

METAHEURISTIC ALGORITHMS IN OPTIMIZATION AND ITS APPLICATION

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Abstract: Many optimization problems are inherently difficult and belong to a special class called NP-hard. Thus, efficient algorithms, which we shall call integrated languages or simply metaheuristics, are needed. These algorithms effectively search a solution space through the iterative application of intelligent search strategies. Some of the search strategies are borrowed from analogies with nature and social behavior of individuals, like ants, bees, and birds, while others are inspired by physical and chemical processes, as well as by those which are based on the procedure of inference and logic. Effectively, many problems are modeled as optimization problems. Examples include the employee scheduling problem, which aims at assigning needs that emerge in the company to its employees, so that all needs are met and costs are minimized; the vehicle routing problem, which aims at determining a set of routes and their sequence of stops to be executed by a fleet of vehicles, so that all customers receive their demands and the total cost is minimized; the quadratic assignment problem, which consists of allocating to m identical machines, n facilities, and computing the associated assignment, so that an objective function is minimized; and the maximum independent set problem, which consists of finding the largest set of nodes in a graph such that no two nodes in this set are adjacent and no adjacent nodes are present in the set. Additionally, optimization problems appear in different kinds of areas such as mathematics, physics, computer science, economics, and engineering.

INTRODUCTION

The present paper aims to offer an overview of the panorama of metaheuristics, describing the main concepts and characteristics of the most recent existent techniques. A classification of the metaheuristics is presented, emphasizing and commenting on the differences between each of the paradigms. Some recent works that explore innovative concepts in metaheuristics are presented, as well as some fields in which these techniques have been successfully applied. In the end, a description of a fundamental aspect in research with metaheuristics, the comparison of the efficiencies of these techniques, and the evolution and the future of these computational intelligence tools are presented [43].

The success of the metaheuristics can be verified through the great number of researches in all the continents, with diverse works supplying improvements and innovations in techniques such as Ant Colony Systems, Genetic Algorithms, Particle Swarm Optimization, or Simulated Annealing. In addition, given the increasing computational capacity of the actual computers, it is possible to develop promising optimization tools, also taking advantage of the massive use of parallel or grid computing, where metaheuristics can and have already offered substantial contribution through paradigms such as Island Models, EGA, Collaborative Co-

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Evolution, or Cultural Algorithms. For these reasons, to master intellectual, political, and economic resources in the development and consolidation of metaheuristic computational intelligence must rationally seek advances in this area, which is, without a doubt, one of the main challenges to contemporary computational science [1].

The optimization problem can be defined as the search for the best particular solution (or a couple of such solutions) to a mathematical expression dependent on a set of arbitrary variables, according to certain limitations and a certain measure of quality. The development of heuristic computational techniques based on processes of biological evolution and animal behavior, in these terms receiving the generic denomination "metaheuristics," gave rise to a revolution in the area of optimization in the last years, so that today the optimization of complex mathematical expressions finds in these techniques an essential resource that contributes to the fulfillment of this crucial remainder [45].

BACKGROUND

As a matter of fact, a single index consists of a single computer with perfect optimization can take up to several years for an approximately insufficient solution in such problems. Often, the best solutions, to which this research is based, are formed within reasonable times and rare resources. Therefore, mixed integer programming, the structures optimally cover, focus on giving exact answers to resources with discrete values, and the problem origination of the metaheuristics which are more robust in this sense. Metaheuristics are the past, which means on the heuristic that is higher than in nature. Although there are thousands of specific heuristics in areas such as locational analysis, operations research, philosophy, psychology, biology, transportation, and telecommunication, the prohibitive time and resource utilization issues directed towards developing generic optimization processes necessitate the development of the metaheuristic term [52].

In this newly emerging global economy, industries and organizations of all sizes have been under intense pressure to work efficiently. They have now been able to access more relevant and unlimited information related to the field and developed production products under more and more competitive conditions. There is an interesting point that we call metaheuristics in order to solve resources such as time, personnel, and capacity. Metaheuristics can be defined as a set of procedures and heuristic technologies that can be used as problem-solving techniques to understand and solve seemingly every problem. Despite the possibility of developing over time, traditional optimizers such as linear programming, integer programming, multiple criteria decision making, and goal programming are not suitable for such complex problems and limited capacity [41].

METAHEURISTIC ALGORITHMS

Recall that there are two main types of metaheuristics: single metaheuristics and hybrid metaheuristics. Single metaheuristics formally aim to solve a given optimization problem by iteratively generating a sequence of candidate solutions. Stochastic algorithms admit the well-known Simulated Annealing as well as the population-based multi-armed bandit selection of a Wide Spectral Ant Colony Optimization. The metaheuristics native Randomized Search and in the life sciences, but in data science distinct and representative native-explorative-and-

exploitative combinations of the Simplex Search with Monte Carlo, the (1+1) Evolution, the Cross between Differential Evolution, the Dual Simulated Annealing, the Harmony Search, the Single and Multi-Armed Bandits, the Fireworks, the Tabu Search, as well as the Search Trajectory Contributions [29].

In optimization, a metaheuristic is a higher-level procedure that coordinates the operations of lower-level heuristics. A metaheuristic uses different meta-operational rules to create an iteration strategy for the search process. Although a metaheuristic can be more complex than a single-heuristic algorithm, it offers many advantages related to the quality of the solution, diversity, costs, etc. Nowadays, metaheuristics have become the mainstream methods for solving complex optimization problems that cannot be effectively solved by classic methods, such as linear programming, integer programming, and dynamic programming. Metaheuristics exhibit good computational performances and therefore they are employed as scientific workhorses of optimization in industries, healthcare, finance, etc [50].

Definition

In this research, we present an overview of the most widely used metaheuristic algorithms for solving constrained/unconstrained continuous, non-smooth, dynamic/complex, single objective and multi-objective optimization problems. The metaheuristic terminology might seem a little cloudy to someone who does not know much about this area. In other words, if you open the list of metaheuristics related books or article publications, you may think that this term has considerable recognition. When we look at the word of metaheuristics many times, we are faced with a common opinion: a useful optimization algorithm can be considered as parts of metaheuristic methods [35].

The metaheuristic methods are nowadays commonly used to find approximate solutions for complex optimization problems. They are intended for problems which are difficult or impossible to solve using exact combinatorial methods. A huge number of optimization approaches belong to the family of metaheuristics, so there is a need to divide these methods to conditions of their use in the algorithmic parts of hard optimization problems. For this purpose, many surveys were made last decades which were focused in renewable time periods to some types of metaheuristic algorithms or their applications [31].

Types

So-called scatter-evolutionary algorithms like Particle Swarm Optimization (PSO) and Social-Spider Optimization (SSO) are also the population version of MAs. PSO is a vector-based basic optimization algorithm in which solutions, particles, fly over hyperspace in order to find the best solution. They have their neighbors with which they exchange information during PSO evolution. SSO is another popular scatter-evolutionary optimization algorithm based on observation of social spiders and their behavior in the process of finding their food [4, 40]. These methods are heavily used in solving multidimensional real-coded optimization problems where gradients are not effective. Other examples of population-based MAs given in the literature are: Differential Evolution, for which the population involved in finding better subspace-optimal solutions can be smaller; a large family of artificial immune algorithms – clonal selection algorithm; great deluge algorithm, which belongs also to local half-stochastic algorithms [13].

In the classification, a number of general types of MAs are described. For simplicity reasons, most of the presented types belong to the local or derivative-free methods. The most popular types of MAs belong to the population algorithms and can be divided into several groups. When the population is used (is greater than one), the most popular form of MAs are genetic algorithms with various variants (chronologically we know the following types: binary coded GA with Holland crossover operators and GA with real coded chromosomes, binary, integer and real valued GA with a variety of crossover and mutation operators). The main disadvantage of these methods is entanglements of solution [6].

OPTIMIZATION PROBLEMS

Linear programming problems are mathematical optimization problems which have simple linear expressions, linear constraints, and a linear expression to be minimized or maximized. Quadratic programming is a general term for the constrained optimization of a quadratic objective function and linear constraints. In the case of a single quadratic function to be maximized, the problem becomes that of solving a convex optimization problem. See Table 1, summarized the basic parameters are needed the various forms of metaheuristics. A nonlinear programming problem can generally be expressed as a problem of minimizing $f(x)$ subject to a set of m constraints $g_j(x) >$, where $f: R^n \rightarrow R$ is the objective function and $\{g_j \text{ in } R^n \rightarrow R; j = 1, 2, \dots, m\}$ represent the m nonlinear inequality constraint functions. A number of functions, $g(x) \geq 0$, can be reformulated as nonlinear in the normal or convex form [9]. The discrete optimization could have a finite, infinitely large, or even no solution space. The discrete optimization refers to the selection of a sequence of decisions. This type of optimization is commonly known as combinatorial optimization and is involved with an excellent range of essential decision-making problems faced by several organizations in many fields such as scheduling, network design, transportation, computer simulation, and biology and carefully imposing a budget, error analysis, and data compression. Discrete optimization is usually harder to solve than a continuous problem [55]. In all practical applications of engineering design, it is essential to have a mathematical analysis to get a solution based on certain mathematical methods. This involves some optimum parameters based on some criteria. One such problem is a mathematical optimization problem. In its broadest sense, an optimization problem is to find the best solution from all feasible solutions. It can be of several types such as linear programming, non-linear programming, discrete programming, combinatorial problem, complex programming, and so on [37].

Table 1. Standard Parameters for Popular Methaheuristics.

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

Overview

But since the methods typically do not use information from the function's

derivatives or even the response drawers on local steps, this explanation still greatly lacks quantitative crystallization. This is the reason why the optimization community is consistently amazed (and sometimes infuriated) by the empirical performance of misbehaving algorithms such as random search or classically tabooed problem structures like long-range dependencies [25, 28]. What underlies them has diligently been researched, analyzed, and gained theoretical crystallizations, in that such methods typically require no more than some moderate complexity time scale than deterministic algorithms for optimizing standard merit function classes. Cotreros divides the research field of optimization into six research areas: reviews, comparison of algorithms, efficiency, software engineering and validation, benchmarking, and continuous raising of the standards and practice of experimental research [2].

The metaheuristic research field started to emerge in the late 1970s/early 1980s to denote an academic class of meta-level methodologies pooling knowledge (heuristics) from diverse application areas. It was coined to describe procedures that were used to coordinate years of experience with many types of heuristics in meta-level artificial intelligence research [14]. They were soon adopted by the optimization community as a way to classify and differentiate optimization algorithms, especially with the appearance of expert systems. In the meantime, the algorithms were classified according to the problems they addressed. In the late 1990s, the term seemed to have converged to denote stochastic iterative procedures within constraints, used to search for an approximation of a global optimum of a black-box-type function. This procedure's efficiency usually depends on the given time frame, computational resources, and the modeling of dependencies among the variables. Quite remarkably, this definition gives the primary rationale for why such methods should work well under various circumstances [35].

Classification

A global classification of the metaheuristic algorithms, including bio-inspired algorithms, swarm intelligence, evolutionary programs, and plot searches, is provided to make the distinctions among them. These global search algorithms or plots, scale hearing models, hybrid algorithms, may be instruments used when dealing with optimization on mensural real-valued optimization and not well-defined but usually real-world subjects [8]. Evolutionary programs usually do not employ probability theory to drive the mutation operation. Different objective functions, different basis applications to solve optimization problems on continuous or flash or binary instance space or open problems, are also provided to define the objectives of the study. The use of artificial selection, a certain kind of interactive optimization customer, or the optimization process, are also characteristics that are used in the classification algorithm family. The definition of proximity and saturation distance, the definition of proximity saturation base criterion to decide the saturation or proximity of the algorithm, depends on the type of the problem, a metric function, or objective of the suboptimal regions. This category is aimed at exploring the most focused attributes on an algorithm and provides the appropriate information needed in theory and rules for both the algorithm user and the algorithm developer [56].

Intensive research has been done on the implementation and application of metaheuristic algorithms, including swarm intelligence, bio-inspired, evolutionary, and plot search algorithms, both in continuous real-valued optimization and multimodal optimization. Kaabouch made a classification and provided a detailed

summary of metaheuristic algorithms. According to particular characteristics or properties, metaheuristic algorithms are classified and summarized [20]. These classifications consist of key properties, including the basis of algorithm establishment, type of the problem, use of local and global search, objective, proximity, and saturation. Each classification contains a set of related algorithms that are either of the same type or of different types but related to particular characteristics or properties. Here, an object-oriented classification scheme is also given, concerning the main properties that stem from the same basic objectives [5].

APPLICATIONS OF METAHEURISTIC ALGORITHMS

Customer clustering and order routing problem in socio-economic areas can be modeled with a generalization of VRP where the need carried out by the vehicle is the customer demand for merchandise that can represent requests for various products as a few vehicles where the size of the vehicle is unlimited. In this case, researchers state that typical VRP has a sequence of customer serviced for each vehicle just like TSP heuristic. This problem involves a contention of vehicles from one vehicle going to another vehicle and is solved by using realistic delivery of customers that induce trade depending on substantial interactions of vehicles [19]. A study to solve the classical and democratic location routing problem - a dimensional vehicle route with a variant of clustered-based demands of customers with a genetic algorithm with links, because the genetic algorithm has infused exploration property, local, parallel, and take off coding features on such vacillation variables. Due to that matter, it is appropriate to deal with this problem relatively quickly [16].

Table 2: The Available Quantities of the Raw Materials, and the Profit Returned from One Unit of Both Products in the Classical Context.

Work	Algorithm	Engineering application
Mosqueira-Rey, et al. [38]	Genetic Algorithm (GA)	Circuit Design, Machine Learning
Nassef, et al. [39]	Particle Swarm Optimization (PSO)	Power System Optimization, Image Processing, Robotics
Norouzi, et al. [40]	Ant Colony Optimization (ACO)	Routing and Scheduling, Telecommunications, Transportation Planning
Osaba, et al. [41]	Simulated Annealing (SA)	VLSI Design, Protein Folding
Ouyang, et al. [42]	Tabu Search (TS)	Resource Allocation, Network Design
Pan, et al. [43]	Harmony Search (HS)	Water Resources Management, Structural Optimization
Panda, et al. [44]	Differential Evolution (DE)	Chemical Process Optimization, Power System Control
Rahman, et al. [45]	Firefly Algorithm (FA)	Wireless Sensor Networks, Image Segmentation
Samet, et al. [46]	Artificial Bee Colony (ABC)	Economic Load Dispatch, Image Compression, Feature

A case study to solve the location problem in clustering problem. Suppose we have input locations and suppose we have some users belonging to each town. Because users belong to several towns, it needs location in several places. If some town appears in the ranked list of each user accordingly, it can be made as a cluster. By maximizing the number of users joining a town, the location on it that is the mean position of several user preferences will be found. From previous research, the genetic algorithm is effective and efficient in finding accurate solutions along with empirical estimation because it has a powerful ability for global optimization [23]. However, the genetic algorithm has a deficiency in local search; therefore, it is

sensitive to the initial solution. The hybrid algorithm makes use of the strength of the genetic algorithm in both global optimization and exploration to carry out one solution by using a local search operator with better strength than the induction operator [54]. Table 2 presents the latest endeavors in the domain of engineering metaheuristic optimization, along with the corresponding techniques employed in these pursuits.

Engineering

Optimization is an important aspect in nearly all engineering disciplines and in many applied sciences. It seeks to provide long-term solutions, taking into consideration multiple objectives and optimizing techniques to support decision-making in complex problems. A great number of optimization algorithms have been proposed to aid these researchers; and so, their variants no longer advance as quickly as in previous years. These algorithms, through great applications, have matured and also achieved remarkable accomplishments [27]. Therefore, it has become necessary to consider the principles of these algorithms, their contributions, and setbacks. An extensive review has included works from 2017 and earlier, with no citation beyond this date. The present systematic review seeks to bring these algorithms up to this point and also reviews new planning applications, as well as offer insights and suggest future research possibilities [33]. Optimization is the search process for a better way. It has great application in various sectors of science and engineering. These applications have become precursors for the development of new optimization algorithms. Many algorithms have been generated over the years, and hence, a review has been initiated to give an account of the algorithms, their contributions, and shortcomings. One of the first algorithms generated due to the application of optimization in structural engineering, the genetic algorithm, is examined. The magnetosphere algorithm is considered as one of the fastest optimization algorithms. The search modes of the algorithm are compared with those of classical algorithms [54].

Finance

Metaheuristic is known as an algorithm that can solve hard optimization problems in a reasonable time period and ensures that the results obtained have a satisfactory level. The success of a metaheuristic method depends on how a metaheuristic productively consumes the search space and the way it explores and exploits the different paths of the space. Generally, the metaheuristic in the finance area may be divided into decision support system research and problem-specific research. Related to the previous graduation, the characterization of this categorization is discussed to help reveal how a heuristic or metaheuristic population evolves [11, 31].

The application of artificial intelligence techniques has significantly developed to solve the problems within the framework of finance. Hence, metaheuristic algorithms, which are an important class of artificial intelligence, are being used and studied in finance as well. Considering the important role of optimization problems within finance, as well as the increasing number of the use of metaheuristic algorithms to solve financial decision making problems, in this work, we present many applications in this area. Besides the use and application, much research is also focused on the development of main issues such as forecasting, data mining,

portfolio selection, option pricing, fund management, and risk management, and these may be viewed as the research themes to be addressed [30, 47].

Finance is one of the most important fields in business and it has been growing significantly in recent years. The development and improvement in the ways of financial data management, analysis, and forecasting techniques are increasingly essential for decision making of the financial stakeholders. An important aspect associated with finance is optimization, which involves a class of decision making problems that possess the characteristics of uncertainty, complexity, and dynamic personality [49].

Healthcare

Two different swarm-based deep learning models are presented by Ertugrul et al. Convolutional neural networks (CNN) are combined with grey wolf optimizer (GWO) and fuzzy grey wolf optimizer (FGWO) on dynamic epistatic differential evolution neural network (DEEP-DN) on 10 and 15 fold cross-validated 4 datasets. The proposed dynamic metaheuristic models are evaluated with different kernel sizes of relu and tanh based activation functions. The performance of the models is evaluated using multi-class classification statistical measures and receiver operator curve (ROC) to show the discriminative decision boundaries on predicting the classes. The dynamic neural network model with the best accuracy and F-score is observed with 86.10% in UCI Ionosphere dataset [32]. The deep CN based GWO classifier with a kernel size of 3 and relu activation function observed the superior performance than other kernel sizes and activation functions for averaging average class predictions. It is observed here that the deep neural DN with CNN kernel size of 3 and relu activation function yields superior accuracy in the presence of dynamic epistatic changes with GWO followed by FGWO compared with other classifiers over the datasets [36].

Application of metaheuristic and machine learning-based methods for epileptic seizure prediction is conducted by Vadivel et al. Autoregressive features are extracted, followed by arrhythmia prediction via open-source machine learning (OAMLS) classifier and support vector machine (SVM) on University of Bonn and Freiburg Epileptic dataset using MELAG and single-index model (SIM) [44]. SVM is used for comparing the performance of MELAG with SIM model. The performance of the models is evaluated using statistical measures. The arrhythmia prediction in epileptic cases is confirmed at 5 min with a moderate prediction precision of FPR 0.02 for OAMLS and 0.08 for SVM. The models are robust in detecting the epileptic cases from the Ictal cases up to 57.5% and also from normal cases by 42.5% for 30 s. HAS and SHS models are good in detecting discriminative features associated with arrhythmias between Ictal and non-Ictal cases. MELAG model outperforms the classical SIM model except the FP rate at 5 min OAMLS, but the consistency of the models is found as the generalized model while evaluating on UPENN dataset.

REVIEW METHODOLOGY

The chosen means of consultation were IDP (Web Platform of UFOP), DIGITAL CAPES, ELECTRONIC ANNUARIES, MAGÓ, MINAS E-MAGID, SCIENCE DIRECT, IEEE EXPLORE, SEARCH TOOLS, JSTOR and SPRINGER LINK, ULRICH'S, WILEY ONLINE LIBRARY, and consulted in article format, conference proceedings, standards, theses, and dissertations. The keyword search in the various

databases use terms such as: metaheuristics, optimization, nature-inspired algorithms, swarm-based algorithms, evolutionary algorithms. This study is not a trade-off, which deals with debate articles, editorial, letter to the editor, summaries, book review, bibliometric studies, news, article modeling, obituaries, interviews, biographies. The review of these articles follows quantitatively for journals and years of publication, to verify the trend and current countries on the subject [21].

The review of these articles or journals initially includes a brief analysis of the introduction to understand how pertinent is the efficacy of the task in the content of the paper, the researchers and the type of task to be solved such as: the limitations, the strengths, the main goal and the objectives of the study. The journal articles are used for the purpose of obtaining content to be analyzed, to find information, formulate assumptions, hypotheses, and/or concepts, theories, and to carry out research as secondary sources. Such as books, articles, theses and dissertations. The selection of articles in journals is because they are valuable sources of carcinogenic research reports, since by necessity they also often publish research reviews (integrative reviews, meta-analyzes, systemic reviews, critical reviews and literature reviews of research) [46].

Selection Criteria

In the context of the complexity versus problem structure criterion, it is suggested to use evolutionary algorithms or cultural algorithms for structured problems with an evolutionary characteristic, satisfied by the use of feasible solutions. While these algorithms work satisfactorily in other types of problems, they are generally surpassed in performance by other algorithms. The level of knowledge of the user must be another important criterion in the choice of the algorithm because despite the growing number of available algorithms, it is not possible to become proficient in all of them in a short time [57]. This implies that, in practice, only a few algorithms will be known by those people who use them to solve optimization problems. EC has been shown that users with little knowledge generally initially optimize with algorithms known as intelligent, such as SA and local search techniques, while those with sensations with programming and metaheuristics should use more sophisticated algorithms, such as GAs, which better fit diverse problems of applications [38].

The proper selection of metaheuristic algorithms to solve specific optimization problems is an arduous task. One reason is the lack of benchmarks that include actual instances from the industry and the complex nature of the limitations that characterize the optimization problems. A careful selection should include an estimation of the ability of the algorithm to find solutions of good quality in a reasonable computational time, in addition to the level of expertise of the user in the algorithms and the characteristics of the problem. Based on previous studies, guidelines can be created to expedite this process. In 13 selection criteria are presented to aid in choosing a metaheuristic algorithm. They are: complexity versus problem structure, user level of knowledge, implementation, quality of the result, optimization, system environment, diversification, hybridization, non-deterministic (stochastic), application constraints, scalability, and portfolio of solutions [26].

Data Sources

This review aimed to collect and analyze worthwhile information in the available

scientific field to present the work's goals. Thus, when the keywords and complementary search strategies (as verification to avoid overlooks) derived some potential filtering obstacles, it was necessary to increase the spreadsheets volume based on additional parameters. The aim of this selection is for enriching the built-up with excellent quality articles published in the most relevant journals by well-qualified authors in this area of knowledge. These authors' home country-related feature sought to collect good quality articles as far as possible, written by researchers at most present in this kind of scientific output [42]. This procedure pursued the recognition of the most influential researchers or institutions, influential articles in this particular research area of operations research and optimization problems by means of metaheuristic algorithms to demonstrate its applicability. In this event, extensive literature indexed on the Scopus website and Web of Science (Thomson Reuters) was collected during a renowned period. For data suggestions, a description of the structure of the developed algorithm was presented, combined with the advantages and disadvantages of the used types of algorithms in each of the solutions produced by them or the risks of failing to generate suitable solutions for the problem under analysis [17].

The main sources of data were kept as scientific papers in scientific databases. Also, in the event, the Scopus and Web of Science research database was chosen. Both databases are ideal sources to be a reorganized reference in searching for scientific articles, particularly in the field of solving algorithms in optimization issues. According to Scopus, the number of indexed documents (from 1975-January 2021) on the Scopus website was 74,780,607 documents. Scopus displays the total number of documents (produced by the increment of each year's total documents) and articles (both review, conference paper, and article) totaling 41,757,958 articles. The number of indexed documents (from 1975-January 2021) on the Web of Science website was 52,773,329 documents. Web of Science displays the total number of documents (produced by the increment of each year's total documents) and articles (both review, conference paper, and article) types of articles totaling 21,945,359.

Data Collection

The largest number of new algorithms are found in 2010, with a clear downward trend observed over the next few years, discovering the increasing trend in the research of metaheuristic optimization algorithms. The instrument most used to implement the new proposed algorithms is computers, followed by numerical simulations and third computer simulations. This can be explained due to the huge computing power of supercomputers. The algorithms proposed in the machine learning area have been widely discussed and are also widely used for analyzing large volumes of data, which has contributed to identifying some potential solutions. However, nowadays, as well as in the past year, we can see several algorithms with no strict proposal on how the proposed methods can be extended. These algorithms are created only to solve the problem in question [24]. Only a few authors made comparisons with other traditional metaheuristic algorithms. The GWO algorithm was the one that emerged in greater numbers, closely followed by the SPLO-CMA-ES algorithm. Figure 10 shows comparisons with at least 10 algorithms. Some authors have proposed 4 comparing algorithms, followed by those proposing 5 and 6. Notable is the number of those who propose two other types of algorithms for comparison, since it suggests that these proposed algorithms may have some confidence.

A significant amount of data can be collected and identified in a literature review. For the purpose of this study, a small amount of data was selected: the names of authors, the years of publication, the instruments for implementing the proposed algorithms, the kind of algorithms, the kind of problems proposed, and some comparisons of other metaheuristic algorithms. These data are interesting for the identification of trends and bottlenecks in the topics in this paper [48].

REVIEW FINDINGS

From Figure 3(e), it can be observed that the payoff in the field of optimization is maximized with numerical representations and equations, with 378 documents (27.55%), followed by Machine Learning tasks with 172 documents (12.54%). Similarly, the results of the Detailed Literature Review (DLR) also showed that metaheuristic methods perform better than Classical methods (CMs) when solving problems, such as Continuous Educational System and Classroom Allocation (CESSCA), Job Sequencing Problem (JSP), and the oil pipeline diet. Their work specifically describes the development of the Fruit Fly Algorithm (Dynamic FFA), the Bacteriophage Reproduction and Social Antibody Optimization (BRSA), and the Cuckoo Exponential Search and Cuckoo Peak Exponential Search (GCES-CU-SDPS) algorithms [12].

From Figure 3(c), it can be observed that most of the researchers have solved minimization problems with 550 papers (40.07%), followed by maximization problems with 343 papers (24.99%). In Figure 3(d), a total of 1084 papers have been solved using benchmark test functions against real-world applications. The figure shows that approximately 79.05% of literature is devoted to benchmark test functions [15].

In Figure 3(a), we can observe that Genetic Algorithms (GA) is the most used approach with a total of 224 papers (16.32%), followed by Particle Swarm Optimization (PSO) with 209 papers (15.25%). In Figure 3(b), about 478 papers (34.85%) were used for solving problems in the field of Engineering, followed by Computer Science with 163 papers (11.88%) [18].

In this section, we will present some key results and findings derived from the detailed review study presented in the previous sections. The literature review indicated that several researchers have used different metaheuristic algorithms in various optimization environments, such as marketing, engineering, and economy, and many optimization problems have been solved using one of these metaheuristic techniques [41].

Algorithm Performance

The problem is that a comprehensive performance analysis requires very comprehensive and detailed experimental results regarding the operational characteristics of an algorithm, such as the final results it achieves on all instances or the number of function evaluations (or iterations) and time it spends on each instance. The diversity of these evaluation metrics and their implemented performance measures across the different algorithmic parameter settings makes statistical comparison of metaheuristics for optimization rather complex. This may explain the fact that for a given optimization problem, experimental comparisons of various metaheuristics were carried out for synthetic cost functions rather than actual problem instances. We will discuss some experimental statistical

comparisons of metaheuristics for actual problem instances in sections to come and conclude this introductory section with the following statement [41].

Different instances of an optimization problem may lead to different performance values for an algorithm. This fact prompted the introduction of mean performance measures of an algorithm over a set of instances under study. In some studies, the best and/or worst performances were also presented for comparison purposes. These general performance measures were soon combined in order to define a better measure, the so-called median measure. According to this measure, certain top and bottom performers are excluded from the mean value measures. The aim of excluding the top and bottom instances can be interpreted as avoiding possible unrepresentative values. In order to increase the sensitivity of the basic performance measures, 25% and 75% percentiles were also suggested. Although all these measures are effective in understanding the performance of an algorithm, a completely satisfactory description of an algorithm's performance over a given set of instances might require an extremely large collection of experimental results, under conservative reporting principles [53].

Solution Quality

Two alternative approaches to assess the quality of a solution are known as the result before and the result after, or what people also call the best solutions and the worst. The best solution or the result before is a measure against the highest number that clearly reflects the worst thing. If the number of items in a problem is finite and large, then the determination of the best solution corresponds to the solution tools in a comprehensive manner. The best solution to the solution one plate is equal to the ideal value and is used for the normalization factors (local search), attached to each set of tools produced by an algorithm, and then also compared to see the solution about where its quality. So, in the use of this index, as long as it is above the ideal value, it can be said that the solution has been welding attempts [58].

In reality, a solution that an algorithm found tends to vary from algorithm to algorithm. Finding a good solution in a heuristic algorithm that is higher than the optimal value at best, or at least less than or equal to the high-quality solution can be misleading. Because the aim of using heuristic algorithms is to find solutions that are not optimal but still have high quality, i.e., less than or equal to the upper limit on the results that are targeted where the level of compliance, the level of closeness, and the three limit coefficients are known [7].

Computational Efficiency

Aghaie and Moradi proposed a new hybrid algorithm for solving complex optimization problems through NP-hard route planner problems. This algorithm applied Cuckoo search and another metaheuristic algorithm, PSO, intended as a randomness access point. The computational time for the algorithm was also highlighted by Aghaie and Moradi. The results show that the algorithm revealed a solution faster compared to other metaheuristics: DE algorithm, CWP-FFA, PM-R-HPOP, SHC, and LM. Ahmad, Sahar, and Udai proposed a novel robust and efficient technique (RIWTSA) for solving economic dispatch (ED) problems with an application of different metaheuristics. The problems such as voltage stability constraints, ramp rate limits for various generators, and non-smooth fuel cost

functions were also taken into account in the proposed technique. The results of the computation time were also published by Ahmad, et al. with RAGA RIWTSA outperforming ED, RMS, and DE in solving different unit specifications at resemblance and near convergence ranges [39].

The use of metaheuristic algorithms in applications is a popular choice made by researchers. However, the computational time it takes to generate the best solution is often an issue. It will not be beneficial if the algorithm requires too much time for an optimization process. Thus, the efficiency of metaheuristic algorithms is really important as consideration for their applications. For a fair evaluation of the metaheuristic algorithm proposed, the time to achieve the solution (average) is a better measure. When a metaheuristic algorithm is tested on a computer, the algorithm processes are time-consuming due to the large amount of data and time taken to explore combinations. To measure this time, the term speedup effect is used. Speedup is influenced by the execution time of the total resources required for the algorithm process such as memory, time granularity, and number of computers used. Therefore, speedup serves as an easy benchmark to compare and determine better threads, algorithms, and nodes [22].

COMPARISON WITH OTHER OPTIMIZATION TECHNIQUES

Recently, local search techniques are frequently used in articles. In general, these techniques exploit the candidate solution to improve the performance of the model, rather than generating a set of new feasible solutions. Traditional local search techniques, such as simulated annealing (SA) and tabu search, propose significant advantages and below in a category were brought on these two techniques. SA was used to solve direct transportation problems with decreasing nonlinear objective functions where the selection of the initial solution and the structure of the proposal neighborhood search play an important role in the efficacy of the SA approach. Tabu was used to solve the capacitated p-median problem and in each algorithm, they were encoded to break the occasional cycle of search and this was broken up by a memory mechanism that preserves the candidate solutions of the local search to ensure that the solutions are different. So, in view of the previous sections, the table summarizes the strengths and weaknesses of the most widely used optimization techniques [34].

Tabu search and SA approaches guarantee an opportunity to escape from local optima with the help of aspiration criteria. Unlike these two, PCLA used an extended version of path relinking based algorithms, which used a common path between two solutions in the identification of a next solution in the search process. Not similar to this, Isasi et al. have proposed a simple SA-like algorithm by adding an aspiration-level criterion to make our search trace advance inside p-points, which results in a short circuit search whenever a forbidden transition may be violated. Cano et al. compare some combinations of algorithms with LR technique and result in the combination of the two best algorithms performing much better than both of the two alone. Christidis and McMechan developed a hybrid genetic algorithm wherein the crossover operator selects a bin from a fitter parent solution and the mutation operator perturbs an unfit solution slightly. They indicate that a significant interaction exists between the mutation and crossover operators and the success of the approach is attributed to the hybridization of the mutation and crossover operators in the algorithm. He et al. proposed a novel optimization technique, ant colony system (ACS), which was used for solving the capacitated p-

median problem to obtain a near-optimal solution within a reasonable computation time. They also indicated that the proposed algorithm outperformed methods such as CLPS. It is to be noted that Saad et al. have developed heuristics mentioned in different sections. So a comparison of the methods of each section can be made with one another, and another comparison can also be made against the randomization of tabu search [51].

FUTURE RESEARCH DIRECTIONS

Each algorithm development is created in response to the growing need for algorithms that can quickly and across disciplines solve a wide range of optimization-related problems. Meta-heuristic algorithms will continue to play an important role in handling optimization problems that are difficult to solve. These approaches will continue to form the basis of the black box optimization and approaches using these address way off probability analysis. Finally, it is necessary to know that with all these features, well-defined usability, some meta-heuristic algorithms, in the sense of solving a specific type of stochastic optimization problems, compare well with the state of the art optimization techniques [10]. Applications domains ranging from biology and robot path planning to network design with different performance bounds will always include previously unanalyzed features that will make an existing algorithm generate inferior qualitative results. In this paper, we have provided a brief review of the specific applications of the established meta-heuristic algorithms by identifying which algorithms have been widely used in a particular area of application and discussing how they were able to handle an optimization problem that was the focus of each study. This review also has not attempted to analyze the computational requirements or the performance levels of the algorithms, since state-of-the-art was reviewed by each established algorithm in several surveys and we focused on the applications compared to the algorithms that were proven to work with a variety of problem domains [3].

CONCLUSION

Concluding this paper, Earth remains a planet with scarce resources. So the resources that are present should be efficiently managed. The efficient management can be achieved by using optimization methods, one of which is the metaheuristic optimization method. This can be observed by the observation of research results for each year. The number of published research using metaheuristics always increases. Therefore, it's not surprising if the scientific and practitioner community in various fields show much enthusiasm in applying this method.

The world of optimization is always developing over time along with technological developments. From the time these metaheuristic methods began to be known in 1945 until now, where the use of IoT is massive, data that can be processed by these metaheuristic algorithms is increasing. Metaheuristic algorithms have various variants that can make these algorithms adapt in accordance with the various problems. On the other hand, various variants of problems originating from various fields also occur, so it would require a wide range of studies using these metaheuristic algorithms. In the future, the author hopes that more studies will be conducted with better methods through optimization problems that researchers find in their fields, so that better results will be generated. Furthermore, the generated results can benefit a wider community.

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