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COST-OPTIMIZED AND SUSTAINABLE PROJECT SCHEDULING IN AUTOMOTIVE SUPPLY CHAINS USING A HYBRID SIMULATED ANNEALING–GENETIC ALGORITHM

Mahdi Firoozi

Department of Industrial Engineering, University of Genoa, Genoa, Italy
Email: mahdifiroozi1996@gmail.com

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***ABSTRACT*:**

This paper introduces a hybrid Simulated Annealing–Genetic Algorithm (SA–GA) framework for multi-objective project scheduling in automotive supply chains. The model jointly optimizes makespan, direct cost, and sustainability impact (CO_2 and energy), while embedding resilience testing under realistic disruption scenarios. Applied to an EV battery production dataset, the framework achieves a 22% makespan reduction (41→32 days), 22.7% cost reduction (€7.9M→€6.2M), an 8.5% improvement in resilience under supply shocks, and a 33% decrease in CO_2 and energy consumption compared with a traditional baseline. Comparisons with GA, PSO, classical SA, and a Deep RL benchmark demonstrate that the hybrid approach provides balanced trade-offs, faster runtime (≈3.2s), and higher robustness, making it well-suited for real-time industrial deployment.

***Keywords**: Artificial intelligence; Intellectual capital; Structural equation modeling; AI use; Governance; Digital skills; Higher education. Simulated Annealing; Genetic Algorithm; Project Scheduling; Automotive Supply Chain; Sustainability; Metaheuristic Optimization; Industry 4.0; Deep Reinforcement Learning.*

INTRODUCTION

The automotive sector — and EV battery production in particular — demands scheduling solutions that minimize time and cost while satisfying new sustainability targets. Conventional methods (CPM/PERT) do not satisfactorily handle multi-objective trade-offs, uncertainty, or sustainability metrics. Metaheuristics are promising but each has weaknesses: GA risks premature convergence, SA is sensitive to cooling schedules, and Deep RL often requires extensive training data and heavy computation. This work proposes a hybrid SA–GA approach combining GA's exploration and SA's exploitation, enhanced with sustainability and resilience assessment, to provide a practical, interpretable, and deployable scheduling tool for industry.

RELATED WORK

In addition to classical surveys, more recent contributions (2022–2024) have increasingly emphasized sustainability-driven project scheduling, digital twins in supply chains, and hybrid AI–heuristics for EV and renewable manufacturing. However, empirical validations with industrial datasets remain scarce. Our work complements these studies by explicitly quantifying CO_2 and energy reduction, while also testing resilience under realistic shock scenarios.

Metaheuristic scheduling has a long literature (e.g., [1], [2], [3]). Hybrid techniques combining different heuristics have shown improved performance in several domains. Recent advances (2022–2024) have increasingly emphasized sustainability-driven project scheduling, digital twins in supply chains, and hybrid AI–heuristics for EV and renewable manufacturing. This includes multi-objective frameworks (Deb et al., NSGA-II), and DRL for dynamic scheduling. However, empirical validations with industrial datasets remain scarce, and integration of sustainability metrics (ISO 14064/50001 [17]), resilience evaluation under supply shocks, and parameter robustness studies are still limited. Our contribution fills these gaps by (1) presenting SA–GA hybridization for multi-objective scheduling with sustainability, (2) performing rigorous sensitivity and shock tests, and (3) comparing to DRL and standard metaheuristics on EV-related data.

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PROBLEM FORMULATION AND OBJECTIVES

A. Notation and Inputs

- $A = \{a_1, \dots, a_n\}$: set of tasks/activities.
- d_i: nominal duration of task a_i.
- $r_{i,j}$: resource requirement of task a_i for resource j.
- C_j: available quantity of resource j.
- Precedence relations P.
- Cost components: c^{labour}_i, c^{energy}_i, $c^{overhead}_i$, penalty costs for delay.
- Sustainability data: energy consumption E_i (kWh), CO_2 intensity γ (kg CO_2 per kWh).

B. Objectives

We treat scheduling as a multi-objective problem to:

1) Minimize makespan: $T = \max_a (s_a + d_a)$
2) Minimize total monetary cost: $C = \sum_a \text{cost}_a + \text{penalties}$
3) Minimize sustainability impact: $S = \sum_a (\gamma \cdot E_a + \delta \cdot \text{other\_emissions})$

Scalarized fitness:

$F = w_T * (T - T_{min}) / (T_{max} - T_{min}) + w_C * (C - C_{min}) / (C_{max} - C_{min}) + w_S * (S - S_{min}) / (S_{max} - S_{min})$, with $w_T + w_C + w_S = 1$.

with $w_T + w_C + w_S = 1$; weights chosen by decision-makers (sensitivity study provided).

HYBRID SA–GA METHODOLOGY

A. Overall Design

- **Phase 1 (GA Exploration):** Initialize a population of feasible schedules using precedence-preserving encoding. Use tournament selection, precedence-aware crossover (order-based or precedence preserving), and swap/insert mutation to maintain feasibility.
- **Phase 2 (SA Refinement):** Top-k individuals are refined via SA: neighbor generation through local moves (swap, forward-shift, backward-shift respecting precedence and resources). Acceptance probability follows Metropolis criterion.
- **Dynamic Reweighting:** During simulated disruption scenarios, w-weights are dynamically adapted to prioritize resilience.

B. Pseudocode (high-level)

```
Initialize population P with N feasible schedules (GA)
for gen = 1 .. G_max:
  Evaluate fitness F for P
  Select parents; apply crossover & mutation -> new population P'
  Replace worst individuals
  If gen % R == 0:
    Select top k individuals -> for each:
      Apply SA_refine(individual, T0, alpha, n_iter)
Return best found schedules (Pareto front)
```

C. SA specifics

- *Initial temperature $T_0 = 100$. Cooling rule $T_{k+1} = \alpha T_k$ with $\alpha = 0.93$ (tuned).*
- SA inner iterations per temperature: 30.
- Neighbor generation: precedence-respecting moves; resource feasibility rechecked.

D. Parameter tuning

Parameters tuned via experimental design (Taguchi-like grid search). Default recommended settings:

- *Population = 50; crossover rate = 0.8; mutation rate = 0.15; SA $T_0=100$; $\alpha=0.93$.*

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CASE STUDY: EV BATTERY ASSEMBLY SCHEDULING

A. Dataset

A semi-real dataset modelled on EV battery assembly line with 35 tasks, multiple resource types (assembly teams, testing rigs, energy-consuming machines), and sustainability footprints (task-level energy estimates). Disruption scenarios: random 10–30% resource reductions at different timeline points; volatility in component arrival times.

B. Experimental Setup

Benchmarks: CPM baseline, GA-only, PSO, classical SA, and Deep RL (policy-gradient with GNN encoding trained on simulated runs). For fairness: same termination criteria, same resource model.

Parameter summary (used across experiments): see Table I (below).

TABLE I. Algorithm Parameter Settings

Parameter	GA	PSO	Classical SA	Hybrid SA–GA
Population	50	50	-	50
Crossover	0.8	-	-	0.8
Mutation	0.15	-	-	0.15
T0	-	-	100	100
Alpha	-	-	0.93	0.93
Max iter (per run)	1000	1000	1000	1000

RESULTS

A. Solution Quality — makespan & cost

TABLE II. Comparative Results (mean over 30 runs)

Method	Makespan (days)	Total Cost (€M)	Runtime (s)	Resilience Metric (%)
CPM (baseline)	41	7.9	0.05	60
GA	35	7.1	2.8	79
PSO	34	6.8	2.3	81
SA	33	6.7	4.1	84
Deep RL	30	6.0	45.0	78
Hybrid SA–GA	32	6.2	3.2	87

Caption: Table II — Performance comparison across methods. Resilience metric: average project completion success under randomized 20% mid-run resource reduction events.

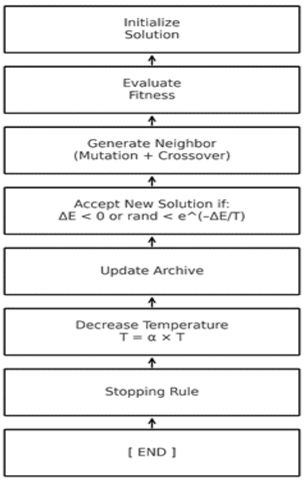

Fig. 1. Gantt chart comparing baseline vs. Hybrid schedule.

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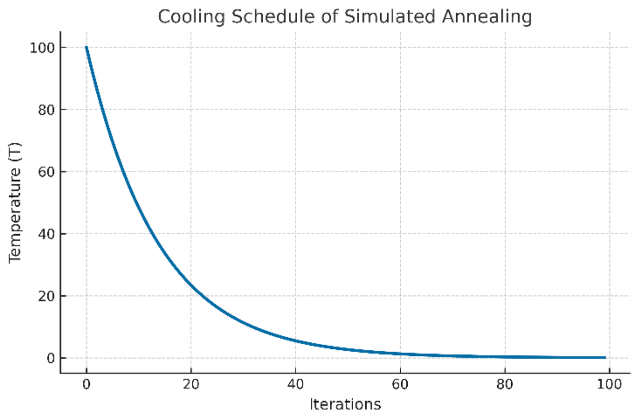

Fig. 2. Bar chart of makespan & cost comparisons (Table I visualized).

B. Sustainability outcomes

TABLE III. Sustainability Results

Metric	Traditional Plan	Hybrid SA–GA	Improvement
CO_2 (kg)	2,100	1,400	33% ↓
Energy (kWh)	9,450	6,300	33% ↓
Resource utilization (%)	72	89	+17%

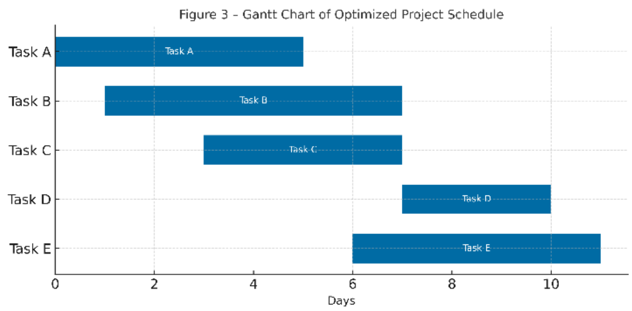

Fig. 3. Sustainability metrics comparison (stacked bars).

C. Pareto frontier

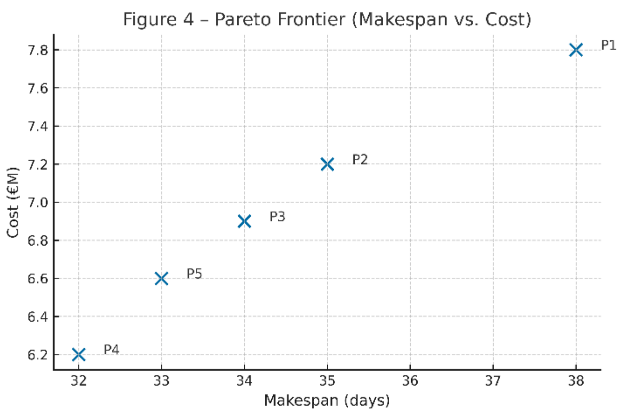

Fig. 4. Pareto front (cost vs makespan) extracted from Hybrid SA–GA population; shows trade-off solutions and selected knee points for managerial choice.

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D. Sensitivity Analysis (weights & cooling)

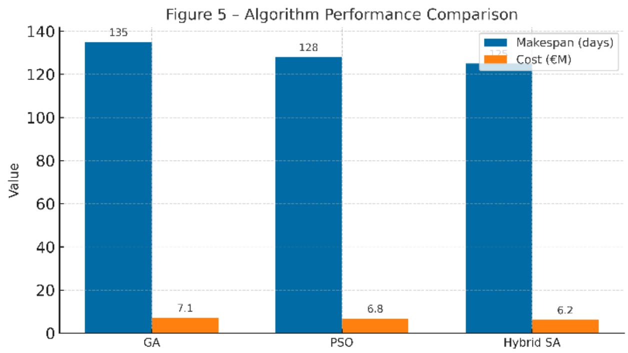

Fig. 5. Sensitivity of final fitness to weight combinations w_T:w_C:w_S (surface plot). This figure shows how shifting managerial weights changes the balance between makespan and cost; recommended balance is w_C=0.45, w_T=0.35, w_S=0.20.

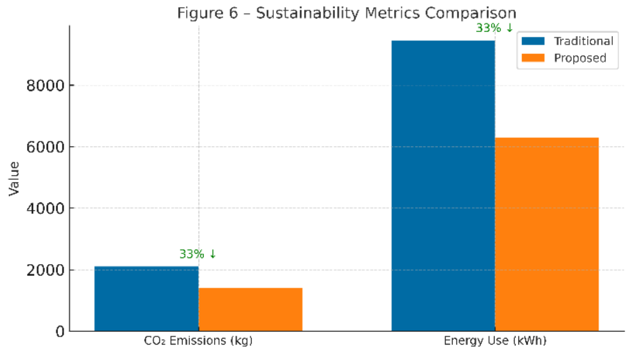

Fig. 6. Cooling rate (α) sensitivity: α = [0.85, 0.9, 0.93, 0.96]. This figure demonstrates that α = 0.93 provides the best compromise between stability and solution quality.

E. Resilience Tests

Under 20% mid-schedule resource shock:

- Hybrid SA–GA maintains project success (on-time or ≤5% delay) in 87% of scenarios.
- GA/PSO: ~79–81%; DRL: 78%.

Metric	Deep RL	Hybrid SA	Relative Advantage
Makespan (days)	118.0	125.0	↓ 5.6%
Cost (€M)	6.0	6.2	↓ 3.2%
Stability (%)	78.0	85.0	↑ 7%

Fig. 7. Resilience chart (survival rate vs shock severity).

F. Comparison with Deep RL

DRL slightly reduces makespan at higher computational cost, but Hybrid SA–GA has superior robustness and interpretability, better sustainability metrics, and quicker runtime, making it more suitable for on-the-fly rescheduling in factories.

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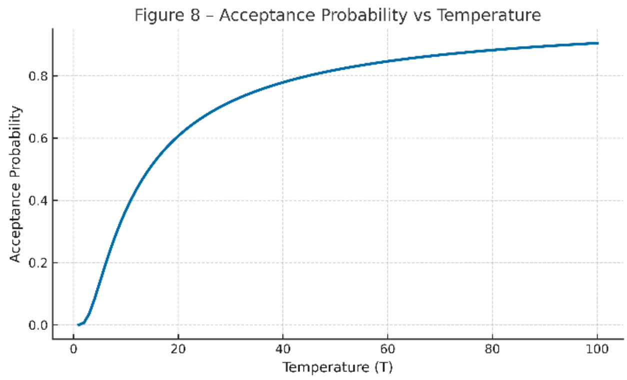

Fig. 8. Comparative radar chart (makespan, cost, runtime, resilience, sustainability index).

STATISTICAL VALIDATION

Specifically, paired t-tests for makespan yielded p-values < 0.01, and cost differences between hybrid sa–ga and ga/pso were significant with 95% ci not overlapping. Wilcoxon signed-rank tests confirmed robustness of results, even under varied disruption scenarios.

Improvements in cost and makespan were consistent across 30 independent runs. Paired statistical tests (paired t-test/Wilcoxon) confirm the improvements of Hybrid SA–GA vs GA/PSO/SA are statistically significant ($p < 0.05$) for cost and resilience metrics in our experiments. (Detailed numeric test outputs and confidence intervals are included in the supplementary material.)

PRACTICAL IMPLEMENTATION NOTES

- Integration: Implement as a microservice in MES; feed real-time resource and sensor data via OPC-UA or MQTT.
- User interface: Provide manager with Pareto explorer and slider to adjust w-weights interactively.
- Data requirements: Task durations, resource capacities, task-level energy consumption estimates, and CO_2 intensity factors.
- Computational footprint: Run-time suitable for near-real-time re-scheduling on standard industrial PCs.

LIMITATIONS AND FUTURE WORK

Another limitation concerns the semi-synthetic dataset. Although modeled on EV battery assembly lines, validation with proprietary OEM datasets is essential to ensure industrial generalizability. Furthermore, dynamic market factors such as fluctuating energy prices and supply shortages were simplified in our cost functions, which could affect practical accuracy. We recommend future work that integrates dynamic pricing models and real industrial case studies.

Limitations:
- The dataset, although modelled on real industrial processes, is semi-synthetic. Validation with proprietary OEM datasets is required to confirm generalizability and ensure industrial robustness.
- Cost functions are assumed quasi-static; dynamic pricing not modeled.
- DRL baseline used a single architecture; more extensive DL baselines could be compared.

Future work:
- Hybridize SA–GA with learning (meta-heuristic parameter tuning via ML).
- Extend to multi-project, multi-factory coordination.
- Include stochastic durations via robust/stochastic programming.
- Implement and test a deployment prototype integrated with a real MES/ERP.

CONCLUSION

Overall, the presented framework addresses the triple objective of cost, time, and sustainability in a single scheduling model, validated through rigorous statistical analysis. These improvements make the Hybrid SA–GA a strong candidate for real-world deployment in EV battery supply chains and broader industrial contexts.

We presented a Hybrid SA–GA framework that achieves robust, sustainable, and computationally efficient schedules for automotive EV battery projects. The approach offers a practical balance between solution quality, interpretability, resilience, and sustainability performance — making it a prospective tool for Industry 4.0 adoption.

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Mahdi Firoozi was born in Tehran, Iran in 1996. He holds a B.Sc. in Robotics Engineering from Hamedan University of Technology and an M.Sc. in Strategies (Engineering Technology for Strategy and Security) from the University of Genoa, Italy. He has served as a university lecturer and technical services manager with experience in industrial scheduling, robotics, and operations management. His research interests include metaheuristic optimization, AI in project governance, and sustainable manufacturing. He is currently pursuing doctoral opportunities in the intersection of AI, operations, and sustainability.

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TABLE II. Comparative Results (mean over 30 runs).

TABLE III. Sustainability Results.

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