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Optimization of Agricultural Machinery Loan Scheduling Using Metaheuristic Algorithms

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ABSTRACT

Agricultural machinery allocation and scheduling at the West Java Provincial Agricultural Mechanization Center relied on the First-In-First-Out method, which did not simultaneously consider machinery availability, service locations, loan periods, operational capacity, land requirements, and logistics costs. This study developed a multi-objective scheduling model to minimize logistics costs and maximize the total served land area. Genetic Algorithm, Particle Swarm Optimization, and Differential Evolution were implemented and compared under identical experimental conditions. The evaluation used operational data consisting of 52 agricultural machinery units and 423 Agricultural Machinery Service Business Units, with each algorithm executed independently 50 times. Multivariate analysis of variance showed significant overall performance differences among the algorithms. Although Particle Swarm Optimization produced slightly better mean objective values, Differential Evolution generated statistically comparable solutions with lower variability and the most stable logistics-cost performance. Differential Evolution was selected as the preferred method on this basis. Compared with the First-In-First-Out (FIFO) baseline, Differential Evolution reduced mean logistics cost by 18.51% and increased mean served land area by 10.16% across 50 independent runs. The resulting DE schedules satisfied the operational constraints.

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1. INTRODUCTION

The agricultural sector plays a strategic role in supporting food security and economic development, particularly in Indonesia. Improvements in agricultural

productivity are closely associated with the utilization of agricultural machinery and equipment, which enhances production efficiency and reduces operational time. However, the limited availability of agricultural machinery relative to user demand creates allocation and utilization challenges that require optimization [1]-[3]

The problem becomes increasingly complex when a single unit of agricultural machinery must serve multiple loan requests across different locations and time periods. Shared agricultural machinery scheduling must account for machinery availability, work locations, and time windows to reduce waiting times and transportation costs [4]. Previous studies have also developed cooperative scheduling and dynamic job allocation approaches to efficiently assign tasks across multiple agricultural machines [5]-[7]. In the context of agricultural machinery loan management at the West Java Agricultural Mechanization Center (BP Mektan), the allocation process still follows the First-In-First-Out (FIFO) principle and does not simultaneously account for field location, loan period, duration of use, and unit availability. This condition may lead to scheduling conflicts and suboptimal utilization of agricultural machinery when demand increases during the planting season.

Previous studies have shown that time windows are important constraints in agricultural machinery scheduling because each task must be completed within a specified period [4], [7]. Wang and Huang [4] proposed a two-step framework for dispatching shared agricultural machinery with time-window constraints by considering spatial and temporal characteristics of agricultural operations. Guo et al. [7] further developed a multiobjective cooperative scheduling approach for agricultural machinery across regions, considering transfer distance and nonoperational scheduling costs. Other studies have addressed dynamic cooperative scheduling and job allocation among multiple agricultural machines using evolutionary and swarm-based optimization approaches [5], [6], [10]. More recent work has turned to deep reinforcement learning [8], [9] and to hybrid or improved evolutionary and swarm algorithms [15], [16], [17], largely in response to the growing complexity of operational conditions in the field.

Despite these developments, most existing studies focus on field-operation scheduling, machine dispatching, or cooperative agricultural operations. The decision context differs from agricultural machinery loan allocation, in which a limited number of machinery units must be assigned to multiple service requests while simultaneously considering machinery suitability, availability, loan periods, operating duration, logistics cost, and service coverage. In a loan-management environment, the scheduling decision is not limited to determining how machinery performs or moves between agricultural fields, but also involves determining which machinery unit should serve each request and when the service should be scheduled.

The research gap addressed in this study lies in the limited attention given to agricultural machinery loan scheduling as a specific multi-objective resource allocation problem. Existing studies have demonstrated the application of optimization techniques to

agricultural machinery dispatching and operational scheduling, but they do not directly examine the trade-off between logistics cost and served land area in a loan allocation context while simultaneously evaluating the consistency of alternative metaheuristic algorithms through repeated independent experiments and comparing the resulting schedules with a conventional First-In-First-Out (FIFO) policy.

The gap has a methodological side as well. Direct comparisons of GA, PSO, and DE, and hybrids that combine them, have been reported mainly for manufacturing problems such as distributed flow-shop, parallel-machine, and batch scheduling [11]–[14]. Conclusions drawn in those settings do not transfer automatically to machinery loan allocation, where eligibility rules, loan windows, and spatially dispersed service units shape the search space in quite different ways. How consistently an algorithm behaves across repeated runs also receives less attention than its best result, even though benchmarking guidelines treat run-to-run variability as a core property of stochastic optimizers [26], [28]. For a public agency such as BP Mektan, which will normally act on the output of a single run, that consistency may matter nearly as much as the average quality of the solutions.

Accordingly, this study formulates agricultural machinery loan scheduling as a multi-objective optimization problem with two competing objectives: minimizing logistics cost and maximizing served land area. The formulation incorporates operational feasibility constraints related to machine suitability, availability, loan timing, service duration, and schedule conflicts. Three established metaheuristic approaches, namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), are evaluated under identical computational conditions. The evaluation considers mean solution quality, variability across independent runs, and execution time, followed by statistical analysis to determine whether the observed differences are supported by the experimental results.

The contributions of this study are threefold. First, it develops a loan-specific multi-objective scheduling formulation that integrates operational allocation constraints with logistics efficiency and service coverage. Second, it provides a controlled empirical comparison of GA, PSO, and DE using repeated independent runs to examine both solution quality and algorithmic stability. Third, it compares the selected metaheuristic scheduling approach with the existing FIFO allocation policy to quantify differences in logistics cost and served land area. The novelty of this study is therefore positioned at the problem-formulation and empirical-evaluation levels rather than in proposing a new metaheuristic algorithm.

Based on the identified research gap, this study developed and evaluated a multi-objective agricultural machinery loan scheduling model using GA, PSO, and DE. The proposed model integrates machine eligibility, operational capacity, availability, loan timing, service duration, schedule-conflict prevention, logistics cost, and served land area into a unified scheduling framework. The resulting schedules are further compared with the conventional FIFO allocation approach to assess their operational implications.

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2. RESEARCH METHOD

This study employed a computational experimental approach based on the Design Science Research Methodology (DSRM) framework [18]. This approach was selected to develop a technological artifact in the form of an optimization model capable of addressing an NP-hard problem [19] within an agricultural resource allocation scheduling system. The methodology included the exploration of operational data, the formulation of multi-objective functions, the implementation of metaheuristic algorithms, and statistical testing of algorithmic stability and significance presented in Figure 1.

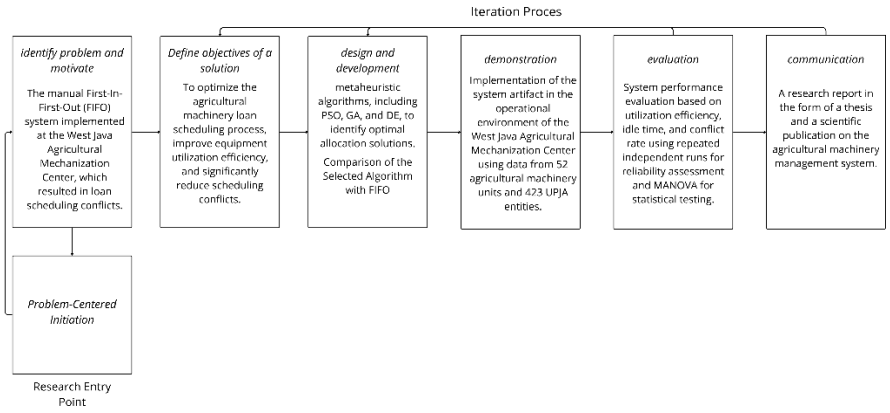

Figure 1. DSRM Method

2.1. Problem Identification and Dataset Exploration

Field-level problems were identified through a Focus Group Discussion (FGD) conducted at the West Java Provincial Agricultural Mechanization Center. The discussion revealed that the conventional First-In-First-Out (FIFO) scheduling method contributed to route inefficiencies and loan scheduling conflicts.

The dataset used in the computational modeling was obtained from operational administrative records and consisted of two main groups. The first group comprised a fleet dataset of 52 agricultural machinery units, including 22 combine harvesters, 15 rotavators, and 15 tractors. The second group consisted of service demand points represented by 423 Agricultural Machinery Service Unit (UPJA) entities across West Java. The spatial and operational interactions between the 52 machinery units and the 423 service entities created an extensive solution search space, thereby requiring an advanced heuristic optimization approach.

2.2. Multi-Objective Mathematical Modeling

The mathematical formulation employed a Multi-Objective Optimization (MOO) approach to generate a set of non-dominated solutions along the Pareto frontier. This approach enabled schedule selection based on the trade-off between logistics efficiency and service performance [20], [21].

The logistics minimization function (f_1) aimed to reduce agricultural machinery fleet movements by considering travel distance (d_{ij}) and mobilization cost (c_{ij}). The weights (w_1) and (w_2) were used to adjust the relative priority of these two components. Minimizing travel distance and mobilization cost can reduce inefficiencies, operating costs, and nonproductive travel [7], [22], [23].

$$\text{Minimize } f_1 = \sum_{i=1}^{m}\sum_{j=1}^{n}(d_{ij} \cdot w_1 + c_{ij} \cdot w_2) \cdot X_{ij} \quad (1)$$

The utility maximization function (f_2) aimed to extend the benefits of agricultural machinery services by increasing the area of land served (L_j) and the number of farmers receiving services (N_j). These two indicators represented service coverage and the social benefits of agricultural mechanization, while (v_1) and (v_2) denoted the priority weights assigned to each indicator [4], [24].

$$\text{Maximize } f_2 = \sum_{i=1}^{m}\sum_{j=1}^{n}(L_j \cdot v_1 + N_j \cdot v_2) \cdot X_{ij} \quad (2)$$

In Equations (1) and (2), i indexes machinery units and j indexes service requests. The binary decision variable X_{ij} equals 1 when machinery unit i is assigned to service request j and 0 otherwise. Only assigned machine–request pairs contribute to the objective functions. The logistics objective f_1 combines travel distance and mobilization cost, weighted by w_1 and w_2, respectively. The service objective f_2 combines served land area and the number of farmers served, weighted by v_1 and v_2, respectively. To describe the operational performance of the resulting schedules, the results tables report logistics cost in Indonesian rupiah (IDR) and served land area in hectares (ha)

To ensure that the generated solutions were operationally feasible, the computational model incorporated constraints that prohibited schedule overlap for each machinery unit and ensured that the loan duration did not exceed the machine's maximum daily operating-hour capacity (H_{max}).

2.3. Metaheuristic Algorithm Configuration

Three metaheuristic algorithms were evaluated for agricultural machinery loan scheduling: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE). All three algorithms used the same input data, operational constraints, and

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objective functions. The population size was set to 20 candidates, and each run was terminated after 50 iterations. Each algorithm was run independently 50 times. Table 1 summarizes the control parameters used in the experiments.

Table 1. Control parameters of the metaheuristic algorithms

Algorithm	Empirical Control Parameter	Parameter Value
All algorithms	Population size	20
All algorithms	Maximum number of iterations	50
GA	Crossover operator	One-point crossover
GA	Mutation probability (P_m)	0.10
PSO	Inertia weight (w)	0.50
PSO	Cognitive and social coefficients (c_1, c_2)	1.50 each
DE	Differential mutation factor (F)	0.50
DE	Crossover rate (CR)	0.70

GA generated new candidates through parent selection, one-point crossover, and mutation. PSO generated new candidates by updating particle velocities and positions. DE generated trial vectors through differential mutation and crossover. The candidates produced by these operators were evaluated using the common procedure described in Section 2.4

2.4. Optimization Procedure

The optimization procedure used operational data from 52 agricultural machinery units and service requests associated with 423 Agricultural Machinery Service Unit (UPJA) entities. Each candidate was decoded into machinery assignments and a service sequence. The resulting schedule was checked for machinery suitability and availability, compliance with the requested loan period, overlap between assignments to the same unit, and compliance with the unit's daily operating-hour limit.

Candidates that violated an operational constraint were rejected. For each feasible candidate, the two objective values were calculated and combined into a normalized fitness score. Lower fitness scores indicated better schedules. The same decoding, feasibility checks, and evaluation procedure were applied to the initial population and to new candidates generated during the search. Algorithm 1 summarizes the procedure.

Input Machinery data, service requests, and the parameters in Table 1 Output Best feasible schedule and performance measures for each run. For each algorithm (GA, PSO, and DE):

1) Repeat for 50 independent runs:
   - Start the timer and generate an initial population of 20 candidates.
   - Decode each candidate into machinery assignments and a service sequence.
   - Reject infeasible candidates and evaluate the remaining schedules.
   - Record the best feasible schedule found.
2) For each of the 50 iterations:

- Generate new candidates using the selected algorithm.
- Decode the new candidates and check operational feasibility.
- Evaluate feasible candidates using the same objectives and fitness score.
- Update the population and retain the best feasible schedule found.
- Stop the timer.
- Record logistics cost, served land area, fitness, and execution time for the run.

The selected DE method was evaluated against the First-In-First-Out (FIFO) policy in a separate experiment consisting of 50 independent DE runs. FIFO processed requests in order of arrival and returned the same schedule for the same input data. The resulting schedules were compared in terms of logistics cost, served land area, and fitness.

2.5. Performance Evaluation and Statistical Validation Procedures

Computational performance was evaluated using solution quality, variability, and execution time. For each independent run, logistics cost, served land area, scheduling feasibility, and computational time were recorded. Mean values were used to describe average algorithmic performance, while standard deviation was used to characterize the consistency of the stochastic optimization results across independent runs. To provide a fair comparison, GA, PSO, and DE were executed using the same population size, maximum number of iterations, input data, operational constraints, and computational conditions. Each algorithm was independently executed 50 times because a single stochastic execution is insufficient to represent the overall behavior of a metaheuristic algorithm [26], [27].

A Multivariate Analysis of Variance (MANOVA) was used to examine whether the algorithm type had an overall effect on the combined performance variables of logistics cost and served land area. The significance level was set at 0.05. When a significant multivariate effect was identified, Tukey's Honestly Significant Difference (HSD) test was used for pairwise comparison between algorithms. The statistical results were interpreted together with the descriptive performance measures. An algorithm was not evaluated solely on the basis of its lowest mean objective value; variability across independent runs was also considered because consistency is an important characteristic when comparing stochastic optimization algorithms [26]–[29].

3. RESULTS AND DISCUSSION

This section presents an in-depth evaluation of the agricultural machinery fleet scheduling optimization model implemented using metaheuristic algorithms. The evaluation focused on comparing the computational performance of the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), conducting multivariate statistical significance testing, and performing a final comparison with the existing First-In-First-Out (FIFO)-based scheduling method.

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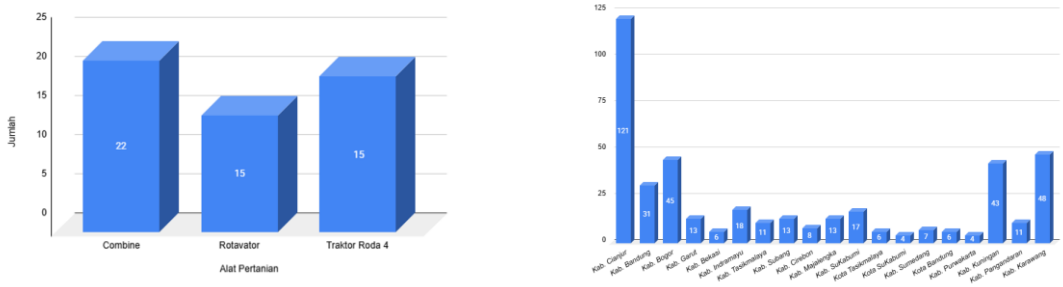
3.1. Solution Space Complexity and Operational Constraint Evaluation

The computational experiments were conducted using an operational dataset comprising 52 agricultural machinery units, including 22 combine harvesters, 15 rotavators, and 15 tractors, to fulfill service requests from 423 Agricultural Machinery Service Unit (UPJA) entities across West Java Province presented in Figure 2.



(a) (b)

Figure 2. (a) List of Agricultural Machinery Units and (b) List of UPJA Entities in West Java

The spatial interaction between 52 agricultural machinery units and 423 UPJA entities produced 21,996 potential machine-service assignment pairs before feasibility filtering. These pairwise relationships represent the basic allocation possibilities; a complete scheduling solution additionally involves assignment, sequencing, timing, and non-overlap decisions. Therefore, the actual combinatorial search space is substantially larger than the number of pairwise relationships, which motivates the use of population-based metaheuristic optimization rather than exhaustive enumeration.

Operational feasibility constraints were applied before objective evaluation. For example, a candidate solution that assigned Tractor-01 simultaneously to UPJA 012 and UPJA 015 was identified as a schedule overlap and rejected. Similarly, an assignment of Combine-04 to UPJA 088 with a service duration of 14 hours was rejected because it exceeded the maximum daily operating-hour capacity. These constraints ensure that the optimization process evaluates scheduling configurations that are operationally feasible for implementation.

3.2. Algorithm Performance Evaluation and Multivariate Statistical Testing

Each algorithm was run 50 times independently, with a population of 20 and a limit of 50 iterations. Table 2 summarizes the resulting performance of GA, PSO, and DE.

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Table 2. Comparative computational performance of GA, PSO, and DE

Evaluation Parameter	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)	Differential Evolution (DE)
Average Execution Time	0.302 seconds	0.329 seconds	0.615 seconds
Logistics Cost (f_1)	IDR 82,396,279	IDR 74,102,854	IDR 75,248,434
Land Coverage (f_2)	167.44 ha	174.69 ha	172.98 ha
Cost Standard Deviation (σ)	3,588,276	4,082,965	3,124,329

GA was the fastest of the three, needing 0.302 seconds per run on average (Table 2). That speed came at a price: GA returned the highest mean logistics cost (IDR 82,396,279) and the smallest mean land coverage (167.44 ha). PSO sat at the opposite end, with the lowest mean cost of IDR 74,102,854 and the largest coverage of 174.69 ha, which makes it the strongest performer on mean objective values.

DE landed between the two, averaging IDR 75,248,434 in logistics cost and 172.98 ha in coverage. What set it apart was consistency. Its logistics-cost standard deviation of IDR 3,124,329 was the lowest of the three (against IDR 3,588,276 for GA and IDR 4,082,965 for PSO), so DE appears to return similar cost levels from one run to the next.

The results therefore reveal a trade-off between average objective quality and algorithmic stability. PSO provided the strongest average objective values, whereas DE exhibited the lowest variability in logistics cost. This trade-off was subsequently examined using multivariate statistical analysis. The statistical significance of the overall performance differences was subsequently examined using Multivariate Analysis of Variance (MANOVA) presented in Table 3.

Table 3. MANOVA results for logistics cost and land coverage.

Multivariate Test	Value	F-Value	Hypothesis df	Error df	Sig
Pillai's Trace	0.639	34.495	4.000	294.000	< 0.001
Wilks' Lambda	0.362	48.329	4.000	292.000	< 0.001
Hotelling's Trace	1.760	63.804	4.000	290.000	< 0.001
Roy's Largest Root	1.759	129.272	2.000	147.000	< 0.001

The MANOVA results in Table 3 indicate a statistically significant overall difference among GA, PSO, and DE when logistics cost and land coverage are considered jointly ($p < 0.001$). This result indicates that algorithm type had a statistically significant effect on the combined performance measures.

Table 4. Tukey HSD post-hoc comparison results

Dependent Variable	Algorithm Comparison	Mean Difference	Significance (Sig.)	Result
Logistics Cost (f_1)	DE vs. GA	−7,147,844.45	< 0.001	Significant Difference
	DE vs. PSO	1,145,580.01	0.256	Not Significant
	PSO vs. GA	−8,293,424.46	< 0.001	Significant Difference

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Land Coverage (f_2)	DE vs. GA	5.5431	< 0.001	Significant Difference
	DE vs. PSO	−1.7145	0.456	Not Significant
	PSO vs. GA	7.2576	< 0.001	Significant Difference

The pairwise results in Table 4 provide a more detailed interpretation. DE and GA differed significantly in logistics cost ($p < 0.001$) and land coverage ($p < 0.001$). PSO and GA also differed significantly for both objectives ($p < 0.001$). However, DE and PSO did not show statistically significant differences in logistics cost ($p = 0.256$) or land coverage ($p = 0.456$). Read together, the tests suggest that DE and PSO reach solutions of comparable quality, with DE doing so more consistently in terms of cost. DE was chosen on a stability-oriented criterion: when two algorithms cannot be separated statistically on solution quality, the one with lower run-to-run variability is preferred, since a planner will usually act on the result of a single run rather than an average over fifty. The choice rests on this criterion and on the present data. It should not be taken as evidence that DE outperforms PSO in general.

3.3. Comparison of DE-Based Optimization and Conventional FIFO Scheduling

The selected DE-based scheduling model was then compared with the conventional FIFO allocation method. This comparison was carried out on a separate set of 50 independent DE runs, which is why the DE values in Table 5 differ slightly from those reported in Table 2.

Table 5. Comparative performance of DE and FIFO

Evaluation Parameter	Existing Method (FIFO)	Optimization Method (DE)	Improvement
Decision-Making Characteristics	Static	Dynamic	-
Average Logistics Cost (f_1)	Rp92,269,945	Rp75,191,323	18.51% Cost Efficiency
Average Land Coverage (f_2)	156,53 hectares	172.44 hectares	10.16% Increase in Utilization
Average Fitness Value	0.9622	0.8171	Optimization
Cost Standard Deviation (σ)	0 (None/Constant)	Rp3,120,338	-
Decision Execution Time	0.0006 seconds (without evaluation)	0.7048 seconds (50-generation evaluation)	Computational Automation

As shown in Table 5, the mean logistics cost across the 50 DE runs was IDR 75,191,323, which was 18.51% lower than the FIFO baseline of IDR 92,269,945. Mean served land area increased from 156.53 ha under FIFO to 172.44 ha under DE, an improvement of 10.16%. The resulting DE schedules satisfied the operational constraints.

The improvement over FIFO can be interpreted from the decision structures of the two methods. FIFO primarily follows the order in which service requests are received, whereas the proposed optimization evaluates multiple operational attributes

simultaneously, including machinery assignment, timing, availability, and logistics-related factors. The optimized schedule can therefore avoid inefficient assignments that may arise when requests are processed only according to their arrival order.

Under the same input conditions, FIFO returned a fixed fitness value of 0.962223. A one-sample t-test was used to compare the fitness values from 50 independent DE runs with this baseline. The Shapiro–Wilk test did not detect a significant departure from normality in the DE fitness values ($W = 0.957$, $p = 0.065$). The mean DE fitness was 0.8171 and was significantly lower than the FIFO baseline, $t(49) = -83.72$, $p < 0.001$, with an absolute Cohen's d of 11.84. All 50 DE runs achieved lower fitness values than FIFO. A separate one-sample t-test showed that DE also reduced logistics costs relative to FIFO, $t(49) = -38.70$, $p < 0.001$. Figure 3 shows the convergence patterns and the distribution of fitness values across the DE runs.

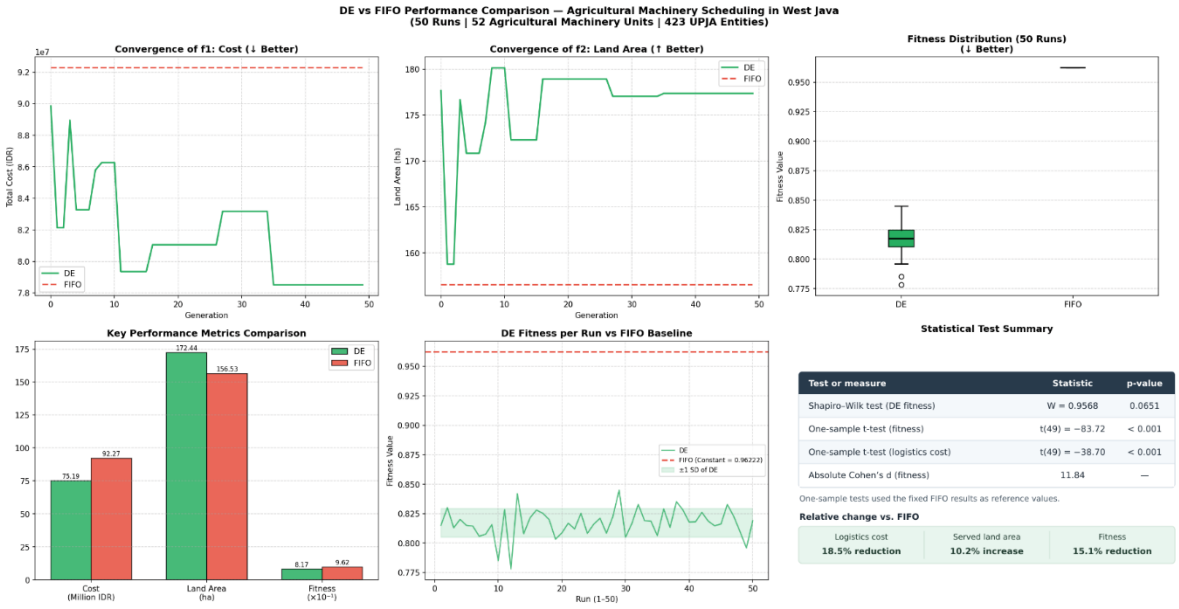

Figure 3. Comparison of Differential Evolution (DE) and First-In-First-Out (FIFO) scheduling performance across 50 independent DE runs.

3.4. Pareto Frontier Analysis and Multi-Objective Sensitivity

To examine the trade-off between logistics cost and served land area, a Pareto frontier analysis was performed using the solutions generated by the DE-based optimization process. Under the experimental configuration of 20 individuals and 50 iterations, 1,000 candidate evaluations were considered in the analyzed optimization run. Eight non-dominated scheduling configurations formed the resulting Pareto frontier, corresponding to 0.8% of the evaluated candidate solutions, presented in Figure 4.

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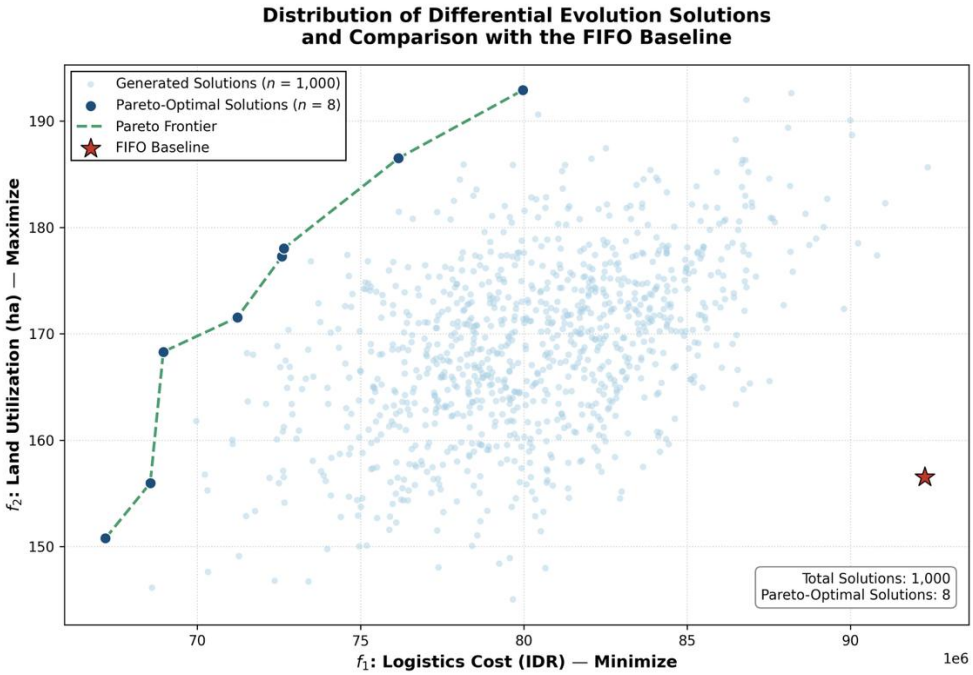

Figure 4. Pareto frontier generated by DE and comparison with FIFO

As shown in Figure 4, six of the eight Pareto-optimal DE schedules achieved both lower logistics costs and greater served land area than the FIFO baseline. The other two schedules also reduced logistics costs but served less land than FIFO. The compromise schedule selected using normalized distance had a logistics cost of IDR 72,649,693 and served 178.01 ha. The Pareto frontier thus provides feasible scheduling options for planners with different priorities for logistics cost and service coverage.

3.5. Comparison with State-of-the-Art Studies

The findings of this study can be positioned relative to recent research on agricultural machinery scheduling. Wang and Huang [4] developed a two-step framework for dispatching shared agricultural machinery with time windows, emphasizing the spatial and temporal coordination of machinery movements. The present study addresses a different decision context by focusing on agricultural machinery loan allocation, in which machinery must be assigned to multiple service requests while considering operational feasibility and service coverage. Thus, the present model extends the scheduling perspective from machine dispatching toward institutional loan allocation. Guo et al. [7] formulated agricultural machinery scheduling as a multiobjective cooperative operation problem across regions with time-window constraints. Their study emphasized cooperative machinery operations and transfer-related costs. In contrast, the present study evaluates the trade-off

between logistics cost and served land area within a machinery loan-management context. The difference demonstrates that agricultural machinery scheduling objectives depend on the operational and managerial context being modeled.

Zhang et al. [6] investigated dynamic job allocation for multiple agricultural machinery units using an improved Ant Colony Optimization approach. Their study primarily addressed cooperation among machines involved in agricultural operations. The present study instead evaluates GA, PSO, and DE under a common experimental configuration for machinery loan allocation. This controlled comparison enables the analysis of differences in mean solution quality, variability, and computational time. Recent studies have further explored advanced optimization approaches. Wu and Fang [8] employed deep reinforcement learning for agricultural machinery scheduling under time-window constraints, while Huanyu et al. [15] investigated a hybrid NSGA-II-SA approach for agricultural machinery scheduling in hilly and mountainous areas. These studies reflect the development of increasingly adaptive and hybrid optimization strategies. The present study complements this direction by providing a transparent benchmark of three established metaheuristics under identical experimental conditions and by explicitly evaluating algorithmic stability through repeated independent runs.

The algorithmic findings can also be read against studies that combine or compare DE and PSO directly. Hybrid designs that embed differential operators within swarm or multi-objective frameworks have been proposed for distributed flow-shop and batch scheduling [11], [12], [14], and DE and PSO have been compared head-to-head on parallel-machine scheduling with job splitting [13]. A common motivation behind such hybrids is the view that swarm-based search converges quickly but can drift between runs, whereas differential mutation helps sustain population diversity. The pattern observed here fits that view reasonably well: PSO achieved the best mean objectives but also the widest cost spread, while DE traded a small, statistically insignificant loss in mean quality for more stable outcomes. This correspondence hints that a DE-PSO hybrid could be worth testing on the loan scheduling problem. A direct numerical comparison with [4], [6], [7], or [15] is not attempted, because those studies rely on different instances, objectives, and cost structures, so their reported values are not on a common scale with the present results. The comparison offered here is positioned at the level of problem formulation and algorithmic behavior instead.

The results also provide an important interpretation of algorithm selection. PSO achieved the strongest mean objective values in the present experiments, whereas DE produced the lowest logistics-cost variability. The statistical analysis showed that the differences between DE and PSO were not significant for either logistics cost or land coverage. Therefore, the results do not establish universal superiority of one algorithm over another. Instead, they demonstrate that algorithm selection in agricultural machinery loan scheduling can consider the trade-off between average objective quality and consistency

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across stochastic runs. Taken together, the comparison with recent studies indicates that the contribution of this study lies in the combination of a loan-specific scheduling formulation, integrated operational constraints, multi-objective optimization, repeated algorithmic benchmarking, and direct comparison with FIFO. This combination addresses an agricultural machinery management context that differs from the field-operation dispatching and cooperative scheduling settings commonly investigated in previous studies.

4. CONCLUSION

This study formulated agricultural machinery loan scheduling as a multi-objective optimization problem and evaluated three metaheuristic approaches, namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE). The proposed formulation integrates machinery allocation, operational feasibility, scheduling constraints, logistics cost, and served land area within a unified scheduling framework.

The computational results revealed a trade-off between average solution quality and algorithmic stability. PSO obtained the lowest average logistics cost of IDR 74,102,854 and the highest average land coverage of 174.69 ha. DE obtained intermediate mean objective values but produced the lowest logistics-cost standard deviation of IDR 3,124,329. MANOVA indicated an overall statistically significant difference among the three algorithms ($p < 0.001$). However, Tukey HSD showed that DE and PSO were not significantly different in logistics cost ($p = 0.256$) or land coverage ($p = 0.456$). Based on these findings, DE was selected under a stability-oriented criterion that considered both solution quality and variability.

Compared with FIFO, DE reduced mean logistics cost from IDR 92,269,945 to IDR 75,191,323 (18.51%) and increased mean served land area from 156.53 ha to 172.44 ha (10.16%) across 50 independent runs. These results indicate that the proposed scheduling model can reduce logistics costs while expanding service coverage under the operating conditions represented in the West Java dataset.

The main contribution of this study is not the development of a new metaheuristic algorithm, but the formulation and evaluation of an agricultural machinery loan scheduling problem that combines resource allocation, logistics efficiency, service coverage, operational constraints, and algorithmic stability. The study provides an empirical basis for evaluating established metaheuristics in this specific scheduling context.

The main limitation is that the computational model was calibrated to the operational characteristics and geographic scope represented by the West Java dataset. Future research can extend the model to larger multi-depot and cross-regional scenarios and investigate adaptive or hybrid optimization approaches for more dynamic agricultural machinery allocation environments.

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