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Metaheuristic scheduling benchmarks and a transparent SWARA–WASPAS decision study for flexible manufacturing systems

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Abstract

Abstract Flexible Manufacturing System (FMS) design requires both operational optimization and strategic configuration selection. This paper presents two linked but distinct studies for standalone FMS planning. First, Genetic Algorithm (GA), Differential Evolution (DE), and Simulated Annealing (SA) are benchmarked on small, medium, and large scheduling instances over 50 independent trials per algorithm-instance pair. Second, 15 candidate FMS configurations generated from a reproducible surrogate configuration model are ranked using a transparent SWARA–WASPAS decision model over throughput, utilization, cycle time, work-in-process, and cost. The scheduling benchmark shows that all three algorithms behave similarly on small instances, but SA becomes clearly superior as problem size grows. On large instances, SA achieves mean make span 203.42 compared with 259.37 for GA and 318.47 for DE, while preserving the best observed solution of 189.13. In the separate decision study, the corrected ranking shows perfect stability across $\lambda \in \{0, 0.25, 0.5, 0.75, 1\}$, with Config 11 ranked first under every weighting blend. Because the decision layer is driven by surrogate-generated alternatives and explicit SWARA weights, the resulting “optimal” configuration should be interpreted as optimal within the stated decision model rather than as a universal FMS prescription. The paper therefore contributes a reproducible scheduling benchmark and a transparent multicriteria ranking study that can guide future simulation-based planning work.

Keywords: Index Terms Flexible manufacturing systems, scheduling, make span, simulated annealing, genetic algorithm, differential evolution, SWARA, WASPAS, multi-criteria decision making

1. Introduction

FMS planning is inherently a multilevel optimization problem. At the operational level, schedules must allocate work to shared resources under combinatorial complexity. At the strategic level, designers must select machine counts, transporter capacity, buffering, and flexibility levels while balancing cost against multiple performance criteria. Solving only one of these layers is insufficient: strong scheduling on a poor configuration remains limited, while a good configuration without effective scheduling leaves value unrealized.

The optimization literature offers many heuristics for FMS loading and scheduling, including genetic algorithms, evolutionary methods, and hybrid search procedures [1, 3]. Simulated annealing also remains attractive because of its principled escape from local minima through probabilistic uphill moves [4, 5]. Meanwhile, Multi-Criteria Decision-Making (MCDM) methods such as SWARA and WASPAS have become useful in manufacturing selection problems where cost, throughput, and responsiveness must be considered simultaneously [6, 9]. This paper combines these viewpoints through two linked but methodologically distinct studies. The first benchmarks metaheuristic scheduling quality across increasing problem sizes. The second ranks candidate FMS configurations using a transparent SWARA–WASPAS model and tests the stability of the ranking over multiple λ values. The paper makes the following contributions.

1. It provides a size-dependent empirical comparison of GA, DE, and SA on common FMS

Scheduling benchmarks.

2. It defines the optimization objective explicitly as makespan and documents the benchmark instance structure.
3. It provides a fully stated SWARA–WASPAS decision stage, including the surrogate configuration model, normalization rule, criterion weights, and corrected ranking outputs.

2. Related work

Early FMS research established scheduling and control as central operations-research problems [10]. Genetic algorithms have been widely used for machine loading and sequencing because they can navigate discrete solution spaces effectively [1, 11]. Differential evolution has shown strong global search behavior in continuous optimization and has also been adapted to FMS scheduling [3, 12]. Simulated annealing remains relevant because its acceptance mechanism can reduce premature convergence on rugged landscapes [4, 13].

On the decision side, SWARA provides a structured approach for deriving criterion weights, while WASPAS blends weighted-sum and weighted-product reasoning to rank alternatives [6, 7]. Applications in manufacturing have shown that WASPAS can discriminate among alternatives that are difficult to compare by throughput or cost alone [8]. However, fewer studies integrate a scheduling benchmark and a strategic MCDM layer within a common FMS study. This paper addresses that gap while explicitly separating the optimization benchmark from the surrogate-based decision layer and by avoiding claims of full pipeline integration that are not supported by the experimental design.

Two-stage framework

A. Stage1: scheduling benchmark

Three metaheuristics are compared: GA with population 50 and 50 generations.

- DE with population 50 and 101 generations.
- SA with 181 iteration and a cooling schedule.

Each algorithm is run independently 50 times on small, medium, and large scheduling instances. The objective is makespan, defined as

$$C_{\max} = \max_j C_j \quad (1)$$

Where C_j is the completion time of job j . Lower fitness therefore indicates a shorter overall schedule. The benchmark instances contain 5 jobs on 3 machines (small), 10 jobs on 5 machines (medium), and 20 jobs on 8 machines (large). Each job contains 3–5 operations, and each operation can be processed on 1–3 capable machines with machine-dependent processing times.

B. Stage2: configuration ranking

Fifteen candidate FMS configurations are evaluated on throughput, utilization, cycle time, work-in-process, and cost. The second stage is a decision-layer study rather than a full DES rerun: candidate configurations are produced from a reproducible surrogate generator with random seed 42. For configuration i with machine count m_i , AGV count a_i , buffer size b_i , AGV speed v_i , routing flexibility f_i , and independent uncertainty multipliers ξ_i (0.9, 1.1), the surrogate metrics are

$$TH_i = 80 \frac{m_i}{5} (1 + 0.05(v_i - 1))(1 + 0.1f_i) \frac{b_i}{10} \xi_i \quad (2)$$

$$U_i = \min(0.95, 0.6 + 0.05 \frac{b_i}{10} (1 + 0.1f_i) \xi_i) \quad (3)$$

$$CT_i = \frac{30\xi_i}{(b_i/10)(1 + 0.05(v_i - 1))(1 + 0.1f_i)} \quad (4)$$

$$WIP_i = \frac{TH_i \cdot CT_i}{60} \quad (5)$$

$$Cost_i = 100m_i + 50a_i + 10b_i + 200f_i \quad (6)$$

SWARA is used to define criterion weights and WASPAS is used to rank alternatives. Benefit criteria are normalized by $x_{ij} / \max_j x_{ij}$ and cost criteria by $\min_j x_{ij} / x_{ij}$. For alternative i , the WASPAS score is computed by blending the weighted-sum and weighted-product models:

$$Q_i(\lambda) = \lambda Q_i^{(s)} + (1 - \lambda) Q_i^{(p)} \quad 0 \leq \lambda \leq 1 \quad (7)$$

Robustness is assessed over $\lambda \in \{0, 0.25, 0.5, 0.75, 1.0\}$. During manuscript revision, the ranking stage was rechecked and the score-to-alternative mapping was corrected so that the reported results align with the original alternatives rather than with an internally sorted WASPAS output. The resulting ranking should therefore be read as a transparent surrogate-based decision study, not as a final simulation-validated capacity selection result.

Table 1: SWARA criterion weights used in the decision stage

Criterion	Weight
Throughput	0.4365
Utilization	0.3118
Cycle time	0.1299
WIP	0.0812
Cost	0.0406

Solution Quality – Algorithm Comparison (diamond = mean, bar = median)

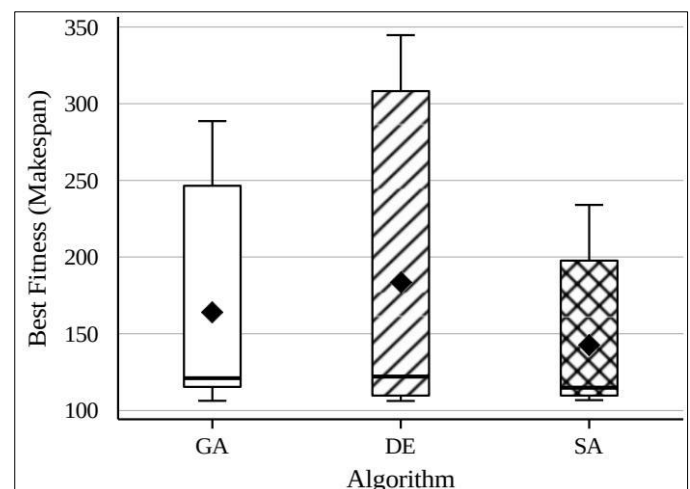


Fig 1: Distribution of best makespan values across the scheduling experiments. The lower and tighter SA distribution on the larger instances supports its use for complex offline FMS scheduling.

3. Scheduling results

A. Size-dependent performance

Table II reports the empirical scheduling results computed from 50 trials per case. The small instances are easy for all methods, with mean makespan values near 110–111. As instance size grows, SA separates from the other algorithms. Two patterns are clear. First, there is no universal winner on trivial instances; DE obtains the best single small-instance solution, while GA is fastest. Second, SA becomes the best mean performer as the search landscape grows more difficult. On large instances, SA improves mean makespan by approximately 21.6% relative to GA and 36.1% relative to DE.

B. Interpretation

The performance gap suggests that larger FMS scheduling instances have a rugged search landscape with more local minima. SA benefits from its probabilistic acceptance rule, which permits temporary worsening moves and therefore helps selection result. The search leaves local basins. Population-based search remains competitive, but the present benchmark indicates that GA and DE degrade more quickly as complexity increases. The computational cost of SA is higher, but the absolute running time remains modest even for the largest instance. This makes SA attractive for offline scheduling, rescheduling between shifts, or scenario analysis where solution quality dominates sub-second time savings.

Table 2: Meta heuristic scheduling performance

Problem Size	Algorithm	Mean Make span	Std .Dev.	Best Make span	Mean Time(s)	Std. Time(s)
Small	GA	111.42	2.62	109.72	0.144	0.011
Small	DE	109.71	1.65	107.57	0.200	0.013
Small	SA	109.80	0.58	109.72	0.365	0.021
Medium	GA	121.59	5.39	106.17	0.266	0.016
Medium	DE	122.28	5.76	106.12	0.383	0.019
Medium	SA	114.87	4.63	106.70	0.672	0.026
Large	GA	259.37	14.98	228.04	0.515	0.026
Large	DE	318.47	14.12	277.79	0.794	0.034
Large	SA	203.42	8.91	189.13	1.334	0.037

Convergence of Optimization Algorithms

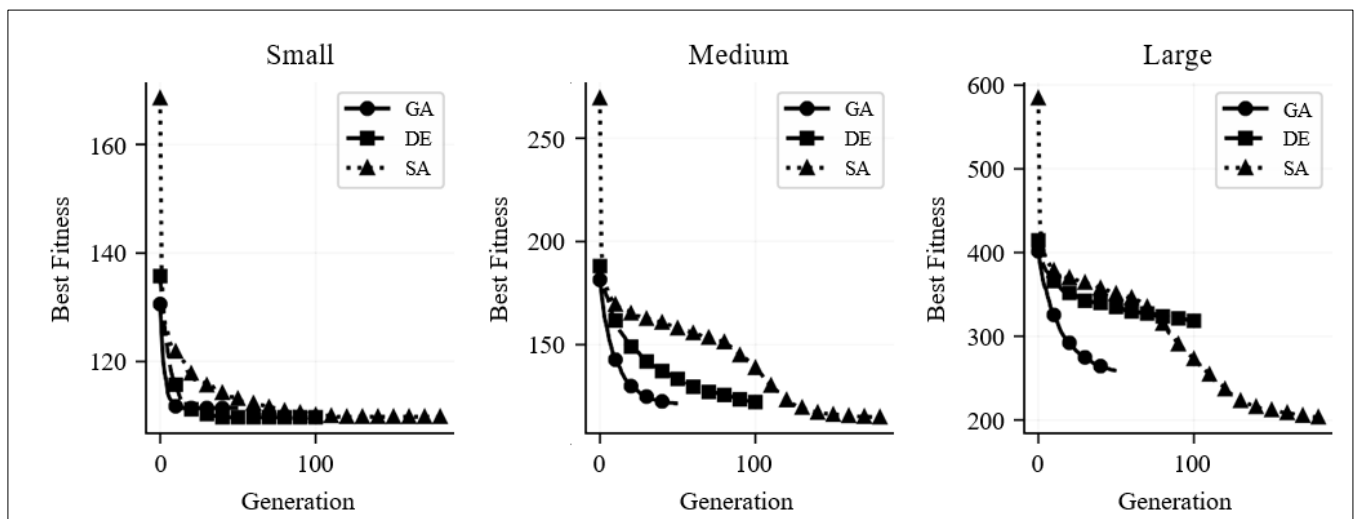


Fig 2: Convergence behavior of GA, DE, and SA across small, medium, and large scheduling problems. The separation widens with problem scale, showing the stronger large-instance search behavior of SA

Table 3: Corrected top five configurations at $\lambda=0.5$

Config.	Throughput	Util.	Cycle Time	Cost	Score
Config11	292.64	0.704	12.86	1230	0.89496
Config2	297.93	0.699	14.69	1330	0.87536
Config13	275.72	0.709	14.65	1050	0.85920
Config15	275.41	0.698	14.46	1320	0.85029
Config14	241.53	0.696	14.00	1050	0.81851

Table 4: Rank stability of config11 across λ

λ	Score	Rank
0.00	0.87638	1
0.25	0.88567	1
0.50	0.89496	1
0.75	0.90426	1
1.00	0.91355	1

4. Mcdm results

A. Candidate alternatives

The strategic decision stage evaluates 15 surrogate generated configurations. Table III lists the corrected five highest-ranked alternatives at $\lambda = 0.5$. The first-ranked design, Config 11, combines very high through put and utilization with a competitive cycle time and only moderate cost after normalization.

B. Rank robustness

The corrected ranking result is unusually stable. Config 11 remains first for every tested λ value, and the top six configurations retain their exact ordinal positions across the full additive–multiplicative blending range. Table IV shows the score trajectory of Config 11.

This result matters because MCDM methods are often criticized for sensitivity to weighting assumptions. In the present case, the chosen design remains dominant under both the weighted-product and weighted-sum extremes.

C. Why config 11 wins

The winning configuration has eight machines, one AGV, buffer size 20, AGV speed 1.54 m/s, and routing flexibility 0.9. It does not have the lowest cost, but it combines very high through put (292.64), the best or near-best utilization among the top candidates (0.704), and the shortest cycle time in the top two (12.86). This profile aligns with the SWARA weights in Table I, which strongly favor through put and utilization and assign relatively low weight to cost. This interpretation is conditional on both the stated weight structure and the surrogate equations used to generate the decision alternatives. This finding is valuable because it warns against over-reliance on a single KPI. A configuration with extremely high throughput can still lose if it sacrifices utilization, cycle time, or normalized cost performance. By considering multiple criteria simultaneously, the decision model favors structurally strong, high-output alternatives that remain efficient after normalization rather than one-dimensional extermination.

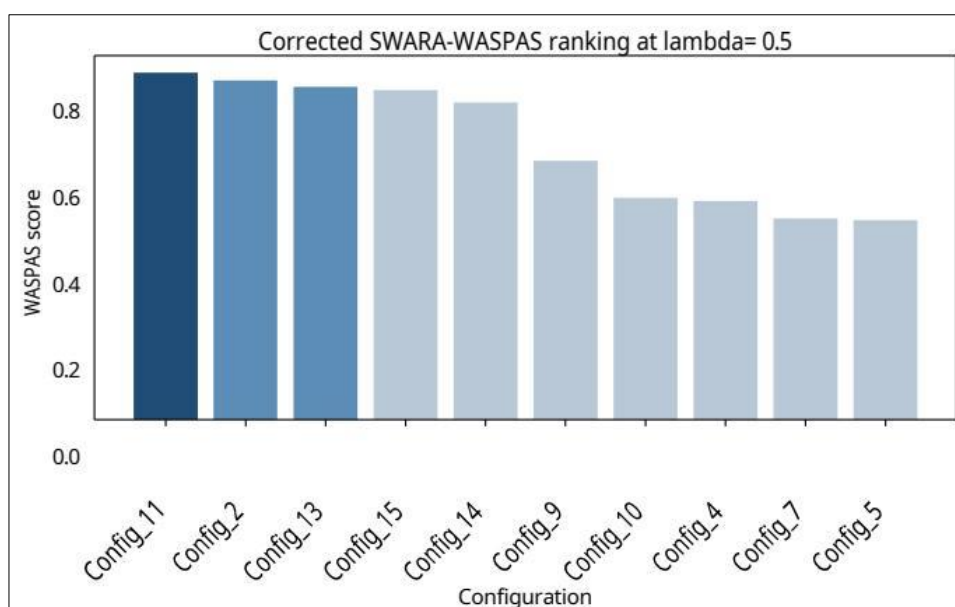


Fig 3: Corrected WASPAS scores of the candidate configuration sat $\lambda = 0.5$. The ranking shown here is aligned to the original alternatives rather than to the internally sorted WASPAS output.

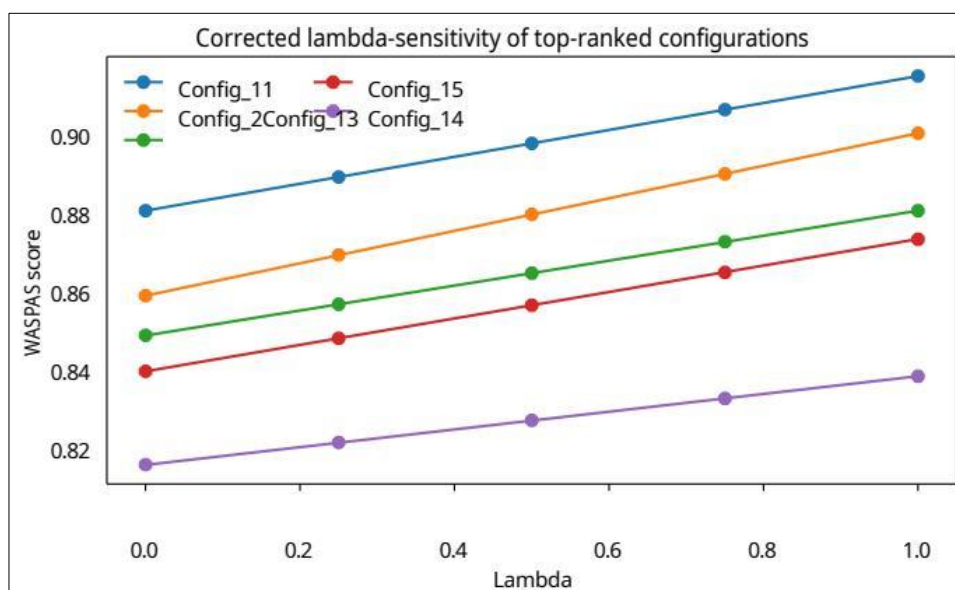


Fig. 4 Corrected sensitivity of WASPAS scores to the blending parameter λ for the top-ranked configurations. Config 11 remains dominant across the full range.

5. Planning implications

The two studies are complementary rather than fully coupled. The scheduling benchmark shows that algorithm choice should depend on problem size: GA is attractive when speed dominates, DE remains viable on small search spaces, and SA should be preferred as complexity increases. The MCDM study then addresses a different planning question: under an explicitly stated surrogate decision model and weight structure, which structural design would be preferred?

Taken together, the results suggest the following policy for FMS projects.

- 1) Use SA as the primary optimizer for medium and large offline scheduling instances.
- 2) Reserve GA for rapid approximate schedules when speed is more important than final quality.
- 3) Do not select strategic configurations on throughput alone; rank those using a multi-criteria model with published weights and normalization rules.
- 4) When cost is intentionally assigned a low decision weight, expect capacity-intensive, high-throughput alternatives to dominate the final ranking.

6. Conclusion

This paper presented a Meta heuristic scheduling benchmark together with a transparent SWARA–WASPAS decision study for FMS planning. At the operational level, Meta heuristic scheduling experiments showed that SA scales more favorably than GA and DE as problem complexity grows, achieving the best mean and best observed large-instance make span values. At the strategic level, a corrected SWARA–WASPAS analysis identified Config 11 as the consistently top-ranked surrogate configuration across all tested λ values within the stated decision model.

The main contribution is the combination of an operational benchmark and a fully stated decision-model specification in a form suitable for standalone FMS planning studies. Future research should couple the two studies more tightly by using simulation-derived alternatives instead of surrogate-generated ones, incorporating stochastic breakdown scenarios directly into the ranking stage, and testing hybrid Metaheuristics for dynamic rescheduling.

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