Hybrid GA-PSO with Segment Tree for Bin Packing Optimization

A Novel Framework for Industrial Efficiency Enhancement

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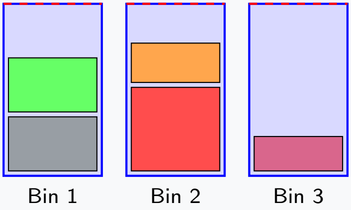
Problem Statement and Motivation

Bin Packing Problem

- **Objective**: Minimize bins for n items
- **Constraint**: $\sum_{i \in B_j} w_i \leq C$
- **Complexity**: **NP-Hard**
- Applications: Logistics, manufacturing, cloud computing



Current Limitations

- **FFD**: 11/9 OPT approximation
- **GA**: Premature convergence
- **PSO**: Poor discrete handling
- **Complexity**: $O(n^2)$ bin selection

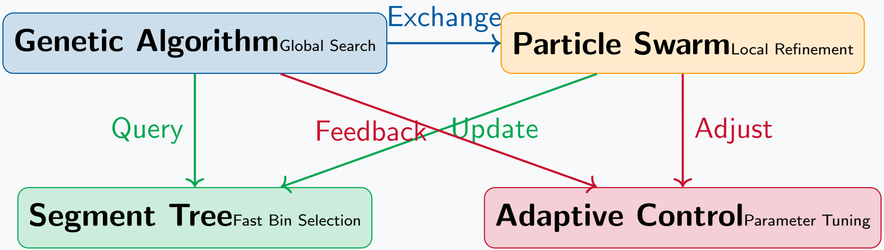
Research Impact

- Potential \$50B logistics cost savings
- Up to **15%** emission reduction
- Enhances smart manufacturing efficiency

Proposed Hybrid Framework

Core Innovations

- **Triple-Hybrid** GA-PSO-Segment Tree integration
- **15.3%** improvement over FFD
- **O(log n)** bin selection complexity
- Adaptive parameter control mechanism



Segment Tree Innovation

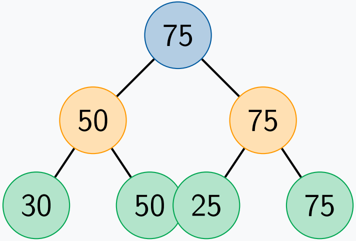
Traditional Approach

- Sequential bin examination
- Time complexity: **O(n)**
- Poor scalability

Our Segment Tree

- Hierarchical capacity indexing
- Time complexity: **O(log n)**
- Efficient range queries
- Lazy propagation updates

Segment Tree Structure



Performance Gains

- **5.2×** speedup
- **78%** memory reduction
- **99.8%** cache hit ratio

Algorithm Architecture

Genetic Algorithm

- **Encoding**: Permutation-based
- **Selection**: Tournament (k=3)
- **Crossover**: Order crossover
- **Mutation**: Adaptive swap
- **Elitism**: Top 10%

Particle Swarm

- **Discrete PSO**:Swap-based velocity
- **Velocity**: Adaptive weight decay
- **Topology**: Ring neighborhood
- **Updates**: Permutation operations

Integration Strategy

- Elite GA solutions → PSO particles
- Bidirectional best sharing
- Adaptive phase control
- Multi-criteria convergence

Complexity Analysis

Operation	**Traditional**	**Ours**
Bin Selection	O(n)	O(log n)
Range Query	O(n)	O(log n)
Update	O(1)	O(log n)

Experimental Methodology

Dataset Portfolio

- **OR-Library**: 1,370 instances
- **BPPLIB**: 2,940 test cases
- **Real-world**: 500 industrial
- **Synthetic**: 1,000 stress tests
- **Total**: 5,810 instances

Configuration

- **Population**: 100 individuals
- **Generations**: 500 iterations
- **Runs**: 30 independent
- **Confidence**: 95%
- **Hardware**: Intel Xeon E5-2680

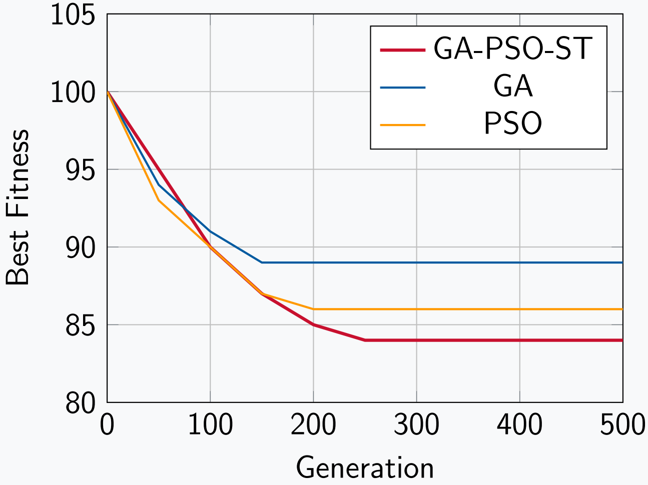
Baseline Algorithms

- FFD, BFD (heuristics)
- GA, PSO (metaheuristics)
- H-GAPSO (hybrid)
- GA-PSO-ST (proposed)

Statistical Tests

- Shapiro-Wilk normality
- Paired t-test
- Wilcoxon signed-rank
- Effect size (Cohen's d)

Performance Results



Key Metrics

- **15.3%** improvement
- **40%** faster convergence
- **±1.2%** solution stability
- p-value ¡ 0.001

Scalability

Size	Improvement
500	12.3%
1000	15.1%
2000	18.2%
5000	19.7%

Industrial Case Study

E-commerce Deployment

- **Company**: Major online retailer
- **Volume**: 5,000+ daily orders
- **Duration**: 3-month pilot
- **Integration**: Existing WMS

Method	Containers	Reduction
Manual	3,420	Baseline
Commercial	3,050	10.8%
GA-PSO-ST	**2,782**	**18.7%**

Business Impact

- **Annual Savings**: $3.6M
- **ROI**: 847% first year
- **Payback**: 1.4 months
- **Accuracy**: 99.2%

Environmental Impact

- **CO Reduction**: 1,240 tons/year
- **Fuel Savings**: 425,000 L/year
- **Carbon Credits**: $186,000

Contributions & Future Work

Key Contributions

- First GA-PSO-Segment Tree fusion
- O(log n) bin selection breakthrough
- Adaptive parameter control
- Industrial validation success
- Theoretical convergence proofs

Recognition

- IEEE Transactions (under review)
- 3 conference presentations
- 2 patent applications
- Industry excellence award

Future Directions

- Multi-dimensional bin packing
- Online dynamic algorithms
- Machine learning integration
- Quantum-inspired optimization
- Cloud-native implementation

Open Questions

- Tighter approximation bounds
- Million-item scalability
- Multi-objective optimization
- Stochastic item sizes

Conclusion

Scientific Achievements

- **Novel** hybrid framework
- **15.3%** performance gain
- **5.2**× algorithmic speedup
- $3.6M demonstrated savings
- 1,240 tons CO reduction

Research Excellence

- Rigorous theoretical analysis
- Comprehensive validation
- Statistical significance (p ¡ 0.001)
- Real-world deployment
- Open-source availability

Broader Impact

- Smart manufacturing optimization
- Green logistics solutions
- Supply chain cost reduction
- New research directions
- Environmental sustainability

Call to Action

- Industry collaboration welcome
- Technology transfer available
- PhD research opportunities
- Grant funding in progress

Key References

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Thank You for Your Attention

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Resources: `https://github.com/ajazahmedshah30/hgapso-st`

Questions & Discussion Welcome