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Multi-objective optimization for integrated production scheduling and maintenance planning

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Abstract:

The search for integrated solutions in the machining industry, particularly in job shop production scheduling and maintenance planning, is crucial. This development aims to simultaneously inform production scheduling decisions and maintenance planning, thereby minimizing makespan and operational costs. The limited time for decision-making on an industrial scale presents a challenge in providing fast and optimal decisions. Therefore, optimization is carried out using an approximation approach: NSGA-II and MOALNS. A multi-objective optimization model has been successfully developed and can provide optimal results for the integrated production and maintenance scheduling. The mathematical model demonstrated robustness in various solved cases. NSGA-II reduced operational costs by up to 28% but increased makespan by 4%. In comparison, MOALNS reduced the makespan by up to 4% but only reduced operational costs by up to 16%. Finally, NSGA II consistently provides better performance results than MOALNS. With significant reductions in operational costs, the industry can save significantly on total operational costs, such as machine maintenance, labor costs, and maintaining output quality, from existing operations and can continue to serve customers more sustainably. NSGA-II is superior in covering the objective function space, achieving solution quality close to the Pareto front, and maintaining a consistent distribution of solutions.

Key words:

Job shop, maintenance, scheduling, integration, NSGA-II, MOALNS.

1. Introduction

Numerous obstacles and uncertainties associated with the production process must be addressed during the planning phase. Determining a mission based on industrial capabilities and capacity necessitates a multitude of factors, including quality, maintenance, and distribution (Bakon et al., 2022). Consequently, optimization steps constitute an alternative approach.

Maintenance planning is as important as production planning (Nazabadi et al., 2024). Machine reliability may decline due to continuous production processes, leading to reduced industrial productivity and a decline in the quality of finished products. The reliability of its equipment significantly influences a machine's lifespan; therefore, maintaining reliability correctly is essential. Generally, production costs can be influenced by the maintenance of reliability (Hajej et al., 2021; Liu et al., 2018).

There is a recurring causal relationship (causal loop) between production and maintenance, in which the machine continues to operate until a predetermined time is reached due to production scheduling. The likelihood of the machine failing increases as it is operated more frequently. Reduced output quality is associated with an increased likelihood of machine failure. It is widely recognized that an increase in the

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quality of the output necessitates a revision process or the disposal of defective products, which can impact the planned production schedule. If decisions are not made concurrently, the interactions between production and scheduling components become significant (Xiao et al., 2019).

The manufacturing industry must enhance its planning strategies by simultaneously considering both scheduling factors and machine maintenance. Integrated planning strategies have been demonstrated to reduce operational costs by approximately 20% compared to conventional planning costs. Additionally, integrated scheduling can decrease the likelihood of defective products and rework by 25%, reducing the need for product disposal (Lopes, 2018).

Optimization is essential for implementing an integrated strategy that maximizes profits while minimizing expenses. It is necessary to optimize the search for integrated solutions in job shop production scheduling and maintenance planning to simultaneously obtain production scheduling decisions and maintenance planning, thereby minimizing makespan and operational costs. The challenge of providing rapid and optimal decisions on an industrial scale is exacerbated by the limited time available for decision-making. Multi Obejctive Optimization Problem (MOOP) metric evaluation is carried out to determine whether spread, diversity, and uniformity are met close to the ideal point, ensuring that the algorithm built is robust (Rifai et al., 2021).

Previous research addressed how the optimization and production processes are significantly impacted. The GA method can be compared with the SA and TLBO methods, but in general, the GA method provides a better solution (Sharifi & Taghipour, 2021). Minimizing operational costs in integrated scheduling, beyond using GA, can be achieved by combining it with recursive GA, providing opportunities to find more efficient solutions. The next step is to simulate the expected values in the objective function (Hu et al., 2023). There is something more interesting about the prediction of inspection schedules, which utilizes the method of decomposing predicted uncertainty into epistemic and aleatory components, thereby reducing the number of inspections by up to 85% while maintaining the same level of predicted uncertainty (Kim et al., 2022).

Several researchers have integrated production and maintenance aspects with various optimization approaches. Searching for solutions using exact methods, especially Branch and Bound (B&B) in the case of minimizing costs with makespan and maintenance, as proposed by Babaeimorad (2021), can determine optimal production scheduling. The concern is minimizing makespan in production scheduling by considering maintenance (Babaeimorad et al., 2021). Nazabadi et al. (2024) carries out more advanced integration. Nazabadi et al. (2024) integrates three operational components, production, maintenance, and quality control, to minimize cumulative values (Nazabadi et al., 2024).

2. Main contribution

Previous studies mostly focus on single-objective formulations or treat the two problems sequentially. This study explicitly addresses a research gap by proposing a truly integrated multi-objective optimization framework that simultaneously minimizes makespan and operational cost considering production scheduling and maintenance planning. Due to the complexity of the problem, two complementary approximation methods, NSGA-II and MOALNS, are developed and adapted to solve the proposed model. NSGA-II is employed to explore the global trade-off structure and generate a diverse set of Pareto-optimal solutions, while MOALNS is used to intensify the search for high-quality solutions in specific regions of the solution space. Furthermore, a statistical analysis is conducted to rigorously evaluate and compare the performance of both methods, thereby providing not only algorithmic solutions but also methodological insights into their relative effectiveness for solving the integrated scheduling and maintenance problem.

3. Methods

This research generally uses optimization or operations methods to determine optimal production and preventive maintenance scheduling. The designed optimization development stages include several steps, as shown in Figure 1.

Step 1: input data and parameters for the production and maintenance system, such as production time, maintenance, Weibull distribution parameters (η, β), etc.

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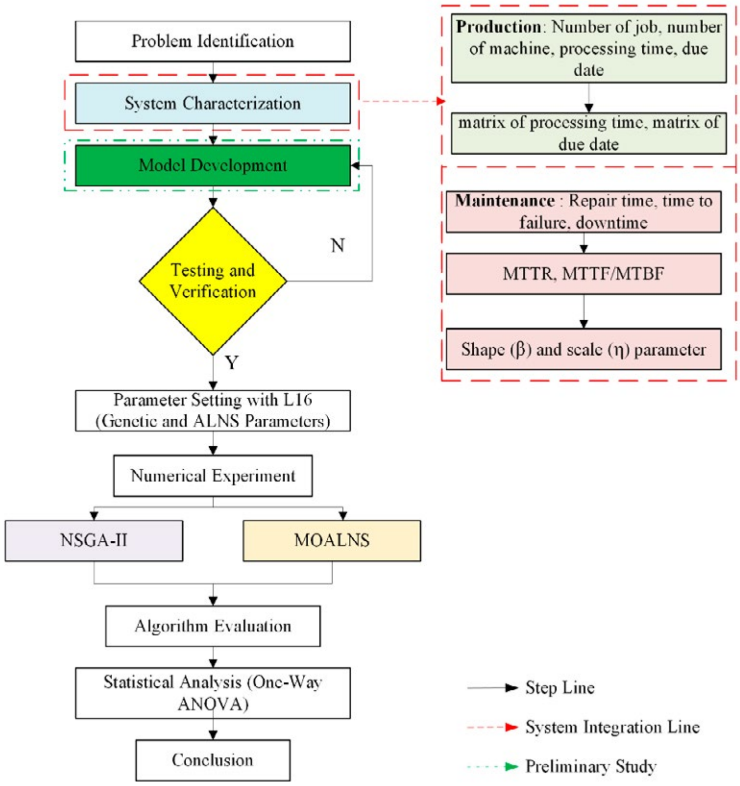

Figure 1. Research Flowchart.

Step 2: Development of a model formulation that starts with a single objective, minimizing makespan and total expected maintenance cost. In this step, the conference proceedings are published. This stage is followed by the model's verification and testing, which will be corrected if they do not match logically or in real-world conditions.

Step 3: Determine parameter settings to identify representative genetic and ALNS parameters for solving more complex cases. Parameter determination was carried out using a four-level, four-factor experiment design, which was divided into 16 (Taguchi L16) experiments with varying parameters.

Step 4: Solving numerical experiments on real problems using the NSGA-II and MOALNS approximation approaches using MATLAB 2022a with Ryzen 5500 CPU and 16 GB RAM laptop specifications.

Step 5: Evaluate the algorithm using performance indicators with hypothetical data that varies in terms of machine numbers, job numbers, and character types. Then, proceed with statistical testing of the performance indicators from the two methods above, so that conclusions can be drawn regarding the research results.

3.1. System description

The problem is a real problem in one of the metal processing industries in Yogyakarta. The metal processing industry has M machines (M_1, M_2, ..., M_m) with J jobs (J_1, J_2, ..., J_n), where each job has a different deadline. Every machine has three critical components that require supervision, as the industry must schedule the production of the job. However, it has the drawback of requiring a constant maintenance schedule, which makes it possible to have components with high reliability ($R(t)$) without maintenance. Therefore, it is necessary to carry out integrated scheduling in production and maintenance planning simultaneously to obtain the minimum cost.

Existing conditions in manufacturing apply production scheduling based on deadlines (Earliest Due Date). In manufacturing, operational cost considerations are carried out individually in each

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department. The production department will refer to production operational costs, while the maintenance department will refer to maintenance costs only. Based on existing conditions, with 53 jobs and 9 machines, it achieves a makespan of 1737.23 minutes and total individual operational costs of Rp 96 874 267. Based on existing conditions, the problem of job shop scheduling integrated with maintenance planning needs to be addressed to find alternative solutions that are more optimal than the existing conditions. This can be achieved by employing a multi-objective optimization problem, comparing approximation approaches, namely NSGA II and MOALNS. The population and trajectory-based solutions will be compared and analyzed for both solutions.

3.2. Multi-objective optimization problem (MOOP)

MOOP is a method for solving optimization problems with multiple objective functions. There are two treatments for addressing MOOP, depending on the nature of the problem. The first is a priori, where this treatment will give a particular priority to each objective function. The second treatment in MOOP is posteriori. This treatment does not prioritize each objective function, so all objective functions are assumed to have equal weight. This approach will provide several alternative solutions that do not dominate each other in terms of the objective functions. This research will use a non-dominated approach using a heuristic method. Determining non-dominance has two criteria or dominance tests. If we are going to carry out a dominance test, x_1 is dominant over x_2 if:

$$f(x_1) < f(x_2) \tag{1}$$

$$f(x_1) \leq f(x_2) \tag{2}$$

Solution x_1 is a solution that is no worse than x_2 in all objective functions (1). Solution x_1 is better than x_2 in at least one objective function (2). The criteria above show that x_1 dominates x_2 or x_2 is dominated by x_1. The non-dominated solution is a set of solutions referred to as the Pareto optimal solution (Rifai et al., 2021).

3.3. Mathematical formulation

the formulation of the mathematical model involves several assumptions, particularly regarding the job shop scheduling problem, which in this case will be integrated with optimal preventive maintenance on critical machine components. The model is developed based on several assumptions from Tambe & Kulkarni. (2022), which closely relate to the problems in the research object and can be addressed through integrated multi-objective optimization. The development of a mathematical model consists of notation descriptions, including indices and sets, parameters, and decision variables as Tables 1, 2, and 3:

Table 1. Table of indices and sets.

	Marking
n	Number of jobs
m	Number of machines
O	Number of components
K	Number of operations
J	Set of jobs, $J = \{1, 2, 3,\dots, n\}$
M	Set of machines, $M = \{1, 2, 3,\dots, m\}$
L	Set of components, $L = \{1, 2, 3,\dots, O\}$
N	Set of operations, $N = \{1, 2, 3,\dots, K\}$
i,j	Index of job, $i, j \in J$
k	Index of operation, $k \in N$
l	Index of component, $l \in O$

Table 2. Table of parameters.

Parameters	Marking
M	Big number (9999)
p_{ij}	Processing time for job j at operation i
c_{max}	Maximum completion time
$R_{(tk)}$	Reliability at t time in machine k
CMC_l	Corrective Maintenance Cost at component l
τ	Total time each period
t_l	Interval time at component l
PMC_l	Preventive Maintenance Cost at component l
ub_t	Upper bound of t
lb_t	Lower bound of t

Table 3. Table of decisions variables.

DV	Marking
c_{ij}	Completion time for job j at operation i
y_{ijk}	Binary variables indicating sequence of jobs, 1 if job j is processed by machine k at operation i, 0 otherwise
t_l	Maintenance interval time (hours)

The mathematical formulation of multi-objective optimization involves sequencing jobs or job orders n for each machine m and determining the optimal preventive maintenance interval t for each component l. The job sequence is like solving the travel sales problem for routing distribution. Job J will conduct the fitness evaluation process to minimize delays, which will impact expected production costs. Apart from that, it will simultaneously determine the (preventive maintenance) PM interval necessary to obtain a balanced time and approach the optimal solution with an adequate decision-making process time. The mathematical formulation below aims to minimize total operational costs, which consist of production costs and expected maintenance costs, while also minimizing makespan in flexible job shop scheduling problems.

Objective Functions:

Minimize Makespan

$$minimize f_1 = max c_j \forall j \in 1, \ldots, n \quad (3)$$

Minimize Operational Cost

$$minimize f_2 = \sum_{j=1}^{n} TC * max\{0, c_{ij} - D_{ij}\} + \sum_{l=1}^{n} \left(1 - e^{-\left(\frac{t_l}{\eta_l}\right)^{\beta_l}}\right) * CMC_l + \frac{\tau}{t_l} * PMC_l \quad (4)$$

Subject to:

$$\sum_{i=1}^{n} x_{ijk} = 1 \forall j \in 1, \ldots, n \quad (5)$$

$$c_{ij} = \sum_{i=1}^{n} \sum_{k=1}^{j} p_{ik} * x_{ijk} \forall j \in 1, \ldots, n \quad (6)$$

$$c_{ij} \geq p_{ij}, \forall i \in stages, \forall j \in jobs \quad (7)$$

$$c_{ij} \geq c_{(i-1)j} + p_{ij}, \forall i \in stages\left\{1\right\}, \forall j \in jobs \quad (8)$$

$$(c_{ij} - c_{ik}) + M * y_{ijk} \geq p_{ij}, \forall i \in stages\left\{1\right\},$$

$$(c_{ij} - c_{ik}) + M y_{ijk} \geq p_{ij}, \forall i \in stages\{1\}, \forall j, k \in jobs, j > k \quad (9)$$

$$c_{max} \geq c_{ij}, \forall i \in stages,\ if\ i = laststage \quad (10)$$

$$c_{ij}, c_{max} \geq 0, \forall i \in stages, \forall j \in jobs \quad (11)$$

$$y_{ijk} + y_{ikj} = 1 \forall i \in stages, \forall j, k \in jobs, j > k \quad (12)$$

$$0 \leq t_l \leq \tau \quad (13)$$

$$y_{ijk} = \{0,1\} 1\ job\ j\ processed\ machine\ i\ at\ operation\ k,\ 0\ otherwise \quad (14)$$

$$t_l > 0 \quad (15)$$

Based on the proposed mathematical formulation, the problem is classified as a multi-objective optimization problem (MOOP) that simultaneously minimizes the makespan and the total operational cost, which consists of production-related and maintenance-related costs. The first objective function $f1$ in Equation (3) minimizes the makespan by considering the maximum completion time among all jobs, thereby directly reflecting the overall production completion time. The second objective function $f2$ in Equation (4) minimizes the total operational cost, including tardiness-related production costs, expected corrective maintenance costs derived from the reliability function, and preventive maintenance costs determined by the maintenance interval decisions.

There are limits to these two objective functions to ensure that each machine can process only a job in Equation (5). Then completion time calculated from sum of processing time for each machine in Equation (6). Each job has a completion time that is at least equal to the processing time at each stage in Equation (7). Constraints in Equation (8), (9), and (12) are sequencing and non-overlapping constraints. Additionally, the model enforces that the job completion time on each operation follows a sequence constraint, ensuring that if one job precedes another, the completion time reflects this sequence in Equation (8). Specifically, Constraint in Equation (9) uses a big-M formulation to prevent two jobs from being processed simultaneously on the same machine by enforcing a precedence relationship between any pair of jobs, while in Equation (12) guarantees that for any pair of jobs, one and only one processing order is selected. Together, these constraints ensure machine capacity feasibility and directly affect the resulting makespan in the schedule.

Constraint in Equation (10) defines the makespan variable c_{max} as the maximum completion time among all jobs at the final stage, which provides the basis for evaluating the first objective function. Constraint in Equation (11) ensures the non-negativity of all time-related variables, thereby maintaining the physical validity of the solution.

Constraints in Equation (13) until in Equation (15) define the feasible domain of the preventive maintenance interval decision variable t_l. Constraint in Equation (13) limits the maintenance interval within the planning horizon τ, while Constraint in Equation (15) ensures that the interval is strictly positive, preventing meaningless or infeasible maintenance policies.

3.4. NSGA-II

Searching for optimal solutions using multi-objective functions can be done by sorting the Pareto front non-dominant solutions. This approach can provide multiple alternative solutions and serve as a managerial insight. NSGA is an example of an evolutionary algorithm in evolutionary computing. Two versions of the algorithm are commonly used: classic NSGA and canonical NSGA-II. This method aims to improve the adaptive adjustment of the population of candidate solutions for a front limited by the objective function rules (Lestari & Belluano, 2016).

The NSGA-II algorithm uses an evolutionary process with replacement evolutionary operators, including selection, genetic crossover, and genetic mutation. The population will be sorted into a hierarchy of sub-populations based on Pareto dominance order. The similarity between members of each sub-group will be evaluated on the Pareto front, and the resulting groups, along with similarity measures, are used to promote a diverse front of non-dominated solutions (Lestari & Belluano, 2016).

The parameters used in NSGA-II are the population size, the number of generations, the mutation rate, and the crossover rate. Determination of genetic parameters was carried out using a Taguchi L16 design of experiment. The process of finding a solution using NSGA-II can be explained in Table 4 of pseudo code (Lestari & Belluano, 2016):

Table 4. Table of Pseudocode of NSGA II.

	Pseudocode of NSGA-II
1	Input: populationSize, numGenerations, crossoverProbability, mutationProbability
2	Generate an initial population P
3	Calculate the fitness values for each individual in P
4	While generation < numGenerations
5	Perform selection of parents based on fitness values
6	Perform a crossover operation to generate off spring
7	Perform a mutation operation on the offspring
8	Calculate the fitness values for each offspring
9	Combine population P and offspring to form a new population Q
10	Perform non-dominated sorting and calculate crowding distance for Q
11	Select the best individuals from Q to form the next generation population P
12	End while
13	Define the Pareto front and non-dominated solutions

The initial population is randomly initialized using a hybrid solution representation that simultaneously encodes the production schedule and the preventive maintenance decisions. Specifically, each individual consists of two parts: (i) a permutation-based encoding of job sequences on machines, which defines the processing order of all jobs, and (ii) a real-valued vector $t=[t_1,t_2,\ldots,t_l]$, where each element represents the preventive maintenance interval of a component and is generated within the feasible range defined by Constraints (18) and (20).

Each individual is decoded into a feasible schedule by computing the start and completion times according to Constraints (11)–(17). The fitness evaluation then calculates the makespan using Equation (8) and the total operational cost using Equation (9), which includes tardiness-related production costs as well as preventive and expected corrective maintenance costs derived from the maintenance interval vector t. The selection process is performed using tournament selection, where two individuals are randomly chosen and the better one is selected based on Pareto dominance and crowding distance. The crossover operator is applied separately to the two parts of the solution: permutation-based crossover (e.g., order-based crossover) is used for the job sequence part to preserve feasibility, while real-coded crossover is applied to the maintenance interval vector. Similarly, mutation is performed by swapping or inserting jobs in the sequence part and by slightly perturbing one or more elements of the maintenance interval vector within their feasible bounds.

The offspring generated by crossover and mutation are then evaluated using the same decoding and fitness evaluation procedure. The parent and offspring populations are combined and sorted using non-dominated sorting and crowding distance. The best individuals are selected to form the next generation. This process is repeated until the termination criterion (maximum number of generations) is reached. The final output of the algorithm is a set of non-dominated solutions that approximate the Pareto front, representing different trade-offs between makespan and operational cost.

3.5. MOALNS

Multi-Objective Adaptive Large Neighborhood Search is an approximation approach for solving multi-objective functions based on weights in adaptive destroy and repair operators, thereby balancing the exploration and exploitation processes for finding solutions. MOALNS will initiate solutions depending on representative solutions to the problems being solved. The solution search process will be carried out by destroying the current initialization of the solute using the destroy operator. In the destruction process, there are random removal operators (where nodes will be selected at random) and worst removal (the farthest distance between nodes will be selected). Meanwhile, during the repair process, several operators are employed, including random insert (repairing a solution by randomly selecting alternative solutions) and greedy repair (utilizing a greedy algorithm to replace damaged solution nodes). Apart from that, there is a weighting for the destruction and repair processes, where the weights will be updated at each iteration. The destruction process will randomly select several nodes based on the degree of destruction (DoD) parameter (Rifai et al., 2016). The number of nodes taken (destroyed) is calculated using the equation

$$length(job) * (DoD(2) - ((DoD(2) - DoD(1)) * t/T))) \tag{16}$$

When selecting the operator used, the probability of selecting the operator can be calculated using the following formula:

$$P(c) = \frac{w_c^{-/+}}{\sum_{d \in DM} w_d^{-/+}} \forall c \in \tag{17}$$

If the operator has been selected, weight updates will be carried out in the next iteration with the following equation:

$$w_{d,t+1}^{-} = \alpha\left(w_{d,t}^{-}\right) + \left(1 - \alpha\right)\beta \tag{18}$$

$$w_{d,t+1}^{+} = \alpha\left(w_{d,t}^{+}\right) + \left(1 - \alpha\right)\beta \tag{19}$$

$$\beta = \begin{cases} Z_1 iff(Xnew) \geq f(X) \\ Z_2 iff(Xnew) > f(X) \end{cases} \tag{20}$$

β is a decay parameter that controls the sensitivity or weight of change. The higher the value, the more reluctant the weight is to change. Meanwhile, α is a score that determines the change in weights based on the operator's performance in the previous iteration (Windras Mara et al., 2022). Table 5 presents the pseudocode used in MOALNS.

Table 5. Table of Pseudocode of MOALNS.

Pseudocode of MOALNS	
1	Input: T, D
2	Generate an initial solution X and archive A
3	Calculate the fitness values of the solution $f_m(X)$
4	Set initial weights w− and w+
5	While t < T
6	Select the destroy and repair method based on its weight
7	Perform destroy operation DX ← d(X)
8	Perform repair operation Xnew ← r(DX)
9	Perform an adjustment to the new solution Xnew
10	Calculate the fitness values of the solution f(Xnew)
11	Update the weights based on previous performance
12	Solution acceptance only accepts Xnew if it is not dominated by X
13	End while
14	Define the Pareto front and non-dominated solutions

Notes: T = Maximum number of iterations; D = degree of destruction; w- = weight of the destroy method; w+ = weight of repair method; m = objective function index

In MOALNS, each solution is represented using a hybrid structure consisting of two parts: (i) a permutation-based encoding of job sequences on machines and (ii) a real-valued vector $t = [t_1, t_2, \ldots, t_l]$, representing the preventive maintenance intervals of all components. This representation allows the algorithm to simultaneously explore the scheduling decisions and the maintenance policy decisions in a unified search space.

The MOALNS procedure starts from an initial solution generated randomly, where both the job sequence and the maintenance interval vector are initialized within their feasible domains. The search process is then performed iteratively by applying destroy and repair operators to the current solution. In the destroy phase, a subset of jobs is removed from the job sequence part of the solution, creating partial schedules. Two destroy operators are used in this study: (i) random removal, in which jobs are selected randomly, and (ii) worst removal, in which jobs that contribute most to the objective deterioration (e.g., based on sequence distance or cost impact) are removed. The number of removed jobs is controlled by the degree of destruction (DoD) parameter, as defined in Equation (16).

In the repair phase, the removed jobs are reinserted into the partial solution using two different operators: (i) random insertion, which reinserts jobs into randomly selected feasible positions, and (ii) greedy insertion, which reinserts jobs into positions that yield the best local improvement with respect to the objective functions. In parallel with the modification of the job sequence, neighborhood operators are also applied to the maintenance vector t by slightly increasing or decreasing one or more maintenance intervals within the bounds defined by Constraints (13). This ensures that MOALNS explores not only different schedules but also different preventive maintenance policies.

The selection of destroy and repair operators is guided by an adaptive weight mechanism. The probability of selecting an operator is computed using Equation (17), and the operator weights are updated using Equations (18)–(20) based on their historical performance. This adaptive mechanism allows the algorithm to balance exploration and exploitation by favoring operators that have been more successful in generating high-quality solutions.

After each destroy–repair cycle, the new solution is decoded into a feasible schedule by computing the start and completion times according to Equations (5)–(15). The makespan and the total operational cost are then evaluated using Equations (3) and (4), respectively. A solution is accepted if it is not dominated by the current solution and is stored in an external archive that maintains the set of non-dominated solutions. The iterative process continues until the maximum number of iterations T is reached, and the final output of the algorithm is an approximation of the Pareto front.

3.6. Performance metrics

Performance metrics or indicators are important in measuring and comparing the effectiveness of NSGA-II and MOALNS multi-objective optimization algorithms. Indicators such as Hypervolume HV, Spread SP, Spacing Metric SM, Euclidean Distance ED, Purity PU, and Computation Time CT are used to assess and illustrate key aspects, including uniformity of solution distribution, diversity, convergence, and the relative quality of the resulting Pareto front. Using these metrics enables a comprehensive analysis of how well each algorithm explores and exploits the search space, as well as its effectiveness in generating diverse and near-ideal solutions. The performance of this indicator follows the description by Rifai et al. (Rifai et al., 2021), which was developed to address specific problems.

4. Result

This research data processing was carried out in several stages. This is because the approach is an approximation approach, so it depends on solution search parameters based on the NSGA II and MOALNS methods. The stages of data processing to the discussion of results are as follows:

4.1. Verification of formulation and illustrative example

Verify the model using a simple data set consisting of 3 machines and 5 jobs, assuming each period has 882 hours. The results of data processing show that the model developed has been logically verified and is valid according to actual conditions, with the results in Table 6 below:

Table 6. Two Alternative solutions for the above data set.

Solution 1 (Makespan = 13; Minimize Operational Cost = Rp462440)		
Machine	Job Sequencing	Preventive Maintenance Interval
1	2 4 1 5	112.7115 hours
2	2 3 4	128.5357 hours
3	4 1	135.5252 hours
Solution 2 (Makespan= 12; Minimize Operational Cost= Rp464420)		
Machine	Job Sequencing	Preventive Maintenance Interval
1	2 4 1 5	111.6241 hours
2	2 4 3	104.5733 hours
3	4 1	135.5252 hours

Based on the results of data processing, it is verified and validated that the model developed ensures a tradeoff between the two objective functions: minimizing makespan and minimizing total expected operational cost. In this process, two alternative solutions are obtained, each with various decision variables. Determining the best solution can be done with managerial considerations. According to the verification results, the developed equation model can be used to solve more complex cases.

4.2. Parameters

The solution search process using NSGA II and MOALNS requires several input parameters, which are used to explore and exploit feasible solutions. Based on parameter searches using simple data sets, genetic parameters in NSGA II were obtained using four levels and four factors (Nessari et al., 2024; Wang et al., 2024), including the following at Table 7:

Table 7. Table of genetic parameter.

Population Size	Generation	Crossover Rate	Mutation Rate
20	400	0.2	0.1
50	500	0.4	0.2
100	**600**	**0.6**	**0.3**
200	700	0.8	0.4

Based on parameter searches using a fractional factorial Taguchi L16 design, it was found that Experiment 3, with a population size of 20, 600 generations, a crossover rate of 0.6, and a mutation rate of 0.3, can provide optimal results. Therefore, these parameters can be utilized to search for solutions in real-world datasets.

The parameter search is continued in MOALNS, which uses 4 levels and 3 factors (Liu et al., 2024; Rifai et al., 2021, 2023) with the parameter β assumed to be constant at Table 8 as follows:

Table 8. Table of ALNS Parameter.

α	T	DoD	β
0.5	500	[0.3 0.15]	**[0.9 0.1]**
0.7	1000	[0.3 0.2]	**[0.9 0.1]**
0.8	**1500**	**[0.5 0.35]**	**[0.9 0.1]**
0.9	2000	[0.7 0.5]	**[0.9 0.1]**

Based on parameter searches using fractional factorial Taguchi L16, it was found that experiment 3 had a decay parameter (α) of 0.5, maximum iteration (T) of 1500, degree of destruction (DoD) of [0.5 0.35], and a constant β parameter of [0.9 0.1]. These parameters will be used to find solutions for real data sets

4.3. Result

Searching for solutions in both multi-objective approximation approaches obtained the Figure 2 optimal pareto front. In the image of the NSGA optimal Pareto front results, 5 non-dominating solutions are found that can be implemented in metal-producing companies. These solutions include Table 9.

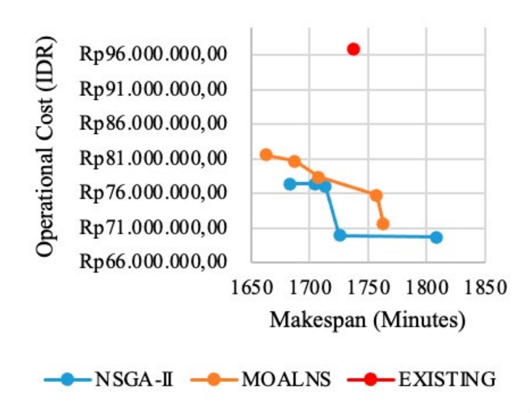

Figure 2. Result of Pareto Front Optimal (Operational Cost vs Makespan).

Table 9. Table of NSGA II's Non-Dominated Solutions.

	NSGA-II		Difference with Existing	
Solutions	f1 (minutes)	f2 (IDR)	f1	f2
1	**1683.45**	**Rp77,413,825**	**3%**	**20%**
2	1704.72	Rp77,340,738	2%	20%
3	1713.43	Rp76,939,907	1%	21%
4	1725.75	Rp69,945,137	1%	28%
5	**1808.93**	**Rp69,634,779**	**-4%**	**28%**
	MOALNS			
1	**1662.53**	**Rp81,587,806**	**4%**	**16%**
2	1687.15	Rp80,672,22	3%	17%
3	1707.85	Rp78,372,323	2%	19%
4	1757.27	Rp75,703,233	-1%	22%
5	**1763.35**	**Rp71,560,739**	**-2%**	**26%**

Meanwhile, the MOALNS produces five alternative non-dominance solutions, which can be used as suggestions for production-maintenance scheduling.

In Table 9, the lowest f1 and f2 values are presented in comparison to existing conditions. At f1, the lowest NSGA-II and MOALNS have a difference of 3% and 4% in makespan and 20% and 16% in operational costs. While at f2, the lowest NSGA-II and MOALNS have a difference of -4% and -2% in makespan and 28% and 26% in operational costs. Illustration of integrated production-maintenance scheduling using Figure 3 below, which is solution 1 as an illustrative representation of all non-dominant solutions. Below is an illustration of scheduling solution 1 for each approach.

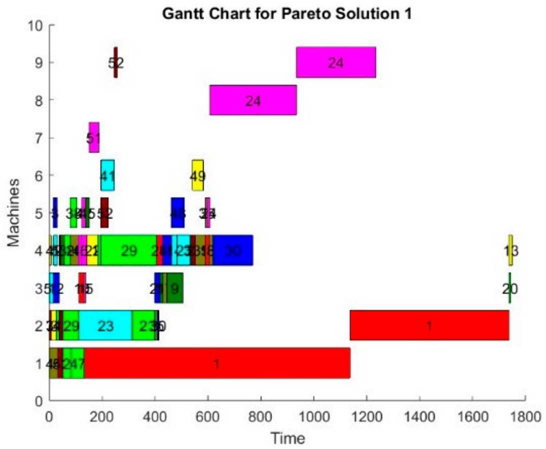

Figure 3. Result of NSGA II's Gantt Chart Solution 1.

If minimizing makespan is considered, the first solution in MOALNS is the best alternative; however, it has higher operational costs than NSGA-II. As shown in Table 9, NSGA-II in solution 1 yields the best alternative solution in minimizing operational costs, but not in minimizing makespan. These results can provide insight into the tradeoff between the two objective functions addressed in this research.

4.4. Evaluation of the algorithms

In this study, we employ a range of performance metrics to rigorously assess and compare the effectiveness of the NSGA-II and MOALNS algorithms. These metrics offer nuanced insights into each algorithm's ability to generate diverse, high-quality solutions across various optimization scenarios, with the number of jobs, *j*, the number of machines, *m,* and the number of components each machine*, k,* should maintain.

In comparing the effectiveness of the NSGA-II and MOALNS algorithms, this study focuses its analysis on several key Performance Indicators (PI), which include hypervolume HV, Euclidean distance ED, spread SP, spacing metric SM, purity PU, and Computation Time CT. The results showed that Hypervolume (HV) exhibits a significantly higher average value compared to MOALNS in NSGA II. This suggests that NSGA II is more effective in covering a broader solution space within the Pareto front, indicating its superiority in identifying more optimal solutions overall. Conversely, when examining the Euclidean Distance (ED) metric, NSGA II demonstrates a smaller value than MOALNS. A smaller ED value implies that the solutions generated by NSGA II are closer to the optimal point, suggesting that NSGA II is more effective in approximating the optimal solution.

Regarding Spread (SP), MOALNS again shows better performance with a lower average value, indicating that its solutions are more evenly distributed along the Pareto front. This reflects MOALNS's ability to maintain solution diversity more effectively. However, when it comes to the Spacing Metric (SM), NSGA II outperforms MOALNS with a smaller value, indicating that the solutions it generates are more uniform in their distribution, which reflects greater consistency in the spacing of the solutions along the Pareto front.

Furthermore, in terms of Purity (PU), NSGA II is superior, with a significantly higher value compared

Table 10. Table of comparison result in average.

			HV		ED		SP	
j	*m*	*k*	NSGA II	MOALNS	NSGA II	MOALNS	NSGA II	MOA-LNS
53	9	27	**0.565**	**0.565**	0.786	**0.642**	**0.454**	0.794
210	35	105	**0.668**	0.269	**0.713**	0.883	**0.548**	**0.548**
360	60	180	**0.650**	0.270	**0.729**	0.933	0.536	**0.334**
510	85	340	**0.821**	0.451	**0.628**	0.893	0.727	**0.522**
660	110	440	**0.892**	0.470	**0.527**	0.813	0.687	**0.470**
Mean			0.719	0.405	**0.676**	0.833	0.590	**0.534**

			SM		PU		CT	
j	*m*	*k*	NSGA II	MOALNS	NSGA II	MOALNS	NSGA II	MOALNS
53	9	27	**0.247**	0.311	**0.193**	0.085	40.362	**18.837**
210	35	105	**0.159**	0.294	**0.391**	0.026	**480.410**	598.388
360	60	180	**0.124**	0.222	**0.359**	0.023	**816.430**	1405.916
510	85	340	**0.198**	0.262	**0.323**	0.029	**1992.832**	3186.807
660	110	440	**0.208**	0.264	**0.264**	0.029	**3284.322**	4583.361
Mean			**0.187**	0.270	**0.306**	0.038	**1322.871**	1958.662

Table 11. Table of statistical analysis.

	Metric	HV	Metric	ED	Metric	SP
	p-value	0.007	p-value	0.056	p-value	0.550
METHOD	MEAN		MEAN		MEAN	
NSGA II	**0.719**		**0.676**		0.590	
MOALNS	0.405		0.833		**0.534**	
	Metric	SM	Metric	PU	Metric	CT
	p-value	0.015	p-value	0.002	p-value	0.557
METHOD	MEAN		MEAN		MEAN	
NSGA II	**0.187**		**0.306**		**1322.871**	
MOALNS	0.270		0.038		1958.662	

to MOALNS. This indicates that the solutions generated by NSGA II are more often close to or achieve the optimal solution, making it a better choice when the quality of the solution is the primary concern. Lastly, regarding Computational Time (CT), NSGA II is faster than MOALNS, demonstrating higher efficiency in the time required to reach solutions.

Overall, NSGA II tends to outperform MOALNS in key aspects such as coverage of the Pareto front, solution quality, and computational efficiency, making it more suitable for situations where optimal solutions and time efficiency are highly prioritized. On the other hand, MOALNS offers advantages in approximating optimal solutions and maintaining a more evenly distributed set of solutions, which may be more appropriate in contexts where solution diversity and proximity to the optimal are critical.

4.5. Statistical analysis

The results of the t-test analysis, as presented in the Table 11, provide insights into the comparative performance of the NSGA II and MOALNS algorithms across several key metrics. The Hypervolume (HV) metric, which measures the volume covered by the Pareto front, shows a statistically significant difference between the two algorithms, with a p-value of 0.007. Although NSGA II has a higher mean HV value, this difference is insignificant. For the ED metric, which evaluates the proximity of solutions to the ideal point, the p-value of 0.056 indicates that the difference between NSGA II and MOALNS is not statistically significant. MOALNS exhibits a smaller mean ED value, suggesting closer solutions to the optimal point, but this difference lacks statistical significance.

Regarding the SP metric, which assesses the evenness of solution distribution along the Pareto front, the p-value is 0.550. This suggests that the difference between the algorithms is not statistically significant, despite MOALNS showing a slightly better spread with a lower mean value. The SM, which measures the consistency in spacing between neighboring solutions, has a p-value of 0.015, indicating a significant difference between the two algorithms. Although NSGA II demonstrates a lower mean SM value, which would typically suggest more uniform spacing, this difference is not statistically significant.

Meanwhile, the Purity (PU) metric, which reflects the proportion of solutions close to the optimal front, reveals a statistically significant difference between NSGA II and MOALNS, with a p-value of 0.002. NSGA II's significantly higher mean PU value indicates that it more consistently produces solutions near the optimal front than MOALNS. Finally, for Computational Time (CT), which measures the efficiency of the algorithms in terms of time taken to reach a solution, the p-value is 0.557. This indicates that the difference in computational time between NSGA-II and MOALNS is not statistically significant, although NSGA-II is observed to be faster on average.

4.6. Discussion

Developing mathematical models to solve production and maintenance scheduling problems can provide several alternative solutions. The total number of jobs completed was 53, with a specific processing time and simultaneously providing preventive maintenance time decisions for each of the three critical components on the 9 machines used. Solving integrated scheduling problems using the NSGA II and MOALNS methods. The search for alternative solutions characterizes two approaches. The model developed carries out more complex experiments with several representative cases to ensure the robustness of the model. Table 10 presents five experiments that measure the performance indicators of mathematical

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models and algorithms, demonstrating that these models and algorithms exhibit quite robustness. The consistency of the results across these scenarios demonstrates that the proposed model and algorithms are not overly sensitive to specific problem instances, indicating a satisfactory level of robustness. However, it is also observed that the quality of the obtained solutions is influenced by the parameter settings of the metaheuristics, which directly control the balance between exploration and exploitation. This behavior is typical of advanced metaheuristic methods and confirms that careful parameter tuning plays a critical role in achieving good performance.

The comparison of the objective function values with the existing condition shows that the proposed approach consistently improves the makespan-related performance (f1), as indicated by the positive improvement percentages. In contrast, for the second objective (f2), although the model succeeds in significantly reducing total operational costs by integrating production and maintenance decisions, a slight degradation in makespan is observed in some cases. This result clearly highlights the intrinsic trade-off between production efficiency and maintenance-related costs: reducing maintenance and operational expenses may require accepting longer completion times, while aggressively minimizing makespan may increase maintenance frequency and associated costs.

The comparative analysis between NSGA-II and MOALNS across the six performance metrics provides insight into the relative strengths and weaknesses of each algorithm. NSGA-II competes in key areas, particularly HV, ED, SM, PU, and CT. The higher mean HV value for NSGA-II suggests its superiority in covering a larger portion of the Pareto front, and the difference was statistically significant (p-value = 0.007). While NSGA-II may provide broader coverage, this advantage is not definitive across all problem instances.

NSGA II, on the other hand, shows a notable advantage with a lower mean ED value, indicating that it generates solutions closer to the ideal point in the objective space. However, the difference in ED between NSGA-II and MOALNS is not statistically significant (p-value = 0.056). This suggests that while NSGA-II may have a slight edge in generating solutions closer to the ideal, this advantage does not hold consistently across different scenarios.

When examining the SP metric, MOALNS displays a slightly better mean value, indicating a more even distribution of solutions along the Pareto front. However, this difference is also not statistically significant (p-value = 0.550), which suggests that both algorithms are comparable in maintaining solution diversity.

A significant finding in this analysis is observed in the SM, where NSGA-II outperforms MOALNS with a lower mean value, and this difference is statistically significant (p-value = 0.015). This indicates that NSGA-II is more effective in producing evenly spaced solutions along the Pareto front, ensuring that all regions of the front are well-represented. This is particularly important in applications where a comprehensive exploration of tradeoffs between objectives is necessary. In terms of PU, NSGA-II again demonstrates a significant advantage with a higher mean value, indicating that it more consistently produces solutions closer to the ideal Pareto front. The statistical significance of this difference (p-value = 0.002) underscores the reliability of NSGA-II in delivering high-quality solutions.

Finally, in the analysis of CT, NSGA-II shows a lower mean value, indicating greater computational efficiency. However, this difference is not statistically significant (p-value = 0.557), suggesting that while NSGA-II may be faster, the time required by both algorithms to converge to a solution is comparable under the given conditions.

In summary, while NSGA-II exhibits statistically significant advantages in HV, SM, and PU, which are crucial for ensuring a well-distributed and high-quality set of solutions, the differences in other metrics, such as ED, SP, and CT, are not statistically significant. Therefore, the choice between NSGA-II and MOALNS should be made in consideration of these strengths in the context of the specific requirements of the optimization task at hand. NSGA-II may be preferred when solution quality and even distribution are of paramount importance.

5. Conclusions

This study has successfully developed an integrated multi-objective optimization model for simultaneously solving production scheduling and maintenance planning. The results confirm that the problem is inherently multi-objective. It can

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simultaneously minimize makespan and operational cost. If focused on minimizing makespan, MOALNS solution 1 is the good choice because it can minimize makespan by up to 4% but only minimizes operational costs by up to 16%. In general, it has positive impacts such as speeding up processes, reducing downtime, and reducing labor costs. However, the NSGA-II solution 5 is the better choice. It can minimize operational costs by up to 28% but makespan by 4%. The increase in makespan has not had a significant impact because the industry is a government unit that tends to focus on the long term. Furthermore, due dates are often extended by up to 5% to avoid delays. With significant reductions in operational costs, the industry can save significantly on total operational costs, such as machine maintenance, labor costs, and maintaining output quality, from existing operations and can continue to serve customers more sustainably.

The main limitation of this study is that it is based on only five test cases, which should be extended to include larger and more diverse problem instances, particularly for scenarios involving a high volume of orders. In addition, the proposed model is deterministic, which may limit its ability to fully capture the uncertainties and variability commonly encountered in real-world industrial environments.

Extending this study to include other emerging multi-objective optimization algorithms could also provide a richer comparative as a sensitivity analysis, varied cases, and help refine existing methodologies or develop new ones that leverage the strengths observed in MOALNS and NSGA-II. Furthermore, potential hybrid algorithms could be tested and it should be considered to provide a combined analysis of population-based and trajectory-based approaches.

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