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Research Article

Overview of Metaheuristic Algorithms

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ABSTRACT

Metaheuristic algorithms are optimization algorithms that are used to address complicated issues that cannot be solved using standard approaches. These algorithms are inspired by natural processes such as genetics, swarm behavior, and evolution, and they are used to explore a broad search space to identify the global optimum of a problem. Genetic algorithms, particle swarm optimization, ant colony optimization, simulated annealing, and tabu search are examples of popular metaheuristic algorithms. These algorithms have been widely utilized to address complicated issues in domains like as engineering, finance, and computer science. In general, the history of metaheuristic algorithms spans several decades and involves the development of various optimization algorithms that are inspired by natural systems. Metaheuristic algorithms have become a valuable tool in solving complex optimization problems in various fields, and they are likely to continue to play an important role in the development of new technologies and applications.

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1. INTRODUCTION

Metaheuristic algorithms are optimization algorithms that are used to find the optimal solution for complex problems that cannot be solved using traditional methods. These algorithms are inspired by natural phenomena such as genetics, swarm behavior, and evolution, and they are used to find the global optimum of a problem by exploring a large search space. Some popular metaheuristic algorithms include genetic algorithms, particle swarm optimization, ant colony optimization, simulated annealing, and tabu search. These algorithms have been widely used in various fields such as engineering, finance, and computer science to solve complex problems(Fister, Yang, et al., 2013a). One of the advantages of metaheuristic algorithms is that they do not require an initial starting point for the optimization problem. This makes them particularly useful for solving complex problems where the initial conditions are not known. Additionally, metaheuristic algorithms can handle large and complex search spaces, which traditional optimization methods cannot. However, one of the main drawbacks of metaheuristic algorithms is that they may not always find the global optimum(M. Almufti, Boya Marqas, et al., 2019). Due to the random nature of the algorithm, there is no guarantee that the algorithm will find the best solution. Additionally, the algorithms can be computationally expensive, especially when dealing with large search spaces. Overall, metaheuristic algorithms are powerful optimization tools that can be used to solve complex problems. However, they should be used with caution and with a thorough understanding of the problem being solved(M. Almufti et al., 2023). In general, metaheuristic algorithms have several advantages and disadvantages, and the choice of algorithm depends on the characteristics of the optimization problem and the available computing resources (Rai & Tyagi, 2013). Metaheuristic algorithms can provide an effective tool for solving complex optimization problems, but their limitations should also be considered.

2. Metaheuristic Algorithms

The term "metaheuristics" refers to a "higher level of heuristics" and is a combination of the words "meta" and "heuristic," where "meta" means beyond or higher level and "heuristic" refers to finding or discovering a goal by trial and error. Historically, methods with stochastic mechanisms were frequently referred to as "heuristic algorithms." often, metaheuristic algorithms function as "master strategies that direct and modify other heuristics to produce solutions beyond those that are typically generated in a quest for local optimality". These algorithms modify local search and randomization in a specific way. In a fair amount of time, excellent solutions to challenging optimization issues can be developed. But in general, there is no guarantee of finding optimal solutions(S. Almufti, 2017).

The term "metaheuristic" refers to a higher-level procedure or heuristic in the fields of computer science, mathematical optimization, and engineering that is used to search for, find, generate, or select a heuristic that may offer a good solution to an optimization problem, particularly for large problems like (NP-hard problem) or in cases of limit, incomplete, or imperfect information. The collection of solutions in a metaheuristic is too big to sample entirely. Metaheuristics can be used for a range of issues since they may not make many assumptions about the optimization problem being handled(S. M. Almufti, 2022a). In contrast to iterative or optimization techniques, metaheuristics do not ensure that the optimum solution for a given class of problems can be identified. Numerous metaheuristics use stochastic optimization in some way, which means that the solution is based on the set of produced random variables(Ihsan et al., 2021). Metaheuristics may frequently identify good solutions in combinatorial optimization with less computing work than optimization algorithms, iterative techniques, or basic heuristics since they search through a vast range of viable alternatives. Because of this, they are effective strategies for solving optimization issues (Sadeeq et al., 2021).

Most literature on metaheuristics is experimental in nature, describing empirical results based on computer experiments with the algorithms. But some formal theoretical results are also available, often on convergence and the possibility of finding the global optimum. Many metaheuristic methods have been published with claims of novelty and practical efficacy. While the field also features high-quality research, many of the publications have been of poor quality; flaws include vagueness, lack of conceptual elaboration, poor experiments, and ignorance of previous literature (Agrawal et al., 2021).

These are properties that characterize most metaheuristics:

- Metaheuristics are strategies that guide the search process.
- The goal is to efficiently explore the search space in order to find near–optimal solutions.
- Techniques which constitute metaheuristic algorithms range from simple local search procedures to complex learning processes.
- Metaheuristic algorithms are approximate and usually non-deterministic.
- Metaheuristics are not problem-specific.

3. Wel-Known Metaheuristic Algorithms

There are many metaheuristic algorithms that have been developed over the years, each with its own strengths and weaknesses. Here are some of the most well-known metaheuristic algorithms, along with a brief description of how they work:

1. Genetic Algorithms (GA): GA is inspired by the principles of natural selection and genetics. It starts by randomly generating an initial population of solutions, and then evolves the population by applying operators such as selection, crossover, and mutation. These operators simulate the process of natural selection, where individuals with higher fitness are more likely to reproduce and pass on their traits to the next generation. GA has been widely used in optimization problems that involve finding the best combination of parameters or features(Acan et al., n.d.).

2. Particle Swarm Optimization (PSO): PSO is a swarm intelligence algorithm that is inspired by the collective behavior of social organisms, such as birds flocking or fish schooling. It starts by randomly generating a swarm of particles, each representing a potential solution to the optimization problem. Each particle moves in the search space based on its own position and velocity, as well as the best position found by the swarm so far. PSO has been widely used in optimization problems that involve finding the best configuration of weights in neural networks or other machine learning models(M. Almufti, Yahya Zebari, et al., 2019).

3. Simulated Annealing (SA): SA is a stochastic optimization algorithm that is inspired by the process of annealing in metallurgy. It starts by randomly generating an initial solution, and then gradually reduces the temperature of the system. As the temperature decreases, the algorithm becomes more likely to accept worse solutions in order to escape local optima. SA has been widely used in optimization problems that involve finding the best configuration of parameters in complex models or simulations(Asaad & Abdulnabi, 2018).

4. Tabu Search (TS): TS is a metaheuristic algorithm that is inspired by the concept of memory in human decision-making. It starts by randomly generating an initial solution, and then searches the neighborhood of the solution by applying operators such as swapping or reversing. The algorithm uses a tabu list to remember recently visited solutions and avoids revisiting them. TS has been widely used in optimization problems that involve finding the best sequence of actions or decisions, such as scheduling or routing(Acan & Ünveren, 2015; Ridwan B. Marqas et al., 2020).

5. Ant Colony Optimization (ACO): ACO is a swarm intelligence algorithm that is inspired by the behavior of ants in finding the shortest path between their nest and a food source. It starts by randomly generating an initial set of pheromone trails, which represent the quality of the solutions found so far. As ants move through the search space, they deposit or follow pheromone trails based on the quality of the solutions they find. ACO has been widely used in optimization problems that involve finding the best routes or paths, such as in logistics or transportation(Agrawal et al., 2021).

These are just a few examples of the many metaheuristic algorithms that have been developed over the years. Each algorithm has its own strengths and weaknesses, and the choice of algorithm depends on the characteristics of the optimization problem and the available computing resources(Dubey et al., 2014; Fister, Yang, et al., 2013a; Mishra & Mishra Scholar, 2017).

4. Metaheuristic Algorithms Classifications

Metaheuristic algorithms can be classified in several ways based on different criteria. Here are some common classifications (S. Almufti, 2017, 2021; S. M. Almufti, Saeed, et al., n.d.):

1. Nature-inspired vs. non-nature-inspired: Metaheuristics can be classified based on whether they are inspired by natural processes or not. Nature-inspired metaheuristics include algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization. Non-nature-inspired metaheuristics include algorithms such as simulated annealing and tabu search.
2. Single-solution vs. population-based: Metaheuristics can also be classified based on whether they operate on a single solution or a population of solutions. Single-solution metaheuristics include algorithms such as simulated annealing and hill climbing. Population-based metaheuristics include algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization.
3. Deterministic vs. stochastic: Metaheuristics can be classified based on whether they use deterministic or stochastic processes. Deterministic metaheuristics use deterministic processes to generate new solutions. Examples include hill climbing and deterministic annealing. Stochastic metaheuristics use stochastic processes to generate new solutions. Examples include genetic algorithms and simulated annealing.
4. Trajectory-based vs. population-based: Metaheuristics can also be classified based on whether they focus on finding a single solution or multiple solutions. Trajectory-based metaheuristics focus on finding a single solution and use iterative improvement to refine that solution. Examples include hill climbing and simulated annealing. Population-based metaheuristics focus on finding multiple solutions and use a population of solutions to explore the search space. Examples include genetic algorithms and particle swarm optimization.
5. Local search-based vs. global search-based: Metaheuristics can be classified based on whether they focus on exploring the local search space or the global search space. Local search-based metaheuristics focus on finding solutions in the immediate vicinity of the current solution. Examples include hill climbing and tabu search. Global search-based metaheuristics focus on exploring the entire search space. Examples include genetic algorithms and ant colony optimization.

Unlike traditional optimization techniques that rely on mathematical models and assumptions, metaheuristics are problem-independent and can adapt to different types of problems with minimal modifications. Some of the main features of metaheuristic algorithms are (Bhuvaneswari et al., 2014; Fister, Yang, et al., 2013b; Selvaraj & Kumar, n.d.):

a) Exploration and exploitation: Metaheuristics balance the exploration of the search space to discover new promising solutions and the exploitation of the already discovered solutions to refine them further.
b) Stochastic search: Metaheuristics use randomization to generate new solutions and avoid being trapped in local optima.
c) Iterative improvement: Metaheuristics improve the quality of the solutions iteratively by repeatedly applying modifications to the existing solutions.
d) Robustness: Metaheuristics are designed to handle noisy and uncertain problem instances by avoiding the dependence on specific problem characteristics and assumptions.
e) Flexibility: Metaheuristics can be customized and adapted to different problem domains by changing the selection criteria, neighborhood structures, and search strategies.
f) Parallelism: Metaheuristics can be easily parallelized to speed up the search process and solve large-scale problems efficiently.

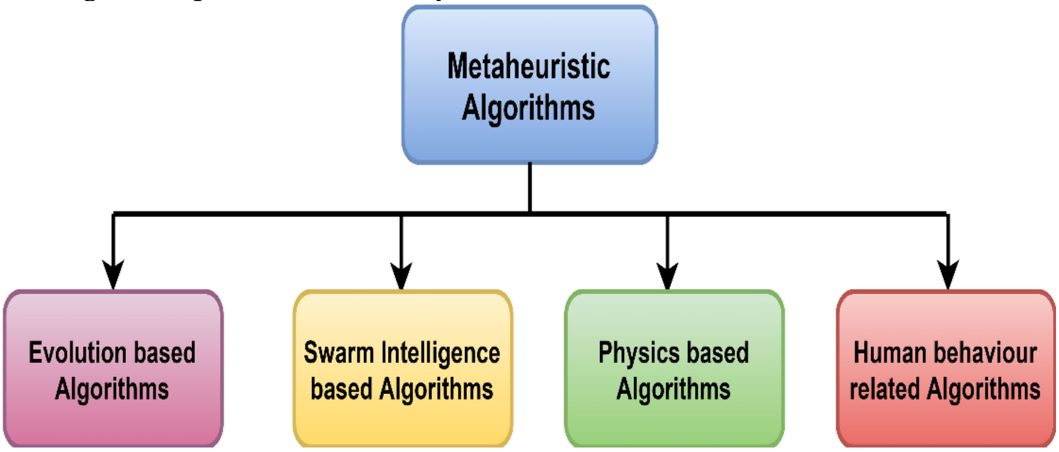

Figure 1: Metaheuristic Algorithm classifications

Evolutionary based algorithms

Evolutionary algorithms (EAs) are a class of metaheuristic algorithms that are inspired by the process of natural evolution. They are based on the principles of survival of the fittest, reproduction, and mutation. EAs work by creating a population of potential solutions to a problem and then iteratively evolving and improving that population through selection, crossover, and mutation operations(Bäck & Schwefel, 1993; Bartz-Beielstein et al., 2014).

Some common types of evolutionary algorithms include:

1. Genetic algorithm (GA): GA is one of the most widely used EAs. It is based on the principles of natural selection and genetic inheritance. GA has been applied to a wide range of problems such as optimization, classification, and clustering(Acan et al., n.d.; Luis & Sequera, n.d.).
2. Evolutionary programming (EP): EP is a stochastic optimization technique that is used to solve a wide range of problems. It is based on the idea of genetic algorithms and is typically used for function optimization(Bäck & Schwefel, 1993; Bartz-Beielstein et al., 2014; Sinha et al., 2003).
3. Evolution strategies (ES): ES is a family of optimization techniques that are based on the idea of natural evolution. It is used for function optimization and is known for its ability to handle noise in the fitness function(Sun et al., 2009).
4. Differential evolution (DE): DE is an optimization algorithm that is used to solve problems in continuous search spaces. It is based on the idea of differential mutation and is known for its robustness and efficiency(Sadeeq et al., 2021).

Evolutionary algorithms have been applied to a wide range of problems in fields such as engineering, finance, biology, and computer science. They are particularly useful for solving problems that involve high-dimensional search spaces, nonlinearity, and noisy or imprecise fitness functions(Sharif et al., 2009).

Physics-based Algorithm

Physics-based metaheuristic algorithms are a class of metaheuristic algorithms that are inspired by physical laws and principles. These algorithms use concepts from physics, such as energy and force, to guide the search for optimal solutions in a problem space(Zhengming Wan & Zhao-Liang Li, 1997).

Some examples of physics-based metaheuristic algorithms are:

1. Gravitational Search Algorithm (GSA): This algorithm is inspired by the law of gravity and the motion of celestial bodies. In GSA, the solutions are treated as particles that interact with each other through gravitational forces. The algorithm uses these forces to update the positions of the particles in the search space, with the goal of finding the optimal solution(Rashedi et al., 2009).

2. Electromagnetic Field Optimization (EMO): This algorithm is inspired by the behavior of electromagnetic fields. In EMO, the solutions are treated as charged particles that interact with each other and with an electromagnetic field. The algorithm uses these interactions to update the positions of the particles, with the goal of finding the optimal solution(Ahmad, 2022).

3. Quantum-inspired Evolutionary Algorithm (QEA): This algorithm is inspired by the principles of quantum mechanics. In QEA, the solutions are represented as quantum states, and the search process is guided by quantum operators such as rotation and reflection. The algorithm uses these operators to explore the search space and find the optimal solution(Narayanan & Moore, n.d.).

4. Harmony Search Algorithm (HSA): This algorithm is inspired by the process of musical improvisation. In HSA, the solutions are treated as musical notes that are combined to form a melody. The algorithm uses a process of improvisation and adaptation to generate new melodies, with the goal of finding the optimal solution(Yang, n.d.).

Physics-based metaheuristic algorithms have been successfully applied to a wide range of optimization problems, including engineering design, scheduling, and image processing. They offer a unique approach to optimization that can be particularly effective in problems with complex search spaces and multiple objectives.

Swarm Based algorithm

Swarm intelligence is a branch of artificial intelligence that is inspired by the behavior of social animals, such as ants, bees, and birds. It refers to the collective behavior of decentralized, self-organized systems, where individual agents interact with each other and with their environment to achieve a common goal(S. Almufti, 2017; Sherinov & Ünveren, 2018).

Swarm intelligence algorithms are typically based on the following principles:

1. Decentralization: There is no centralized control over the system. Instead, each agent follows simple rules that are based on local information and interaction with its neighbors.

2. Self-organization: The agents interact with each other and with their environment to form a pattern or structure that emerges from the collective behavior of the system.

3. Adaptation: The system is capable of adapting to changes in its environment, either through the individual behavior of the agents or through the emergence of new collective patterns.

Some examples of swarm intelligence algorithms include:

1. Ant colony optimization (ACO): A metaheuristic algorithm inspired by the behavior of ants searching for food. It is used to solve optimization problems such as the traveling salesman problem(S. M. Almufti, n.d.-a).

2. Particle swarm optimization (PSO): A metaheuristic algorithm inspired by the flocking behavior of birds. It is used to solve optimization problems such as function optimization and feature selection (Kennedy & Eberhart, n.d.).

3. Bee colony optimization (BCO): A metaheuristic algorithm inspired by the foraging behavior of honeybees. It is used to solve optimization problems such as function optimization and feature selection.

4. (Fister, Fister, et al., 2013) algorithm (FA): A metaheuristic algorithm inspired by the flashing behavior of fireflies. It is used to solve optimization problems such as function optimization and clustering.

5. Artificial bee colony (ABC): A metaheuristic algorithm inspired by the foraging behavior of honeybees. It is used to solve optimization problems such as function optimization and feature selection(S. M. Almufti, Alkurdi, et al., n.d.).

Swarm intelligence algorithms have found applications in many fields, such as engineering, finance, biology, and computer science. They are particularly useful in solving complex optimization problems that are difficult to solve using traditional optimization methods.

Human-based algorithms

Human-based metaheuristic algorithms are a class of optimization techniques that incorporate human intelligence, knowledge, and experience into the optimization process. Some examples of human-based metaheuristic algorithms are(Dehghani et al., 2022):

1. Expert-guided Evolutionary Algorithm (EEA): The EEA is a metaheuristic optimization technique that combines evolutionary algorithms with expert knowledge. In this algorithm, the expert knowledge is used to guide the evolution process towards solutions that are likely to be good(Qian et al., 2017).
2. Human-guided Search (HGS) algorithm: The HGS algorithm is a metaheuristic optimization technique that incorporates human guidance into the search process. In this algorithm, a human expert provides guidance to the optimization process, which helps to direct the search towards promising areas of the solution space(Klau et al., 2010).
3. Interactive Evolutionary Computation (IEC) algorithm: The IEC algorithm is a metaheuristic optimization technique that involves interaction between the optimization algorithm and a human evaluator. In this algorithm, the optimization algorithm generates candidate solutions, and the human evaluator provides feedback on the quality of the solutions. The feedback is then used to refine the search process(Marques et al., 2010).
4. Human-in-the-Loop Optimization (HILO) algorithm: The HILO algorithm is a metaheuristic optimization technique that involves active participation of humans in the optimization process. In this algorithm, humans interact with the optimization algorithm in real-time, providing feedback and guidance to the algorithm as it searches for solutions(Zhang et al., 2017).

These algorithms are examples of how human-based optimization techniques can be effective in solving complex optimization problems. By incorporating human intelligence, knowledge, and experience into the optimization process, these algorithms can often find high-quality solutions more quickly and efficiently than traditional optimization techniques.

5. Applications of metaheuristics algorithms

Metaheuristics algorithms have been applied to a wide range of optimization problems in various fields, such as engineering, finance, logistics, and healthcare. In this report, we will discuss some of the notable applications of metaheuristics algorithms(Mohammed Almufti et al., 2022; Rere et al., 2016; Sherinov et al., 2011; Sun et al., 2009).

1. Engineering:
   Metaheuristics algorithms have been used to solve various engineering problems, such as designing efficient structures, optimizing manufacturing processes, and scheduling production. For example, in the design of structures, genetic algorithms and particle swarm optimization have been used to optimize the shape and material of the structure to reduce weight and improve performance. In manufacturing, simulated annealing has been applied to optimize the cutting parameters of a CNC machine, while ant colony optimization has been used to optimize the layout of a production line(S. M. Almufti et al., 2018; Dhiman & Kumar, 2017).

   Generally, Metaheuristics algorithms have been widely used in engineering for solving various optimization problems. Here are some of the notable applications of metaheuristics algorithms in engineering(S. M. Almufti, 2022b):

   - Design optimization: Metaheuristics algorithms such as genetic algorithms and particle swarm optimization have been used to optimize the design of various engineering structures, such as aircraft wings, bridges, and buildings. These algorithms can optimize the shape and material of the structure to reduce weight, improve performance, and minimize cost.
   - Manufacturing optimization: Metaheuristics algorithms such as simulated annealing and tabu search have been applied to optimize manufacturing processes. For example, these algorithms can optimize the cutting parameters of a CNC machine, reduce tool wear and machining time, and improve the quality of the manufactured parts.
   - Supply chain optimization: Metaheuristics algorithms such as genetic algorithms and ant colony optimization have been used to optimize supply chain operations, such as production planning, inventory management, and transportation. These algorithms can optimize the allocation of resources, reduce transportation costs, and improve delivery times.
   - Energy system optimization: Metaheuristics algorithms such as genetic algorithms and particle swarm optimization have been used to optimize the design and operation of energy systems, such as power grids, renewable energy systems, and energy storage systems. These algorithms can optimize the system parameters, such as the capacity of power plants and the location of renewable energy sources, to maximize efficiency and minimize cost.
   - Process optimization: Metaheuristics algorithms such as simulated annealing and tabu search have been used to optimize chemical and industrial processes. These algorithms can optimize the process parameters, such as temperature, pressure, and flow rate, to maximize the yield and quality of the products.
   - Structural optimization: Metaheuristics algorithms such as genetic algorithms and particle swarm optimization have been used to optimize the topology, size, and shape of structures, such as trusses and frames, to minimize weight, reduce material usage, and improve strength.

2. Finance:
Metaheuristics algorithms have been applied to financial problems, such as portfolio optimization, risk management, and algorithmic trading. In portfolio optimization, genetic algorithms and particle swarm optimization have been used to optimize the allocation of assets in a portfolio to maximize returns while minimizing risk. In risk management, simulated annealing has been applied to optimize the hedging strategy of a financial institution, while ant colony optimization has been used to optimize the allocation of insurance policies to customers(Soler-Dominguez et al., 2018).

   Generally, Metaheuristics algorithms have been widely used in finance for solving various optimization problems. Here are some of the notable applications of metaheuristics algorithms in finance:

   - Portfolio optimization: Metaheuristics algorithms such as genetic algorithms and particle swarm optimization have been used to optimize the allocation of assets in a portfolio to maximize returns while minimizing risk. These algorithms can find the optimal portfolio composition by considering multiple factors such as return, volatility, and correlation among assets.
   - Risk management: Metaheuristics algorithms such as simulated annealing and tabu search have been applied to optimize the hedging strategy of a financial institution. These algorithms can identify the optimal combination of financial instruments to mitigate the risk associated with market fluctuations.
   - Algorithmic trading: Metaheuristics algorithms such as genetic algorithms and ant colony optimization have been used to develop trading strategies that can generate profits by exploiting market inefficiencies. These algorithms can analyze large amounts of data and identify trading opportunities in real-time.
   - Credit scoring: Metaheuristics algorithms such as genetic algorithms and particle swarm optimization have been used to develop credit scoring models that can predict the probability of default for a borrower. These algorithms can analyze multiple factors such as credit history, income, and employment status to provide a more accurate assessment of creditworthiness.
   - Fraud detection: Metaheuristics algorithms such as simulated annealing and tabu search have been used to detect fraudulent activities in financial transactions. These algorithms can identify patterns and anomalies in transaction data to identify potential fraudsters.
   - Forecasting: Metaheuristics algorithms such as genetic algorithms and ant colony optimization have been used to develop forecasting models for financial time series data. These algorithms can analyze historical data and identify trends and patterns to make predictions about future market conditions.

3. Logistics:
Metaheuristics algorithms have been used to solve various logistics problems, such as vehicle routing, inventory management, and facility location. For example, in vehicle routing, genetic algorithms and tabu search have been used to optimize the routes of delivery trucks to reduce transportation costs and improve delivery times. In inventory management, simulated annealing has been applied to optimize the ordering policies of a retailer to minimize inventory holding costs while ensuring customer satisfaction. In facility location, ant colony optimization has been used to optimize the location of warehouses and distribution centers to minimize transportation costs and improve efficiency(Gogna & Tayal, 2013).

   In general, Metaheuristics algorithms have been widely used in logistics for solving various optimization problems. Here are some of the notable applications of metaheuristics algorithms in logistics:

- Vehicle routing: Metaheuristics algorithms such as genetic algorithms and tabu search have been used to optimize the routing of delivery vehicles to minimize distance traveled and delivery time. These algorithms can consider multiple factors such as traffic congestion, delivery time windows, and vehicle capacity to find the optimal route.
- Facility location: Metaheuristics algorithms such as simulated annealing and ant colony optimization have been applied to optimize the location of warehouses, distribution centers, and production facilities. These algorithms can consider multiple factors such as transportation costs, demand, and labor costs to find the optimal location.
- Inventory management: Metaheuristics algorithms such as genetic algorithms and particle swarm optimization have been used to optimize inventory levels to reduce costs while maintaining service levels. These algorithms can consider multiple factors such as demand variability, lead time, and ordering costs to find the optimal inventory level.
- Supply chain network design: Metaheuristics algorithms such as simulated annealing and tabu search have been used to optimize the design of supply chain networks to reduce costs and improve efficiency. These algorithms can consider multiple factors such as transportation costs, facility costs, and demand variability to find the optimal network design.
- Container loading: Metaheuristics algorithms such as genetic algorithms and particle swarm optimization have been used to optimize the loading of containers to maximize space utilization and minimize transportation costs. These algorithms can consider multiple factors such as container dimensions, cargo characteristics, and loading constraints to find the optimal loading plan.
- Warehouse layout optimization: Metaheuristics algorithms such as simulated annealing and ant colony optimization have been used to optimize the layout of a warehouse to improve efficiency and reduce operational costs. These algorithms can consider multiple factors such as storage capacity, product flow, and material handling costs to find the optimal layout.

4. Healthcare:
   Metaheuristics algorithms have been applied to healthcare problems, such as patient scheduling, resource allocation, and treatment planning. For example, in patient scheduling, simulated annealing has been applied to optimize the scheduling of patients in a hospital to reduce waiting times and improve resource utilization. In resource allocation, genetic algorithms and particle swarm optimization have been used to optimize the allocation of healthcare resources, such as hospital beds and medical equipment, to maximize the quality of care. In treatment planning, ant colony optimization has been used to optimize the radiation therapy plan for cancer patients to minimize side effects and improve treatment outcomes(S. Almufti, 2022; Dhiman & Kumar, 2017; Marashdih et al., 2018; Selvaraj & Kumar, n.d.).

   Metaheuristic algorithms have been successfully applied in various healthcare domains, such as medical diagnosis, treatment planning, drug discovery, and healthcare management. Some specific applications of metaheuristic algorithms in healthcare include:

   - Medical image analysis: Metaheuristic algorithms can be used to analyze medical images and extract useful information for disease diagnosis and treatment planning. For example, genetic algorithms can be used to optimize the segmentation of brain tumors from magnetic resonance imaging (MRI) scans.
   - Drug discovery: Metaheuristic algorithms can be used to optimize the molecular structure of new drugs and predict their efficacy and safety. For example, particle

swarm optimization can be used to optimize the docking of ligands to protein targets in order to discover new drug candidates.

- Healthcare scheduling: Metaheuristic algorithms can be used to optimize healthcare scheduling and resource allocation, such as staff scheduling, patient appointment scheduling, and bed allocation. For example, ant colony optimization can be used to optimize nurse scheduling in a hospital.
- Disease diagnosis: Metaheuristic algorithms can be used to diagnose diseases based on patient symptoms and medical history. For example, genetic algorithms can be used to diagnose diabetes based on patient data such as age, weight, and blood glucose levels.
- Medical equipment design: Metaheuristic algorithms can be used to optimize the design of medical equipment, such as prosthetic limbs and medical implants. For example, simulated annealing can be used to optimize the design of a prosthetic limb for a patient with a missing limb.

Overall, metaheuristic algorithms have the potential to revolutionize the healthcare industry by providing efficient and effective solutions to complex healthcare problems.

5. Computer Science:
Metaheuristic algorithms have a wide range of applications in the field of computer science, including optimization, machine learning, computer vision, and natural language processing. Some specific applications of metaheuristic algorithms in computer science include(Acan & Ünveren, 2020; Agarwal & Mehta, 2014; Jahwar et al., 2021):

- Optimization problems: Metaheuristic algorithms are widely used to solve optimization problems in computer science, such as scheduling, routing, and resource allocation. For example, genetic algorithms can be used to optimize the routing of vehicles in a transportation network(Acan & Unveren, 2007; S. M. Almufti, n.d.-b).
- Machine learning: Metaheuristic algorithms can be used to optimize the parameters of machine learning models, such as neural networks and support vector machines. For example, particle swarm optimization can be used to optimize the weights and biases of a neural network for image classification(Rere et al., 2016; Vergin et al., 2015).
- Computer vision: Metaheuristic algorithms can be used to solve computer vision problems, such as object detection, segmentation, and tracking. For example, ant colony optimization can be used to optimize the segmentation of objects in an image(M. Almufti, 2022).
- Natural language processing: Metaheuristic algorithms can be used to optimize the performance of natural language processing systems, such as text classification, sentiment analysis, and machine translation. For example, genetic algorithms can be used to optimize the feature selection for text classification(Sun et al., 2009).
- Network design: Metaheuristic algorithms can be used to design efficient and robust computer networks, such as wireless sensor networks and ad hoc networks. For example, simulated annealing can be used to optimize the routing and topology of a wireless sensor network(S. M. Almufti & Shaban, 2018).

Overall, metaheuristic algorithms have the potential to provide efficient and effective solutions to a wide range of computer science problems, making them a valuable tool in the field of computer science.

6. Advantages and Disadvantages of Metaheuristic Algorithms

Metaheuristic algorithms have several advantages and disadvantages, which are important to consider when choosing an optimization algorithm for a particular problem. Here are some of the advantages and disadvantages of metaheuristic algorithms(Abdel-Basset et al., 2018; M. Almufti, 2019):

Advantages:

a) Can find good solutions to complex problems: Metaheuristic algorithms are designed to handle complex optimization problems that cannot be solved by traditional optimization methods. They can search large solution spaces and find good solutions that may not be found by other methods.

b) Can handle non-linear and non-differentiable problems: Metaheuristic algorithms do not require the objective function to be differentiable, which makes them suitable for non-linear and non-differentiable optimization problems.
c) Can be parallelized: Metaheuristic algorithms can be easily parallelized, which allows them to exploit the power of modern parallel computing architectures.
d) Robustness: Metaheuristic algorithms are generally robust to noise and uncertainties in the optimization problem. They can handle noisy or incomplete data, and they are not sensitive to the initial conditions.

Disadvantages:

a. No guarantee of optimality: Metaheuristic algorithms are not guaranteed to find the optimal solution to an optimization problem. They may find a good solution, but not the best possible solution.
b. Computationally expensive: Metaheuristic algorithms can be computationally expensive, especially for large-scale optimization problems. They may require a large number of function evaluations to find a good solution.
c. Tuning parameters: Metaheuristic algorithms have several parameters that need to be tuned to achieve good performance. Finding the optimal values for these parameters can be a difficult task.
d. Black-box approach: Metaheuristic algorithms do not provide insights into the underlying structure of the optimization problem. They are a black-box approach that searches for good solutions without providing information on how the solutions were found.

In conclusion, metaheuristic algorithms have several advantages and disadvantages, and the choice of algorithm depends on the characteristics of the optimization problem and the available computing resources. Metaheuristic algorithms can provide an effective tool for solving complex optimization problems, but their limitations should also be considered.

7.Historical overview of metaheuristic algorithm

The history of metaheuristic algorithms can be traced back to the mid-20th century, when researchers began to develop optimization algorithms that were inspired by natural systems (M. Almufti, 2019).

In 1953, George Dantzig developed the simplex algorithm, which is a linear programming algorithm that has been widely used in optimization problems. In the 1960s, researchers began to develop optimization algorithms that were inspired by natural systems, such as genetic algorithms, simulated annealing, and tabu search.

In 1975, John Holland published his seminal book "Adaptation in Natural and Artificial Systems", which introduced the concept of genetic algorithms. Genetic algorithms are optimization algorithms that are based on the principle of natural selection, and they are inspired by the process of evolution in biological systems. Genetic algorithms have been widely used in optimization problems, such as scheduling, routing, and resource allocation.

In 1983, Kirkpatrick, Gelatt, and Vecchi developed simulated annealing, which is a stochastic optimization algorithm that is inspired by the process of annealing in metallurgy. Simulated annealing has been widely used in optimization problems, such as traveling salesman problem and protein folding(Gogna & Tayal, 2013; M. Almufti, 2019).

In the 1990s, researchers began to develop optimization algorithms that were based on swarm intelligence, such as particle swarm optimization, ant colony optimization, and bee colony optimization. Swarm intelligence algorithms are inspired by the collective behavior of social organisms, such as ants, bees, and birds. Swarm intelligence algorithms have been widely used in optimization problems, such as feature selection, data clustering, and routing.

In the 2000s, researchers began to develop optimization algorithms that were based on machine learning, such as reinforcement learning and deep learning. Machine learning algorithms are used to learn from data and make predictions or decisions based on the learned patterns. Machine learning algorithms have been widely used in optimization problems, such as game playing, robotics, and control systems(Shivan Othman et al., 2020).

In recent years, metaheuristic algorithms have become increasingly popular due to their ability to solve complex optimization problems in various fields. The development of high-performance computing and parallel processing has made it possible to apply metaheuristic algorithms to large-scale optimization problems(Acan & Ünveren, 2020; Sherinov et al., 2018).

#		Year	Algorithm	Author
1.	Older than 2000	1949	Monte Carlo Method	Metropolis and Ulam
2.		1961	Pattern Search	Hooke and Jeeves
3.		1965	Nelder-Mead Method	Nelder and Mead
4.		1966	Evolutionary Programming	Fogel
5.		1967	Hill Climbing	Pohl
6.		1975	Genetic Algorithm	Holland
7.		1983	Simulated Annealing	Kirkpatrick et al.
8.		1986	Tabu Search	Glover
9.		1987	Niching Genetic Algorithm	Goldberg and Richardson
10.		1989	Simulated Quenching	Ingber
11.		1989	Search Via Simulated Annealing	Ingber
12.		1989	Memetic Algorithm	Moscato
13.		1991	Ant Colony Optimization	Dorigo et al.
14.		1992	Genetic Programming	Koza
15.		1992	Artificial Life Algorithm	Beer
16.		1994	Cultural Algorithm	Reynolds
17.		1994	Cooperative Coevolution	Potter and De Jong

18.		1994	Cultural Algorithm	Reynolds
19.		1995	Particle Swarm Optimization	Kennedy and Eberhart
20.		1995	Immune Algorithm	Dasgupta and Yu
21.		1995	Simulated Binary Crossover	Deb and Agrawal
22.		1997	Cross-Entropy Method	Reuven Rubinstein
23.		1997	Differential Evolution	Storn and Price
24.		1997	Scatter Search	Glover and Laguna
25.		1998	Hybrid Particle Swarm Optimization Algorithm	Shi and Eberhart
26.		1999	Multi-Objective Genetic Algorithm	Deb
27.	2000 to 2009	2001	Cooperative Particle Swarm Optimization	Kennedy et al.
28.		2001	Harmony Search	Geem et al.
29.		2002	Estimation of Distribution Algorithm	Pelikan et al.
30.		2002	Particle Swarm Optimization with Mutation Operator	Clerc and Kennedy
31.		2002	Bacterial Foraging Optimization Algorithm	Passino
32.		2002	Quantum-Behaved Particle Swarm Optimization	Kennedy and Mendes
33.		2003	Electromagnetism-Like Algorithm	Birbil and Fang
34.		2004	Hybrid Taguchi-Genetic Algorithm	Ho and Yang
35.		2005	Bee Algorithm	Pham et al.
36.		2005	Artificial Fish Swarm Algorithm	Li and He
37.		2005	Memetic Differential Evolution	Liang et al.
38.		2005	A Hybrid Genetic Algorithm for the Quadratic Assignment Problem	Hao and Moon
39.		2006	Cat Swarm Optimization	Chu, Tsai, and Pan
40.		2007	Artificial Bee Colony Algorithm	Karaboga and Basturk
41.		2007	Imperialist Competitive Algorithm	Atashpaz-Gargari and Lucas
42.		2007	Scatter Search	Glover and Laguna
43.		2007	Enhanced Differential Evolution	Zhang and Sanderson
44.		2008	Firefly Algorithm	Yang

45.		2009	Cuckoo Search	Yang and Deb
46.		2009	Gravitational Search Algorithm	Rashedi et al.
47.		2009	Improved Harmony Search Algorithm	Zhang and Liu
48.		2009	Harmony Search Algorithm with Mutation Operator	Liu et al.
49.		2009	Biogeography-Based Optimization Algorithm	Simon
50.	2010 to 2019	2010	Bat Algorithm	Yang
51.		2011	Teaching-Learning-Based Optimization	Rao et al.
52.		2011	Krill Herd Algorithm	Gandomi et al.
53.		2011	Multi-Objective Differential Evolution	Das and Suganthan
54.		2011	Big Bang-Big Crunch Algorithm	Esmat et al.
55.		2011	Chaotic Genetic Algorithm	Karaboga and Kaya
56.		2012	Differential Search Algorithm	Civicioglu
57.		2012	Lion Algorithm	Rajakumar B.
58.		2013	Harmony Search Algorithm with Exponential Function	Gandomi et al.
59.		2013	Social Spider Optimization	Erik Cuevas et al.
60.		2014	Magnetic Optimization Algorithm	Ghorbani and Yusof
61.		2014	Fish School Search Algorithm	Bastos Filho et al.
62.		2014	Brain Storm Optimization Algorithm	Zhao et al.
63.		2014	Grey Wolf Optimizer	Mirjalili et al.
64.		2015	Plant Propagation Algorithm	Mohammadi-Ivatloo et al
65.		2015	Water Cycle Algorithm	Abdi et al.
66.		2015	Monkey Algorithm	Kaveh and Talatahari
67.		2015	Black Hole Algorithm	Karaboga and Basturk
68.		2015	U-Turning Ant Colony Optimization	Saman M. Almufti
69.		2016	Whale Optimization Algorithm	Mirjalili and Lewis
70.		2016	Dragonfly Algorithm	Mirjalili et al.
71.		2016	Genetic Algorithm with Dual-Population	Wang et al.
72.		2017	Vibrating Particles System	Kaveh and Ilchi Ghazaan

73.	2020 to 2023	2020	Multi-objective Dragonfly Algorithm	Niknam et al.
74.		2020	Cuckoo Search with Differential Evolution and Simulated Annealing	Baris and Akay
75.		2020	Hybrid Firefly Algorithm with Simulated Annealing	Baris and Akay
76.		2020	Biogeography-Based Global Optimization Algorithm	Simon
77.		2020	Fuzzy Adaptive Imperialist Competitive Algorithm	Salehi et al.
78.		2020	Multi-objective Elephant Herding Optimization Algorithm	Lashkari and Tavakkoli-Moghaddam
79.		2020	Symbiotic Organisms Search Algorithm	Heidari and Mirjalili
80.		2021	Pareto Local Search with Tabu and Line-Search Techniques	Almohallami and Zalzala
81.		2021	Invasive Weed Optimization with Opposition-Based Learning	Mohan et al.
82.		2021	Social Spider Optimization Algorithm	Dong et al.
83.		2022	Fire Hawk Optimizer	Azizi, Mahdi et al.

8. Conclusion

In conclusion, the history of metaheuristic algorithms spans several decades and involves the development of various optimization algorithms that are inspired by natural systems. Metaheuristic algorithms have become a valuable tool in solving complex optimization problems in various fields, and they are likely to continue to play an important role in the development of new technologies and applications.

Generally, metaheuristics algorithms have been applied to a wide range of scientific, engineering, finance, logistics, Healthcare problems and have demonstrated their effectiveness in finding near-optimal solutions. The use of metaheuristics algorithms is expected to become even more prevalent in engineering as the complexity and scale of optimization problems continue to increase.

In the real life the daily problems are becoming more and more complex in a way that it become very difficult for a traditional method to solve them within a reasonable time. Metaheuristics algorithm have been used to solve the real-life problems in an optimal time and effort. In the past many algorithms have been developed that belongs to metaheuristic algorithms. This paper is an attempt to provide a historical list of some of metaheuristic algorithms that have been used between 1961 and 2023, it provides the year of establishments, authors name, abbreviations and the reference of the algorithm.

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