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Metaheuristic Algorithms in Optimization and its Application: A Review

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***Abstract*—Metaheuristic algorithms are computational intelligence paradigms especially used for solving different optimization issues. Metaheuristics examine a collection of solutions otherwise really be wide to be thoroughly addressed or discussed in any other way. Metaheuristics can be applied to a wide range of problems because they make accurate predictions in any optimization situation. Natural processes such as the fact of evolution in Natural selection behavioral genetics, ant behaviors in genetics, swarm behaviors of certain animals, annealing in metallurgy, and others motivate metaheuristics algorithms. The big cluster search algorithm is by far the most commonly used metaheuristic algorithm. The principle behind this algorithm is that it begins with an optimal state and then uses heuristic methods from the community search algorithm to try to refine it. Many metaheuristic algorithms in diverse environments and areas are examined, compared, and described in this article. Such as Genetic Algorithm (GA), ant Colony Optimization Algorithm (ACO), Simulated Annealing (SA), Particle Swarm Optimization (PSO) algorithm, Differential Evolution (DE) algorithm, etc. Finally, show the results of each algorithm in various environments were addressed.**

***Keywords—component, formatting, style, styling, insert** (key words)*

I. INTRODUCTION

The metaheuristic is an iterative development algorithm that directs and modifies hierarchical heuristics by integrating smartly key variations for discovering and manipulating the objective function using adapted learning strategies to construct memory problems and to find a reliable approximate solution using analytical learning strategies to design memory content [1]. Several serious issues can be conceived as optimization problems, and many of them are NP-Hard [2], meaning that there are no effective algorithms for finding their exact global optima. As a result, researchers have been motivated to create new algorithms, such as metaheuristics, which are also inspired by nature. Evolutionary algorithms, for example, are based on Darwin's theory of nature's survival of the fittest process [3]. These algorithms have the advantage of requiring no advanced mathematical knowledge of the problems to be solved. Several algorithms have emerged in recent decades, and they have found their way into solving a wide system of differential equations. One benefit of population-based optimization algorithms is the big search capability [4] since the dataset contains a variety of people who search the solution space and exchange their information about the problem in collaboration with others [5]. There are two types of metaheuristic algorithms, which are also known as optimization techniques: evolutionary algorithms and genetic algorithms [6]. ACO method, PSO method, bee's algorithms, and bacterial foraging optimization are examples of swarm intelligence algorithms [7]). Memetic and cultural algorithms are examples of population-based algorithms [8]. A classification of metaheuristic optimization methods is given in Figure 1. These methods have been successfully utilized in a variety of issues in fields ranging from technology to nature to natural scientists since their conception [9]. Metaheuristic algorithms were used in various areas of machine control systems easy fabrication and relevance.

Three types of metaheuristics and hybrids could be found in the metaheuristics group. The first is greedy random novel optimization procedures, greedy random adaptive memory programming search (GRAMPS), ant colony optimization, confirm programming, and rewritten branch and bound – breadth-first BS and depth-first procedures [10]. Simulated annealing, chaotic processes, directed local search methods, ejection chains, and compound movements, limit accepting, computed local scan, complex systems, tabu search, and

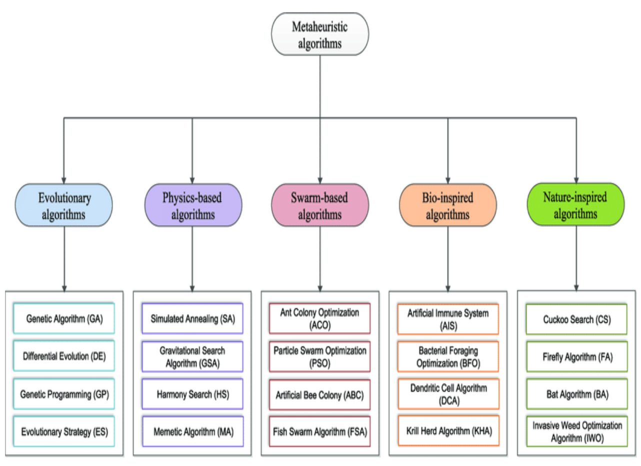

Fig. 1. Metaheuristic algorithms

vector neighbourhood search are among the guided neighbourhood-search metaheuristics in the second group. Guided population metaheuristics are the third group, which includes evolutionary algorithms; GA algorithms, route relinking, and scatter search are some of the techniques used. Hybrid metaheuristics are the last group [1]. This paper's material will be organized as follows: section 2 presents brief information about metaheuristics algorithms, section 3 presents the metaheuristics algorithm classification, section 4 presents Modeling of Metaheuristics Algorithms, section 5 presents parameters of metaheuristics, and finally, section 6 provides a description and ideas for possible directions for research.

II. Background overview

A metaheuristic is an elevated, issue algorithmic paradigm for developing heuristic optimization algorithms [11]. Many metaheuristic algorithms have been successfully used to solve difficult problems. Except for very big problem sizes, the benefit of using these algorithms are used to solve complex issues is that they provide the best results in the shortest possible time [12]. Metaheuristics are techniques for locating an optimal solution with a very low numerical cost. In most other phrases, metaheuristics are a collection of sophisticated techniques for making heuristic operations more effective. Teaching approaches are used to organize knowledge to discover effectively fairly close solutions. They are an adaptive generation mechanism that directs a delegated heuristic by integrating constructively various concepts for testing and maximizing the computational complexity [13]. A metaheuristic is an algorithmic main mechanism that directs and reconfigures the activities of specific heuristics to guarantee better solutions rapidly and easily. As replication, it may exploit a single actual solution or a series of solutions. Low/high-level operations, a basic local scan, or simply a building process are examples of direct heuristics. Different metaheuristics have different structure principles [14]. Many researchers structure the optimization process through concepts that don't seem to have much to do with optimization, such as natural evolution artificial annealing, or animal swarm behaviour e.g., ACO method, such as tabu search, avoid using an intermediate level of clarification and instead concentrate on manipulating the problem context to enhance the ability to reasonable alternatives. While some fully mechanistic solutions have been suggested, metaheuristics systems generally depend heavily about the use of unpredictability [15]. Metaheuristics have been classified in a variety of forms depends on the nature chosen:

A. *Nature versus non-nature inspired*

That classifier is based mostly on the algorithm's beginnings. Inspired algorithms including such as (ACO), (PSO), and (GA) Algorithms comprise the majority of metaheuristics [16]. Some of them, including Iterated Local Search and Tabu Search, are not influenced by nature [17].

B. *Single point versus population-based search*

Metaheuristics could also be categorized based on how many approaches will be used around the same time. As trajectory methods are algorithms that run for a technical cause at any given time and provide location recommendation metaheuristics like swarm-based metaheuristics, population-based algorithms search for several basic positions in addition [18].

C. *Static versus dynamic objective function*

How the specific immune is used is another attribute that can be used to classify metaheuristics. In several other terms, many algorithms keep the optimal solution in the specific problem. This strategy aims to break free from solution space by altering the discovery environment. As a result, the target function is changed by adding the data gathered during the search [19].

D. *Single versus different neighborhood structure*

A single neighbourhood configuration is used by many metaheuristic algorithms. In several other terms, the configuration of the behavioural condition does not change during the algorithm, while some, such as the Variable neighbourhood search (VNS) method, use a collection of neighbourhood frameworks. This last arrangement allows you to broaden your quest by switching between various exercises environments [20].

E. *Memory consumption versus memory-free approaches*

The most significant aspects for categorizing metaheuristics with the use of storage. To put it another way, memory use is regarded as among the most important aspects of a successful metaheuristic. Where the details used to decide the next operation is the original form of the search operation, memory-free algorithms perform a Markov process [21]. Memory can be seen in a variety of ways. In addition, through use of selective memory differs from the use of a strong constitution. The first typically takes care of current efforts, options visited, or choices made in general. The second is normally a set of artificial factors linked to the search [22].

F. *Continuous Versus Discrete optimization*

Continuous optimization issues exist for models with discrete variables, while discrete optimization problems exist for models with continuous variables. In general, continuous optimization issues are simpler to solve than discrete optimization problems; the smoothness of the functions allows the values of the objective function and constraint function at a location to be utilized to infer information about nearby positions. However, algorithmic and computer technology advancements have significantly expanded the scale and complexity of discrete optimization problems that can be addressed effectively. Numerous significant discrete optimization problems are known to be NP-hard; in the worst-case scenario, the time needed to solve a problem instance to optimality exponentially grows with its size; therefore, these issues are simple to define and comprehend but difficult to solve. Even for moderate-sized issues, it is virtually difficult to discover all potential solutions to decide the optimal. As a result, heuristic methods, i.e., approximation solution algorithms, are often regarded as the only rational way to tackle complex discrete optimization problems. As a result, there is a large and increasing body of research on metaheuristics for discrete optimization that seeks to balance the trade-off between computation time and solution quality. However, many well-known metaheuristics were initially designed for continuous spaces, which may be naturally expressed in a real domain [23].

G. Modeling of Metaheuristics Algorithms

For nonlinear system simulation, a variety of approaches may be used [18]. Each technique has its own set of benefits and disadvantages. Modelling engineering systems is complex due to the need to specify both the configuration and requirements of the systems. In behavioural modelling, statistical regression methods are commonly used [24]. For behavioural modelling, multiple substitute metaheuristic methods have been established. In the last two decades, advances in computer hardware have created an opportunity for these methods to evolve into more functional architectures. Furthermore, metaheuristics can be used as effective methods in situations where traditional techniques struggle or work terribly [25].

In a range of international, Artificial Neural Network (ANNs) and Gaussian Process (GP) are two excellently classes of metaheuristic methods. Several engineering design challenges have been solved using ANNs. [25]. ANNs, despite their popularity, seldom have a detailed understanding of the mechanism by which they arrive at a solution. As a continuation of GAs, GPs have entirely different particularities [26]. GP is a supervised machine-learning technique that scans a function space rather than a data space to produce computer software that is described as tree structures and written in a functional programming language [27]. One of the key advantages of GP over correlation and ANN approaches is the ability to create statistical models without taking the shape of established relationships [16]. For serious challenges, GP and its derivatives are commonly used.

III. Optimization parameters of metaheuristics

Before the algorithm is executed, a set of indicators should be defined with each actual responsibility of the metaheuristic. Take a look at Table I, which lists the basic parameters that are needed for the various forms of metaheuristics. Although these are criteria for the limited set of elements common in various types of algorithms, many metaheuristics get more parameters in use [28]. A simple tabu search protocol, for example, can only have one parameter: the tabu list length. Such processes, But on the other hand, users can fit a lot more into one parameter. There are 32 parameters in the TS used in the transportation problem. Similarly, by adding parameters with the same value, algorithms may have less than the number of parameters [29]. There is the only single parameter in the GA method for the minimum label distance-vector problem, which serves as a population size regulation as well as a termination parameter [30].

Table I. Standard Parameters for Popular Metaheuristics

Name	Parameter
ACO algorithm	Parameter for pheromone evaporation Parameter for pheromone weighting
GA algorithm	Probability of a crossover Probability of mutation Height of the population
HS algorithm	Bandwidth at a distance Pitch change rate for memory size Picking from memory at a high rate
SA algorithm	Annealing rate The temperature at the start
TS algorithm	The length of the tabu list
VNS algorithm	None

IV. Related works

Learning techniques are used to organize knowledge in addition to finding effectively relatively close solutions, and a metaheuristic method is formally explained as an adaptive generation mechanism that directs a specific heuristic by integrating smartly various principles for exploring and leveraging the computational complexity. Among the approximate methods that will be used to address difficult issues are metaheuristic algorithms.

For the Problem, a comparative study was conducted by Otubamowo et al. [31], between simulated-annealing (SA) and the genetic algorithm (GA); they contrasted the success of SA and GA in this study. Their findings indicate that SA outperforms the GA and that the runtime of the GA grows exponentially with the number of towns [31].

Ma et al. in [32], the properties of several common evolutionary algorithms were investigated. The authors contrasted the simple and specialized versions of GA, biogeography-based optimization (BBO), differential evolution (DE), evolution strategy (ES), and particle swarm optimization (PSO) on a series of meaningful optimization problems in their research. In addition, a theoretical discussion of the BBO, PSO, ES, DE, and GA equivalences was discussed. The traditional versions of ES, BBO, PSO, and DE are equivalent to the GA with general standard recombination (GA/GUR) within certain test conditions, according to one of the findings of the experiments. Their important component, nevertheless, demonstrates that the similarity of mathematical algorithms is reinforced also by fact that computational improvements resulted in significantly different performance levels [32]. Civicioglu and Besdok [33], the findings of the Cuck-Search algorithm (CS), PSO, DE, and ACO conceptual comparison were studied. As a method of assessment, the operating difficulty and the necessary number of objective functions for obtaining a regional minimizer have been used. They contrasted the four algorithms' classical optimization problem-solving performance rates and backed up their assertions with statistical analyses using over 50 various computational evaluation metrics. The analytical findings of their research showed that the CS algorithm's problem-solving effectiveness can be positively accurate equal to the DE method, or, there was no significantly meaningful discrepancy among the two algorithms' results [33]. Another research found that Dynamic-Programming (DP) requires a huge amount of data and memory as contrasted to metaheuristic methods like GA, PSO, and ACO. They carried out a hydropower optimization analysis for a 75-plant large-scale hydropower grid. Models of linear, nonlinear, and successive linear programming were used. In terms of energy production, it was found that linear programming outperformed other models [34].

In 2017, Bewoor et al. [35] utilized different metaheuristic methods for the m-machine No Wait for Flow Shop Scheduling (NWFSS) issue, using communication overhead as a long way in ensuring. Since the NWFSS issue is NP-hard and direct force methods struggle to obtain solutions, metaheuristic algorithms are used to find optimal solutions. Present metaheuristic methods are used to satisfy the clear measures. For larger and smaller problems, Tabu Search (TS), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) are used, and their performance is calculated using statistical metrics [35]. However, in 2017, Lidbe et al. [36] suggested Genetic Algorithm (GA), Virtual Annealing (SA), and Tuba Search (TS) as solutions to the issue of micro-simulation model tuning, which is still unsolved. Thus, micro-simulation technology is a modern technology that can make centralized distribution analyses more effective, simpler, and less costly. Micro-simulation models, on the other hand, must be well optimized to produce accurate and consistent performance. The micro-simulation cable is made up of several sub-models, each with several variables, the majority of which are a consumer and optimized for model calibration [36]. In addition, Jadon et al. in [37] proposed combining the Differential Evolution (DE) and Artificial Bee Colony (ABC) algorithms to create a much more powerful metaheuristic method than the ABC and DE algorithms. The individual bee step of ABC is influenced by DE in the suggested optimization technique, Hybrid Artificial Bee Colony with Differential Evolution (HABCDE). The appointed bee process has been changed to include the idea of the quality individual, and the employed bee phase has been changed to allow for further experimentation. To demonstrate the effectiveness of the proposed method, HABCDE appears to be a successful algorithm throughout the area of metaheuristics, according to the findings [37].

Wang et al. in [38] Firefly-Algorithm (FA) with Neighborhood Attraction were introduced as a promising FA alternative (NaFA). Instead of being drawn to the whole community, each firefly in NaFA is connected to other stronger fireflies from a predetermined area. Many good benchmark functions are used in the simulations [38].

Wang et al. in [39] to improve embedding capacity, a self-learning-based feature selection method using the PSO algorithm was used, as well as a successful learning-based simulation plan to make sure algorithm efficiency. We devise a tolerance-based quest path change system to strike a good balance between discovery and development. When compared to five separate PSO algorithms, the experimental findings on 40 standard test functions suggest [39]. Cao et al. in [40] suggested a new LS starting strategy based on their established quasi-entropy index to solve the problem's central question, namely when to begin LS. Numerical checks are used to evaluate the changes in the index as the optimization progresses. The suggested PSO algorithm is put to the test using a variety of benchmark problems. To show its reliability, a function sensitivity analysis is carried out [40]. Ashish et al. in [41] by using the map-reduce framework, suggested a flexible and effective parallel bat algorithm (PBA) for clustering techniques. It's more efficient to use an adaptive solution for grouping rather than just another conventional algorithm like k-means, and it's faster because it's constrained by map-reduce technology. The PBA algorithm clusters the reduced feature frames in sequence after splitting the huge set of data into smaller chunks. To group the data collection, the suggested algorithm borrows features from the bat algorithm. The suggested method is based on Particle Swarm Optimization (PSO) with various numbers of nodes on five benchmark problems. Experiments reveal that In terms of efficiency, the PBA system tops the PSO method [41].

Many real-world implementations have been proposed by Liu et al. in [42], multi-objective subset feature selection problem. Multipurpose ant colony optimization is a powerful and compassionate tool for resolving these problems. It does, furthermore, have two flaws that the writers must address. One, the solution-building process is incompatible with the disorder properties of solutions, preventing it from obtaining better results. Two, multi-object conventions Strong objective optimization techniques are difficult to solve for ACOs that struggle with objective combinatorial optimization the most [42]. Song et al. in [43] suggest an optimized cuckoo search algorithm for 3D route scheduling problems focused on portable and simultaneous approaches. The portable cuckoo search algorithm is implemented in this article, and then a new concurrent contact approach is introduced. The controlled robot's storage can be easily saved using the portable method. The simultaneous scheme will improve precision while still allowing for quicker integration. The suggested algorithm is put to the test on several different tasks as well as 3D route planning. As opposed to other approaches [43].

V. METHODOLOGY

Most Metaheuristic algorithms were created to solve meaningful solution space optimization issues. The number of real issues has a high level of complexity, anti-constraints, parameter interconnections, and a wide combinatorial optimization. In this part, some of the metaheuristic algorithms such as GA, SA, ES, TS, and ABC in different applications and environments are reviewed and compared.

The implementation of the SA algorithm begins with an initial solution. By using district strategy, a new approach is developed. When the optimization problem value of the current approach is less than that of the initial solution, the technical model is used and the existing one is updated. The GA algorithm starts with the identification of resolutions, also known as an original solution, which can be developed using a variety of techniques, including solution sets configured with pseudo-random quantities and alternatives produced in a different, separate manner. The TS algorithm begins with a first (randomly chosen) solution. It keeps track of previously visited options in a tabu short-term memory. Any alternative that has been saved in the tabu list is not permitted. This stops the algorithm from being caught in a loop. Random initial approaches have been implemented with each optimization. These SA, GA, and TS metaheuristic methods are used for the calibration of microsimulation models. In this environment, TS's best solution and convergence to best solution outperform GA and SA's.

TABLE II. THE ADVANTAGES AND DISADVANTAGES OF THE SA, GA, AND TS ALGORITHMS

Algorithms	Advantage(s)	Disadvantage(s)
GA	It's simple to upgrade and has a lot of other advantages, such as the ability to handle combinatorial or discontinuous goals and constraints. It may be used to solve a specific problem on its own, as well as to reduce the computing work required to solve difficult problems.	It is inaccurate and takes longer. Unexpected effects and a challenging transcription procedure
SA	Probabilistic element, low computing time, no localized optima, simple deployment	The consistency of the solution is dependent on the internal loop's maximum validation samples.
TS	It has a sub aspect so it can be used for both national and global searches. Mostly with the current implementation, tabu search still returns the same answer from the beginning.	It's the challenge in determining the proper parameter.

PSO often starts with a random population that resembles a flock of birds. Each solution is referred to as an object and the community as a swarm. To ensure the discovery potential, the PSO approach was used in a self-learning-based applicant generation technique and is also used in local search (LS) starting strategy and clustering techniques by using the map-reduce framework. PSO algorithm in all cases has good performances. Also, PSO with GA and TS algorithms are used for solving NWFSS problem is NP-hard method, the result by having a PSO algorithm is high performance. ACO algorithm uses Artificial Ants to generate iterative stochastic solutions. The procedure begins with the development of a random group of ants. Their suitability is assessed using an analytical function tailored to the issue at hand. ACO algorithm is used in dynamic programming that requires a huge amount of data and memory and is Multi-objective in many real-world applications. In both cases to solve the problem of convergence rate, an ant colony optimization ACO algorithm is used. Since ants generate solutions independently and simultaneously, the production period for the ACO algorithm is effectively concurrent. Despite this, the ACO is based on a sequence of arbitrary actions performed by a variety of human ant colonies. CSA algorithm was used in 3D route scheduling problems. CSA satisfies the requirements of standardization aids analysis abilities at both international and national levels. Also, CS, PSO, DE, and ACO algorithms are used for problem-solving performance rates, DE is ideal for experimenting and diversifying since it can handle cost functions that are highly computationally complex.

VI. DISCUSSION

Metaheuristic algorithms have proven to be very useful in solving a variety of optimization problems. In this section, each metaheuristic algorithms are used in the study of this paper is summarized based on the algorithms/methods, the results of each method, as seen in Table III.

TABLE III. SUMMARIZATION OF THE LITERATURE

Method(s)	Result(s)
SA, GA methods	Outperforms simulated Annealing in form of solution consistency [31].
GA, BBO, DE, ES methods	Major finding strongly indicates into the essential analysis and assessment of the application dependent metaheuristic algorithms [32].
CS, PSO, DE, ACO methods	Problem-solving effectiveness can be positively accurate [33].
GA, PSO, ACO methods	The SLP model decreased solution time [34].
TS, GA, and PSO methods	Minimize total completion time [35].
TS, SA, and GA methods	The standardization of micro-simulation models can be automated, which saves time [36].
ABC, DE methods	Demonstrate the results effectively [37].
FA method	Effectively improves solution accuracy while reducing computing execution time [38].
PSO method	It exceeds the competition in terms of integration accuracy and speed in several respects [39].
PSO method	The convergence rate and accuracy are higher than those of CLPSO [40].
PSO, PBA methods	Provides a major increase in performance as the number of users increases [41].
ACO method	a strong convergence potential and achieves a stronger mix of convergence and variety [42].
CS method	Produces more competitive outcomes and has a faster execution time [43].

VII. CONCLUSION

In conclusion, some of the largest and most complex problems are being solved by machines. To solve these issues, we'll need to build some sophisticated algorithms. Optimization techniques for such problems may need unacceptably large amounts of time and space to find solutions. To create a way to solve algorithms Basic forms that are suitable have been created. To solve problems, these approximation algorithms use metaheuristics functions. Metaheuristics are search-process-guiding methods. The aim is to explore the computational complexity as quickly as possible to determine or come close to optimal solutions. Metaheuristic algorithms are due to excessive and approximate. Metaheuristic approaches are excellent options for solving NP-hard optimization problems and complex search problems. This paper discussed metaheuristic classification, which can also be categorized in a variety of ways depending on the problem form, then different optimization problems described of the metaheuristics. So that many algorithms in this field are conducted in the literature, such as GA, SA, PSO, ABC, etc. finally discussed the results of each algorithm that are used in a different area.

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