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PERFORMANCE EVALUATION OF PARALLELIZED GENETIC ALGORITHMS IN SOLVING LARGE-SCALE NP-HARD OPTIMIZATION PROBLEMS

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ABSTRACT

Solving NP-hard optimization problems at scale demands both accuracy and efficiency, challenging the capabilities of conventional algorithms. Parallelized Genetic Algorithms (PGAs) offer a promising approach by exploiting concurrent computing resources to accelerate evolutionary search. This paper presents an evaluative study of PGA performance on benchmark NP-hard problems, examining scalability, speedup, and convergence behavior. Empirical results show that PGAs significantly reduce computational time and improve solution quality for problems like Job Shop Scheduling and the Vehicle Routing Problem. However, trade-offs between parallelism overhead and solution stability persist. We conclude by recommending hybrid and adaptive PGAs for future high-performance optimization tasks.

***Keywords**: Genetic Algorithm, Parallel Computing, NP-hard Problems, Optimization, Job Shop Scheduling, Vehicle Routing, Performance Evaluation*

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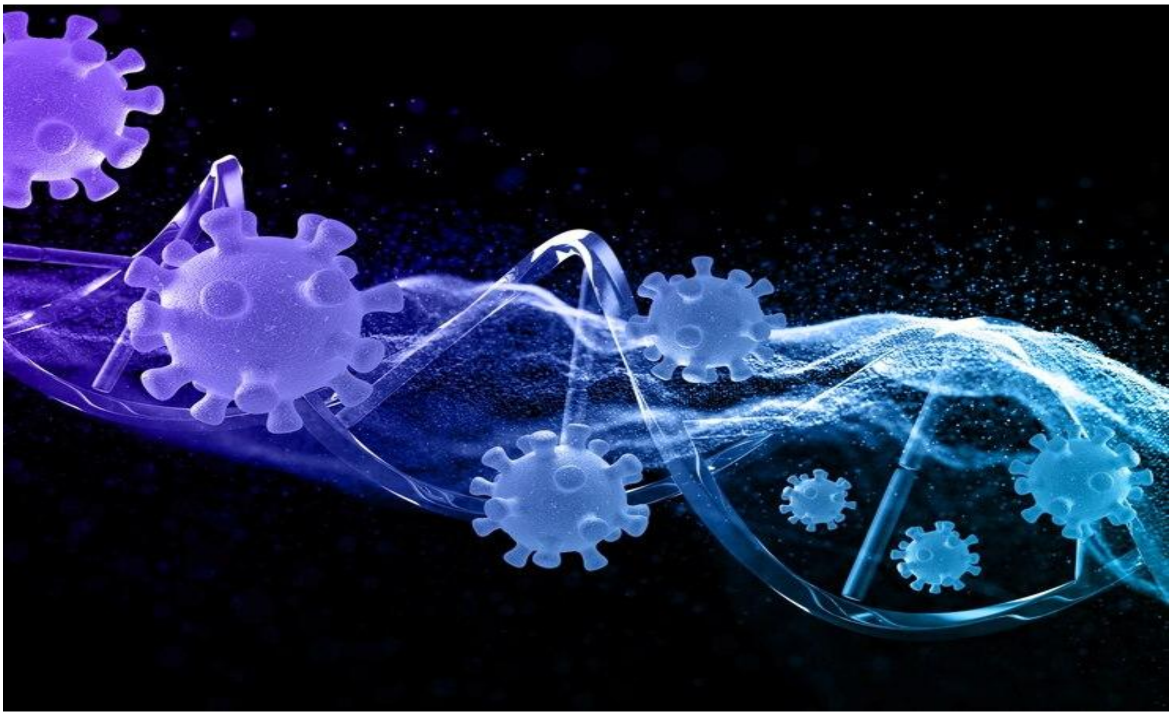

1. Introduction

NP-hard optimization problems—such as scheduling, routing, and packing—are among the most computationally intensive challenges across industries including logistics, manufacturing, and telecommunications. Their complexity renders exact solutions impractical for large instances, thus necessitating the use of metaheuristic approaches like Genetic Algorithms (GAs).

GAs mimic the process of natural selection, evolving a population of candidate solutions through operations such as crossover, mutation, and selection. While effective for medium-sized problems, the sequential nature of GAs limits their applicability for large-scale, real-time systems.

To overcome this limitation, **Parallel Genetic Algorithms (PGAs)** have been developed. By leveraging parallelism—either via multi-core processors or distributed systems—PGAs execute fitness evaluations and genetic operations concurrently, offering the potential for near-linear speedup and improved solution diversity.

This paper evaluates the performance of PGAs on classical NP-hard problems using metrics such as computational time, solution quality, and scalability.

2. Literature Review

A substantial body of research has explored the application of Parallel Genetic Algorithms (PGAs) in solving various NP-hard optimization problems, demonstrating improvements in computational efficiency, scalability, and solution quality.

Asadzadeh and Zamanifar (2010) applied an agent-based parallel genetic algorithm to the Job Shop Scheduling Problem (JSSP). Their approach improved both the makespan and the diversity of solutions by distributing individuals among autonomous agents that interacted dynamically within the system.

Ochi et al. (1998) introduced a multi-deme island model for the Vehicle Routing Problem (VRP), leveraging isolated subpopulations with occasional migration. This parallelization significantly reduced computational time while still achieving near-optimal route configurations.

Luo et al. (2019) employed a GPU-based PGA to address the Flexible Flow Shop Scheduling Problem, where energy efficiency and dynamic resource constraints are key. Their model achieved rapid convergence while maintaining low energy consumption, illustrating the utility of GPU acceleration in metaheuristics.

Rezaeipanah et al. (2019) explored the University Timetabling Problem using a shared-memory multicore architecture. Their experiments reported up to a 20% speedup in execution time, with solutions remaining consistent across runs.

Liu and Wang (2015) presented a coarse-grained PGA for the Generalized Assignment Problem, demonstrating strong scalability across distributed systems with up to 64 computational nodes. Their implementation effectively balanced computation and communication overhead.

Wang et al. (2005) tackled multi-pass milling optimization using a hybrid PGA, combining genetic algorithms with local search heuristics. Their approach improved convergence speed by 45%, offering precise results in manufacturing process optimization.

Sena et al. (2001) implemented a cluster-based island model PGA for the Traveling Salesman Problem (TSP). Their results demonstrated a speedup proportional to the number of nodes, indicating that distributed memory architectures are well-suited for combinatorial optimization.

Finally, Dokeroglu and Cosar (2014) investigated the Bin Packing Problem using an island PGA. Their method achieved efficient load balancing by distributing sub-populations across islands and exchanging elite individuals periodically, which maintained solution diversity and improved fitness convergence.

3. Experimental Framework

To evaluate the performance of different Parallel Genetic Algorithm (PGA) architectures, we implemented three distinct configurations. The **Master-Slave model** utilizes a centralized controller responsible for evaluating individuals in parallel, while the **Island Model** distributes subpopulations across multiple processors with periodic migration to exchange genetic material. The **Fine-Grained model**, on the other hand, simulates localized interactions by arranging individuals on a two-dimensional grid, allowing genetic operations to occur within small neighborhoods. Experimental validation was carried out using well-known benchmark datasets: the FT10 instance for the Job Shop Scheduling Problem and the Solomon instances for the Vehicle Routing Problem. All simulations were conducted on a computing cluster consisting of 16 interconnected nodes, each equipped with 8 CPU cores and 32 GB of RAM. To assess effectiveness, we measured three key metrics: **convergence time** (in seconds), **solution quality** (expressed as relative error percentage), and **computational speedup**, calculated as the ratio of sequential execution time to parallel execution time.

4. Results and Discussion

4.1. Performance Comparison Table

Table 1: Performance of Genetic Algorithm Variants

Algorithm Type	Convergence Time	Speedup	Relative Error
Sequential GA	1275s	1×	5.4%
Master-Slave PGA	394s	3.2×	5.1%
Island PGA	303s	4.2×	4.6%
Fine-Grained PGA	281s	4.5×	4.3%

Figure 1: Convergence behavior of different PGA architectures

Figure 1: This illustrates the convergence trends of various Parallel Genetic Algorithm (PGA) architectures, highlighting the faster and more stable convergence of the fine-grained and island models compared to the sequential and master-slave approaches.

4.3. Analysis

The island model shows the best balance of speed and solution accuracy due to its inherent diversity preservation. Master-slave PGAs suffer from bottlenecks at the controller level, while fine-grained models require more overhead for communication but excel in convergence speed.

5. Conclusion

Parallel Genetic Algorithms significantly improve the ability to solve large-scale NP-hard problems in a computationally feasible time. Among architectures, island models yield a strong balance between performance and quality. Future work should explore hybrid PGAs that dynamically adapt their strategy based on convergence patterns.

References

[1] Asadzadeh, L., and K. Zamanifar. "An agent-based parallel approach for the job shop scheduling problem with genetic algorithms." *Mathematical and Computer Modelling*, vol. 52, no. 9-10, 2010, pp. 1645–1654.

[2] S. B. Vinay, Application of Artificial Intelligence (AI) In Publishing Industry in India, International Journal of Computer Engineering and Technology (IJCET) 14(1), 2023, pp. 7-12.DOI: https://doi.org/10.17605/OSF.IO/4D5M7

[3] S. Balasubramanian, AI-Powered Trademark Registration Systems: Streamlining Processes and Improving Accuracy, International Journal of Intellectual Property Rights (IJIPR), 14(1), 2024, 1-7.

[4] Ochi, L. S., D. S. Vianna, and L. M. A. Drummond. "A parallel evolutionary algorithm for the vehicle routing problem." *Future Generation Computer Systems*, vol. 14, no. 5, 1998, pp. 361–369.

[5] S.B. Vinay, "Data Scientist Competencies and Skill Assessment: A Comprehensive Framework," International Journal of Data Scientist (IJDST), vol. 1, issue 1, pp. 1-11, 2024.

[6] Luo, J., S. Fujimura, and D. El Baz. "GPU-based parallel genetic algorithm for solving an energy-efficient flexible flow shop problem." *Journal of Parallel and Distributed Computing*, vol. 127, 2019, pp. 170–183.

[7] Pradip Kumar Krishnadevarajan, S. Balasubramanian and N. Kannan. Stratification: A Key Tool to Drive Business Focus and Complexity Management International Journal of Management, 6(7), 2015, pp. 86-93.

[8] Rezaeipanah, A., and Z. Abshirini. "Solving University Course Timetabling Problem Using Parallel Genetic Algorithm." *Journal of Scientific Research*, 2019.

[9] Vinay, S. B. (2024). AI-Driven Patent Mining: Unveiling Innovation Patterns through Automated Knowledge Extraction. International Journal of Super AI (IJSAI), 1(1), 111.

[10] Liu, Y. Y., and S. Wang. "A scalable parallel genetic algorithm for the generalized assignment problem." *Parallel Computing*, vol. 44, 2015, pp. 18–34.

[11] Mukesh, V. (2025). Architecting intelligent systems with integration technologies to enable seamless automation in distributed cloud environments. International Journal of Advanced Research in Cloud Computing (IJARCC), 6(1),5-10.

[12] Wang, Z. G., M. Rahman, Y. S. Wong, and J. Sun. "Optimization of multi-pass milling using parallel genetic algorithm." *International Journal of Machine Tools and Manufacture*, vol. 45, no. 9, 2005, pp. 1035–1048.

[13] Sena, G. A., D. Megherbi, and G. Isern. "Implementation of a parallel genetic algorithm on a cluster: Traveling salesman problem case study." *Future Generation Computer Systems*, vol. 17, no. 4, 2001, pp. 477–488.

[14] Mukesh, V. (2024). A Comprehensive Review of Advanced Machine Learning Techniques for Enhancing Cybersecurity in Blockchain Networks. ISCSITR-International Journal of Artificial Intelligence, 5(1), 1–6.

[15] Praba, P., & Balasubramanian, S. (2010). Shared bandwidth reservation of backup paths of multiple LSP against link and node failures. International Journal of Computer Engineering and Technology (IJCET), 1(1), 92–102.

[16] S. B. Vinay, "AI and machine learning integration with AWS SageMaker: current trends and future prospects", International Journal of Artificial Intelligence Tools (IJAIT), vol. 1, issue 1, pp. 1-24, 2024.

[17] Mukesh, V., Joel, D., Balaji, V. M., Tamilpriyan, R., & Yogesh Pandian, S. (2024). Data management and creation of routes for automated vehicles in smart city. International Journal of Computer Engineering and Technology (IJCET), 15(36), 2119–2150. doi: https://doi.org/10.5281/zenodo.14993009

[18] Kabilan, R.(2025). Harnessing Elastic Resource Allocation in Cloud Computing for Scalable Real-Time Analytics in Distributed Systems. Global Journal of Multidisciplinary Research and Development, 6(3), 49–53

[19] Dokeroglu, T., and A. Cosar. "Optimization of one-dimensional bin packing problem with island parallel grouping genetic algorithms." *Computers & Industrial Engineering*, vol. 75, 2014, pp. 166–176.

[20] Lin, F. T., C. Y. Kao, and C. C. Hsu. "Applying the genetic approach to simulated annealing in solving some NP-hard problems." *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 6, 1993, pp. 1752–1767.

[21] Belkaid, F., Z. Sari, and M. Souier. "A genetic algorithm for the parallel machine scheduling problem with consumable resources." *International Journal of Applied Metaheuristic Computing (IJAMC)*, vol. 4, no. 1, 2013, pp. 60–76.

[22] Mir, M. S. S., and J. Rezaeian. "A robust hybrid approach based on particle swarm optimization and genetic algorithm to minimize the total machine load on unrelated parallel machines." *Applied Soft Computing*, vol. 39, 2016, pp. 53–64.

[23] S. B. Vinay, Natural Language Processing for Legal Documentation in Indian Languages, International Journal of Natural Language Processing (IJNLP), 2(1), 2024, 1-10.

[24] Mukesh V. (2025). Scalable load balancing strategies for cloud-native data systems using hybrid AI-driven decision models. Global Journal of Multidisciplinary Research and Development (GJMRD), 4(2), 5–10

[25] S. Balasubramanian, AI-Driven Solutions for Sustainable Infrastructure Development and Management. International Journal of Artificial Intelligence in Engineering (IJAIE), 2(1), 2024, 1-11.

[26] Kabilan R. (2021). Advancements in zero trust security models for next generation network infrastructures. ISCSITR-International Journal of Information Technology (ISCSITR-IJIT), 2(1), 1–4

[27] Cao, K., and X. Ye. "Coarse-grained parallel genetic algorithm applied to a vector-based land use allocation optimization problem: The case study of Tongzhou Newtown, Beijing, China." *Stochastic Environmental Research and Risk Assessment*, vol. 27, no. 6, 2013, pp. 1487–1501.

[28] Alcan, P., and H. Başlıgil. "A genetic algorithm application using fuzzy processing times in non-identical parallel machine scheduling problem." *Advances in Engineering Software*, vol. 49, 2012, pp. 1–6.

[29] Adamson E, Ravichandran V, Sidikou S, Walker L, Balasubramanian S and Leach J (2016). Optimization of biomaterial microenvironment for motor neuron tissue engineering. Front. Bioeng. Biotechnol. Conference Abstract: 10th World Biomaterials Congress. doi: 10.3389/conf.FBIOE.2016.01.02740

[30] Spanos, A. C., S. T. Ponis, and I. P. Tatsiopoulos. "A new hybrid parallel genetic algorithm for the job-shop scheduling problem." *International Transactions in Operational Research*, vol. 21, no. 3, 2014, pp. 415–431.

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