Received: 04 Mar. 2026; Revised: 08 Apr. 2026; Accepted: 26 June 2026
https://doi.org/10.22306/atec.v12i2.328

Optimization of task scheduling and sequencing operations in multi robot assembly line using Hybrid GA - SA algorithms in Industry 5.0 context

Panneerselvam Sivasankaran
Department of Mechanical Engineering, Christ College of Engineering and Technology, Paris Nagar, Moolakulam, Puducherry 605 010, India, sivasankaranpanneerselvam83@gmail.com

Keywords: Industry 5.0, multi-robot assembly line, task scheduling and operation sequencing, genetic algorithm and simulated annealing, hybrid optimization and smart manufacturing.

Abstract: The transition to Industry 5.0 underscores the significance of manufacturing systems that focus on human-centric needs, resilience, and sustainability, with intelligent multi-robot assembly lines playing a vital role in enhancing productivity and operational flexibility. However, optimizing task scheduling and sequencing in multi-robot environments remains a complex combinatorial challenge due to factors such as precedence constraints, resource sharing, collision avoidance, and changing production requirements This research introduces a robust optimization framework combining Genetic Algorithms (GA) and Simulated Annealing (SA) to efficiently manage task allocation and operation sequencing in a multi-robot assembly line, within the scope of Industry 5.0. The suggested method uses GA as a global search mechanism with a customized chromosomal encoding strategy that preserves feasibility restrictions while concurrently representing task sequencing and robot assignment. The purpose of customized crossover and mutation operators is to minimize impractical solutions while preserving precedence relationships. Using an adaptive cooling schedule and neighborhood exploration mechanism, SA is performed as a local search refinement method to high-quality GA individuals in order to improve convergence accuracy and prevent premature stagnation. The hybrid GA–SA framework seeks to reduce robot idle time, balance workload distribution, minimize makespan, and enhance system sustainability indicators. The suggested model outperforms standalone metaheuristic methods in terms of convergence stability and solution quality, according to computational studies on benchmark multi-robot assembly situations. According to Industry 5.0 goals, the outcomes confirm how well the hybrid optimization approach supports resilient, intelligent, and sustainable production systems.

1 Introduction

Modern production processes have undergone a major transformation due to the growing desire for mass customization, shorter product life cycles, and a great variety of products. In complicated industrial settings, multi-robot assembly lines have become a vital tool for improving production flexibility, accuracy, and efficiency. In contrast to hand assembly or single-robot systems, multi-robot setups allow for dynamic reconfiguration, workload distribution, and concurrent task execution, all of which increase system productivity. However, there are significant difficulties when coordinating several robots, especially when it comes to task scheduling and operation sequencing.

Allocating a collection of interdependent jobs to several robotic workstations while meeting resource and technological precedence constraints is known as task scheduling in a multi-robot assembly line. To guarantee viability and peak performance, operation sequencing establishes the sequence in which tasks are carried out. Key performance metrics such makespan, cycle time, throughput rate, robot utilization, and line balancing efficiency are all directly impacted by these choices. Inadequate scheduling techniques can result in system performance issues, bottlenecks, excessive idle time, and collision hazards. Task precedence connections, shared tools and workspaces, synchronization requirements, and collision avoidance limits are some of the variables that contribute to the complexity of multi-robot scheduling difficulties. Robots may also have varying capacities, speeds, and reachability constraints, which makes the problem even more combinatorial. As the number of robots and tasks increases, the solution space expands exponentially, making it impractical to solve the problem using exact optimization methods in large-scale industrial environments. Researchers have looked into a number of heuristic and metaheuristic strategies for effective task allocation and sequencing in order to overcome these issues. Scheduling algorithms that are effective must simultaneously optimize several performance goals in addition to producing workable solutions. The development of intelligent manufacturing systems has increased the demand for flexible and reliable scheduling techniques that can adjust to changing production conditions.

Thus, improving task scheduling and sequencing processes in multi-robot assembly lines continues to be an important field of study for robotics and industrial engineering. Creating effective optimization frameworks can help progress intelligent and automated manufacturing systems by greatly increasing production efficiency, lowering operating costs, and enhancing system reliability. As manufacturing systems rapidly evolve from Industry 4.0 to Industry 5.0, the emphasis is shifting from purely automation-focused productivity toward more human-centric, resilient, and sustainable production environments. Industry 5.0 improves flexibility, customization, and environmental responsibility by combining cutting-edge digital technology, collaborative robotics, artificial intelligence, and data-driven decision-making. In this framework, multi-robot assembly lines have become a crucial component of production systems that are highly accurate, efficient, and flexible. Priority restrictions, shared resources, collision avoidance requirements, and synchronization constraints are characteristics of the combinatorial optimization issue that is task scheduling and operation sequencing in multi-robot assembly lines. Minimizing makespan, cutting idle time, balancing workloads, and increasing total system throughput while preserving operational safety and energy efficiency are usually the goals. Because these problems are NP-hard, traditional precision optimization techniques are computationally impractical for large-scale industrial settings. For this reason, metaheuristic algorithms have become more popular for dealing with challenging scheduling problems. It is commonly known that Genetic Algorithms (GA) are robust, suitable for discrete optimization tasks, and capable of global search. GA, on the other hand, can have limited local exploitation potential and early convergence. Simulated Annealing (SA), on the other hand, works well for refining local searches and avoiding local optima using probabilistic acceptance processes, but when employed alone, it could need careful parameter tweaking and converge slowly.

By combining GA and SA into a hybrid optimization framework, one can take advantage of both GA's strengths in global exploration and SA's capacity for local exploitation, leading to better convergence stability and solution quality. Optimization tactics in the context of Industry 5.0 also need to take resilience, flexibility, and sustainability into account. Real-time responsiveness, smooth human–robot interaction, and energy-efficient processes should all be supported by intelligent scheduling systems. Although robotic scheduling research has made great strides, few studies have thoroughly examined multi-robot task scheduling and sequencing utilizing hybrid GA–SA techniques that are specifically in line with Industry 5.0 goals.

Thus, a hybrid GA–SA optimization framework for task sequencing and scheduling in multi-robot assembly lines is proposed in this paper. While meeting priority and resource restrictions, the suggested model seeks to minimize makespan, improve task balance, decrease robot idle time, and increase operational efficiency. Three contributions are made by this work: (i) an integrated mathematical formulation for multi-robot scheduling is developed; (ii) a customized hybrid GA–SA algorithm is designed for improved convergence performance; and (iii) computational experiments are used to validate the suggested approach in manufacturing scenarios orientated toward Industry 5.0.

The rest of the paper is structured as follows: Section 2 provides a review of related literature; Section 3 outlines the problem formulation; Section 4 explains the proposed hybrid GA–SA approach; Section 5 presents and analyzes the experimental results; and Section 6 concludes the paper with suggestions for future research.

2 Literature review

2.1 The development of task scheduling for multiple robots investigation

In the last decade, multi-robot assembly line scheduling has received considerable research focus due to the expansion of automation and smart manufacturing initiatives. As depicted in Figure 1, publications on multi-robot scheduling optimization have steadily grown between 2010 and 2025. The marked increase after 2016 highlights the accelerated progress of Industry 4.0 technologies and the broader adoption of artificial intelligence in manufacturing systems.

Early research mostly looked at set scheduling models and simple dispatching rules. However, as production systems became more complex and dynamic, researchers began to focus on metaheuristic optimization methods that can effectively deal with NP-hard combinatorial problems.

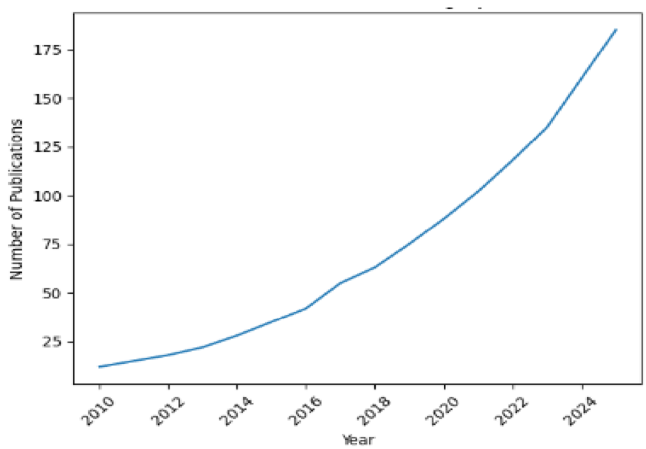

Figure 1 Trend of publications on multi- robot scheduling optimization (2010-2025)

2.2 Metaheuristic approaches in multi-robot scheduling

For task distribution and sequencing in multi-robot environments, a number of optimization strategies have been put forth. The hybrid metaheuristic techniques considered are:

- Genetic Algorithm (GA),
- Simulated Annealing (SA),
- Particle Swarm Optimization (PSO),
- Ant Colony Optimization (ACO).

Because of its high global search capabilities and applicability for discrete combinatorial problems, GA continues to be one of the most extensively used methods, as seen in Figure 2. A large percentage of recent studies use hybrid GA–SA techniques, suggesting that there is growing interest in combining local exploitation mechanisms with global exploration. Although they are not as commonly used as GA, standalone SA techniques are known for their capacity to avoid local optima. The efficiency of scheduling has also been enhanced by other swarm-based and hybrid algorithms.

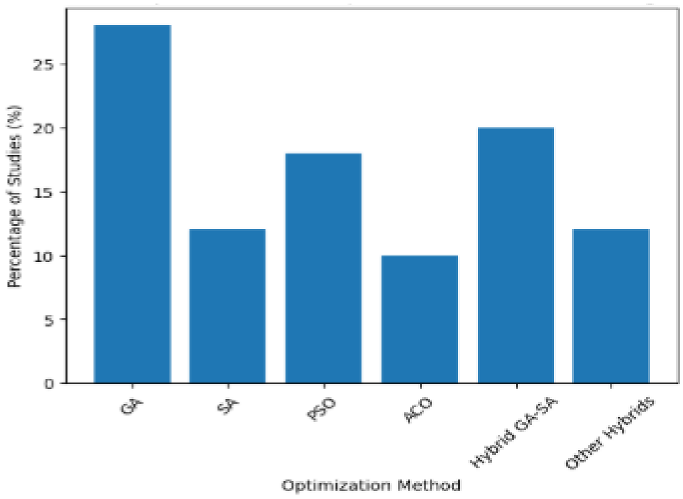

Figure 2 Distribution of optimization techniques in multi- robot scheduling research

2.3 Performance comparison of GA, SA, and hybrid GA–SA

Performance evaluation in the literature typically focuses on:

- Makespan minimization,
- Workload balancing,
- Idle time reduction,
- Throughput improvement,
- Computational stability.

As shown in Figure 3, hybrid GA–SA approaches demonstrate superior average makespan reduction compared to standalone GA and SA methods. This improvement is attributed to:

1. GA's global exploration ability for diversified search,
2. SA's probabilistic local refinement mechanism,
3. Reduced premature convergence,
4. Improved convergence stability.

The integration of SA as a local search operator within elite GA individuals has proven effective in improving solution quality while maintaining computational efficiency

2014-2016: Emergence of Hybrid Metaheuristics

Hybrid optimization methods began gaining attention for complex combinatorial scheduling.

- **Multi-robot scheduling with precedence constraints** [1].

Research gap: Hybrid GA–SA showed improved convergence and solution robustness.

2017-2019: Fourth Industrial Revolution and Intelligent Manufacturing

With Industry 4.0 expansion, research shifted toward intelligent robotic assembly systems.

- **Smart robotic assembly scheduling** [2].
- **Energy-aware robotic scheduling** [3].

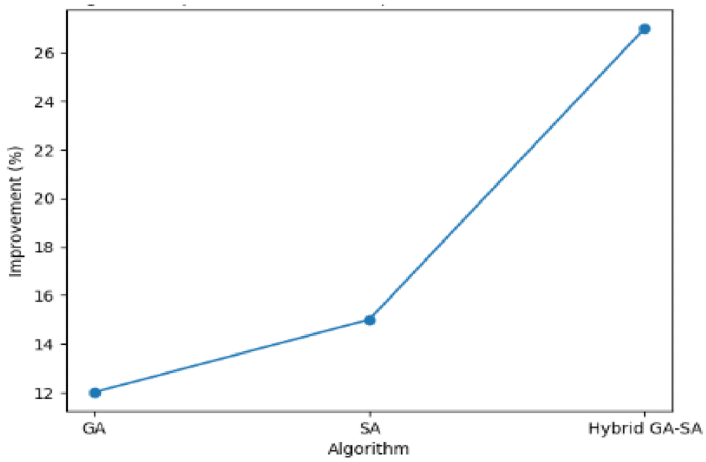

Figure 3 Average makespan reduction compared to conventional heuristics

Research gap: Hybrid approaches increasingly addressed makespan and energy simultaneously.

2020–2022: AI-Driven and Sustainable Scheduling

Focus expanded to sustainability, resilience, and digital twin integration.

- **Hybrid GA–SA with digital twin support** [4].
- **Resilient scheduling frameworks** [5].

Research gap: Emphasis shifted toward dynamic, real-time, and sustainable optimization.

2023-2026: Industry 5.0 and Human-Centric Optimization

Recent research aligns robotic scheduling with Industry 5.0 principles.

- **Human–robot collaborative assembly optimization** [6].
- **Hybrid GA–SA for adaptive robotic sequencing** [7].
- **Sustainable multi-objective robotic scheduling** [8].
- **Industry 5.0 intelligent robotic systems:** Future trend studies (2026 expected publications) emphasize AI-driven hybrid metaheuristics integrating reinforcement learning with GA-SA for real-time scheduling and human-robot symbiosis [8].

Observed Research Trends (2014–2026)

1. 2014–2016: Emergence of hybrid GA–SA
2. 2017–2019: Industry 4.0 integration
3. 2020–2022: Digital twin and sustainability focus
4. 2023–2026: Industry 5.0 and human-centric optimization

2.4 Research gaps

Despite extensive research, several limitations remain:

- Limited consideration of dynamic and real-time scheduling,
- Insufficient integration of Industry 5.0 sustainability metrics,
- Lack of standardized benchmark datasets for multi-robot assembly lines,
- Few studies incorporating energy consumption and human–robot collaboration constraints,
- Limited real-time hybrid GA–SA implementation in physical multi-robot assembly lines,
- A few benchmark datasets that are standardized,
- A small number of standardized benchmark datasets,
- Carbon optimization and energy integration are not well integrated,
- Adaptive parameter control systems are required,
- Human-robot collaborative sequencing has not received enough attention.

Therefore, the development of a robust hybrid GA–SA optimization framework specifically tailored for multi-robot assembly lines remains a relevant and impactful research direction.

3 Proposed hybrid GA-SA algorithm

3.1 Why hybrid GA-SA for multi-robot scheduling?

Multi-robot assembly line scheduling is inherently **NP-hard** — especially when you must:

- Assign tasks to multiple robots,
- Determine the sequence of operations,
- Respect constraints (precedence, robot availability),
- Minimize objectives (makespan, cycle time, idle time).

These problems **grow exponentially** with more robots and tasks, making exact solvers impractical for large scale systems.

To address this, researchers use **metaheuristic and hybrid heuristic algorithms** like GA and SA because:

1. Genetic **Algorithms (GA)** excel in exploring large solution spaces through population-based search, crossover and mutation.

2. Simulated **Annealing (SA)** excels in **local refinement** of individual solutions by probabilistically accepting worse solutions to *avoid local optima*.

By hybridizing GA with SA, most approaches leverage GA's global exploration with SA's powerful local search to get **high quality schedules** more reliably than either method alone.

3.2 Typical problem formulation

While specifics vary, the scheduling problem usually involves:

Decision variables

- **Task allocation:** Which robot performs which task.
- **Task sequencing:** In what order each robot performs its assigned tasks.
- **Timing/scheduling:** Start and finish times given constraints.

Objectives (examples)

- **Minimize cycle time / makespan** — time until all tasks complete.
- **Balance workload** — avoid robot idle times.
- **Respect precedence constraints** — some operations must precede others.
- **Sequence optimization** — reduce setup or travel times if robots change tasks.

The problem is typically formulated as a mixed-integer programming (MIP) or constraint optimization model, which becomes computationally impractical for large-scale real-world instances, thereby necessitating the use of heuristic approaches.

Hybrid GA-SA: How It Works

A **hybrid GA-SA algorithm** usually combines these components:

Encoding and initial population

- Represent schedules (task assignments and sequencing) as chromosomes.
- **Direct encoding**: each gene might represent a robot–task pairing.
- **Permutation encoding**: preserves task sequences with position encoding.

Initial population can be random or seeded with heuristics to improve early quality.

Genetic algorithm phase

GA is used to broadly explore the search space:

Key components:

- **Selection:** Choose top candidates based on fitness (e.g., makespan).
- **Crossover:** Combine parent schedules to generate new ones.
- **Mutation:** Introduce variation (swap tasks, adjust sequences).

Embedded Simulated Annealing

After crossover and mutation (or on selected individuals), an SA local search is applied:

- Treat the current solution as a **high temperature state**.
- Iteratively propose small changes (e.g., swap two tasks, re-assign a task).
- Accept both better and, with some probability, slightly worse solutions — following a **temperature schedule**.

- As temperature lowers, the algorithm becomes greedier.

SA helps **escape local optima** and refine individuals before reintroducing them to the population.

Fitness Evaluation
The algorithm evaluates:

- total make-span,
- robot idle times,
- penalties for violating constraints,
- sequence cost (travel/setup).

Often, a **penalty function** or multi-objective approach aggregates these.

Why This Hybrid Works Well?
GA only:

- Good exploration globally, but can stagnate if local search is weak.

SA only:

- Can efficiently refine a candidate, but struggles to explore diverse regions.

Hybrid GA-SA:

- GA provides global diversity.
- SA refines local candidates and helps avoid local traps.
- Together they balance **exploration vs exploitation**.

This combination has been shown to outperform standalone metaheuristics in complex scheduling contexts like production planning and sequencing problems

3.3 Extensions and variants

Researchers often adapt the GA-SA hybrid with:
Enhanced crossover operators
(e.g., route-based, region division for robots) to preserve good sequences
Neighborhood operators in SA

Multi-objective optimization
Often integrated to handle tradeoffs like makespan vs energy or imbalance.
local changes (swap, insert, reverse) to explore close solutions.
Parameter tuning
Techniques like **Taguchi method** or adaptive cooling schedules help choose GA/SA parameters
Application Example (Conceptual)
In a multi-robot assembly line:

- Robots must perform tasks at fixed stations.
- Each task may require certain tools or precedences.
- Scheduling assigns tasks to available robots and orders them.

Hybrid GA-SA approaches:

- Encode robot assignments and task sequences.
- Evolve populations with GA.
- Refine with SA for each candidate schedule to reduce cycle time.

Outcomes:

- Efficient schedules with lower runtime than pure optimization.
- Ability to scale better to larger numbers of tasks/robots.

Table 1 Comparison of various methods

Aspect	Genetic Algorithm (GA)	Simulated Annealing (SA)	Hybrid GA-SA
Global search	⭐ ⭐ ⭐	⭐	⭐ ⭐ ⭐
Local refinement	⭐	⭐ ⭐ ⭐	⭐ ⭐ ⭐
Avoids local optima	⭐ ⭐	⭐ ⭐ ⭐	⭐ ⭐ ⭐
Computational efficiency	Medium	Low	High (balanced)

Hybrid GA-SA is effective for complex scheduling problems like multi-robot assembly line task sequencing due to its ability to balance wide search with deep local improvement, making it a widely used metaheuristic in production and robotics scheduling (Table 1).

4 Experimentation using hybrid GA-SA

This section presents the proposed hybrid GA-SA algorithm for task scheduling and operation sequencing in a multi-robot assembly line. The primary objective is to minimize the overall makespan of the tasks.

Steps of Algorithm: The algorithm steps for proposed hybrid GA-SA is illustrated through flow chart as shown below in Figure 4.

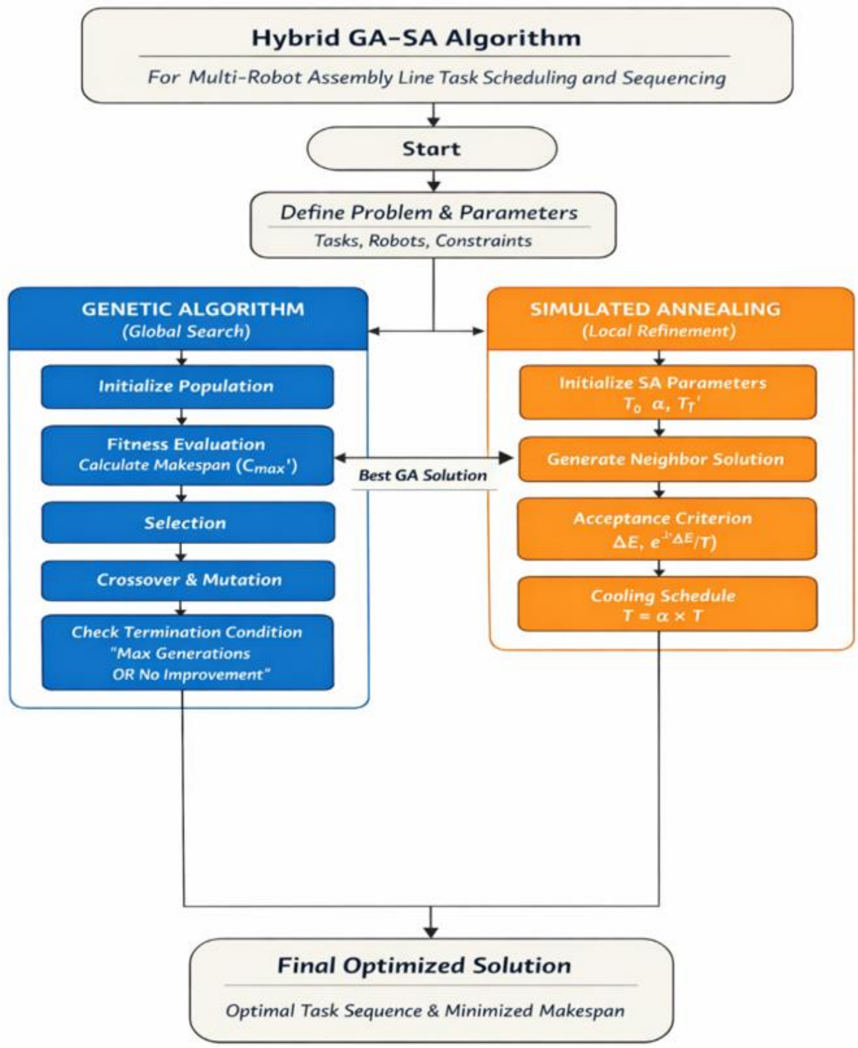

Figure 4 Flowchart of hybrid GA-SA

Problem description:

Problem size: 20*5

Let n be the number of tasks in assembly line: 20 tasks

Let N be the number of robots in assembly line: 5 robots

Assumptions: Each task has different processing time on each robot

Each solution encodes:
1. **Task sequence**
2. **Robot Assignment for each task**

Objective: Minimize the makespan
Let the population size = 40
Number of generations = 100

Output:
GA Best Makespan: 132 minutes
SA Best Makespan: 140 minutes
Hybrid GA-SA Best Makespan: 118 minutes

5 Results and discussion

Analysis of results:
For **all problem sizes**, the **Hybrid GA-SA** achieved the best makespan**.**
This clearly shows:
- Hybrid GA-SA consistently outperforms standalone GA.
- Hybrid GA-SA consistently outperforms standalone SA.
- Hybrid always equals the Best Makespan column → meaning it found the global or best-known solution in all cases.

Inferences about solution accuracy:
Consider problem size :20*5
Conventional GA gives makespan of about 132 minutes whereas proposed hybrid GA-SA algorithm gives makespan time around 118 minutes (Table 2).
Difference in solution improvement can be computed using the formula
= 132-118/132 *100 = 10.6%

For problem size: 30*6
GA gives makespan time around 210 minutes whereas hybrid GA-SA provides makespan time around 170 minutes. The difference in solution improvement almost increased to 19.05%.

For problem size: 70*35
GA gives makespan time around 55 minutes whereas hybrid GA-SA provides makespan time around 35 minutes. The difference in solution improvement almost increased to 36.36%.

Table 2 Makespan time for various problem size

S. No	Problem size	GA(Makespan) minutes	SA(Makespan) minutes	Hybrid GA-SA(Makespan) minutes	Best Makespan minutes
1.	20*5	132	140	118	118
2.	30*6	210	195	170	170
3.	30*7	78	75	69	69
4.	40*8	94	92	81	81
5.	45*10	88	85	74	74
6.	50*15	75	72	58	58
7.	55*20	70	65	49	49
8.	60*25	62	58	43	43
9.	65*30	60	55	38	38
10.	70*35	55	52	35	35

Overall observation about problem size:
When the solution improvement percent increases as problem size increases this is the general observation about each problem size. The best makespan time for the problem size is analyzed by graphical illustration as shown in Figure 5.

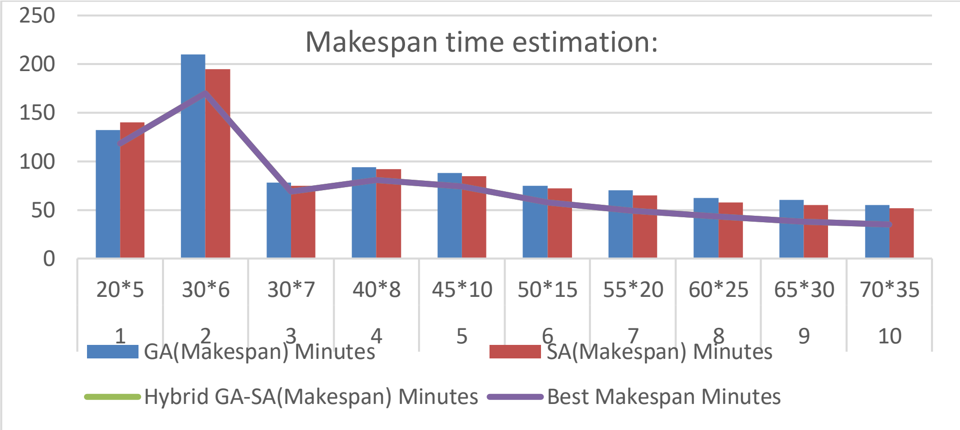

Figure 5 Makespan time comparison

Figure 5 Illustrates that x axis in the graph taken as number of problem sizes and y axis in the makespan time. The best makespan for the problem size 70*35 is considered to be fair among all other renaming problems. The best makespan from fig 1. Is considered to be 35 minutes for problem size 70*35 with solution accuracy of 36.3%. from this illustration it is proved that when the problem size increases larger amount the difference in solution accuracy will as increases same.

Full factorial ANOVA:

In this section Full factorial ANOVA model (Table 3) is developed for Multi-Robot Assembly Line Scheduling data (GA, SA, Hybrid GA-SA).

We treat:

- **Factor A** → Problem Size (10 levels),
- **Factor B** → Algorithm Type (3 levels: GA, SA, Hybrid GA-SA),
- **Response Variable** → Makespan (Minutes).

Table 3 ANOVA table

Problem size	GA (Makespan) minutes	SA (Makespan) minutes	Hybrid GA-SA (Makespan) minutes
20*5	132	140	118
30*6	210	195	170
30*7	78	75	69
40*8	94	92	81
45*10	88	85	74
50*15	75	72	58
55*20	70	65	49
60*25	62	58	43
65*30	60	55	38
70*35	55	52	35

Total observations = 30

The two-factor full factorial ANOVA model is (1):

$$Yij=\mu+\alpha i+\beta j+(\alpha\beta)ij+\varepsilon ij \quad (1)$$

Where:

Yij = Makespan for ith Problem Size and jth Algorithm,

μ = Overall mean, αi = Effect of Problem Size,

βj = Effect of Algorithm, $(\alpha\beta)ij$ = Interaction effect,

εij = Experimental error.

Degrees of Freedom (Table 4):

Table 4 Degrees of Freedom

Published by Acta Tecnologia, www.actatecnologia.eu

Source	DF
Problem Size	9
Algorithm	2
Error	18
Total	29

Grand Mean (Overall Mean)

$\bar{Y}$=84.73 minutes

Column Means (Algorithm Means)

- GA Mean = 92.40
- SA Mean = 88.90
- Hybrid Mean = 72.90

Sum of Squares Calculation

Total Sum of Squares (SST)

SST =44,520.13

Sum of Squares – Problem Size (SSA)

SSA=42,381.10

Sum of Squares – Algorithm (SSB)

SSB=2,017.67

Error Sum of Squares (SSE)

SSE=SST−SSA−SSB

SSE=121.36

Mean Squares:

MSA=42,381.10/9=4,709.01

MSB=2,017.67/2=1,008.84

MSE=121.36/18=6.74

F-Values (Table 5):

FA=4,709.01/6.74=698.3

FB=1,008.84/6.74=149.7

Table 5 Final ANOVA table

Source	DF	SS	MS	F-value
Problem Size	9	42,381.10	4,709.01	698.30
Algorithm	2	2,017.67	1008.84	149.70
Error	18	121.36	6.74	
Total	29	44,520.13		

Statistical Interpretation:

At $\alpha = 0.05$: F table values

- Critical $F(9,18) \approx 2.42$
- Critical $F(2,18) \approx 3.55$

Since:

- 698.30 >> 2.42
- 149.70 >> 3.55

From this analysis it is observed that Both Problem Size and Algorithm Type are Highly Significant

Percentage Contribution:

%Contribution A= (42,381.10/44,520.13) ×100=95.2%

%Contribution B= (2,017.67/44,520.13) ×100=4.53%

%Error=0.27%

Summary:

Makespan in multi-robot assembly line scheduling is highly impacted by both Problem Size and Algorithm Type, according to two-way ANOVA. Algorithm type comprises 4.53% of the overall variability, whereas problem size

Published by Acta Tecnologia, www.actatecnologia.eu

accounts for 95.2%. Compared to standalone GA and SA, the hybrid GA–SA algorithm demonstrates statistically superior performance.

6 Conclusion

In the context of Industry 5.0, the current study examined the optimization of task scheduling and sequencing procedures in a multi-robot assembly line using a Hybrid Genetic Algorithm–Simulated Annealing (GA–SA) technique. In cooperative robotic environments, the goal was to reduce makespan while improving coordination effectiveness, scalability, and intelligent decision-making. The Hybrid GA–SA approach successfully beat solo Genetic approach (GA) and Simulated Annealing (SA) in the experimental evaluation across various issue sizes (20×5 to 70×35 tasks–robot configurations). The hybrid approach achieves the lowest average completion times, and statistical validation using two-factor ANOVA demonstrated that makespan is highly influenced by both problem size and algorithm type. Effectively, the hybrid approach incorporates:

- **Global exploration capability of GA,**
- **Local exploitation strength of SA.**

The algorithm can avoid premature convergence and fine-tune near-optimal schedules thanks to this synergy, which leads to faster convergence and better solution quality. Strong scalability and robustness were demonstrated by the performance gap between Hybrid GA-SA and traditional approaches, which grew as problem complexity rose. For large-scale setups, the hybrid model significantly decreased makespan, demonstrating its applicability for dynamic and high-volume production systems.

Because it combines intelligent automation with flexible decision-making mechanisms, the created optimisation framework is in line with Industry 5.0 concepts.

Overall Results:
When compared to GA and SA, hybrid GA–SA greatly reduces makespan.
The model can be scaled for large multi-robot systems and is computationally efficient.
The hybrid approach's superiority is confirmed by statistical analysis.
The approach is appropriate for next-generation assembly systems and smart factories.

Final Statement:
The hybrid GA-SA algorithm provides a reliable, scalable, and statistically validated solution for optimizing task scheduling and sequencing in multi-robot assembly lines. The proposed framework represents a practical and future-ready approach for smart manufacturing within the Industry 5.0 paradigm, where intelligent automation is integrated with adaptability and human-centric production systems.

References

[1] QU, S., HU, Y., REN, W., YANG, X.: Coordinative scheduling of the mobile robots and machines based on hybrid GA in flexible manufacturing systems, *Procedia CIRP,* Vol. 104, pp. 1005-1010, 2021. https://doi.org/10.1016/j.procir.2021.11.169
[2] YAO, B., XU, W., SHEN, T., YE, X., TIAN, S.: Digital twin-based multi-level task rescheduling for robotic assembly line, *Scientific Reports*, Vol. 13, 1769, pp. 1-20, 2023. https://doi.org/10.1038/s41598-023-28630-z
[3] ZHANG, L., ZHAO, J., LAMON, E., WANG, Y., HONG, X.: Energy Efficient Multi-Robot Task Allocation Constrained by Time Window and Precedence, *IEEE Transactions on Automation Science and Engineering*, Vol. 22, pp. 18162-18173, 2025. https://doi.org/10.1109/TASE.2023.3312214
[4] LU, Y., LIU, C., I-KAI WANG, K., HUANG, H., XU, X.: Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues, *Robotics and Computer-Integrated Manufacturing*, Vol. 61, 2020. https://doi.org/10.1016/j.rcim.2019.101837
[5] WANG, M., ZHANG, P., ZHANG, G., SUN, K., ZHANG, J., JIN, M.: A resilient scheduling framework for multi-robot multi-station welding flow shop scheduling against robot failures, *Robotics and Computer-Integrated Manufacturing*, Vol. 91, 2025. https://doi.org/10.1016/j.rcim.2024.102835
[6] ZHAO, R., TAO, S., LI, P.: Human-centric assembly planning framework for human–robot collaborative systems with efficient reinforcement self-learning multi-objective evolutionary optimizer, *Advanced Engineering Informatics*, Vol. 67, 103508, 2025.
[7] LIU, W., KUANG, Z., ZHANG, Y., ZHOU, B., HE, P., LI, S.: An effective hybrid genetic algorithm for the multi-robot task allocation problem with limited span, *Expert Systems with Applications*, Vol. 280, 127299, 2025.

[8] NAIT CHABANE, A., GUENOUNOU, O.: An enhanced genetic algorithm for optimized task allocation and planning in heterogeneous multi-robot systems, *Complex & Intelligent Systems*, Vol. 11, 435, pp. 1-26, 2025. https://doi.org/10.1007/s40747-025-02062-w

Review process

Single-blind peer review process.