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A Review of Optimization Techniques: Applications and Comparative Analysis

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ABSTRACT: Optimization algorithms exist to find solutions to various problems and then find out the optimal solutions. These algorithms are designed to reach desired goals with high accuracy and low error, as well as improve performance in various fields, including machine learning, operations research, physics, chemistry, and engineering. As technology continues to advance, optimization algorithms are increasingly needed to address complex real-world challenges and drive innovation across all disciplines. Quantitative leaps have been achieved in improving the efficiency of optimization algorithms through the diversity of sources of information feeding these algorithms according to the type of optimization problem, based on scientific and organized foundations. The objectives of this paper are to discuss the most important optimization algorithms, classify the scientific fields involved in their application, and optimize problems involved in this regard, in addition to providing a brief overview for comparison among these algorithms.
Keywords: Optimization algorithms, applications field, comparison approach, algorithm classification.

1. INTRODUCTION

Optimization algorithms have been a suitable approach to solving the most difficult problems in various real-world fields and systems, from engineering and economic sciences to health care. Nowadays, optimization algorithms have become widespread thanks to technological development. To keep pace with development and modernity, there has been an urgent need to develop and improve a wide range of optimization algorithms so that they are classified according to their speed and strength to achieve the required optimization goals with high efficiency. These algorithms have played a pioneering role in making constructive decisions to find optimal solutions to various problems. In this paper, it will be an extensive journey through time to explore and review the wonderful evidence of the most important optimization algorithms from the past to the present day. By delving deeper into the historical development patterns of these algorithms, insight into their development methods, basic principles, and notable applications can be gained. Among the highlights of our journey are early developments in the approach to optimization algorithms, for example, the gradient descent approach, which laid the foundation for many optimization techniques in machine learning as well as parameter optimization [1-3]. In addition, more research has delved into the origins of genetic algorithms, whose influence was inspired by the foundations of natural evolution, where their distinct influence was effective on resource allocation as well as engineering design problems [4-8]. Our journey also includes the detection of the emergence of simulated annealing, which was originally inspired by the physical process of annealing, as well as revolutionary harmonic optimization [9-15]. Particle swarm optimization (PSO) has joined the scope of flight, mimicking nature through organisms in their behavior to address the challenges of control engineering and parameter optimization [16-21], as well as the ant colony algorithm, inspired by the foraging behavior of ants, to solve routing and scheduling problems [22-24]. A motive for progress in various fields [25-27]. In addition, exploring the world of constrained programming, which is concerned with solving combinatorial problems with complex constraints, allows for effective scheduling and resource allocation in various applications [28-29]. The emergence of inner point methods provides efficiency and accuracy for linear and nonlinear programming problems, leading to great strides in optimization techniques [30-31]. Moreover, the innovative approach of Tobu searches with non-convex objectives was discussed, which, in its approach, uses memory-based strategies to navigate complex search spaces and excels in combinatorial optimization problems [32], [33]. The reality of convex optimization is also revealed, the power of which highlights applications in portfolio optimization, signal processing, and beyond [34-36]. By conducting this study and delving into the historical development of optimization algorithms, the tracker can estimate the evolution and transformation of

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optimization techniques over time. A map can be drawn showing each algorithm's contribution to solving real-world problems and shaping developments in various fields, and the recipient can appreciate the evolution and transformation of optimization techniques over time. Our goal is also to provide a comprehensive perspective on the most important optimization algorithms, their basic principles, and their impact on various fields. By understanding their strengths, limitations, and historical context, the current state of optimization algorithms can be better estimated, and the upcoming trends in this area of dynamic development can be predicted. As we embark on a journey into the world of optimization algorithms and reveal their impact on problem-solving, a visual guide awaits us at the doorstep. The following flowchart briefly captures the various types of optimization algorithms, serving as our navigation tool in understanding their multifaceted applications (see Fig. 1).

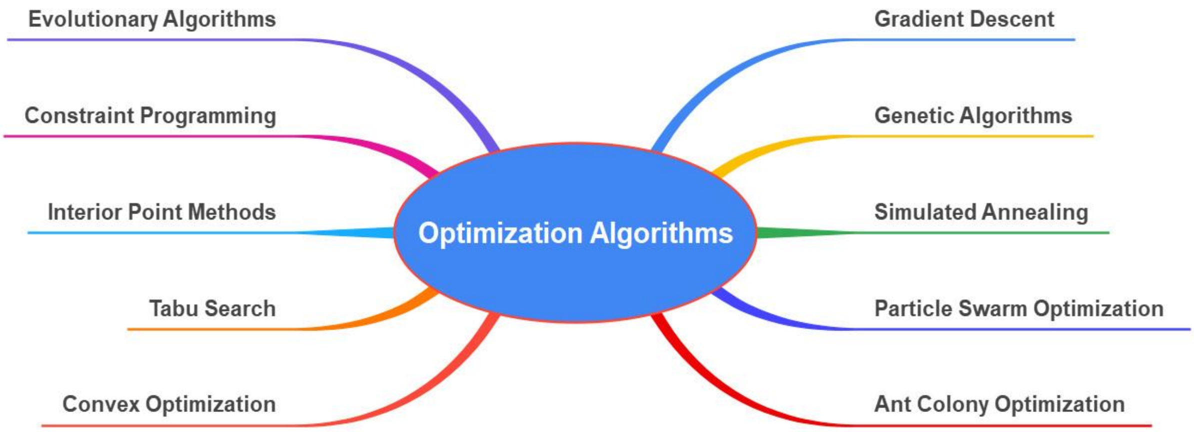

FIGURE 1. **Flowchart depicting target types of optimization algorithms.**

2. EXPLORING OPTIMIZATION ALGORITHMS FOR DIVERSE CHALLENGES

Optimization algorithms serve as guides for navigating the vast landscape of possible solutions to most problems. These algorithms have revolutionized our ability to tackle complex problems across many domains. This section takes a magnifying glass to some of the most important and notable optimization techniques, highlights their basic principles, and unveils quite a few of the applications that have propelled them to the forefront of modern computational methods.

2.1 GRADIENT DESCENT

The gradient descent algorithm is one of the fundamental algorithms that dates back to the early 19th century. In fact, this method was first introduced by French scientist Augustin-Louis Cauchy, and it gained a lot of attention for solving optimization problems during the 20th century [37]. With the introduction of machine learning and neural networks, the gradient descent approach became a basic algorithm for optimizing model parameters, as it played an important role in this regard. By taking the reduction of the cost or loss function as a main goal and by modifying the model parameters iteratively, this is achieved. The technique determines the gradient descent and the steepest descent direction by calculating the gradient of the cost function concerning the parameters, and it updates the parameters step by step accordingly. Right up to the modern era, with the advent of deep learning, the gradient descent approach has been of distinct importance due to its ability to efficiently optimize and process complex models.

2.2 GENETIC ALGORITHMS

Based on natural selection and genetics, the genetic algorithm was inspired, as it is a series of steps that simulate an evolutionary process to obtain optimal solutions. Genetic algorithm procedures involve creating and generating numerous possible solutions, and these solutions are evaluated according to a predetermined objective function, which goes on to select the best individuals for reproduction. Population fitness is gradually improved over generations by generating new offspring through a process of cross-breeding and mutation. John Holland and his colleagues continued to develop the genetic algorithm approach in the 1960s and 1970s [38]. As a result, the inspiration of natural selection and evolutionary biology led to the crystallization of the idea of formulating genetic algorithms as a means to solve optimization problems that are at a level of complexity due to the advantage of this algorithm through large search areas within complex constraints. His book, "Adaptation in Natural and Artificial Systems," was the basis for this field, and it was published in 1975.

2.3 SIMULATED ANNEALING

Simulated annealing is a procedure inspired by the physical annealing process, which includes several procedures to obtain a solution to the optimization problems. This approach is particularly effective and valuable when dealing with optimization problems of discrete or combined types. The first steps are that the algorithm starts with an initial guess of the solution and then explores the solution space iteratively, and suboptimal moves are accepted based on the probability distribution as the approach allows a greater probability of accepting the worst solutions based on simulating the idea of high-temperature annealing, and then the solutions are selected for optimization problems. As the temperature decreases over time, the acceptability of the worst-case solution decreases and converges toward the global optimum. S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi simulated annealing in 1983 [39]. The physical process of annealing in metallurgy, in which a material is gradually heated and cooled to reduce its defects inspired the algorithm. From this principle, simulated annealing applies a similar concept to optimization problems, progressively exploring the solution space with controlled acceptance of suboptimal motions, as the solutions through it are almost ideal for harmonic optimization problems. An algorithm called process annealing is used to reduce defects and improve the crystal structure of the material through a gradual heating and cooling process. Simulated annealing provides the opportunity to explore the search space by accepting the worst-case solutions early in the search process when the temperature is at its highest. The algorithm becomes more selective and tends to converge toward better solutions as the temperature decreases. This balance between exploitation and exploration thus enables the simulated annealing process to escape local optimization and find near-optimal solutions. Applications of this algorithm have taken a wide range and have been successful in solving a range of optimization problems, including scheduling problems, traveling salesman problem, combinatorial optimization, and circuit design in different domains. It is particularly useful for processing when the objective function is not convex or noisy where traditional optimization methods have great difficulty finding good solutions.

2.4 PARTICLE SWARM OPTIMIZATION (PSO)

A population-based metaheuristic method called PSO draws its inspiration from the social behavior of fish schools and bird flocks. A collection of particles that have a function and speed in the solution area show capacity answers in PSO. Based on their collective revel in and the modern best global solution, the particles collaborate and communicate to transport in the direction of superior solutions. PSO has applications in fields such as statistics clustering, photo processing, and neural community education and is specifically a success for non-stop optimization problems. James Kennedy and Russell Eberhart proposed PSO in 1995 [40]. PSO simulates the movement of debris in a multidimensional search area and is stimulated by the social conduct of fish faculties and flocks of birds. The set of rules's success in handling issues involving non-stop optimization helped it end up being broadly used. The approach is based on a set of the particles, each of which represents a capacity answer to the optimization problem and moves around the search space. In addition to the studies of the particles in the swarm, the debris interact with one another and switch positions in reaction to their personal stories. This is acting in a fine manner. In PSO, particles collaborate interact with one another to trade expertise approximately about successful answers discovered within the search area. A particle's speed is altered in step with both its personal highest quality function and the greatest function determined by means of the swarm. The particles can discover the hunting space and converge over iterations to advanced answers thanks to their cooperative behavior. PSO is renowned for solving continuous and discrete optimization problems without difficulty and effectiveness. It has been used for a variety of specific functions, such as characteristic choice, statistics clustering, neural community education, and feature optimization. PSO, however, is susceptible to parameter settings and can be afflicted by untimely convergence to inferior answers. As a result, rigorous parameter adjustment and PSO versions, such as hybrid procedures or adaptive techniques, are frequently applied to enhance their performance on specific problem domains.

2.5 ANT COLONY OPTIMIZATION (ACO)

Ant colony optimization (ACO) phenomenon mimics the foraging conduct of ants to locate the finest paths through networks or graphs. This set of rules is applied to routing, scheduling, and logistics optimization issues. The program mimics the pheromone trail left behind by ants, which draws other ants to useful passageways. As more ants cross the problem vicinity, the pheromone path is bolstered, and the algorithm moves in the ideal direction. ACO has demonstrated its efficacy in resolving complex problems with a lot of boundaries and dynamic situations. Marco Doregio came up with the concept for an ACO task in the early 1990s [41]. Deriving the concept from the foraging pastime of ants, he found the inspiration for his paintings on this route and laid out an approach to ant colony improvement. This optimization method is an effective way to resolve optimization problems regarding graph and network traversal..

2.6 EVOLUTIONARY ALGORITHMS

Evolutionary algorithms (EAs) is a term that refers to a set of optimization algorithms whose suggestions come from the principles of natural selection and genetics. Central to those algorithms are iterative production processes and the assessment of feasible solutions, inclusive of genetic programming (GP) and evolutionary strategies (ES). The basis process of those algorithms is to simulate organic evolution through the incorporation of factors of selection, intersection, and mutation to push a collection of individuals toward optimal solutions. When it involves fixing complicated and multidimensional optimization issues, EAs are very useful. Researchers John Holland, Ingo Rechenberg, and Hans-Paul Schwefel did paintings within the area of EAs in the 1960s and 1970s [42]. EAs represent a distinct family of algorithms made possible by means of their contributions to genetic algorithms, evolutionary techniques, and evolutionary programming.

2.7 CONSTRAINT PROGRAMMING

The constraint programming (CP) method is a pioneering problem-solving method wherein issues are optimized while ensuring that a set of special constraints are met. The problem is formulated with the aid of defining a collection of variables, their respective domains, and a fixed set of constraints. Constraint propagation techniques are then employed to steadily lessen the search space through iterative strategies. Through the utilization of smart seek techniques, computational hassle-solving algorithms efficaciously navigate the solution space while maintaining adherence to the required barriers. The usage of CP is universal within the domains of scheduling, resource allocation, and making plans quandaries. The beginnings of CP can be traced back to the 1960s, when algorithms were first developed to deal with the demanding situations posed with the aid of constraint fulfilment troubles [43]. Over time, scholars have made improvements and expansions to the approach, resulting in the status quo of CP as a distinct and recognized field.

2.8 INTERIOR POINT METHODS

Interior point methods (IPMs) are extraordinarily powerful optimization techniques for the solution of both linear and nonlinear programming issues. In contrast to conventional approaches that contain the exploration of the bounds of the viable region, interior factor techniques (IPMs) navigate into the interiors of the viable area. With barrier features, indoors point techniques (IPMs) have the capacity to transform restricted optimization troubles into unconstrained ones, subsequently allowing the iterative approximation toward the top-of-the-line solution. Integrated pest management (IPM) has demonstrated its efficacy in addressing optimization problems of considerable size, characterized by a substantial number of variables and restrictions. The inception of interior point approaches for optimization occurred throughout the latter years of the 1980s and the early years of the 1990s [44]. Prominent scholars, such as Narendra Karmarkar and Yurii Nesterov, have achieved noteworthy advancements in the realm of interior point techniques, thereby bringing about a transformative impact on the domain of linear and nonlinear programming.

2.9 TABU SEARCH

Tabu search (TS) is a heuristic algorithm that is specially used to optimize model parameters for combinatorial optimization problems. Moreover, descriptive inference is a general strategy used to direct and control actual inference. TS works by incorporating memory structures into local search strategies because local search has many limitations. TS is designed to address common problems of this kind. It was first proposed by Glover and further developed by Hansen [45]. Nowadays, TS is a well-established research procedure, and its applications have been effective and successful in solving a wide range of optimization problems [46]. TS encourages the exploration of unvisited areas in the solution space by imposing restrictions on moves that may lead to revisiting previously encountered solutions. This mechanism facilitates the algorithm's ability to avoid the trap of local optimization and enhances its ability to discover optimal solutions. TS application has shown successful results on combinatorial optimization problems. Fred W. Glover introduced TS during the late 1980s. The algorithm was developed as a means of expanding upon local search approaches by integrating a memory mechanism to overcome the limitations of local optima. Glover's influential publication titled "Tabu Search: Part I," which was released in 1986, included a thorough examination of the algorithm and its various uses.

2.10 CONVEX OPTIMIZATION

Convex optimization pertains to the resolution of optimization problems in which both the goal function and the constraints exhibit convexity. The property of convexity guarantees that any local minimum discovered is, in fact, the global minimum. Convex optimization algorithms, such as inner-point methods and sequential quadratic programming, take advantage of the inherent properties of convex functions to effectively address optimization problems. Convex optimization has been extensively employed in the fields of machine learning and signal processing. The field of convex optimization possesses a significant historical background that can be traced back to the initial decades of the 20th century. Prominent scholars, namely R.L. Graves, D.G. Luenberger, and Stephen Boyd, have made noteworthy advancements in the realm of convex optimization algorithms, in terms of both theoretical foundations and practical implementations [47-49].

3. APPLICATIONS OF OPTIMIZATION ALGORITHM

This extensive section aims to explore the exceptional adaptability of optimization methods in various sectors. Tables 1 and 2 serve as evidence of the significant influence exerted by these algorithms. These tables provide valuable insight into the capabilities of optimization algorithms to bypass practical limitations and deliver solutions and workarounds across a wide range of contexts.

3.1 NAVIGATING OPTIMIZATION PROBLEM TYPES AND CORRESPONDING ALGORITHMS

As a result of the difficulties in the complex world of optimization, there is an urgent need to find specialized techniques to solve these difficulties and to classify the solutions that have been reached according to the type of problem, which saves time and effort for the stakeholders, as Table 1 provides a comprehensive investigation for this purpose. This visual guide serves as a navigational tool, emphasizing the dynamic relationships between algorithms and various problem scenarios as well as the vast terrain of optimization problem-solving.

Table 1. Optimization algorithms and their applications to corresponding optimization problems in the real world.

Optimization Algorithm	Optimization Problems
Genetic Algorithms	Resource allocation
	Scheduling problems
Simulated Annealing	Engineering design problems
	Combinatorial optimization
Particle Swarm Optimization	Parameter optimization in machine learning
	Control engineering problems
	Energy system optimization
Ant Colony Optimization	Routing and scheduling problems
	Data clustering
Evolutionary Algorithms	Multi-objective optimization problems
	Graph problems and optimization
Constraint Programming	Scheduling and resource allocation problems
	Complex constraint optimization problems
Interior Point Methods	Linear programming problems
	Combinatorial problems with complex constraints
Tabu Search	Combinatorial optimization problems
	Nonlinear programming problems
Convex Optimization	Portfolio optimization
	Signal processing applications
	Non-convex and discontinuous objective functions
Gradient Descent	Machine learning model training

Fig. 2 shows a mutually beneficial relationship between problem landscapes and optimization strategies. As we examine the specifics, each row reveals how well an algorithm handles a particular problem. The deliberate coupling of algorithms and their domains is strikingly highlighted by this organized arrangement. Each submission demonstrates the adaptability and creativity these algorithms bring to both practical and theoretical concerns.

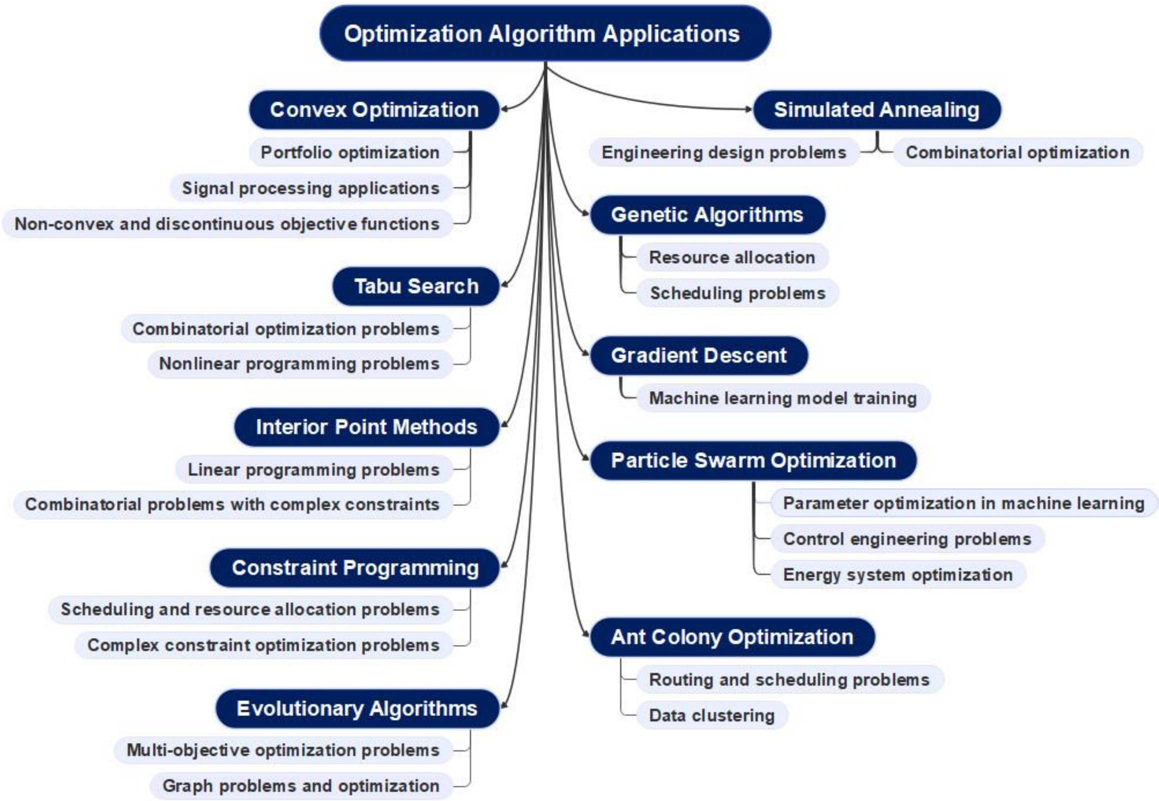

FIGURE 2. A comprehensive mapping for optimization algorithms and corresponding problem types.

4. APPLICATIONS OF OPTIMIZATION ALGORITHMS IN THE APPLIED SCIENCES

Table 2 focuses on particular applications in several sciences, with a particular emphasis on the crucial roles that optimization algorithms play in the fields of chemistry, physics, and engineering. Here, the main situations in which these algorithms have a significant impact will be examined, highlighting their importance and contributions in these dynamic areas.

Table 2. Optimization algorithms applications in applied Sciences

Optimization Algorithm	Optimization Problem	Chemistry	Physics	Engineering
Genetic Algorithms	Resource allocation	Optimal allocation of reagents, materials, and resources.	Optimal resource allocation in experiments.	Allocation of resources in production systems.
	Scheduling problems	Lab experiment scheduling, reaction scheduling, process scheduling.	Experimental setup scheduling.	Task scheduling, project scheduling.
	Engineering design problems	Molecular structure optimization, catalyst design.	Material design, structure optimization.	Optimal design of structures, systems, circuits.
Simulated Annealing Applications	Combinatorial optimization	Molecular conformation search, combinatorial	Spin glass models, Ising model	Optimal configuration of networks,

		library design.		circuits.
	Energy system optimization	Optimal reaction conditions, energy landscape exploration.	Ground state calculations.	Energy-efficient systems, building optimization.
Particle Swarm Optimization Applications	Parameter optimization in machine learning	Molecular property prediction, molecular docking.	Parameter estimation, fitting models.	Optimization of control systems, system identification.
	Control engineering problems	Optimal control of chemical processes, automation systems.	Optimal control of physical systems.	PID controller tuning, trajectory optimization.
	Data clustering	Chemical data clustering, structure-activity relationship analysis.	Cluster identification, phase transitions.	Image segmentation, pattern recognition.
Ant Colony Optimization Applications	Routing and scheduling problems	Supply chain logistics, delivery route optimization.	Network routing, traffic flow optimization.	Production scheduling, vehicle routing.
	Graph problems and optimization	Molecular graph analysis, molecular structure generation.	Network analysis, optimization on graphs.	Circuit design, graph-based optimization.
Evolutionary Algorithms Applications	Multi-objective optimization problems	Drug discovery with multiple objectives, molecular diversity.	Optimization of physical systems with conflicting objectives.	Optimization of complex engineering systems.
	Complex constraint optimization problems	Molecular structure optimization with constraints.	Optimization with physical and mathematical constraints.	Optimization of engineering systems with complex constraints.
Constraint Programming Applications	Scheduling and resource allocation problems	Lab experiment scheduling, production scheduling.	Experimental setup scheduling, equipment scheduling.	Resource allocation, project scheduling.
	Combinatorial problems with complex constraints	Design of molecules with specific properties, combinatorial library design.	Constraint satisfaction problems in physics simulations.	Design optimization with complex constraints, configuration problems.
Interior Point Methods Applications	Linear programming problems	Optimal resource allocation, mixture design.	Optimization of experimental conditions.	Production planning, supply chain optimization.

	Nonlinear programming problems	Reaction optimization, parameter estimation.	Quantum mechanical calculations, model fitting.	Optimal control systems, process optimization.
Tabu Search Applications	Combinatorial optimization	Molecular conformation search, combinatorial library design.	Spin glass models, optimization problems.	Network design, optimization of processes.
	Non-convex and discontinuous objective functions	Optimization of reaction conditions with complex objective functions.	Optimization of physical systems with non-convex objectives.	Optimization of engineering systems with non-convex objectives.
Convex Optimization Applications	Portfolio optimization	Optimal allocation of investments, risk management.	Portfolio optimization, risk analysis.	Optimal allocation of resources, investment planning.
	Signal processing applications	Spectral analysis, signal denoising	Signal processing, image reconstruction.	Image processing, audio signal enhancement.

5. A COMPARISON OF THE OPTIMIZATION ALGORITHMS

In light of the aforementioned, it was necessary to establish a comparative analysis of the characteristics exhibited by the algorithms under investigation in our research. The present analysis presents a comparative examination of the fundamental characteristics of the designated optimization methodologies, as summarized in Table 3.

Table 3. An overview highlighting key attributes of optimization algorithms through comparison.

Algorithm	Approach	Problem Types	Search Space	Memory Usage	Key Advantage
Gradient Descent	Iterative, gradient-based	Continuous, differentiable	Large	Low	Efficient for optimizing machine learning models and neural networks.
Genetic Algorithms	Evolutionary, population-based	Combinatorial	Large, discrete	High	Effective for problems with large search spaces and complex constraints.
Particle Swarm Optimization	Population-based, social behavior	Continuous, combinatorial	Large	Low	Efficient for continuous optimization problems and inspired by natural collective behavior.
Ant Colony Optimization	Stochastic, trail-based, collective	Combinatorial	Large, discrete	Low	Suitable for problems involving routing, scheduling, and logistics,

					effective in dynamic and changing environments.
Evolutionary Algorithms	Evolutionary, population-based	Combinatorial	Large	High	Effective for complex optimization problems with multidimensional search spaces.
Constraint Programming	Constraint-based, intelligent search	Combinatorial	Large, discrete	Low	Suitable for problems with a set of constraints that need to be satisfied.
Interior Point Methods	Convex optimization, interior traversal	Linear, nonlinear	Large	Low	Efficient for solving linear and nonlinear programming problems.
Tabu Search	Metaheuristic, adaptive memory	Combinatorial	Large, discrete	Moderate	Escapes local optima, explores new regions in the solution space.
Convex Optimization	Convex function-based, specific methods	Convex	Large	Low	Efficient for solving optimization problems with convex objectives and constraints.

Finally, Table 4 provides an effective comparison of the characteristics of optimization algorithms. The table addresses key aspects, such as execution speed, computing cost, and compatibility with the real environment, in addition to a comprehensive analysis that enables the user to understand the prominent differences between these algorithms.

Table 4. **Comprehensive comparative analysis of the performance and integration of optimization algorithms.**

Algorithm	Speed of implementation	Computing cost	Compatibility with the real environment	Analysis
Genetic Algorithms	Variable	Medium	Strong	Flexibility and strength in solving complex problems.
Simulated Annealing	Medium to slow	Low to medium	Good	Average performance, change efficiency, balance between exploration and exploitation.
Particle Swarm Optimization	Medium to slow	Low to medium	Good	Fast, versatile adaptation, large-scale problems.
Ant Colony Optimization	Medium to slow	Low to medium	Good	Excellent guidance, environmental adaptation,

				effective in improving distribution.
Evolutionary Algorithms	variable	Medium	Strong	Strength in optimization and design, interest in complexity.
Constraint Programming	variable	Medium	Good	Excellence in problem-solving, strength in resource planning, interest in memory and complexity.
Interior Point Methods	Fast to medium	Low to medium	Strong	Fast, effective in solving specific problems, powerful in software improvement.
Tabu Search	Medium to slow	Low to medium	Good	Average results, good in optimization and scheduling, attention to memory

6. DISCUSSION AND CONCLUSION

Optimization algorithms are important to many scientific disciplines, including chemistry, physics, and engineering. Each algorithm has strengths and distinct features that make it better suited for specific applications. The gradient descent algorithm plays a crucial role in the training of machine learning models and the optimization of parameters, while genetic algorithms demonstrate exceptional performance in addressing resource allocation and engineering design challenges. The simulation annealing algorithm has proven effective in the field of combinatorial optimization and power system optimization, while the particle swarm algorithm has proven effective in the context of parameter optimization and control engineering. The study demonstrated that ACO was useful in addressing routing and scheduling difficulties, while EAs were particularly effective in dealing with multi-objective optimization and complex constraint problems. The comparison showed that constrained programming was characterized by high efficiency in solving scheduling and combinatorial problems that included complex constraints, while internal point approaches excelled in both linear and nonlinear programming. Furthermore, the Tabu search algorithm was suitable for dealing with non-convex targets, which enhances its role in the field of combinatorial optimization. In the context of portfolio optimization and signal processing applications, convex optimization has proven effective. Finally, the nature of the problem dictates the use of certain optimization algorithms over others, as the nature of the problem, its inherent features, and the specific requirements of the application are more compatible with certain types of algorithms than others.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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