexpected events can reduce carbon emissions when environmental objectives are explicitly included in the decision process (Ning et al., 2020). Multi-objective genetic algorithms have also been used to minimize both total carbon footprint and late work in flexible job-shop environments, confirming that environmental and operational objectives can be jointly optimized (Piroozfard et al., 2017). These studies provide a strong basis for incorporating greenhouse-gas emissions into long-term maintenance scheduling, because preventive maintenance affects machine efficiency, production continuity, downtime patterns, and the need for corrective interventions.

Environmental objectives are not limited to factory-level energy consumption. Manufacturing decisions influence logistics, transportation, inventory, and broader supply-chain emissions. Integrated machine-scheduling and vehicle-routing models have shown that coordinating production and distribution decisions can substantially reduce total carbon emissions (Wang et al., 2019). Coordinated algorithms for integrated production scheduling and vehicle routing further demonstrate that isolated optimization may shift costs or delays from one operational stage to another, whereas integrated approaches generate more balanced system-wide solutions (Zou et al., 2018). Reviews of production-scheduling and vehicle-routing integration likewise emphasize that operational coordination can improve responsiveness, capacity utilization, and delivery performance (Moons et al., 2017). Robust pollution-routing models show that demand and travel-time uncertainty must also be considered when minimizing environmental impacts across logistics networks (Eshtehadi et al., 2017). In addition, air-emission assessment research highlights the importance of measuring transportation-related pollutants and incorporating emission consequences into operational decisions (Fan et al., 2018). Although the present maintenance problem is centered on industrial equipment, these studies illustrate a broader principle: environmental effects arise from interconnected operational decisions, and long-term preventive-maintenance planning should therefore be consistent with the sustainability objectives of the entire production system.

Sustainable manufacturing also requires consideration of product quality, defective items, and material waste. Equipment deterioration can increase variability, dimensional errors, rework, scrap, and customer complaints. Preventive maintenance contributes to quality assurance by preserving process capability and reducing the probability that machines operate outside acceptable tolerances. Sustainable supply-chain models involving imperfect products demonstrate that quality problems affect inventory decisions, withdrawal policies, costs, and environmental outcomes throughout the supply chain (Asadkhani et al., 2022). Product quality should therefore be included directly in maintenance optimization rather than treated as a secondary consequence. The inclusion of quality as an objective is also consistent with the Total Productive Maintenance philosophy, which emphasizes zero defects alongside zero failures and zero accidents. From a market perspective, environmental quality and customer awareness are increasingly important. Consumer environmental awareness can influence channel coordination, product substitution, and organizational incentives to adopt environmentally responsible practices (Zhang et al., 2015). Consequently, a long-term maintenance schedule that improves equipment efficiency, reduces emissions, and maintains product quality can create both operational and competitive advantages.

The objectives involved in long-term preventive-maintenance planning are inherently conflicting. Increasing the frequency of maintenance may improve reliability and quality but also increase direct maintenance costs and planned downtime. Reducing completion time may require intensive machine utilization, which can accelerate deterioration and increase energy consumption. Minimizing cost may encourage the postponement of maintenance, while minimizing risk may require earlier intervention. Environmental improvements may also require alternative machine assignments or production sequences that increase operational time. Green scheduling research has demonstrated that carbon-reduction policies can produce different trade-offs among makespan, energy use, emissions, and operational costs (Foumani & Smith-Miles, 2019). Bi-objective scheduling under time-of-use electricity prices similarly reveals conflicts between production performance and energy expenditure (Cheng et al., 2015). These competing goals justify the development of a multi-objective model that produces a set of Pareto-efficient alternatives rather than a single solution based on an arbitrary aggregation of objectives. Such a model enables managers to select a maintenance schedule that reflects organizational priorities, regulatory requirements, production commitments, and acceptable risk levels.

The computational complexity of this problem also necessitates advanced solution methods. Exact mathematical-programming techniques can identify optimal solutions for small instances, but their computational requirements increase rapidly as the number of activities, machines, skills, projects, and planning periods grows. Long-term maintenance scheduling generally involves a large number of binary and continuous variables, precedence relationships, resource limitations, fuzzy parameters, and conflicting objectives. Metaheuristic algorithms are therefore widely used to obtain high-quality solutions within acceptable computational times. A hybrid multi-objective metaheuristic algorithm has been successfully applied to distributed re-entrant flow-shop scheduling with preventive maintenance under uncertainty, demonstrating the suitability of evolutionary search for integrated and complex scheduling problems (Hasani, 2018). The Non-dominated Sorting Genetic Algorithm II is particularly appropriate because it can generate a diverse set of non-dominated solutions while preserving convergence toward the Pareto frontier. Its effectiveness has been demonstrated in computational models involving thermal comfort, environmental performance, and multiple design objectives (Lotfinejad et al., 2025). The combined use of exact optimization for validation and NSGA-II for larger instances can therefore provide both solution credibility and computational scalability.

Despite these developments, the existing literature remains fragmented. Some studies focus on preventive-maintenance thresholds, while others examine inspection planning, risk indicators, spare-parts control, production scheduling, energy consumption, carbon emissions, or logistics integration. Relatively few models combine these dimensions within a unified long-term framework based explicitly on Total Productive Maintenance. Many available studies also emphasize operational or short-horizon decisions and do not adequately represent the cumulative effects of maintenance timing across multiple planning periods. Moreover, deterministic formulations remain common even though long-term maintenance parameters are characterized by substantial uncertainty. There is therefore a need for a comprehensive model that simultaneously addresses cost, completion time, quality, environmental emissions, resource constraints, and uncertainty while coordinating preventive-maintenance activities over an extended horizon.

Accordingly, the aim of this study was to design a fuzzy multi-objective mathematical model for long-term preventive-maintenance scheduling based on the Total Productive Maintenance approach in order to minimize total cost, completion time, and greenhouse-gas emissions while maximizing quality under uncertain operating conditions.

2. Methods and Materials

This applied and model-development research was conducted within the framework of operations research to design a fuzzy multi-objective mathematical model for long-term preventive maintenance scheduling based on the principles of Total Productive Maintenance. The study sought to establish an integrated decision-support framework through which preventive maintenance activities could be scheduled across a multi-period planning horizon while simultaneously considering economic, operational, environmental, and quality-related performance criteria. In accordance with the Total Productive Maintenance approach, maintenance was treated as an integral component of organizational operations rather than an isolated technical function. Accordingly, the model was developed to support the systematic planning of maintenance activities, improve equipment availability and operational continuity, prevent unplanned failures, preserve product quality, and reduce losses associated with machine deterioration, production interruption, excessive resource consumption, and inefficient maintenance timing. The proposed mathematical structure included a finite set of maintenance activities, projects, skill categories, and planning periods. The principal decisions concerned the selection, timing, and allocation of preventive maintenance activities over the long-term planning horizon, subject to the operational and resource constraints incorporated into the model. The multi-objective formulation was designed to minimize total cost, greenhouse gas emissions, and the completion time of scheduled activities while maximizing the quality-related performance of the system. Because the study was computational and mathematical, no human participants were recruited. Instead, the analytical units consisted of simulated problem instances representing preventive maintenance scheduling environments of different sizes and levels of complexity. For the initial verification of the model, benchmark instances were generated with increasing combinations of activities, projects, required skills, and planning periods. These instances ranged from 6 to 15 activities, 2 to 6 projects, 2 to 6 skill categories, and 2 to 4 planning periods, after which more complex instances were used to examine the scalability and computational performance of the solution procedure. The use of progressively larger instances made it possible to evaluate whether the proposed model and algorithm could maintain solution quality as the number of decision variables and constraints increased.

The information required to construct the model was collected through a structured review of scientific literature and the generation of computational data. The literature-review component covered preventive maintenance planning, Total Productive Maintenance, production and maintenance scheduling, multi-objective mathematical programming, sustainable manufacturing, fuzzy optimization, and evolutionary solution algorithms. Relevant scientific articles and previous mathematical models were examined to identify the principal decision variables, objective functions, operational restrictions, uncertainty sources, and performance indicators used in maintenance-planning research. The extracted information was used to define the conceptual boundaries of the problem and to formulate the assumptions, indices, parameters, decision variables, objective functions, and constraints of the proposed model. Particular attention was given to parameters representing maintenance duration and requirements, activity completion time, resource and skill availability, maintenance-related expenditures, operational costs, environmental emissions, machine condition, and quality performance. The Total Productive Maintenance perspective was reflected in the model by linking planned maintenance decisions to equipment effectiveness, operational reliability, quality preservation, waste reduction, and the avoidance of unplanned downtime. Because many of the relevant parameters cannot be estimated with complete precision over a long-term planning horizon, uncertain input values were represented through fuzzy parameters. This approach allowed approximate, ambiguous, and linguistically assessed information concerning processing times, maintenance requirements, machine deterioration, demand conditions, cost coefficients, and environmental effects to be incorporated into the mathematical formulation rather than being treated as completely deterministic values. Following development of the conceptual and mathematical structure, randomly generated numerical data were used to create reproducible test problems. The generated datasets contained the dimensions and parameter values required to represent maintenance activities, projects, skill requirements, and planning periods under different levels of complexity. These data served as the computational input for validating the mathematical formulation, comparing the exact and metaheuristic solution approaches, and assessing the behavior of the model under increasing problem dimensions. No questionnaire, interview protocol, or psychometric instrument was employed because the required evidence consisted of model parameters, computational scenarios, and optimization outputs rather than individual-level responses.

Data analysis was conducted through mathematical programming, fuzzy multi-objective optimization, and computational experimentation. The first stage involved formulating the long-term preventive maintenance scheduling problem as a multi-objective mathematical model. The objective functions were specified to minimize total maintenance and operational costs, minimize greenhouse gas emissions, minimize the overall completion time of scheduled activities, and maximize system or product quality. The objective functions were optimized subject to the model’s structural and operational constraints, including the assignment of maintenance activities to projects and planning periods, the fulfillment of skill requirements, the availability of relevant resources, and the logical coordination of maintenance decisions throughout the planning horizon. Fuzzy modeling was incorporated to represent uncertain coefficients and provide a more realistic representation of long-term operating conditions. The resulting formulation enabled the identification of compromise solutions rather than forcing all conflicting criteria into a single deterministic objective. Therefore, the model generated a set of non-dominated or Pareto-efficient solutions from which decision-makers could select an appropriate maintenance plan according to organizational priorities concerning cost, time, quality, and environmental performance.

The mathematical model was initially coded and solved in the General Algebraic Modeling System to obtain exact solutions for manageable benchmark instances and verify the internal consistency of the formulation. The GAMS results were treated as reference solutions for evaluating the accuracy of the proposed metaheuristic procedure. Because the computational burden of exact optimization increases substantially as the numbers of activities, projects, skills, planning periods, variables, and constraints grow, the Non-dominated Sorting Genetic Algorithm II was subsequently implemented in MATLAB to solve the more complex instances. In the NSGA-II procedure, candidate maintenance schedules were represented as chromosomes and evaluated according to the four objective functions and the feasibility requirements of the model. The evolutionary search proceeded through population initialization, fitness evaluation, non-dominated sorting, crowding-distance calculation, parent selection, crossover, mutation, and replacement. Non-dominated sorting classified candidate solutions according to Pareto dominance, while the crowding-distance mechanism preserved diversity and prevented the algorithm from concentrating excessively on a limited region of the Pareto frontier. Crossover and mutation operators were used to explore alternative maintenance schedules, and infeasible solutions were repaired or penalized according to their violations of the model constraints. The evolutionary process continued until the predetermined termination criterion was reached and a final set of efficient long-term maintenance schedules was obtained.

The validity of the NSGA-II results was examined by comparing its objective-function values with those produced by GAMS for the benchmark instances. Percentage deviation was calculated separately for the cost, greenhouse gas emissions, quality, and completion-time objectives to determine how closely the approximate solutions approached the exact solutions. Algorithmic stability was assessed through repeated independent executions of the computational procedure. For each problem instance and objective function, the best solution, worst solution, mean solution, best-to-worst deviation, mean deviation, and variance were calculated. Small differences among the best, worst, and average values were interpreted as evidence of convergence stability and low sensitivity to random initialization. The overall performance of the multi-objective algorithm was also assessed using indicators related to the number and quality of Pareto solutions, proximity to the ideal point, distribution of solutions, and diversity across the Pareto frontier. Computational time was recorded to evaluate the efficiency and scalability of the exact and metaheuristic approaches as the dimensions of the scheduling problem increased. Through this analytical procedure, the proposed model was evaluated in terms of mathematical feasibility, solution accuracy, convergence consistency, computational efficiency, and its capacity to produce balanced long-term preventive maintenance schedules under fuzzy operating conditions.

3. Findings and Results

Five benchmark instances with progressively increasing dimensions were generated to evaluate the accuracy, stability, and scalability of the proposed fuzzy multi-objective model. The number of preventive maintenance activities ranged from 24 to 72, with a mean of 48.00 and a standard deviation of 18.97. The number of maintenance projects ranged from 4 to 8, with a mean of 6.00 and a standard deviation of 1.58, whereas the number of required technical skill categories ranged from 5 to 9, with a mean of 7.00 and a standard deviation of 1.58. The long-term planning horizon ranged from 12 to 36 months, with a mean of 24.00 months and a standard deviation of 9.49 months. The first instance represented a relatively limited long-term maintenance environment comprising 24 activities, 4 projects, 5 skill categories, and a 12-month planning horizon. The fifth instance represented the most complex environment and contained 72 activities, 8 projects, 9 skill categories, and a 36-month planning horizon. The intermediate instances were constructed by gradually increasing the number of activities, projects, skills, and planning periods. This design enabled the evaluation of the model under different levels of long-term planning complexity and made it possible to determine whether the NSGA-II algorithm could maintain acceptable solution quality as the number of decision variables, resource interactions, and temporal constraints increased. The analytical structure followed the objective functions and scheduling dimensions defined for the proposed preventive maintenance model.

Table 1

Comparison of GAMS and NSGA-II Results for the Quality and Completion-Time Objective Functions in Long-Term Planning

Instance	Maintenance Activities	Projects	Skill Categories	Planning Horizon (Months)	Quality Objective: GAMS	Quality Objective: NSGA-II	Quality Deviation	Completion Time: GAMS (Days)	Completion Time: NSGA-II (Days)	Time Deviation
1	24	4	5	12	1,240	1,228	0.97%	335	340	1.49%
2	36	5	6	18	1,815	1,791	1.32%	492	501	1.83%
3	48	6	7	24	2,460	2,412	1.95%	665	679	2.11%
4	60	7	8	30	3,125	3,042	2.66%	842	864	2.61%
5	72	8	9	36	3,860	3,748	2.90%	1,035	1,072	3.57%

As presented in Table 1, the NSGA-II solutions were consistently close to the exact solutions generated by GAMS for both the quality-maximization and completion-time-minimization objectives. In the first long-term instance, GAMS produced a quality-objective value of 1,240, whereas NSGA-II produced a value of 1,228. The resulting deviation was only 0.97%, indicating that the evolutionary algorithm reproduced the exact solution with a high degree of accuracy. In the same instance, the completion time obtained through GAMS was 335 days, compared with 340 days for NSGA-II, corresponding to a deviation of 1.49%. In the second instance, which expanded the planning horizon to 18 months and included 36 maintenance activities, the quality-objective values were 1,815 for GAMS and 1,791 for NSGA-II, producing a deviation of 1.32%. The completion-time values were 492 and 501 days, respectively, resulting in a deviation of 1.83%. These findings show that the algorithm retained a high level of precision after the number of activities, projects, skill requirements, and planning periods increased.

In the third instance, which represented a 24-month maintenance horizon with 48 activities, the quality deviation increased moderately to 1.95%. GAMS generated a quality value of 2,460, whereas NSGA-II generated a value of 2,412. The exact completion time was 665 days, while the metaheuristic solution was 679 days, corresponding to a deviation of 2.11%. In the fourth instance, the quality value decreased from 3,125 under GAMS to 3,042 under NSGA-II, resulting in a deviation of 2.66%. The completion time increased from 842 to 864 days, with a deviation of 2.61%. In the fifth and most complex instance, the quality deviation was 2.90%, while the completion-time deviation reached 3.57%. Although the difference between the exact and approximate solutions increased with the dimensionality of the problem, all deviations remained below 4%. The mean deviation across the five instances was 1.96% for the quality objective and 2.32% for completion time. Therefore, the results demonstrate that NSGA-II maintained an acceptable approximation to the exact solution throughout the long-term planning horizon. The gradual increase in deviation was expected because the expansion of the planning horizon generated a larger combinatorial search space, additional precedence relationships, more skill-allocation requirements, and a greater number of feasible maintenance sequences. Nevertheless, the limited magnitude of the observed deviations confirms that the proposed algorithm was capable of producing high-quality long-term maintenance schedules while preserving the balance between maintenance quality and project completion time.

Table 2

Comparison of GAMS and NSGA-II Results for the Total-Cost and Greenhouse-Gas-Emission Objective Functions in Long-Term Planning

Instance	Maintenance Activities	Projects	Skill Categories	Planning Horizon (Months)	Total Cost: GAMS (10^3 Monetary Units)	Total Cost: NSGA-II (10^3 Monetary Units)	Cost Deviation	Greenhouse Gas: GAMS (tCO_2e)	Greenhouse Gas: NSGA-II (tCO_2e)	Emission Deviation
1	24	4	5	12	4,820	4,878	1.20%	812	824	1.48%
2	36	5	6	18	6,940	7,045	1.51%	1,135	1,155	1.76%
3	48	6	7	24	9,235	9,432	2.13%	1,488	1,523	2.35%
4	60	7	8	30	11,860	12,194	2.82%	1,886	1,941	2.92%
5	72	8	9	36	14,780	15,293	3.47%	2,334	2,418	3.60%

Table 2 presents the comparison between the exact and metaheuristic solutions for the economic and environmental objectives. In the first instance, GAMS produced a total-cost value of 4,820 thousand monetary units, whereas NSGA-II produced a total-cost value of 4,878 thousand monetary units. The difference between the two methods was 58 thousand monetary units, representing a deviation of only 1.20%. The corresponding greenhouse-gas-emission values were 812 and 824 tCO_2e, with a deviation of 1.48%. In the second instance, the total cost increased to 6,940 thousand monetary units under GAMS and 7,045 thousand monetary units under NSGA-II. The cost deviation was 1.51%, while the greenhouse-gas-emission deviation was 1.76%. These limited differences indicate that the NSGA-II algorithm was able to identify cost-efficient and environmentally acceptable maintenance schedules during the first 18 months of the modeled planning environment.

In the third instance, GAMS generated a total-cost value of 9,235 thousand monetary units, whereas the NSGA-II value was 9,432 thousand monetary units. The deviation of 2.13% remained relatively low despite the substantial expansion of the model to 48 maintenance activities and a 24-month planning horizon. The greenhouse-gas-emission values for the same instance were 1,488 tCO_2e for GAMS and 1,523 tCO_2e for NSGA-II, corresponding to a deviation of 2.35%. In the fourth instance, the total-cost deviation increased to 2.82%, and the emission deviation increased to 2.92%. In the fifth instance, which involved the greatest number of maintenance activities, projects, skill categories, and planning months, the exact cost was 14,780 thousand monetary units, whereas the metaheuristic cost was 15,293 thousand monetary units. The corresponding deviation was 3.47%. Greenhouse-gas emissions increased from 2,334 tCO_2e under GAMS to 2,418 tCO_2e under NSGA-II, producing a deviation of 3.60%.

The mean deviation across all instances was 2.23% for the cost objective and 2.42% for the greenhouse-gas-emission objective. Therefore, the average difference between the exact and metaheuristic methods remained below 2.5% for both objectives. The findings further show that the cost and emission values increased systematically as the planning horizon expanded. This increase was attributable to the larger number of scheduled maintenance interventions, greater use of skilled labor, additional equipment downtime, higher resource consumption, and the accumulation of energy-related emissions over a longer period. However, the relatively small differences between GAMS and NSGA-II demonstrate that the proposed evolutionary algorithm was able to preserve the economic and environmental quality of the solutions even under complex long-term conditions. The fact that the maximum deviations remained below 4% indicates that NSGA-II did not produce substantial cost or environmental penalties in comparison with the exact method. Accordingly, the algorithm provided a reliable approximation for long-term preventive maintenance planning when simultaneous minimization of expenditure and greenhouse-gas emissions was required.

Table 3

Stability of the NSGA-II Algorithm Across Eight Independent Runs for the Total-Cost Objective

Instance	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–Best Deviation	Variance
1	4,878	4,884	4,881	4,879	4,886	4,880	4,878	4,883	4,878	4,886	4,881.13	0.16%	0.06%	7.61
2	7,045	7,061	7,053	7,049	7,068	7,056	7,047	7,059	7,045	7,068	7,054.75	0.33%	0.14%	53.19
3	9,432	9,468	9,449	9,455	9,476	9,440	9,438	9,461	9,432	9,476	9,452.38	0.47%	0.22%	208.73
4	12,194	12,266	12,231	12,208	12,281	12,245	12,217	12,260	12,194	12,281	12,237.75	0.71%	0.36%	811.44
5	15,293	15,418	15,362	15,476	15,325	15,402	15,348	15,510	15,293	15,510	15,391.75	1.42%	0.65%	4,860.19

The results reported in Table 3 demonstrate that the NSGA-II algorithm exhibited strong stability across eight independent runs for the total-cost objective. In the first instance, the obtained solutions varied only between 4,878 and 4,886 thousand monetary units. The best solution was 4,878, the worst solution was 4,886, and the mean value was 4,881.13. The deviation between the best and worst solutions was only 0.16%, while the difference between the mean and best solutions was 0.06%. The low variance of 7.61 further indicates that the algorithm converged to a narrow range of cost values regardless of the random population generated at the beginning of each run. In the second instance, the cost values ranged from 7,045 to 7,068 thousand monetary units. The best–worst deviation was 0.33%, the mean–best deviation was 0.14%, and the variance was 53.19. Despite the increase in the number of activities and planning periods, the repeated executions remained closely concentrated around the best solution.

In the third instance, the best total-cost value was 9,432 thousand monetary units and the worst value was 9,476 thousand monetary units. The mean was 9,452.38, resulting in a best–worst deviation of 0.47% and a mean–best deviation of 0.22%. In the fourth instance, the solutions ranged between 12,194 and 12,281 thousand monetary units. Although the absolute difference increased because of the larger scale of the cost objective, the relative best–worst deviation remained only 0.71%. The mean value was 12,237.75, which differed from the best solution by 0.36%. In the fifth instance, the best result was 15,293 thousand monetary units, the worst result was 15,510 thousand monetary units, and the mean result was 15,391.75 thousand monetary units. The best–worst deviation reached 1.42%, while the mean–best deviation remained limited to 0.65%.

The variance increased from 7.61 in the first instance to 4,860.19 in the fifth instance. This increase was expected because the scale of the objective function and the size of the solution space increased considerably across the five instances. However, the percentage-based indicators show that the relative dispersion remained small. Even in the largest 36-month instance, the mean solution was less than 1% above the best solution. This finding indicates that the majority of independent runs converged toward the same high-quality region of the solution space. The small distance between the best, worst, and average results demonstrates that the stochastic operators of NSGA-II, including initialization, crossover, and mutation, did not lead to unstable or substantially different cost outcomes. Consequently, the algorithm can be considered reliable for repeated application in long-term maintenance planning, where decision-makers require not only a good solution but also a high probability of obtaining a comparable result in successive executions.

Table 4

Stability of the NSGA-II Algorithm Across Eight Independent Runs for the Quality Objective

Instance	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	Best–Mean Deviation	Variance
1	1,228	1,226	1,227	1,225	1,228	1,224	1,227	1,226	1,228	1,224	1,226.38	0.33%	0.13%	1.73
2	1,791	1,788	1,789	1,786	1,791	1,787	1,790	1,789	1,791	1,786	1,788.88	0.28%	0.12%	2.86
3	2,412	2,405	2,409	2,402	2,412	2,407	2,410	2,404	2,412	2,402	2,407.63	0.41%	0.18%	12.23
4	3,042	3,028	3,035	3,022	3,042	3,031	3,038	3,026	3,042	3,022	3,033.00	0.66%	0.30%	48.75
5	3,748	3,725	3,739	3,712	3,748	3,731	3,742	3,719	3,748	3,712	3,733.00	0.96%	0.40%	159.00

Table 4 shows that the NSGA-II algorithm was also highly stable in maximizing the quality objective. In the first instance, the quality values obtained across the eight runs ranged from 1,224 to 1,228. The best solution was 1,228, the worst solution was 1,224, and the mean solution was 1,226.38. The best–worst deviation was 0.33%, while the difference between the best and mean solutions was only 0.13%. The variance of 1.73 confirms that the repeated runs produced nearly identical quality values. In the second instance, the best and worst solutions were 1,791 and 1,786, respectively. The best–worst deviation decreased to 0.28%, and the best–mean deviation was 0.12%. Thus, extending the planning horizon from 12 to 18 months did not result in a meaningful loss of stability.

In the third instance, the repeated quality values ranged between 2,402 and 2,412. The best–worst deviation was 0.41%, while the mean solution of 2,407.63 was only 0.18% lower than the best solution. In the fourth instance, the best solution was 3,042 and the worst solution was 3,022. The mean was 3,033.00, resulting in a best–worst deviation of 0.66% and a best–mean deviation of 0.30%. In the fifth and largest instance, the quality values ranged from 3,712 to 3,748. The mean solution was 3,733.00, which was only 0.40% below the best solution. Although the variance increased to 159.00, the relative deviation between the best and worst solutions remained below 1%.

The results therefore demonstrate that the algorithm maintained consistent quality performance throughout the long-term planning horizon. The limited variation among repeated runs indicates that different random initial populations led to solutions located in approximately the same high-quality region of the Pareto frontier. This result is particularly important because quality maximization may conflict with cost, completion-time, and environmental objectives. An unstable algorithm could produce considerably different quality levels each time it was executed, thereby limiting its usefulness for managerial decision-making. In the present analysis, however, the best–

mean deviation ranged from only 0.12% to 0.40%, and the best–worst deviation ranged from 0.28% to 0.96%. These findings show that the proposed algorithm repeatedly identified maintenance schedules that preserved equipment condition, process reliability, and output quality while simultaneously satisfying the other objectives and operational constraints of the model.

Figure 1

Comparative Performance of GAMS and NSGA-II for Quality, Completion Time, Total Cost, and Greenhouse-Gas Emissions Across Long-Term Planning Instances

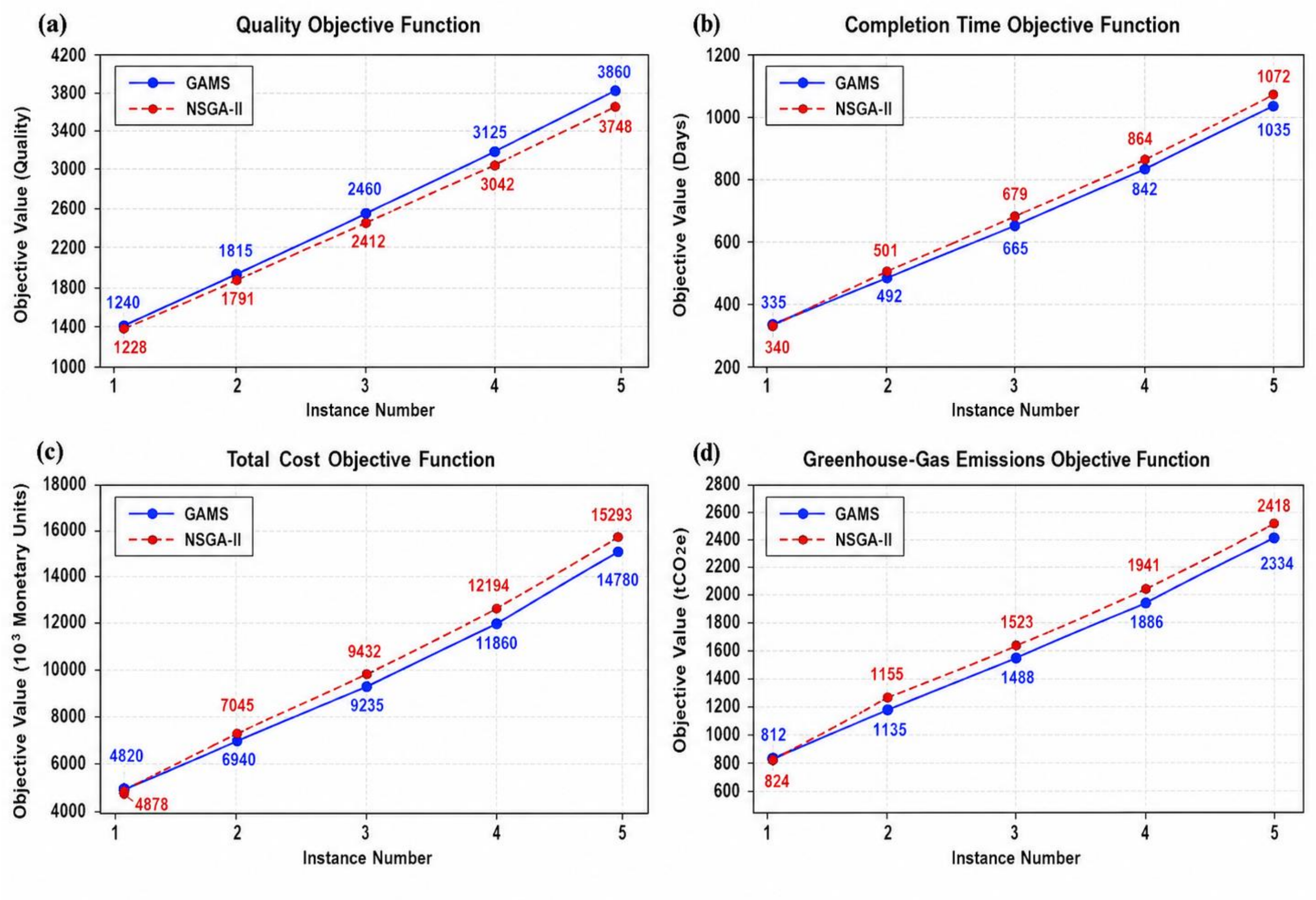

Figure 1 illustrates the comparative trends of the GAMS and NSGA-II solutions across the four objective functions and five long-term maintenance-planning instances. The solution curves for both methods followed highly similar trajectories. As the number of maintenance activities increased from 24 to 72 and the planning horizon expanded from 12 to 36 months, the absolute values of quality, completion time, total cost, and greenhouse-gas emissions increased systematically. This pattern reflected the larger number of maintenance interventions, the longer operating horizon, the additional use of skilled personnel and technical resources, and the accumulation of economic and environmental effects over time. Despite this upward trend, the distance between the GAMS and NSGA-II curves remained relatively narrow in all instances. For the quality objective, the deviations ranged from 0.97% to 2.90%. For completion time, the deviations ranged from 1.49% to 3.57%. Cost deviations ranged from 1.20% to 3.47%, while greenhouse-gas-emission deviations ranged from 1.48% to 3.60%.

Across the 20 comparisons obtained from five instances and four objective functions, the overall mean deviation between GAMS and NSGA-II was approximately 2.23%. The minimum deviation was 0.97%, observed for the quality objective in the first instance, and the maximum deviation was 3.60%, observed for greenhouse-gas emissions in the fifth instance. The slight widening of the distance between the two methods in the fourth and fifth instances was consistent with the increase in computational complexity. As the long-term planning horizon expanded, the number of alternative maintenance sequences, resource allocations, skill combinations, and timing decisions grew substantially. Exact optimization could search these combinations systematically, whereas NSGA-II employed a population-based approximation process. Nevertheless, the evolutionary algorithm reproduced the direction and magnitude of the exact solution curves with only limited deviations.

The combined findings from the comparative and repeated-run analyses indicate that the proposed fuzzy multi-objective model achieved an appropriate balance among economic, environmental, operational, and quality-related objectives. The closeness of the NSGA-II results to the GAMS solutions supports the convergence accuracy of the algorithm, while the small differences among repeated runs support its stability. The gradual rather than abrupt increase in deviations further indicates that the algorithm scaled predictably as the problem dimensions expanded. Overall, the results confirm that NSGA-II provided reliable and robust solutions for long-term preventive maintenance scheduling and could be applied to planning environments in which the use of exact optimization becomes computationally demanding.

4. Discussion and Conclusion

The results of the computational experiments demonstrated that the proposed fuzzy multi-objective model was capable of generating feasible and balanced long-term preventive-maintenance schedules while simultaneously addressing quality, completion time, total cost, and greenhouse-gas emissions. Comparison of the exact GAMS solutions with those generated by NSGA-II showed that the metaheuristic procedure maintained a close approximation to the exact method across all five problem instances. The deviation for the quality objective ranged from 0.97% to 2.90%, with a mean deviation of 1.96%, whereas the completion-time deviation ranged from 1.49% to 3.57%, with a mean of 2.32%. The average deviations for total cost and greenhouse-gas emissions were 2.23% and 2.42%, respectively, and the maximum deviation observed across all objective functions remained below 4%. These results indicate that the proposed evolutionary procedure preserved a high level of solution accuracy despite the progressive increase in the number of maintenance activities, projects, skill categories, and planning periods. The repeated-run analyses further showed that the algorithm was stable, because the differences among the best, worst, and mean solutions remained limited. Even in the largest 36-month instance, the mean total-cost solution was only 0.65% above the best solution, while the mean quality solution was only 0.40% below the best solution. Therefore, the findings support both the computational reliability of the proposed solution method and the suitability of the mathematical model for long-term preventive-maintenance planning.

The close correspondence between the GAMS and NSGA-II solutions is consistent with previous research showing that evolutionary and metaheuristic algorithms can generate high-quality approximations for complex scheduling problems in which exact approaches become computationally burdensome. Hasani developed a hybrid multi-objective metaheuristic algorithm for distributed flow-shop scheduling with preventive maintenance under uncertainty and showed that evolutionary search can effectively manage multiple conflicting objectives and complex maintenance constraints (Hasani, 2018). Similarly, the successful application of NSGA-II to a multi-objective environmental design problem demonstrated its ability to preserve both solution diversity and convergence toward efficient alternatives (Lotfinejad et al., 2025). The present findings extend these results to long-term preventive-maintenance scheduling by showing that NSGA-II maintained deviations below 4% even when the scheduling horizon increased to 36 months and the number of maintenance activities reached 72. This outcome can be explained by the non-dominated sorting and crowding-distance mechanisms of NSGA-II, which guide the population toward the Pareto frontier while preventing excessive concentration in a limited region of the solution space. Thus, the algorithm was able to search a large combinatorial space without losing the diversity required to represent the trade-offs among cost, time, environmental performance, and quality.

The findings also confirmed the value of integrating preventive-maintenance decisions with long-term operational scheduling. The model did not determine maintenance dates independently of production and resource requirements; rather, it coordinated maintenance activities with projects, skill availability, temporal constraints, and performance objectives. This integrated structure is aligned with Qamhan et al., who showed that production scheduling and periodic maintenance should be solved jointly because maintenance interruptions directly affect machine availability and job sequencing (Qamhan et al., 2019). Sharifzadegan et al. likewise found that hybrid production-scheduling models incorporating preventive maintenance can improve the simultaneous management of resource limitations and operational performance (Sharifzadegan et al., 2022). The present results suggest that this integration becomes even more important over an extended horizon. In long-term planning, a maintenance decision made during an early period affects equipment condition, capacity utilization, workforce requirements, and failure exposure in later periods. Consequently, separate maintenance and production plans may generate locally acceptable but globally inefficient decisions. By coordinating these decisions, the proposed model reduced the likelihood of repeated shutdowns, resource conflicts, and poorly timed interventions.

The favorable completion-time results support the argument that preventive maintenance can improve rather than necessarily obstruct operational performance when it is properly scheduled. Although maintenance requires temporary machine withdrawal, planned interventions reduce the probability of unanticipated failures, emergency repairs, and extended production interruptions. In the present study, NSGA-II produced completion-time solutions that remained close to the exact values, with an average deviation of 2.32%. This finding is consistent with research showing that coordinated maintenance and scheduling decisions can reduce makespan and improve machine utilization (Qamhan et al., 2019; Sharifzadegan et al., 2022). The result is also compatible with the dynamic grouping approach proposed by Moazzam Jozi et al., according to which combining compatible maintenance activities can reduce redundant shutdowns and improve the use of limited maintenance opportunities (Moazzam Jozi et al., 2023). From a Total Productive Maintenance perspective, this finding is important because planned downtime is not necessarily a loss when it prevents substantially greater unplanned downtime. The proposed model appears to have balanced these two forms of interruption by placing preventive interventions at times that minimized their cumulative effect on the long-term schedule.

The reduction and control of total cost constitute another important finding. Across the five instances, the average deviation between NSGA-II and GAMS for the cost objective was only 2.23%, indicating that the metaheuristic algorithm consistently identified economically efficient maintenance plans. This result supports previous studies emphasizing that preventive maintenance can reduce the costs associated with breakdowns, corrective actions, production stoppages, defective output, and accelerated equipment deterioration. Molaverdi et al. showed that optimization of preventive-maintenance decisions can improve the balance between intervention costs and failure-related losses (Molaverdi et al., 2020). Shahanaghi et al. similarly demonstrated that optimizing maintenance thresholds can reduce the long-term consequences of performing maintenance either too early or too late (Shahanaghi et al., 2010). The present results can therefore be interpreted as evidence that cost efficiency depends not simply on reducing the number of maintenance activities but on determining their appropriate timing, grouping, and resource allocation. In a long-term planning environment, postponing maintenance may produce apparent short-term savings but increase the expected costs of breakdowns, emergency labor, spare parts, lost production, and quality failures in later periods.

The economic performance of the model may also be explained by its coordination of maintenance with related resource requirements. Maintenance interventions require technicians with specific skills, service equipment, replacement parts, and sufficient access time. When these resources are not available at the scheduled intervention date, organizations may experience additional waiting time, overtime costs, or prolonged downtime. Raeisi showed that the simultaneous planning of maintenance and spare-parts inventory can improve equipment availability and reduce the combined costs of shortages and excessive inventories (Raeisi, 2019). Lotfi's demand-based inspection and preventive-maintenance model likewise demonstrated that maintenance decisions can be improved when equipment deterioration and operational demand are evaluated jointly (Lotfi, 2020). Nouri et al. further showed that simultaneous inspection and maintenance planning under deterioration and demand uncertainty can generate more efficient policies than isolated decisions (Nouri et al., 2020). Although the proposed model focused primarily on long-term maintenance scheduling, its resource-allocation structure reflects the same integrated logic. The observed cost performance likely resulted from reducing conflicts among maintenance timing, skill availability, project requirements, and the sequence of interventions.

The quality objective also produced strong results. Across all instances, the average deviation between the exact and NSGA-II quality solutions was 1.96%, and repeated executions of the algorithm generated highly consistent quality values. This finding reinforces the strategic relationship between maintenance and quality performance. Equipment deterioration may produce vibration, misalignment, temperature variation, reduced precision, unstable processing conditions, and other factors that increase defect rates and process variability. Preventive maintenance protects quality by maintaining machine capability and process consistency before deterioration reaches a critical level. Sajjadi's simulation-optimization study of failure-prone production networks similarly emphasized that reliability-based maintenance affects not only equipment availability but also the wider economic and operational performance of the production network (Sajjadi, 2022). The dynamic grouping of maintenance activities can also improve quality by ensuring that interconnected components are serviced in a coordinated manner rather than through fragmented interventions (Moazzam Jozi et al., 2023). The present findings therefore support a central principle of Total Productive Maintenance: maintenance is not merely a repair function but a direct contributor to zero-defect production, stable operations, and continuous improvement.

The greenhouse-gas-emission results represent another major contribution of the model. The average deviation between NSGA-II and GAMS for this objective was 2.42%, and even in the largest instance, the deviation remained limited to 3.60%. The model was therefore able to preserve environmental performance while simultaneously considering cost, quality, and completion time. This finding aligns with Bok et al., who demonstrated that machine assignment, due dates, and energy-source selection can substantially influence carbon emissions in parallel-machine scheduling (Bok et al., 2024). Ning and Huang likewise showed that low-carbon scheduling can reduce environmental impacts in flexible job-shop systems without necessarily sacrificing operational performance (Ning & Huang, 2021). Piroozfard et al. found that multi-objective genetic algorithms can successfully balance carbon-footprint minimization and production-related criteria (Piroozfard et al., 2017). The current results extend this body of evidence by demonstrating that maintenance timing should also be recognized as an environmental decision. Properly maintained equipment generally operates more efficiently, consumes less energy, and avoids the additional material and energy demands associated with failures, rework, and emergency interventions.

The environmental performance can also be explained by the relationship among maintenance, energy efficiency, and machine deterioration. Energy-efficient scheduling research has shown that operating sequences, machine allocation, and production timing affect both energy consumption and emissions (Lu et al., 2017). Duan et al. demonstrated that collaborative scheduling in heterogeneous multi-stage production environments can improve energy efficiency by coordinating the use of machines and processing stages (Duan et al., 2022). Sun and Li further emphasized the importance of identifying real-time energy-control opportunities in sustainable manufacturing systems (Sun & Li, 2013). When equipment condition deteriorates, machines may require greater energy input, longer processing times, or additional rework to achieve the required output. Preventive maintenance can therefore reduce the environmental burden by restoring operating efficiency and stabilizing processing conditions. Foumani and Smith-Miles also showed that carbon-reduction policies generate trade-offs with conventional production objectives, making multi-objective optimization necessary (Foumani & Smith-Miles, 2019). The proposed model addressed this requirement by treating emissions as an explicit objective rather than an indirect consequence of cost minimization.

The results are further consistent with studies emphasizing the need to coordinate environmental objectives across interconnected operational functions. Wang et al. showed that integrated machine scheduling and vehicle routing can reduce total carbon emissions more effectively than separate planning (Wang et al., 2019). Zou et al. demonstrated that coordination between production and routing improves system-level performance and prevents local decisions from creating inefficiencies elsewhere (Zou et al., 2018). Moons et al. similarly emphasized the operational benefits of integrating production scheduling and transportation decisions (Moons et al., 2017). Robust pollution-routing research has shown that environmental planning should also account for uncertainty in demand and travel time (Eshtehadi et al., 2017), while transportation-emission assessments highlight the importance of accurately representing different emission sources within decision models (Fan et al., 2018). Although transportation decisions were outside the direct scope of the present model, these studies support the broader conclusion that sustainability requires integrated optimization. Long-term preventive-maintenance planning influences energy use, production continuity, spare-parts movement, and resource deployment and should therefore be aligned with wider environmental and supply-chain policies.

The effectiveness of the fuzzy structure constitutes an additional explanation for the model's performance. Long-term maintenance decisions are affected by ambiguity in maintenance duration, equipment condition, deterioration rates, cost estimates, labor productivity, energy prices, and future operating requirements. Azimian et al. showed that fuzzy decision-making can improve the selection of preventive-maintenance periods when the relevant information is imprecise or dependent on expert judgment (Azimian et al., 2021). Damchi and Saebi similarly demonstrated that risk-based preventive-maintenance planning should include uncertain and intangible risk indicators rather than relying exclusively on precisely measurable variables (Damchi & Saebi, 2023). The fuzzy formulation used in the present study made it possible to represent long-term parameters without assuming an unrealistic level of certainty. This feature likely improved the practical robustness of the generated solutions because the schedules were not optimized only for a single fixed prediction of future conditions. Instead, the model represented uncertainty as an inherent characteristic of maintenance planning.

The findings also have implications for sustainable supply-chain and market performance. Asadkhani et al. demonstrated that defective products, inventory decisions, and withdrawal policies are closely connected within sustainable supply chains (Asadkhani et al., 2022). Because equipment condition influences defect generation, effective preventive maintenance can reduce material waste, reprocessing, and the circulation of imperfect products. Zhang et al. further showed that consumer environmental awareness can affect channel coordination and organizational incentives to improve environmental performance (Zhang et al., 2015). Thus, the benefits of maintenance optimization extend beyond the factory floor. More reliable equipment can support consistent quality, lower emissions, reduced waste, and stronger compliance with market expectations. These effects are particularly relevant under growing climate-related pressures, which increasingly require organizations to adopt long-term adaptation and sustainability strategies (Fanourakis, 2025). The proposed model contributes to this strategic objective by combining operational reliability with economic and environmental criteria.

Overall, the findings confirm that a long-term preventive-maintenance plan based on Total Productive Maintenance should be formulated as a fuzzy multi-objective decision problem. No single objective can adequately represent the full consequences of maintenance decisions. A schedule that minimizes cost alone may postpone necessary interventions, whereas a schedule that maximizes quality without considering cost or completion time may become operationally impractical. The proposed model generated a set of balanced solutions and showed that NSGA-II could approximate the exact solutions with limited deviation and strong repeated-run stability. The results therefore support the use of integrated evolutionary optimization as a practical decision-support approach for complex maintenance systems characterized by long planning horizons, multiple resource categories, conflicting performance criteria, and uncertain operating conditions.

The present study has several limitations that should be considered when interpreting its results. First, the model was evaluated using generated computational instances rather than longitudinal data from a specific manufacturing organization; consequently, the numerical outcomes demonstrate computational feasibility and algorithmic performance but may not fully represent the technical, organizational, and behavioral complexities of a particular industrial setting. Second, the long-term scenarios assumed predefined sets of maintenance activities, projects, skills, planning periods, and objective coefficients, whereas real operating environments may experience unexpected machine failures, workforce absenteeism, changes in production demand, spare-parts shortages, and modifications to regulatory requirements. Third, the model primarily addressed preventive maintenance and did not simultaneously incorporate corrective, predictive, and opportunistic maintenance policies. Fourth, the environmental objective focused on greenhouse-gas emissions and did not explicitly include water consumption, hazardous waste, material losses, noise, or life-cycle environmental impacts. Finally, NSGA-II was compared with GAMS for validation, but its performance was not benchmarked against other recent multi-objective metaheuristics under identical computational conditions.

Future studies should validate the model using real maintenance histories, machine-condition records, energy-consumption data, emission factors, workforce information, and cost structures collected from manufacturing organizations. The formulation may be expanded to include predictive maintenance based on sensor signals, remaining-useful-life estimates, and digital-twin data. Researchers should also examine dynamic models in which schedules are revised after machine failures, demand changes, project delays, or resource disruptions. Further extensions could integrate spare-parts inventory, production planning, transportation, workforce learning, and equipment replacement within a unified long-term framework. Additional environmental criteria, including waste generation, water use, and life-cycle impacts, could provide a broader assessment of sustainability. Comparative testing of NSGA-II against algorithms such as NSGA-III, MOEA/D, multi-objective particle swarm optimization, and hybrid machine-learning-assisted approaches would also clarify the relative computational advantages of different solution procedures.

Manufacturing managers should integrate long-term preventive-maintenance scheduling with production planning, quality management, environmental objectives, and workforce allocation rather than assigning these decisions to separate organizational units. Maintenance priorities should be determined using multiple criteria that include failure risk, equipment criticality, quality consequences, energy efficiency, emissions, resource availability, and production commitments. Organizations should establish shared databases linking maintenance records, machine-condition information, energy use, defects, downtime, and costs so that the required model parameters can be estimated and regularly updated. Decision-support systems based on Pareto-optimal solutions should be used to present managers with transparent trade-offs rather than a single rigid schedule. In addition, the implementation of Total Productive Maintenance should involve operators, technicians, engineers, production planners, quality specialists, and sustainability managers to ensure that the selected long-term schedule is operationally feasible, technically justified, and consistent with organizational sustainability goals.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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References

Asadkhani, J., Fallahi, A., & Mokhtari, H. (2022). A Sustainable Supply Chain under VMI-CS Agreement with Withdrawal Policies for Imperfect Items. *Journal of Cleaner Production*, *376*, 134098. https://doi.org/10.1016/j.jclepro.2022.134098

Azimian, M., Karbassian, M., & Atashgar, K. (2021). Selecting the Best Preventive Maintenance Period for Single-Purpose Equipment: A New Fuzzy Decision-Making Approach. *Research in Production and Operations Management*, *12*(4), 21-39. https://doi.org/10.22108/jpom.2021.130857.1401

Bok, Y., Lee, N. K., Jo, S., Lee, S., Kweon, S. J., & Na, H. S. (2024). The Production Scheduling Problem Employing Non-Identical Parallel Machines with Due Dates Considering Carbon Emissions and Multiple Types of Energy Sources. *Expert Systems with Applications*, *238*, 121990. https://doi.org/10.1016/j.eswa.2023.121990

Cheng, J., Chu, F., Chu, C., & Xia, W. (2015). Bi-Objective Optimization of Single-Machine Batch Scheduling under Time-of-Use Electricity Prices. *Rairo - Operations Research*, *50*. https://doi.org/10.1051/ro/2015063

Damchi, Y., & Saebi, J. (2023). A Risk-Based Preventive Maintenance Planning Model Considering Intangible Risk Indicators. *Tabriz Journal of Electrical Engineering*, *53*(3), 171-182. https://doi.org/10.22034/tjee.2023.53875.4540

Duan, J., Feng, M., & Zhang, Q. (2022). Energy-Efficient Collaborative Scheduling of Heterogeneous Multi-Stage Hybrid Flowshop for Large Metallic Component Manufacturing. *Journal of Cleaner Production*, *375*, 134148. https://doi.org/10.1016/j.jclepro.2022.134148

Eshtehadi, R., Fathian, M., & Demir, E. (2017). Robust Solutions to the Pollution-Routing Problem with Demand and Travel Time Uncertainty. *Transportation Research Part D: Transport and Environment*, *51*, 351-363. https://doi.org/10.1016/j.trd.2017.01.003

Fan, Y. V., Perry, S., Klemeš, J. J., & Lee, C. T. (2018). A Review on Air Emissions Assessment: Transportation. *Journal of Cleaner Production*, *194*, 673-684. https://doi.org/10.1016/j.jclepro.2018.05.151

Fanourakis, D. (2025). Climate Change Impacts on Greenhouse Horticulture in the Mediterranean Basin: Challenges and Adaptation Strategies. *Plants*, *14*(21), 3390. https://doi.org/10.3390/plants14213390

Foumani, M., & Smith-Miles, K. (2019). The Impact of Various Carbon Reduction Policies on Green Flowshop Scheduling. *Applied Energy*, *249*, 300-315. https://doi.org/10.1016/j.apenergy.2019.04.155

Hasani, A. A. (2018). A Hybrid Multi-Objective Metaheuristic Algorithm for the Distributed Re-Entrant Permutation Flow Shop Scheduling Problem Considering Preventive Maintenance under Uncertainty. *Research in Production and Operations Management*, *9*(2), 1-22. https://doi.org/10.22108/jpom.2018.92504.0

Lotfi, R. N. A. S. M. M. (2020). Simultaneous Demand-Based Inspection and Preventive Maintenance Planning under Markovian Machine Deterioration for Application in Wind Turbines. *Journal of Mechanical Engineering*, *18*(61), 63-84. https://doi.org/10.22075/jme.2020.19265.1820

Lotfinejad, P., Tarkashvand, A., & Sanaieian, H. (2025). A computational approach for integration of greenhouse and “Shanashir” to enhance thermal comfort of occupants, utilizing NSGA-II algorithm. *Building and Environment*, *273*. https://doi.org/10.1016/j.buildenv.2025.112717

Lu, C., Gao, L., Li, X., Pan, Q., & Wang, Q. (2017). Energy-Efficient Permutation Flow Shop Scheduling Problem Using a Hybrid Multi-Objective Backtracking Search Algorithm. *Journal of Cleaner Production*, *144*, 228-238. https://doi.org/10.1016/j.jclepro.2017.01.011

Moazzam Jozi, A., Tavakkoli-Moghaddam, R., & Abdollahzadeh Sangroodi, H. (2023). A Mathematical Programming Model for Dynamic Grouping of Maintenance Activities Considering Intermittent Operation of a Multi-Component System. *Industrial Engineering and Management*, *39*(1), 3-21. https://doi.org/10.24200/j65.2022.56610.2163

Molaverdi, N., Mousavizadegan, F., & Mehdinia, B. (2020). A Method for Optimizing Preventive Maintenance. *Research in Production and Operations Management*, *11*(3), 117-137. https://doi.org/10.22108/jpom.2021.127885.1354

Moons, S., Ramaekers, K., Caris, A., & Arda, Y. (2017). Integrating Production Scheduling and Vehicle Routing Decisions at the Operational Decision Level: A Review and Discussion. *Computers & Industrial Engineering*, *104*, 224-245. https://doi.org/10.1016/j.cie.2016.12.010

Ning, T., & Huang, Y. (2021). Low Carbon Emission Management for Flexible Job Shop Scheduling: A Study Case in China. *Journal of Ambient Intelligence and Humanized Computing*, *14*. https://doi.org/10.1007/s12652-021-03330-6

Ning, T., Wang, Z., Zhang, P., & Gou, T. (2020). Integrated Optimization of Disruption Management and Scheduling for Reducing Carbon Emission in Manufacturing. *Journal of Cleaner Production*, *263*, 121449. https://doi.org/10.1016/j.jclepro.2020.121449

Nouri, R., Sadeghieh, A., & Lotfi, M. (2020). A Mathematical Model for Simultaneous Planning of Inspections and Preventive Maintenance under Markovian Machine Deterioration and Demand Uncertainty. *Industrial Engineering and Management*, *35.1*(2.2), 151-163. https://doi.org/10.24200/j65.2019.50720.1866

Piroozfard, H., Wong, K. Y., & Wong, W. P. (2017). Minimizing Total Carbon Footprint and Total Late Work Criterion in Flexible Job Shop Scheduling by Using an Improved Multi-Objective Genetic Algorithm. *Resources, Conservation and Recycling*, *128*, 267-283. https://doi.org/10.1016/j.resconrec.2016.12.001

Qamhan, M., Qamhan, A., Al-Harkan, I., & Alotaibi, Y. (2019). Mathematical Modeling and Discrete Firefly Algorithm to Optimize Scheduling Problem with Release Date, Sequence-Dependent Setup Time, and Periodic Maintenance. *Mathematical Problems in Engineering*, *2019*, 1-16. https://doi.org/10.1155/2019/8028759

Raeisi, S. M. A. D. M. T. S. (2019). Simultaneous Planning of Maintenance and Spare Parts Inventory Control: A Case Study of the Paint Pre-Treatment Shuttle Robot in an Automotive Company. *Strategic Management in Industrial Systems*, *14*(49), 19-33.

Sajjadi, M. D. F. A. S. M. (2022). A Simulation-Optimization Model for Networked Failure-Prone Production Systems with a Reliability-Based Maintenance Approach and Revenue Sharing. *Journal of Industrial Management Perspective*, *12*(4), 131-158. https://doi.org/10.52547/jimp.12.4.131

Shahanaghi, K., Jafarian, M., Beikverdi, M., & Nejad Biglari, Z. (2010). Optimization of the Threshold of Preventive Maintenance Actions in a Condition-Based Maintenance Program (CPM) Using a Dynamic Programming Approach. *Industrial Engineering and Management*, *26*(2), 115-119. https://sjie.journals.sharif.edu/article_5185_232f7856250e37cfef4de502d40ed76d.pdf

Sharifzadegan, M., Sohrabi, T., & Jafarnejad Chaghoushi, A. (2022). A Bi-Objective Hybrid Production Scheduling Model with Resource Constraints Using a Preventive Maintenance Approach. *Decision Making and Operations Research*, *6*(Special Issue), 1-17. https://doi.org/10.22105/dmor.2021.278207.1343

Sun, Z., & Li, L. (2013). Opportunity Estimation for Real-Time Energy Control of Sustainable Manufacturing Systems. *IEEE Transactions on Automation Science and Engineering*, *10*(1), 38-44. https://doi.org/10.1109/TASE.2012.2216876

Wang, J., Yao, S., Sheng, J., & Yang, H. (2019). Minimizing Total Carbon Emissions in an Integrated Machine Scheduling and Vehicle Routing Problem. *Journal of Cleaner Production*, *229*, 1004-1017. https://doi.org/10.1016/j.jclepro.2019.04.344

Zhang, L., Wang, J., & You, J. (2015). Consumer Environmental Awareness and Channel Coordination with Two Substitutable Products. *European Journal of Operational Research*, *241*(1), 63-73. https://doi.org/10.1016/j.ejor.2014.07.043

Zou, X., Liu, L., Li, K., & Li, W. (2018). A Coordinated Algorithm for Integrated Production Scheduling and Vehicle Routing Problem. *International Journal of Production Research*, *56*(15), 5005-5024. https://doi.org/10.1080/00207543.2017.1378955