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Optimization by Nature: A Review of Genetic Algorithm Techniques

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Abstract

The Genetic Algorithm (GA) is a technique that uses the selection principle of genetics to optimize the search tool for challenging issues. It is used for research and development as well as machine learning in addition to optimization, the purpose of this literature review is to determine the current state of research on the use and applications of genetic algorithms (GAs) for optimization across a range of sectors. Natural selection and biological evolution serve as the foundation for genetic algorithms (GAs), which replicate solutions through crossover, mutation, and selection. The review accentuates the diversity and universality of GAs in solving numerous complex problems such as path finding, image analytics and data referral systems. It examines the effectiveness of GAs in solving optimization problems as compared to other methods and focuses on GAs efficient properties in searching large and chaotic solution spaces. The results indicate that GAs can be considered as a strong result-oriented tool to further improve the machine learning and artificial intelligence operability.

A. Introduction

Computers play a critical role in resolving difficulties in our everyday life. They provide numerous applications and benefits in biology, chemistry, physics, mathematics, geography, archaeology, engineering, and social sciences fields. Previous studies have shown that a variety of domains, including engineering, management, economics, and politics, can employ metaheuristic algorithms to address complex problems. and the term metaheuristic algorithms is arising, which are introduced to use to solve real-life complex problems arising from different fields such as economics, engineering, politics, management, and engineering, Biological evolution processes, swarm behavior, and physics' laws inspire most of the metaheuristic algorithms. [1]

According to this Classification, a Meta-heuristic optimization algorithm can be viewed as either a single solution-based of population based (Figure. 1). The former class utilizes one candidate solution and improves the solution using local search. However, the solution obtained from single-solution based metaheuristics may get trapped in local optima. Some of the widely known single-solution based heuristics include Simulated Annealing (SA), Tabu Search (TS), Microcanonical Annealing (MA), and Guided Local Search (GLS). A different solution can be employed in population based approaches where population based strategies utilize throughout the search process. Because genetic or population based variants provide more diversity in population and prevent premature convergence of solutions to local optimum some of the well-known population based meta algorithm are: Genetic Algorithms (GAs), Particle Swarm Optimizations (PSOs), Ant Colony (AC), Simulated Annealing (SA), Differential Evolution (DE), Immune Algorithms (IA), Artificial Bee Colony (ABC) and Firefly Algorithm (FA). [1][2][3][4][5]

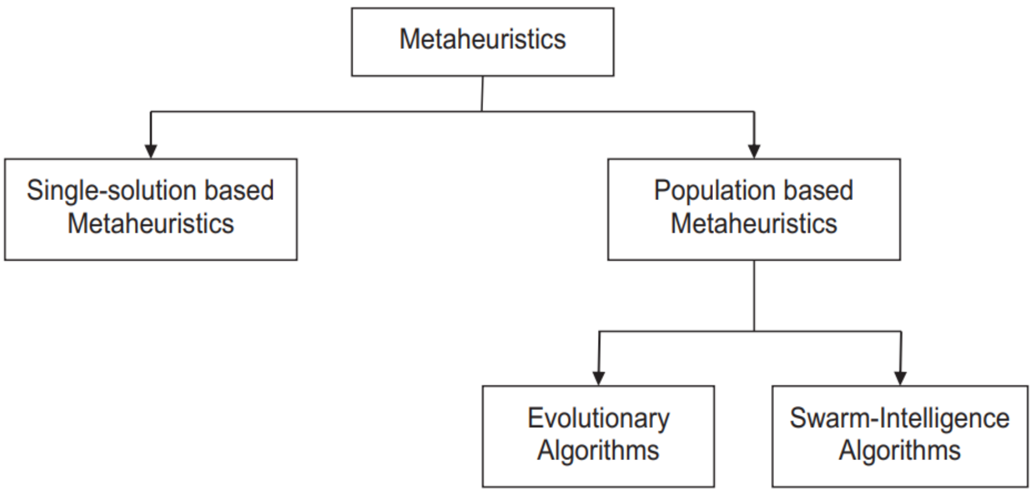

Figure 1. Classification of metaheuristic Algorithms

The largest proportion of algorithms being used are Genetic Algorithms which occupy 56% of applications, showing the continued popularity of this type of optimization algorithm despite the increasing competition from other methods [3] as shown in Figure 2.

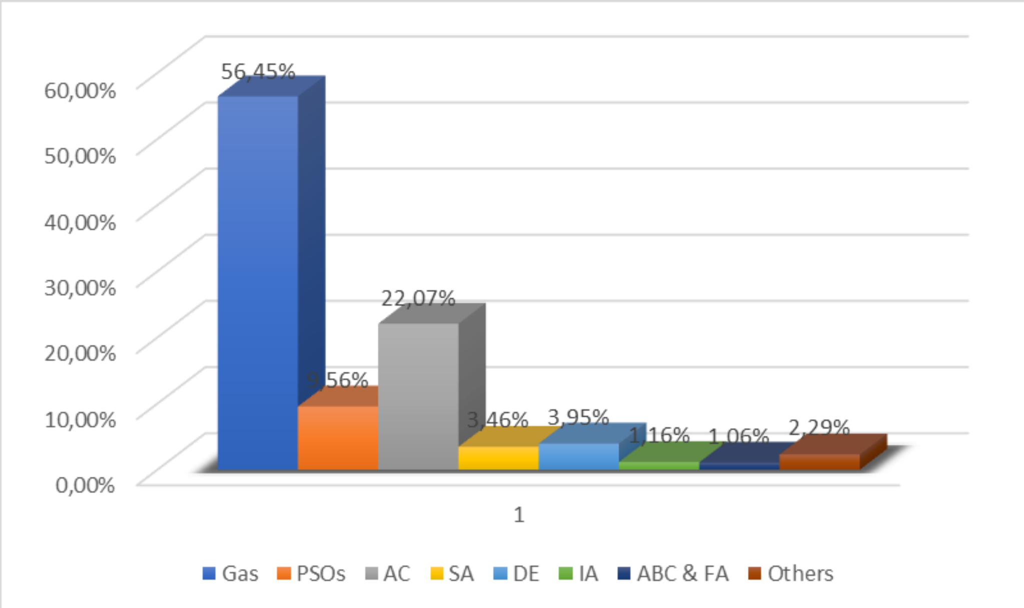

Figure 2. Popular evolutionary algorithms in the past 30 years

B. Genetic Algorithm

Based on Charles Darwin's theory of natural selection, Genetic Algorithm (GA) is one of the most popular evolutionary algorithms. GA was first presented by John Holland of the University of Michigan in 1975 [4] .Important elements of GA include chromosome representation, fitness selection, and biologically inspired operators. One use of GA is for combinatorial optimization issues, which involve finding the best values for solutions to problems with many possible solutions. Every difficulty can be described genetically in terms of adaptation [5][6].

GA processes retain an individual population and are iterative in nature. For the purpose of solving an issue, these individuals are referred to as candidate solutions. GAs are essentially made up of two primary processes: "selection," which produces the next generation, and "manipulation," which uses various methods, such as crossover and mutation, to guide the chosen individuals in the creation of the next generation. Every iteration in GA is referred to as "a generation." For each generation, members of the present population of solutions are evaluated based on how "effective" they are at solving the current problem. A population of new candidate solutions is created employing biologically inspired operators like mutation, crossover, and selection after taking these ratings into account [7].

An individual is shown as a string in GA, sometimes known as a "chromosome." Additionally, they might be viewed as a solution to a problem. These strings contain "genes," or characters, that store certain values known as "alleles." The arrangement of these genes on the chromosome is crucial. These particular locations on the chromosome are also referred to as "loci." [7][8].

C. Flowchart of Genetic Algorithm

The steps involved in a Genetic Algorithm are listed down in Figure 3 [9].

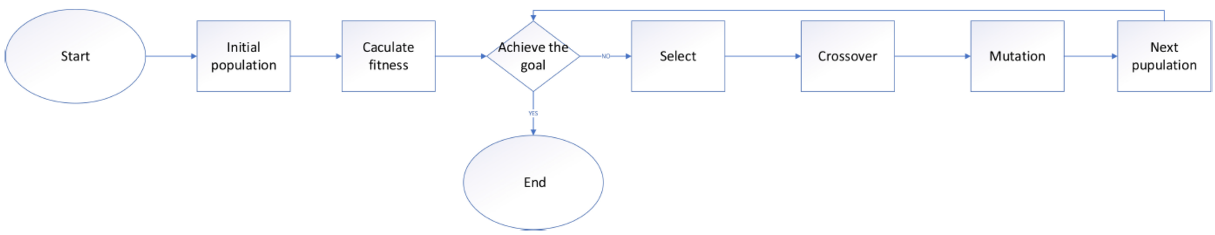

Figure 3. Flowchart of Genetic Algorithm

In contrast to local random search, which employs random solutions and is unable to find the best possible solutions, genetic algorithms are largely probability-based criteria in nature. This is because they incorporate historical data, which makes them sophisticated.
The primary functions carried out in GA are selection, crossover, and mutation [10].

a) Selection

A chromosome will be formatted to provide information about the solution it represents. Binary string format is a commonly used encoding method. Following that, the chromosome will look like that shown in Figure 4.

Chromosome 1	11011 I 00100110110
Chromosome 2	11011 I 11000011110

Figure 4. Chromosomes

A binary string can be used to plot each chromosome. Every bit that the string contains is also in charge of containing certain elements or standards of the solution [11].

b) Crossover

We can proceed to crossover operation as soon as we have confirmation regarding the code that will be used. A new offspring is created when crossover occurs on a section of the parent chromosome's genes. The simplest way to do this is to choose a crossover point at random, taking into account the range from the first parent point to this point. The cross-over point cab image is displayed as follows in Figure 5:

Chromosome 1	11011 | 00100110110
Chromosome 2	11011 | 11000011110
Offspring 1	11011 | 11000011110
Offspring 2	11011 | 00100110110

Figure 5. Crossover of Chromosome

There are numerous approaches to crossover, such as choosing from a wide variety of additional crossover points. Crossover may be more detailed and complicated. It mostly relies on chromosomal encoding. To enhance the effectiveness of genetic algorithms, choose crossover for specific issues [12].

c) Mutation

Following crossover, mutation is the next phase. The purpose of mutation is to prevent all of the population's solutions from falling into a local optimum of the problem that has been solved. Crossover produces offspring that are randomly altered by mutation. We can change a few randomly chosen bits in binary encoding from 0 to 1 or 1 to 0.The following is one way to embellish mutation mentioned in figure 6. [10][13].

Offspring 1	11011 | 11000011110
Offspring 2	11011 | 00100110110
Mutated offspring 1	1100111000011110
Mutated offspring 2	1101101100110110

Figure 6. Mutation of Offspring

Chromosome change is directly proportional to the mutation probability value. A number of 100% indicates a complete chromosome change, whereas a value of 0% indicates no chromosome alteration. The process of mutation aids in keeping GA from degenerating into local extremes. In order to prevent GA from becoming a random search, mutations should not occur frequently [14][15].

D. Different Research Approach applied on GA

Genetic algorithms have evolved significantly through extensive academic research, yielding substantial enhancements in their efficiency and applicability. Various components of genetic algorithms have been refined as showed in figure 7 [1][16].

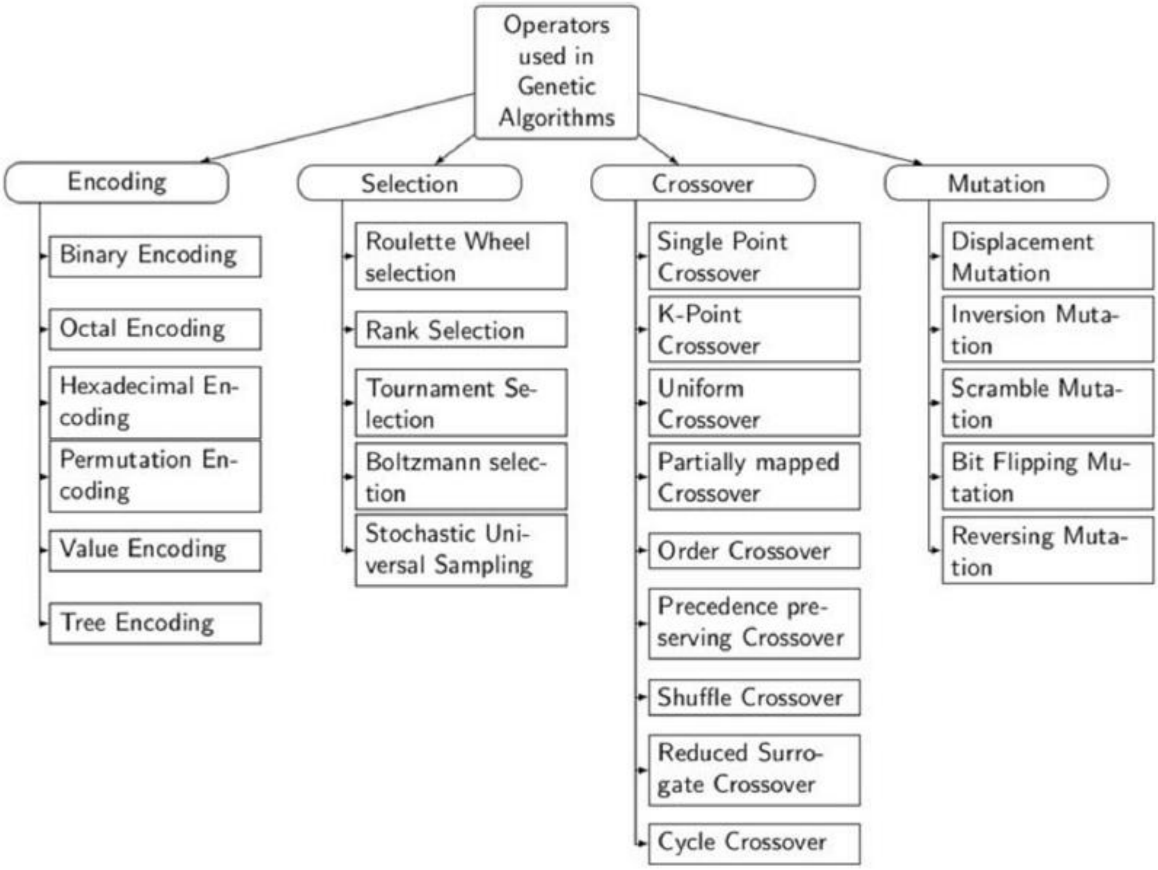

Figure 7. Operation used in GA

The image describes a hierarchy of the foremost operators employed in Genetic Algorithm systems (GAs) and classifies them into four broad classes namely; encoding, selection, crossover and mutation. Each class emphasizes different strategies that researchers may invent, amalgamate or even hybridize to improve how GAs perform. Encoding strategies such as binary, octal, hexadecimal, permutation, value and tree encoding are defined as ways of preparing certain representations of problem solutions and thus new forms of representation that suit the needs of particular problems can be invented. Selection methods such as roulette wheel, rank, tournament, Boltzmann selection and stochastic universal sampling offer many alternatives for selecting the fittest individuals for breeding and therefore create opportunities for hybrid selection methods. Crossover algorithms, which include but are not limited to single-point, k-point, uniform, partially mapped, order, precedence-preserving, shuffle, reduced surrogate and cycle crossover are methods of recombining genetic material wherein new or mixed methods can be utilized in fostering the diversity of offspring and optimization [17][18][19]. Mutation alteration procedures namely displacement, inversion, scramble, bit flipping, and reversing mutation mold genetic heterogeneity and avoid early fixation, thus allowing room for new or composite mutation techniques.[1][20][21].

E. Literature Review

A detailed search has been done through (Springer nature link, Multidisciplinary Digital Publishing Institute (MDPI), ResearchGate, Google Scholar, etc.) For identification of research papers related to GA. Based on the relevance and quality of research, 30 papers were selected for evaluation. The relevance of research is decided through a criteria that the research paper much be published only in year 2024 and it is the most relevant to Genetic algorithm (GA) in special and Metahuristical algorithm in general , and keywords of (Type of the Algorithm , Advantage , Limitation , domain area or used field) has been conducted as mentioned in table 1.

Table 1. Summary of the work Performed by most of the research reviewed in this paper

Ref	Year	Dataset	Advantages	limitations	Domain Area
[22]	2024	hybrid algorithm that combines Grammatical Evolution (GE) and Differential Evolution (DE)	improves predictive accuracy.	Limited to annual data analysis.	optimizes the estimation and prediction of India's primary energy
[23]	2024	a hybrid optimization approach that integrates the Firefly Algorithm (FA) with the Artificial Bee Colony (ABC) and Cultural Algorithm (CA)	Efficient optimization of complex problems with fast convergence.	may get trapped in local optima	optimization of reservoir operation rule curves (RORCs) to improve water management efficiency and mitigate water shortages during varying conditions
[24]	2024	hybrid approach that integrates a Genetic Algorithm (GA) with the Stepwise Weight Assessment Ratio Analysis (SWARA) and the Fuzzy Analytic Hierarchy Process (FAHP)	Robustness, multi-criteria optimization, human intuition.	Computational complexity, parameter tuning challenges.	sequence-dependent setup-based flow shop scheduling to enhance operational efficiency in manufacturing environments.
[25]	2024	hybrid genetic algorithm (HGAPSO) and adaptive particle swarm optimization (APSO)	mproved stability and trajectory optimization	Susceptible to local optima	improving the stability and success rate of mobile robots equipped with adaptive deformed wheels
[26]	2024	a hybrid genetic algorithm (HGA)	Enhances operational efficiency in bike-sharing systems	High computational burden and unvalidated real-world applicability.	the multi-objective optimization problem of inventory rebalancing and vehicle routing in bike-sharing systems to enhance operational efficiency while minimizing

					travel distances and inventory gaps
[27]	2024	hybrid approach integrating Genetic Algorithm (GA) and Tabu Search (TS)	Efficient, optimal solutions, reduced computational time, robust performance.	may struggle with very large-scale problems, sensitivity to parameters.	optimize preventive maintenance scheduling for cogeneration plants.
[28]	2024	a hybrid approach that integrates an improved tabu search algorithm (TSA) with a genetic algorithm (GA)	Efficient scheduling, improved resource allocation, enhanced stability, global search capability.	Complexity in implementation, potential local optima, dependency on parameter tuning.	optimizing ground station scheduling
[29]	2024	a hybrid algorithm combining the Genetic Algorithm (GA) and the Crow Search Algorithm (CSA)	Efficient optimization, hybridization, reduced computational resources.	High variability in estimates, slow convergence, local optima issues.	modeling and optimizing the Escherichia coli (E. coli) cultivation process , ie Fermentation process modelling
[30]	2024	a hybrid algorithm that combines the Beluga Whale Optimization (BWO), Honey Badger Algorithm (HBA), and Jellyfish Search (JS) optimizer.	Enhanced exploration, improved solution quality, versatile applications.	Complexity, parameter tuning, potential computational cost.	solving complex engineering design problems and enhances optimization performance through the integration of multiple optimization techniques.
[31]	2024	utilizes the Honey Badger Algorithm (HBA) and the Sand Cat Swarm Optimization (SCSO)	effective optimization, hybridization, exploration-exploitation balance.	trade-off complexity, sensitivity to parameters.	improve the quality of solutions in global optimization problems
[32]	2024	a hybrid algorithm called HWOA-TTA, which combines the Whale Optimizer Algorithm (WOA) and the Tiki-Taka Algorithm (TTA)	improved convergence and performance.	May struggle with local minima; computationally intensive for complex problems.	optimization problems in engineering design that enhances both exploration and exploitation phases
[33]	2024	a novel hybrid algorithm that integrates the Arithmetic Optimization Algorithm (AOA) and Simulated Annealing (SA) to optimize LightGBM hyperparameters	High accuracy, efficient hyperparameter optimization, robust performance in fault warning.	Complex parameter selection, potential operational cost increases, requires extensive validation.	enhance the performance in industrial fault warning applications
[34]	2024	a hybrid algorithm that combines Particle Swarm Optimization (PSO) and Smell Agent	Improved convergence, robust performance,	Increased computational complexity, potential	addresses global optimization problems by improving the convergence of PSO

		Optimization (SAO)	effective in diverse applications.	efficiency impact.	towards optimal solutions.
[35]	2024	the Chaotic Harris Hawks Optimization Algorithm	Enhanced exploratory behavior, cost reduction, scalability, effective in large networks.	Sensitivity to parameters, potential local optima issues in complex scenarios.	the challenges of efficient charge scheduling for electric vehicles, focusing on optimizing energy usage and grid stability
[36]	2024	a hybrid approach combining a genetic algorithm (GA), simulated annealing (SA), and variable neighborhood search (VNS)	Strong local search, global optimization, effective for dynamic scenarios.	Low convergence rate, potential local optima, longer computational times	optimize scheduling and rescheduling in response to dynamic events such as machine breakdowns and job arrivals.
[37]	2024	a hybrid algorithm combining Genetic Algorithm (GA) and Grey Wolf Optimizer (GWO)	Enhanced convergence speed, improved accuracy, balances global/local optimization.	otential local optima trapping, requires parameter tuning.	optimizing container transportation vehicle scheduling in surface coal mines.
[38]	2024	a hybrid method that combines Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANNs)	High accuracy, efficient feature selection, scalable, biologically relevant.	Parameter sensitivity, overfitting risk, computationally intensive, specific cancer focus.	cancer detection using microRNA analysis
[39]	2024	a hybrid optimization approach combining the Jellyfish Search (JS) algorithm and the Moth Flame Optimizer (MFO)	Efficient convergence, optimal solutions, hybrid approach benefits.	Higher voltage deviation, computational complexity in large systems.	solve the Optimal Power Flow problem.
[40]	2024	a hybrid algorithm that combines a multi-objective ant colony system with a simulated annealing algorithm	Efficient solutions, lower objective values, short computation time.	Limited supply, time constraints, potential for further optimization needed.	scheduling problem for disaster relief distribution
[41]	2024	Genetic Algorithms (GAs) enhanced with Self-Adaptive Simulated Binary Crossover (SBX)	Enhanced optimization, reduced error, efficient computational cost.	Challenges with smaller populations, specific function performance issues.	solving complex global optimization problems by integrating Self-Adaptive Simulated Binary Crossover and elitism.
[42]	2024	a hybrid optimization framework that combines Genetic Algorithms (GA) and Covariance Matrix Adaptation Evolution Strategy	High accuracy in classification; effective exploration of solution space.	Computationally intensive; may struggle with local optima.	classification of chemical compounds
[43]	2024	an improved non-dominated sorted genetic algorithm	fficient resource allocation, reduced greenhouse gas	Complexity in implementation and potential	optimizing project duration, costs, and greenhouse gas

		integrated with magnet-based crossover and mode reassignment techniques	emissions, and improved scheduling.	computational time challenges.	emissions in uncertain environments
[44]	2024	an enhanced genetic algorithm initialized with the Iterative Approximate Method	Improved initial population enhances solution quality and convergence speed.	performance may vary based on problem complexity and parameter settings.	Optimize the Traveling Salesman Problem (TSP)
[45]	2024	Crow Search Algorithm (CSA) for optimization	igh accuracy, effective optimization, diverse solution generation.	Sensitive to parameter tuning, computational resource requirements.	identifying and optimizing the mathematical model parameters to enhance model accuracy.
[46]	2024	a hybrid optimization technique that combines Genetic Algorithms (GA) and Quasi-Newton algorithms, along with Markov Chain Monte Carlo methods	Efficient optimization, handles uncertainty, improves energy modeling accuracy.	Computationally intensive, requires extensive data, may overfit models.	energy consumption and thermal performance of residential buildings, enhancing energy management and efficiency.
[47]	2024	Genetic Algorithm (GA) in conjunction with the Susceptible-Exposed-Infected-Recovered model	Efficient optimization of critical nodes in delay propagation.	May require extensive iterations for optimal results.	identifying critical nodes in route networks.
[48]	2024	improved genetic algorithm (IGA) that incorporates a population initialization method with directional guidance, a non-common point crossover operator, and various mutation techniques	Improved initialization, faster convergence, better global search capability.	Not tested in dynamic environments or multi-robot scenarios.	robot path planning.
[49]	2024	a genetic algorithm for the time-efficient optimization of parameters in wavelength modulation spectroscopy based gas sensors.	Efficient optimization, no derivative calculations, handles complex problems.	May require significant computational resources, risk of local minima.	enhance the signal-to-noise ratio (SNR) efficiently in wavelength modulation spectroscopy
[50]	2024	utilizes the two-phase Taguchi method (TPTM), hyperparameter artificial neural network (HANN), and genetic algorithm (GA)	Enhanced prediction accuracy and reduced computational demands.	Dataset-specific; generalizability may be limited without diverse data.	hyperparameter optimization in cardiovascular disease risk prediction.

[51]	2024	an improved genetic algorithm (GA)	Enhances transport efficiency and reduces congestion in underground mines.	Limited applicability to diverse mining conditions and route planning.	optimize scheduling for trackless transport in underground mines.

F. Discussion

The above table shows several hybrid algorithms which combine different optimization techniques and seeks to solve a variety of problems from different fields. In particular, the Hybrid Genetic Algorithm (HGA) is mentioned many times which indicates its scope in areas such as bike sharing systems and preventive maintenance scheduling. These algorithms tend to improve performance and decrease run time, but have limited effectiveness in high echelons tasks and are sensitive to parameters.

On the other hand, the Particle swarm optimization (PSO) in tandem with artificial neural networks (ANN) for cancer detection points out the focus on feature selection including biological aspects but has some weaknesses concerning overfitting and high computation requirements. The Crow search algorithm (CSA) in succession modeling the anaerobic digestion processes also gives high accuracy results but its performance is affected by parameter tuning.

Application of grammar-based problem formulations in conjunction with differential evolution in energy forecasting in India brings about good results in terms of forecasting but is restricted to yearly information. Jellyfish search (JS) and Moth flame optimization (MFO) hybrid method for optimal power flow is fast the convergence but may center on complexity in bigger systems.

Overall, while these hybrid algorithms exhibit significant advantages in terms of efficiency and solution quality, they also share common limitations, such as sensitivity to parameters and potential local optima issues. The findings suggest that further research is needed to enhance the robustness and applicability of these algorithms in diverse real-world scenarios.

G. Advantages of Genetic Algorithms (GAs)

1. No Derivative Information Required: GAs do not require derivative information, making them suitable for real-world problems where such information is often unavailable .
2. Parallel Capabilities: GAs can explore multiple solutions simultaneously, which enhances their efficiency compared to traditional algorithms .
3. Optimization of Various Functions: They can optimize both continuous and discrete functions, as well as multi-objective problems .
4. Diverse Solutions: Instead of providing a single solution, GAs generate a list of "good" results, offering multiple potential solutions to a problem .

5. Adaptability: GAs are adaptive to changing environments, making them applicable in dynamic scenarios .
6. Effective for Complex Problems: They are particularly effective in finding solutions for complex and real-world problems that may be difficult for other methods .

H. Limitations of Genetic Algorithms (GAs)

1. Computationally Expensive: GAs can be computationally intensive, especially for problems requiring frequent calculation of fitness values .
2. Stochastic Nature: There is no guarantee that GAs will always provide optimal or high-quality results, as their stochastic nature can lead to variability in outcomes .
3. Not Suitable for Simple Problems: GAs may not be the best choice for simpler problems where derivative information is available, as traditional methods may perform better .
4. Implementation Complexity: Proper implementation of GAs requires careful consideration of parameters and operators, which can complicate their use .

These advantages and disadvantages highlight the strengths and limitations of Genetic Algorithms, helping to determine their suitability for specific problems.

I. Applications of Genetic Algorithms (GAs)

1. Strategy Planning: Used in various strategic decision-making processes.
2. Robot Trajectory Planning: Helps in optimizing the paths taken by robots.
3. Traveling Salesman Problem (TSP): Effective in solving scheduling and routing problems.
4. Function Optimization: Applied in optimizing mathematical functions.
5. Control Systems: Used in gas pipeline control, missile evasion strategies, and other control applications.
6. Design Optimization: Employed in aircraft design and communication networks.
7. Manufacturing Scheduling: Useful in optimizing manufacturing processes.
8. Machine Learning: Applied in designing neural networks and improving classification algorithms.

J. Conclusion

This review paper offers a well-rounded analysis of Genetic, Algorithms GAs and the application in many contexts bearing in mind the optimization problems which have been observed to pose a number of challenges. These classes of algorithms are based on natural selection principles and have been shown to successfully deal with sophisticated problems for example well placement optimization in oil and gas, image segmentation problems, and scheduling problems in the healthcare sector. The literature espouses the development of capabilities such as a priori uncertainty quantification and multi-objective GA optimization which strengthen the performance of the GAs based on the literature. In addition, the evidence of GAs usage in different domains such as mobile ad-hoc networks and manufacturing layout design proves GAs to be a suitable computing tool. There is no doubt that they make research contribute to something meaningful because there is a lot of potential in such algorithms, they may help to solve certain tasks and thus help to improve the general decision making. This kind of review has the intent to help researchers and practitioners associate with the current stage and foreseeable perspectives of the development of optimization based on GAs.

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