International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 09 | Sept - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

A Review of Genetic Algorithms and Algorithm Fusion: Is Result Ranking More Effective.

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Abstract - Genetic Algorithms (GAs) are widely recognized as robust optimization techniques inspired by natural evolution [10]. Over the past decades, they have been applied to diverse domains such as scheduling, machine learning, image processing, and data mining [2][8]. With the rapid growth of data-driven applications, researchers have explored the integration of GAs with other algorithms known as algorithm fusion to enhance accuracy, convergence speed, and result ranking performance [1][3][4][7]. This review presents a comprehensive overview of GAs, their core principles, applications, and limitations [11]. Furthermore, it highlights recent trends in algorithm fusion approaches [5][6][9] and critically examines whether the resulting improvements in ranking and decision-making are significant compared to standalone GAs [2][8].

***Key Words*:** Data Mining, Fusion, image processing, Genetic Algorithm, Ranking

1.INTRODUCTION

Optimization in real-world scenarios is often challenging because the problems encountered are nonlinear, highly complex, and span multidimensional search spaces. Classical deterministic algorithms frequently struggle to provide high-quality solutions, as they may become trapped in local optima or demand excessive computational resources [2][8]. To overcome these difficulties, Genetic Algorithms (GAs)originally proposed by John Holland in the 1970s introduced an evolutionary, stochastic search mechanism inspired by natural selection [10].

Despite their adaptability and global search capabilities, GAs are not without drawbacks. Researchers have reported limitations such as slow convergence speed, premature stagnation at suboptimal solutions, and a strong dependence on parameter settings like mutation rate, crossover rate, and population size [11]. To alleviate these issues, hybrid or fusion approaches have been proposed, where GAs is combined with other optimization or learning techniques including Particle Swarm Optimization (PSO), Simulated Annealing (SA), Differential Evolution (DE), and Machine Learning models [1][3][4][5][6].

This article presents a consolidated review of existing research on GAs, emphasizing algorithm fusion strategies and critically assessing whether such integrations provide tangible benefits in terms of accuracy, convergence, and ranking performance compared to standalone GA implementations [7][9].

2. FUNDAMENTALS OF GENETIC ALGORITHMS

Genetic Algorithms follow the principles of natural selection and survival of the fittest. Their workflow typically consists of:

1. **Initialization** – Generate an initial population of candidate solutions.
2. **Fitness Evaluation** – Assess each candidate using a fitness function.
3. **Selection** – Choose parent solutions based on fitness scores.
4. **Crossover (Recombination)** – Exchange genetic material to produce offspring.
5. **Mutation** – Introduce random variations for diversity.
6. **Termination** – Repeat until a stopping criterion is met (iterations or optimal fitness).

2.1 Advantages

Global search capability.

Flexibility across problem domains.

Works well with discrete and continuous optimization problems.

2.2 Limitations

Computational cost.

Risk of premature convergence.

Sensitive to parameter tuning (population size, mutation rate, crossover rate).

3.APPLICATIONS (GENETIC ALGORITHMS)

- **Scheduling**: Task allocation, job-shop scheduling, and resource planning.
- **Machine Learning**: Feature selection, hyperparameter tuning.
- **Engineering Optimization**: Structural design, robotics, and control systems.
- **Data Mining**: Clustering, classification, and rule discovery.
- **Healthcare**: Diagnosis optimization, medical image segmentation.

4. ALGORITHM FUSION APPROACHES

4.1 GA with Particle Swarm Optimization (PSO)

The fusion of Genetic Algorithms and Particle Swarm Optimization leverages the complementary strengths of evolutionary search and swarm intelligence. While GA preserves diversity in the population through crossover and mutation—thereby reducing the likelihood of premature convergence—PSO contributes by accelerating convergence through velocity and position updates inspired by collective learning [1][2][3]. This

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hybridization has been successfully applied in large-scale domains such as power system scheduling, feature selection in high-dimensional data, and neural network optimization. The combined framework ensures robust exploration from GA and efficient fine-tuning from PSO, often achieving superior performance in terms of both accuracy and computational time compared to standalone GA or PSO [4].

4.2 GA with Simulated Annealing (SA)

Integrating GA with Simulated Annealing provides an effective mechanism to escape local minima, thanks to SA's probabilistic acceptance of suboptimal solutions under controlled conditions [5]. This combination enhances GA's exploration while retaining its evolutionary operators. It has been particularly effective in combinatorial optimization problems such as job-shop scheduling, the traveling salesman problem, and VLSI circuit design, where search landscapes are riddled with local optima. In such hybrids, GA contributes global search capability, whereas SA ensures refined local optimization, resulting in more robust and adaptable solutions [6].

4.3 GA with Differential Evolution (DE)

The integration of GA with Differential Evolution exploits DE's self-adaptive mutation and crossover strategies, which strengthen GA's ability to balance exploration and exploitation [7]. GA promotes diversity in the solution space, while DE introduces efficient parameter perturbations that accelerate convergence toward global optima. Applications of this hybrid framework include engineering design optimization, antenna array synthesis, bioinformatics, and supply chain planning. Compared to conventional GA, GA+DE hybrids often achieve higher-quality solutions with fewer generations, making them suitable for computationally demanding problem domains [8].

4.4 GA with Machine Learning Models

Recent advances combine GA with machine learning to build adaptive and intelligent optimization frameworks. GA can evolve fitness functions, hyperparameters, or even neural architectures, while ML models provide predictive insights and feedback that guide the GA's evolutionary search [6][9]. In deep learning, for instance, GA assists with neural architecture search and hyperparameter fine-tuning, whereas reinforcement learning helps GA dynamically adapt in changing environments. Real-world applications include intelligent healthcare systems, adaptive traffic management, financial forecasting, and IoT-driven decision support. This synergy enables GAs to move beyond static optimization and operate effectively in dynamic, real-time environments [5][6].

5. RESULT RANKING PERFORMANCE IN FUSION

- **Improved Convergence** – Hybrids reduce chances of local minima.
- **Higher Accuracy** – Better fitness evaluation leads to more precise ranking.
- **Domain-Specific Impact** – Hybrid GAs often outperform standalone GAs in ranking tasks (e.g., recommender systems).
- **Trade-offs** – Increased complexity, higher computational cost, and parameter tuning challenges.

6. Comparative Review of Studies

Approach	Strengths	Limitations	Applications	Ranking Performance
GA (Standalone)	Flexible, global search, works across domains	Premature convergence, slow in complex spaces	Scheduling, ML tuning, optimization	Moderate; depends heavily on parameter tuning
GA and PSO	Faster convergence, balanced exploration-exploitation	May require careful balance of GA and PSO operators	Neural networks, power systems	High; improved accuracy and ranking stability
GA and SA	Escapes local optima, enhances robustness	Slower execution due to SA acceptance criteria	TSP, job-shop scheduling	Improved ranking resilience, especially in combinatorial tasks
GA and DE	Self-adaptive mutations, fewer generations needed	May still risk stagnation in noisy landscapes	Engineering, supply chain, bioinformatics	High; better solution quality, efficient ranking
GA and ML Models	Adaptive, predictive guidance, real-time optimization	High complexity, requires training overhead	Recommendation, traffic control, smart healthcare	Very High; dynamic ranking and decision-making capabilities

Table 1

Studies on GA-PSO hybrids demonstrate **faster convergence** and **better ranking accuracy** in classification problems.

GA-SA approaches show **robustness** in avoiding premature convergence.

GA-ML fusions (e.g., GA with Neural Networks) outperform standalone GAs in tasks like **recommendation ranking** and **predictive analytics**.

However, some results indicate marginal improvements in ranking, suggesting that the benefits depend heavily on problem characteristics.

6. CONCLUSIONS

Genetic Algorithms have proven to be versatile and effective for a variety of optimization tasks. However, their limitations encourage the exploration of algorithm fusion strategies. Evidence from recent studies suggests that fusion generally enhances result ranking performance, especially in data-intensive and nonlinear problems. Nevertheless, improvements are context-dependent and must be weighed against additional computational complexity. Future research should focus on adaptive, scalable, and explainable fusion frameworks that can provide consistent benefits across domains.

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