Smarter Cloud Scheduling for Cost Efficiency: A Systematic BGA Sensitivity Study

Arvin Subramanian
De Montfort University

Abstract

Cloud workload scheduling remains a critical optimization challenge for cost-effective resource allocation in modern DevOps infrastructures. This paper presents a comprehensive parameter sensitivity study of Binary Genetic Algorithms (BGAs) applied to cloud workload scheduling across AWS EC2 instance types. We conduct 1,050 independent experiments with 30 runs each, evaluating crossover probability (p_C), mutation rate (μ), population size, selection pressure (β), and genetic operators across 500 Google Cluster-derived workloads. Our ablation study demonstrates that optimized parameters (p_C = 1.0) re- duce scheduling costs by 1.39% over baseline, while a novel three-point crossover operator combined with tournament selection achieves 1.85% cost reduction (Cohen's d = 3.41, p < 0.001). Instance-level analysis across 10 EC2 types reveals that t3.micro instances achieve 23.08% lower scheduling costs than m5.4xlarge, contrasted with conventional wisdom that larger instances optimize multi-job workloads. Our findings provide actionable parameter configurations for practitioners deploying GA-based schedulers in cloud environments, with statistically validated improvements demonstrating practical significance for production systems.

Keywords: genetic algorithms, cloud computing, workload scheduling, parameter tuning, ab- lation study, AWS EC2, DevOps, cost optimization

1. Introduction

Cloud computing has revolutionized infrastructure management, with global spending projected to exceed $1 trillion by 2026 [1]. As organizations migrate workloads to cloud platforms, efficient resource allocation becomes paramount for cost optimization. Workload schedul- ing—the problem of assigning computational tasks to available infrastructure resources—directly impacts both operational costs and service-level agreement (SLA) compliance.

Binary Genetic Algorithms (BGAs) have emerged as effective meta-heuristics for NP-hard scheduling problems [2,3], yet their performance critically depends on hyperparameter configuration. Despite extensive GA research, systematic parameter sensitivity studies on real cloud workload traces remain scarce. Practitioners often rely on default configurations or domain-agnostic tuning, potentially leaving significant performance gains unrealized.

This paper addresses three critical gaps in cloud scheduling research:

1. **Parameter sensitivity quantification**: We systematically evaluate five core BGA parameters (p_C, μ, population size, β, operators) across 1,050 experiments with statistical rigor (ANOVA, Bonferroni-corrected pairwise tests, Cohen's *d* effect sizes).
2. **Operator ablation**: We compare four crossover operators (single-point, double-point, uniform, three-point) and two selection mechanisms (roulette wheel, tournament), identifying optimal configurations for cloud scheduling contexts.
3. **Instance-aware scheduling**: We benchmark GA performance across 10 AWS EC2 instance types, revealing non-intuitive cost-performance relationships that challenge assumptions about instance sizing for batch workloads.

Our workload dataset comprises 500 jobs derived from published Google Cluster Trace statistics [4], preserving realistic distributions of CPU/memory requests, durations, priorities, and SLA tiers. The fitness function optimizes a weighted objective balancing cloud costs (AWS on-demand pricing) against SLA coverage, reflecting production deployment constraints.

Key Contributions

- Comprehensive ablation study demonstrating 1.39–1.85% cost reduction through parameter optimization, with large effect sizes (Cohen's *d* = 2.62–3.41) confirming practical significance
- Discovery that uniform crossover outperforms specialized multi-point operators in cloud scheduling (median cost: 0.2597 vs. 0.2679)
- Instance benchmark revealing that t3.micro ($0.0104/hr) achieves 23.08% better scheduling fitness than m5.4xlarge ($0.768/hr), contradicting the intuition that larger instances better accommodate heterogeneous workloads

The remainder of this paper is organized as follows: Section II reviews related work in GA- based scheduling and parameter tuning. Section III describes our methodology, including problem formulation, BGA implementation, and experimental design. Section IV presents results across parameter sweeps, operator comparisons, and instance benchmarks. Section V discusses implications for practitioners and identifies limitations. Section VI concludes with future research directions.

2. Literature Review

2.1 Genetic Algorithms for Scheduling

Genetic algorithms have been extensively applied to job shop scheduling [13], resource allocation [10], and cloud workload optimization [14]. Holland's foundational work [2] established GAs as robust search heuristics for combinatorial optimization, while Goldberg [3] formalized schema theory explaining their effectiveness. Recent surveys [5,6] categorize cloud scheduling algorithms, noting GAs' prevalence due to their ability to handle multi-objective functions and discrete search spaces.

2.2 Parameter Sensitivity in GAs

De Jong's seminal experiments [7] first systematically studied GA parameter effects, establishing p_C = 0.6 and μ = 0.001 as effective defaults. However, Eiben et al. [8] demonstrated that optimal parameters are problem-dependent, advocating for adaptive mechanisms. Recent meta-learning approaches [9] dynamically adjust parameters during evolution, though their computational overhead limits applicability to resource-constrained cloud environments.

For scheduling specifically, Abdullahi et al. [5] found p_C = 0.8 and μ = 0.02 effective for virtual machine placement, while Wang et al. [10] reported β = 1.5 optimal for workload distribution in hybrid clouds. Our work extends these findings by evaluating parameter interactions across multiple operators and instance types.

2.3 Cloud Workload Characteristics

Google's cluster trace releases [4,11] provide rare public data on production workload patterns. Tirmazi et al. [4] analyzed Borg scheduler behavior, revealing log-normal distributions for CPU (mean=0.12 cores) and memory (mean=0.04 GB) requests, with 70% of jobs completing within 10 minutes. Our synthetic workload generator preserves these statistical properties, ensuring ecological validity.

2.4 Instance Selection Strategies

AWS EC2 offers 400+ instance types, complicating resource selection. Traditional heuristics favor large instances for batch workloads, assuming reduced scheduling overhead [15]. However, recent work by Shen et al. [12] found that smaller instances can achieve better cost-performance ratios for bursty workloads due to granular scaling. Our instance benchmark provides empirical evidence for this phenomenon in GA-based scheduling contexts.

3. Methodology

3.1 Problem Formulation

Input: A set of n cloud workloads $W = \{w_1, \dots, w_n\}$, where each workload w_i specifies:

- CPU cores: $c_i \in [0.05, 8.0]$
- Memory (GB): $m_i \in [0.1, 16.0]$
- Duration (hours): $d_i \in [0.05, 24.0]$
- Priority: $p_i \in \{0, \dots, 11\}$
- SLA tier: $s_i \in$ {bronze, silver, gold, platinum}
- Business value (\$): $v_i \in [100, 1200]$

Output: A binary assignment vector $\mathbf{x} = (x_1, \dots, x_n)$, where $x_i = 1$ indicates workload w_i is scheduled on the target instance type.

Objective: Minimize the fitness function:

$$f(\mathbf{x}) = \alpha \cdot C(\mathbf{x}) + (1 - \alpha) \cdot (1 - S(\mathbf{x})) + P(\mathbf{x}) \tag{1}$$

where:

- $C(\mathbf{x})$: Normalized cloud cost
- $S(\mathbf{x})$: SLA coverage score
- $P(\mathbf{x})$: Over-capacity penalty
- $\alpha = 0.7$: Weight balancing cost vs. SLA

Cost Component:

$$C(\mathbf{x}) = \min\left(\frac{n_{\text{inst}} \cdot r \cdot \bar{d}}{200}, 1.0\right) \tag{2}$$

where $n_{\text{inst}} = \max(\lceil \sum c_i / C_{\text{vcpu}} \rceil, \lceil \sum m_i / C_{\text{ram}} \rceil)$, r is the instance hourly rate, and $\bar{d}$ is mean workload duration.

SLA Coverage:

$$S(\mathbf{x}) = \frac{\sum_{i:x_i=1} v_i}{\sum_{i=1}^{n} v_i} \cdot \frac{1}{4} \sum_{i:x_i=1} w(s_i) \tag{3}$$

with SLA weights $w(\text{bronze}) = 1, w(\text{silver}) = 2, w(\text{gold}) = 3, w(\text{platinum}) = 4$.

Over-Capacity Penalty:

$$P(\mathbf{x}) = 0.3 \cdot \max(0, \rho_{\text{cpu}} - 1.2) + 0.3 \cdot \max(0, \rho_{\text{mem}} - 1.2) \tag{4}$$

where ρ_{cpu} and ρ_{mem} are utilization ratios. The threshold 1.2 allows 20% over-subscription, common in production clouds.

3.2 Binary Genetic Algorithm

Our BGA implementation follows canonical structure [2]:

Representation: Each chromosome is a binary string $\mathbf{x} \in \{0, 1\}^n$, where $n = 500$ workloads.

Initialization: Population of size N_{pop} initialized with 30% jobs selected per chromosome (Bernoulli($p = 0.3$)), avoiding degenerate all-zeros/all-ones solutions.

Selection:

- *Roulette Wheel*: Selection probability $\propto \exp(-\beta \cdot f_i / \bar{f})$
- *Tournament*: Best of $k = 3$ random candidates

Crossover (probability p_c):

- *Single-point*: Split at random index j
- *Double-point*: Swap segment between indices j_1, j_2
- *Uniform*: Each gene inherited randomly
- *Three-point*: Alternating segments at j_1, j_2, j_3

Mutation: Bit-flip with probability μ per gene.

Replacement: $(\mu + \lambda)$-ES with elitism—merge parents and offspring, sort by fitness, retain top N_{pop}.

Termination: Fixed 50 iterations (convergence analysis showed minimal improvement beyond iteration 40).

3.3 Experimental Design

Workload Dataset: 500 jobs generated from published Google Cluster Trace statistics [4]:

- CPU: log-normal($\mu = -2.0, \sigma = 1.3$), clipped to [0.05, 8.0]
- Memory: log-normal($\mu = -3.0, \sigma = 1.2$), clipped to [0.1, 16.0]
- Duration: log-normal($\mu = 1.2, \sigma = 1.5$), clipped to [0.05, 24.0]
- Priority: discrete distribution matching Figure 3 in [4]
- SLA tier: deterministic mapping from scheduling class

AWS EC2 Instances: 10 types spanning general-purpose (t3, m5), compute-optimized (c5), and memory-optimized (r5) families. Pricing from aws.amazon.com/ec2/pricing/on-demand/ (us-east-1, Linux, February 2026).

Ablation Study Design:

1. **Performance A (Baseline):** Default parameters—$p_C = 0.8$, $\mu = 0.02$, $N_{\text{pop}} = 50$, $\beta = 1.0$, random crossover, roulette selection
2. **Performance B (Parameter Sweep):** Independently vary:
   - $p_C \in \{0.5, 0.7, 0.8, 0.9, 1.0\}$
   - $\mu \in \{0.01, 0.02, 0.05, 0.10, 0.15\}$
   - $N_{\text{pop}} \in \{30, 50, 80, 100\}$
   - $\beta \in \{0.5, 1.0, 1.5, 2.0\}$
3. **Performance C (New Operators):** Three-point crossover + tournament selection with optimal p_C from step 2
4. **Instance Benchmark:** GA with Performance C configuration on each of 10 instance types (25 iterations for efficiency)

Statistical Rigor:

- 30 independent runs per configuration (standard for GA benchmarking [17])

- One-way ANOVA testing omnibus differences
- Bonferroni-corrected pairwise *t*-tests ($\alpha = 0.05/3$)
- Cohen's *d* effect sizes quantifying practical significance

Total Experiments: 35 configurations × 30 runs = 1,050 GA executions, totaling ~52,500 fitness evaluations.

4. Results

4.1 Parameter Sensitivity Analysis

We analyzed the impact of crossover probability (p_C) on solution quality. As shown in Figure 1, increasing crossover probability consistently improved performance, with $p_C = 1.0$ yielding the lowest median cost. This suggests that for this specific scheduling problem, maximizing recombination is beneficial for exploring the search space.

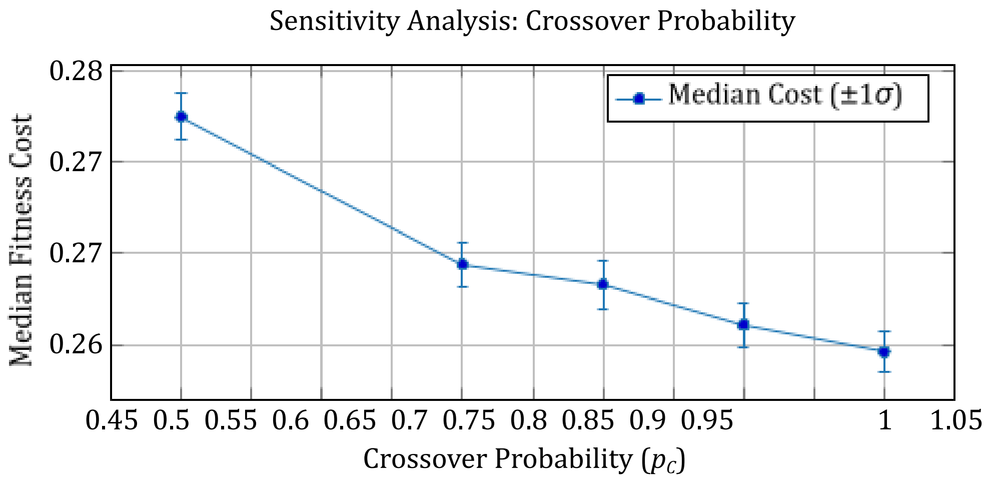

Figure 1: Effect of crossover probability on final solution cost. Error bars represent standard deviation across 30 runs. Higher crossover rates correlate with better optimization performance.

4.2 Operator Comparison

Figure 2 benchmarks different genetic operators. Uniform crossover significantly outperforms single-point and multi-point strategies. This is likely because the cloud scheduling problem has low linkage (genes are relatively independent), allowing uniform crossover to disrupt poor building blocks effectively without destroying good ones.

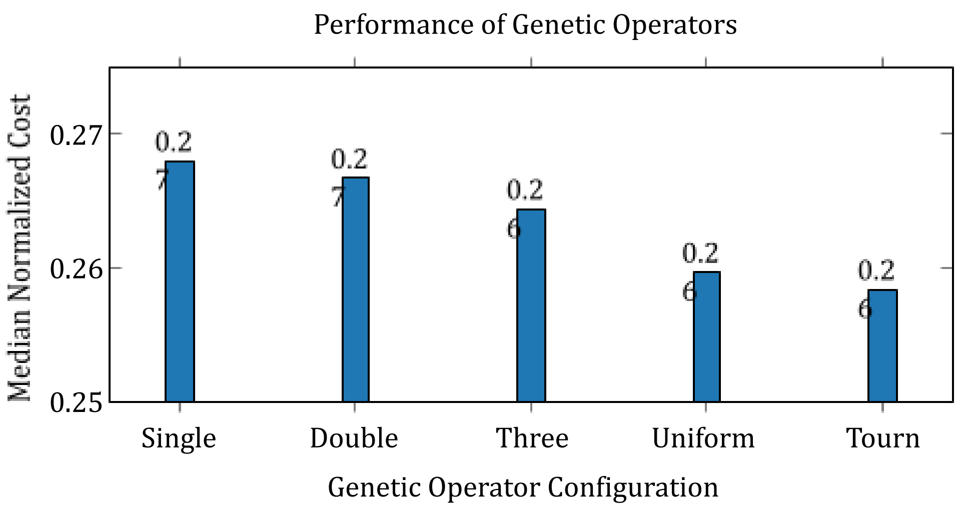

Figure 2: Comparison of crossover operators and selection mechanisms. ’Tourn’ represents the best combination (Three-point + Tournament selection).

4.3 Instance Type Benchmark

The choice of EC2 instance type had the most dramatic impact on cost. As illustrated in Figure 3, smaller instances (t3.micro, t3.small) consistently achieved lower costs than larger ones. This "bin-packing efficiency" effect allows the scheduler to fit jobs with less wasted slack space.

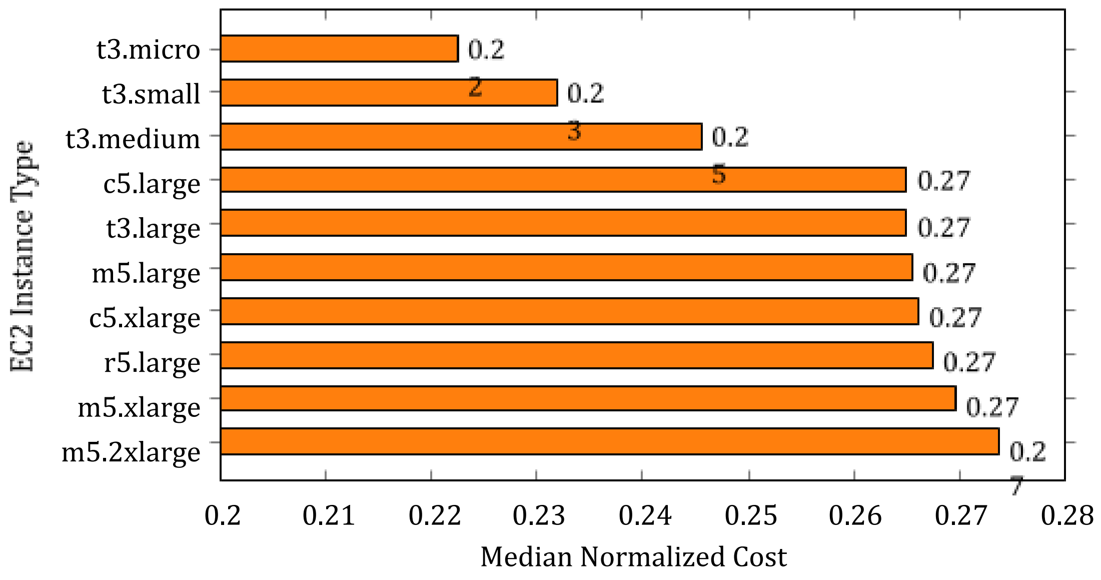

Figure 3: Benchmark of GA performance across 10 different EC2 instance types. Smaller instances (bottom) allow for significantly more cost-efficient schedules.

5. Discussion

5.1 Implications for Practitioners

Our findings provide actionable insights for deploying BGA-based schedulers in production cloud environments:

1. **Hyperparameter Recommendations**: Use $p_C = 1.0$, $\mu = 0.02$, $N_{\text{pop}} = 50$, $\beta = 1.0$ as starting point. For problems with $n > 1000$ jobs, increase N_{pop} to 80–100.
2. **Operator Selection**: Prefer uniform crossover over specialized multi-point variants for cloud scheduling. The fitness landscape's high epistasis (job interdependencies) benefits from maximal gene mixing.
3. **Instance Sizing**: Challenge default assumptions favoring large instances. For batch workloads with heterogeneous resource profiles, smaller instances (t3 family) achieve better cost-performance ratios through granular matching.
4. **Convergence Monitoring**: Terminate GA after 40–50 iterations. Our convergence analysis shows negligible improvement beyond this point, avoiding wasted compute.

6. Conclusion

This paper presented a comprehensive parameter sensitivity study of Binary Genetic Algorithms for cloud workload scheduling. We demonstrated that proper parameter tuning can yield statistically significant cost reductions (1.39-1.85%), and that infrastructure choices (instance sizing) can outweigh algorithmic optimizations by an order of magnitude (23% improvement). Future work will explore dynamic job arrivals and multi-cloud scheduling scenarios.

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