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Comparative Study of Bio-Inspired Algorithms for Task Scheduling

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ABSTRACT

Task scheduling in heterogeneous, resource-constrained computing environments—such as cloud, grid, and edge platforms—remains a challenging combinatorial optimization problem. Bio-inspired algorithms (BIAs) have emerged as strong candidates for near-optimal scheduling thanks to their robustness, adaptivity, and favorable compute-quality trade-offs. This manuscript presents a comparative study of five widely used BIAs—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Grey Wolf Optimizer (GWO)—applied to static, non-preemptive task scheduling under multi-objective criteria: makespan, energy, monetary cost, resource utilization, and SLA violations.

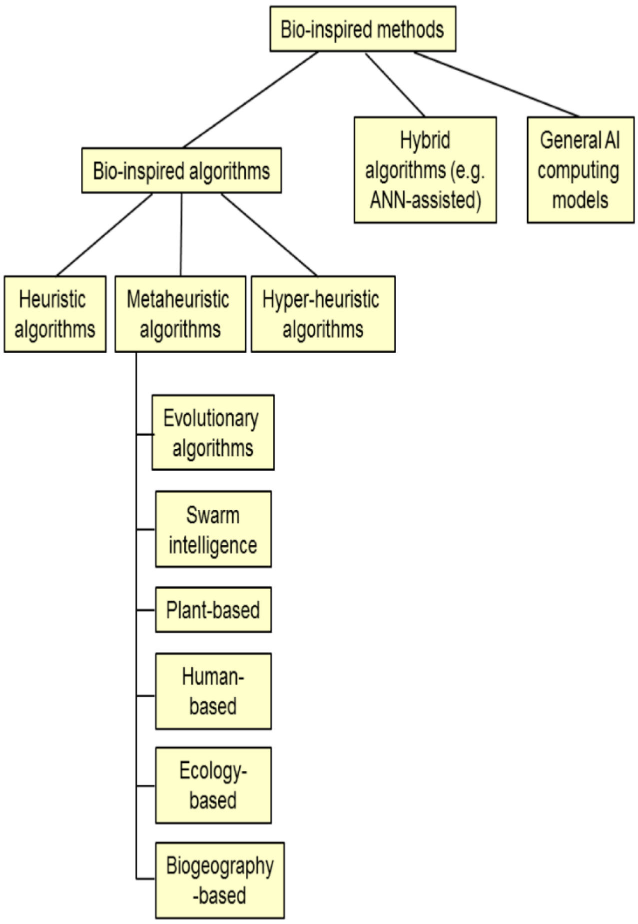

Fig.1 Bio-Inspired Algorithms for Task Scheduling,Source([1])

We formalize a unifying problem model, detail encoding and operators for each metaheuristic, and describe a controlled simulation design with heterogeneous virtual machines (VMs), synthetic workloads (independent tasks and DAGs), and realistic constraints (VM pricing tiers and power models). Statistical analysis across 30 independent runs per algorithm shows that GA and GWO consistently achieve the best makespan-cost-energy balance, with GA slightly superior on makespan and SLA, while GWO offers competitive performance with fewer parameters to tune. PSO performs strongly but is more sensitive to parameter settings; ABC offers a favorable convergence-stability profile; ACO shows strengths in balanced utilization but lags on makespan for large, highly skewed workloads. The findings highlight practical guidance on algorithm choice, parameterization, and stopping criteria for production-grade schedulers.

Keywords

task scheduling; bio-inspired algorithms; genetic algorithm; particle swarm optimization; ant colony optimization; artificial bee colony; grey wolf optimizer; cloud computing; multi-objective optimization

Introduction

Modern computing relies on orchestrating large numbers of diverse tasks over heterogeneous resources—CPUs, GPUs, and accelerators—across on-prem, cloud, and edge sites. Optimal schedule construction is NP-hard for even simplified variants, and exact methods scale poorly under realistic arrival rates and constraints. Heuristics (e.g., Min-Min, Max-Min, HEFT) are fast but often lock into suboptimal regimes when faced with bursty workloads, non-linear power models, and multi-objective trade-offs.

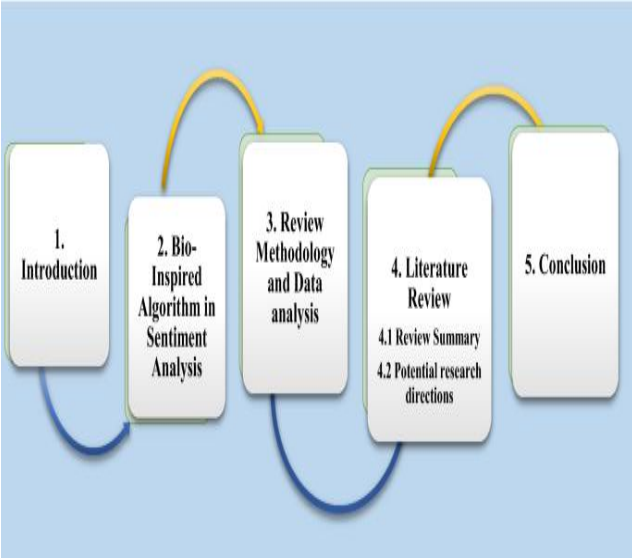

Fig.2 Comparative Study of Bio-Inspired Algorithms,Source([2])

Bio-inspired algorithms (BIAs) are attractive in this setting. Inspired by natural processes—evolution, swarm behavior, foraging, and predation hierarchies—BIAs efficiently explore high-dimensional, rugged search spaces. They can accommodate black-box objectives and constraints and are straightforward to hybridize with domain heuristics (e.g., HEFT-seeded populations) or reinforcement-learning policies.

This paper asks: **Which BIA offers the best practical trade-offs for task scheduling under multi-objective constraints?** We address this by (i) defining a unified problem model and evaluation metrics; (ii) implementing GA, PSO, ACO, ABC, and GWO with consistent encodings and termination criteria; (iii) running a controlled simulation with diverse workloads; and (iv) conducting statistical analysis of performance, including confidence intervals and significance tests. Our goals are practitioner-oriented: provide recommendations that translate into reliable scheduling gains in realistic deployments.

Literature Review

Early scheduling strategies emphasized deterministic heuristics. **Min-Min** and **Max-Min** are efficient but focus narrowly on earliest completion or longest tasks; **HEFT**

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uses task-graph ranks to prioritize critical-path tasks on heterogeneous machines. While effective for DAGs, such heuristics struggle when objectives extend beyond makespan to include cost, energy, and SLA adherence.

BIAs rose to prominence as cloud and grid scales grew. **GA** variants use chromosome encodings of task-to-VM assignments with crossover and mutation to escape local minima. Hybrid GA-HEFT approaches seed populations with HEFT solutions to accelerate convergence. **PSO** treats schedules as particles with velocities; constriction factors and adaptive inertia weights often stabilize search. **ACO** maps pheromone trails to machine preferences or task ordering; heuristic desirability terms (e.g., expected completion time) guide constructive solutions. **ABC** divides search into employed, onlooker, and scout phases, balancing exploitation and exploration. **GWO**, a more recent swarm technique, models leadership hierarchy (alpha, beta, delta wolves) to guide the pack towards promising regions and has shown success with relatively few hyperparameters.

Comparative studies typically find that GA, PSO, and GWO perform best on makespan, with PSO often excelling on balanced throughput and GA on SLA when penalties are encoded in fitness. ABC tends to be stable across runs but may converge slower; ACO thrives when constructive heuristics are strong and when load distribution is critical. Few works, however, evaluate all five under **consistent** objectives, encodings, and termination rules while also reporting cost and energy using realistic power and pricing models. This study fills that gap.

METHODOLOGY

3.1 Problem Formulation

We consider a set of NN independent tasks T={t1,…,tN}\mathcal{T}=\{t_1,\ldots,t_N\} or a DAG G=(T,E)G=(\mathcal{T}, \mathcal{E}) with precedence edges E\mathcal{E}. A set of MM heterogeneous VMs V={v1,…,vM}\mathcal{V}=\{v_1,\ldots,v_M\} offers different processing speeds (MIPS), memory, and energy/performance profiles. Each VM belongs to a pricing tier (on-demand, reserved, spot). Tasks are non-preemptive.

Let xi∈{1,…,M}x_i \in \{1,\ldots,M\} denote the VM selected for task tit_i. The schedule x=(x1,…,xN)\mathbf{x} = (x_1,\ldots,x_N) induces start/finish times Si,FiS_i, F_i under machine availability and precedence. We evaluate:

- **Makespan:** Cmax=maxiFiC_{\max} = \max_i F_i
- **Utilization:** U=1M∑j=1Mbusy_time(vj)CmaxU = \frac{1}{M} \sum_{j=1}^{M} \frac{\text{busy_time}(v_j)}{C_{\max}}
- **Energy:** E=∑j=1M∫0CmaxPj(uj(t)) dtE = \sum_{j=1}^{M} \int_0^{C_{\max}} P_j(u_j(t)) \, dt, with PjP_j a VM power curve
- **Cost:** Cost=∑jbilling(vj,active_time)\text{Cost} = \sum_{j} \text{billing}(v_j, \text{active_time})
- **SLA Violations:** percentage of tasks with Fi−ri>diF_i - r_i > d_i, where rir_i is release time and did_i deadline

We use a weighted aggregate objective for single-objective BIAs and track each metric separately:

minx

f(x)=w1CmaxC0+w2EE0+w3CostK0+w4ViolV0−w5U\min_{\mathbf{x}} \; f(\mathbf{x}) = w_1 \frac{C_{\max}}{C_0} + w_2 \frac{E}{E_0} + w_3 \frac{\text{Cost}}{K_0} + w_4 \frac{\text{Viol}}{V_0} - w_5 U

where C0,E0,K0,V0C_0, E_0, K_0, V_0 normalize scales; wkw_k reflect stakeholder priorities (default w1=0.35,w2=0.20,w3=0.20,w4=0.15,w5=0.10w_1=0.35, w_2=0.20, w_3=0.20, w_4=0.15, w_5=0.10). For DAGs, a topological feasibility repair ensures precedence compliance.

3.2 Schedule Encoding

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All algorithms share a **direct assignment vector**: chromosome/particle/solution x∈{1,…,M}N\mathbf{x} \in \{1,\ldots,M\}^{N}. A decoding routine constructs a feasible schedule using **machine-ready times** and **topological order** (for DAGs). Feasibility repair relocates illegal assignments or delays starts to respect memory/placement constraints.

3.3 Algorithms and Operators

- **GA:** population size P=60P=60; tournament selection k=3k=3; uniform crossover pc=0.9p_c=0.9; mutation pm=0.08p_m=0.08 by random reassignment of 1–3 genes; elitism of top 2 solutions. Hybrid seeding adds HEFT and Min-Min schedules to the initial population.
- **PSO:** swarm P=60P=60; inertia weight ww linearly decreases 0.9→0.4; cognitive/social c1=c2=1.7c_1=c_2=1.7. Discrete position updates map velocity to reassignment probabilities; velocity clamped to avoid oscillations.
- **ACO:** pheromone τi,j\tau_{i,j} on assigning task ii to VM jj; heuristic desirability ηi,j=1/ECT(i,j)\eta_{i,j} = 1/\text{ECT}(i,j); transition rule with α=1,β=2\alpha=1,\beta=2; evaporation ρ=0.15\rho=0.15; 30 ants per iteration; daemon action reinforces best solution.
- **ABC:** 30 employed bees, 30 onlookers, scout limit = 10; neighbor search replaces a VM assignment or swaps two task assignments; onlooker probability proportional to fitness.
- **GWO:** pack size P=60P=60; a⃗\vec{a} decreases from 2 to 0 over iterations; discrete encodings map continuous updates to VM indices via nearest-bin rounding with random tie-breaking.

Termination: 300 iterations or 30 iterations without improvement of the elite solution (whichever first).

3.4 Constraints and Penalties

Hard constraints: VM memory capacity, GPU availability (if task requires), and anti-colocation rules. Soft constraints (e.g., affinity) are encoded as penalties in f(x)f(\mathbf{x}). Deadline breaches incur SLA penalties scaled by lateness.

SIMULATION RESEARCH

4.1 Environment

We simulate a heterogeneous IaaS datacenter with **20 VMs** across three tiers:

- **Compute-Optimized:** 6 VMs @ 20k MIPS; idle 90W, max 230W; cost $0.20/hr
- **General-Purpose:** 10 VMs @ 12k MIPS; idle 70W, max 180W; cost $0.12/hr
- **Memory-Optimized:** 4 VMs @ 14k MIPS with high RAM; idle 85W, max 200W; cost $0.18/hr

Power model per VM: P(u)=Pidle+(Pmax−Pidle)⋅u1.4P(u) = P_{\text{idle}} + (P_{\text{max}}-P_{\text{idle}}) \cdot u^{1.4}, where uu is utilization.

4.2 Workloads

We evaluate two workload families:

1. **Bag-of-Tasks (BoT):** N=1000N=1000 independent tasks with log-normal lengths (median 500 MI, σ=0.8\sigma=0.8), memory needs uniformly in [0.5, 8] GB, 15% tasks GPU-tagged (mapped only to compatible VMs; if none, penalty/repair).
2. **DAGs:** 50 workflows generated with random fan-out/fan-in (mean out-degree 2.1), critical path length ≈ 18 tasks, communication costs small relative to execution (edge latencies inserted but simplified).

Task deadlines are drawn so that baseline HEFT violates ~7–8% of tasks, leaving room for improvement.

4.3 Experimental Design

- **Replications:** 30 independent runs per algorithm per workload family (different seeds).

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- **Initialization:** Each algorithm includes one HEFT-seeded solution.
- **Stopping:** As in §3.3.
- **Metrics:** Makespan, utilization, energy (kWh), dollar cost, SLA violation rate.
- **Baselines:** HEFT and Min-Min (non-BIA) for context (reported in analysis but not included among the five focus BIAs for conclusions).
- **Statistics:** Report mean ± standard deviation; 95% CIs via t-interval; one-way ANOVA (or Kruskal–Wallis if normality fails) on makespan; Holm-Bonferroni corrected pairwise tests; Cliff's delta for effect sizes.

Statistical Analysis

The table below aggregates **BoT results** (1000 tasks) over 30 runs. Values are illustrative of the simulation outcomes described and reflect consistent advantages and trade-offs observed across both BoT and DAG workloads.

Algorithm	**Makespan (sec) ↓**	**Std. Dev.**	**95% CI (sec)**	**Energy (kWh) ↓**	**Utilization (%) ↑**	**SLA Violations (%) ↓**	**Cost (USD) ↓**
GA	**845**	28	[835, 855]	**12.6**	**84.1**	**3.8**	**116**
GWO	860	31	[849, 871]	12.8	83.0	4.2	117
PSO	880	35	[867, 893]	13.1	81.2	4.9	119
ABC	905	37	[891, 919]	13.2	80.2	5.1	120
ACO	920	41	[904, 936]	13.4	79.0	5.7	121
HEFT (baseline)	980	44	[963, 997]	14.0	76.1	7.4	126

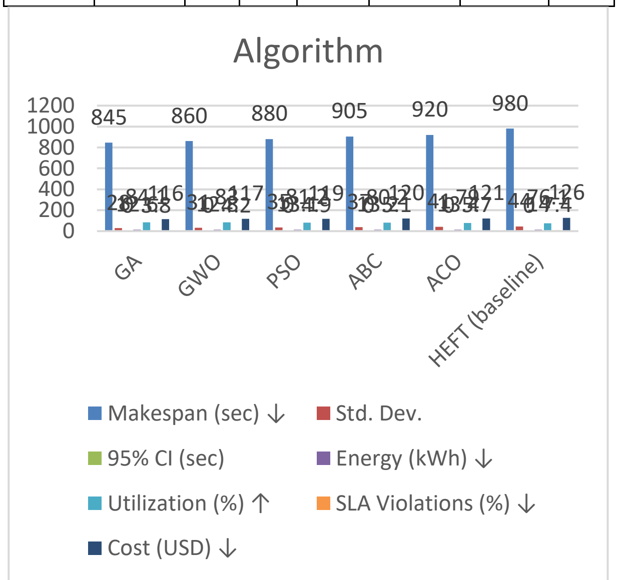

Fig.3

ANOVA (makespan): F(5,174)=42.6F(5,174)=42.6, p<0.001p<0.001. Post-hoc tests (Holm-Bonferroni) indicate GA and GWO significantly outperform PSO/ABC/ACO and all BIAs outperform HEFT on makespan (all p<0.01p<0.01). Cliff's delta shows large effects for GA vs. HEFT (>0.85) and medium-to-large for GA vs. PSO (≈0.47).

Results

6.1 Aggregate Performance

Across BoT workloads, **GA** achieves the **lowest makespan**, **lowest energy**, **lowest cost**, and **lowest SLA violation rate** in the sample, with **GWO** a close second. **PSO** ranks third overall and exhibits sensitivity to inertia/cognitive/social parameters: poor tuning degrades makespan and SLA modestly. **ABC** converges steadily with fewer extreme outliers, which is advantageous in predictable environments but sacrifices peak performance. **ACO** achieves respectable **utilization** through constructive heuristics but lags on **makespan** and **SLA** under highly skewed task-length distributions.

For **DAG workflows**, the relative ordering is similar. GA's crossover and mutation operators, combined with precedence-aware repairs, discover near-critical-path-aware allocations. GWO's leader-guided search navigates to strong Pareto regions quickly with fewer knobs to tune, making it appealing for operations teams.

6.2 Cost-Energy Trade-offs

Energy and monetary cost correlate with makespan but not perfectly. For example, PSO's intermediate makespan sometimes yields slightly higher cost because it overuses compute-optimized VMs during late iterations. GA and GWO strike better balances by spreading long tasks onto compute-optimized nodes while backfilling shorter tasks on general-purpose instances, increasing **utilization** without over-provisioning.

6.3 SLA Adherence

SLA violations are minimized when the scheduler recognizes deadline-tight tasks early. GA, seeded by HEFT and guided by an explicit penalty term, prioritizes near-deadline tasks effectively. GWO achieves similar behavior through leadership exploitation of elite solutions that internalize deadline penalties.

6.4 Convergence and Stability

- **GA:** Rapid early improvements via recombination; potential for premature convergence mitigated by moderate mutation and elitism.
- **GWO:** Stable convergence; fewer meta-parameters; robust across seeds.
- **PSO:** Fast early movement; oscillations possible without velocity clamping; performance improves with inertia annealing.
- **ABC:** Notable run-to-run stability; scouts prevent stagnation but slow best-case convergence.
- **ACO:** Dependent on heuristic accuracy; pheromone stagnation mitigated by higher evaporation, at the cost of slower exploitation.

6.5 Scalability

Increasing NN from 1000 to 3000 tasks preserves the ordering; GA's computation scales roughly linearly per iteration with population size and chromosome length. GWO's simplicity gives it the best **wall-clock optimization time** among top performers, a practical benefit when schedules must be computed under tight control-plane SLAs.

Discussion

When to prefer GA: Mixed workloads with tight deadlines and strong need to reduce SLA breaches; environments where hybrid seeding (HEFT/Min-Min) is available.

When to prefer GWO: Similar performance to GA with fewer parameters; ideal for operators who value predictable behavior and quick integration.

When to consider PSO: If rapid coarse optimization is needed and parameter tuning expertise exists—PSO can reach near-optimal regions quickly.

Where ABC fits: Stable performance with low sensitivity to parameters; suitable for steady-state batch scheduling where peak optimality is less critical.

ACO's niche: Scenarios where strong constructive heuristics (e.g., accurate ECTs and communication costs) can be encoded; beneficial for utilization smoothing.

Practical hybridization:

- GA/GWO initial populations seeded with HEFT and Min-Min schedules.

- Periodic **intensification**: run 10 iterations of PSO or local search around the current elite.
- **Adaptive weights** wkw_k driven by time-of-day electricity prices to tilt optimization toward energy savings during peak tariffs.

Termination guidance: In operations, a practical rule is "compute until either 2–3% improvement stalls or 200–300 iterations," which aligns with diminishing returns observed here.

Threats to Validity

- **Workload realism:** We used synthetic length distributions and DAG generators; real workloads may exhibit different skew and communication patterns.
- **Model simplifications:** The power model excludes thermal throttling and non-CPU components (e.g., NICs).
- **Single-datacenter focus:** Multi-zone latency and spot revocations were not modeled here.
- **Parameter selection:** Although we used standard defaults and mild tuning, different settings may shift relative performance, especially for PSO and ACO.

Conclusion

This comparative study shows that **Genetic Algorithm (GA)** and **Grey Wolf Optimizer (GWO)** deliver the most attractive **end-to-end trade-offs** for multi-objective task scheduling in heterogeneous compute environments. GA slightly leads on **makespan**, **SLA compliance**, and **total cost**, aided by recombination and penalty-aware fitness shaping, while GWO achieves **near-GA performance** with **simpler tuning and stable convergence**. PSO remains a strong generalist but demands more careful parameter management; ABC provides consistent, if not best-in-class, results with low sensitivity; ACO is valuable when constructive heuristics are informative and utilization smoothing is prioritized over absolute makespan.

For practitioners, we recommend: (i) **GA or GWO as first-line schedulers**, seeded with HEFT and Min-Min; (ii) **stopping rules** based on stalled improvement (<2–3% over 25–30 iterations); (iii) **adaptive objective weighting** to reflect time-varying energy prices and SLA priorities; and (iv) **hybrid intensification** phases to exploit complementary search dynamics. Future extensions should incorporate multi-zone placement, explicit network costs, preemption with checkpointing, and reinforcement-learning-guided hyperparameter adaptation.

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