



Metaheuristic Optimization Review: Algorithms and Applications

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Abstract

Metaheuristic optimisation algorithms have become more well liked in recent years due to their success in solving challenging optimisation problems. Only a few of the metaheuristic optimisation techniques covered in this work include genetic algorithms, particle swarm optimisation, simulated annealing, ant colony optimisation, and many others. This paper discusses the history, operation, and applications of each method, including applications in engineering, finance, and bioinformatics.

Keywords: Meta heuristic; Optimization; feature selection.

1. Introduction

To minimize or maximize an outcome, the optimization process seeks the best possible values for a set of parameters in a given problem space. In the last two decades, metaheuristic optimization techniques have become more refined, and optimization techniques in general have found widespread application in a variety of fields for the purpose of solving complex problems in practice; as a result, not only computer scientists but also scientists from other fields are familiar with well-known optimization techniques, thanks to their efficacy and high pertinence [1]. The following characteristics of meta-heuristic methods contribute to their widespread popularity:

- The ease of use of meta-heuristics: The simplicity of these methods reflects a reversion to the traditional, simplistic understanding of approaches as meta-heuristics that draw heavily from the realm of nature. The ideas came from studying swarm behaviour, seeing natural events, or thinking about evolution.
- Researchers and computer scientists are drawn to the simplicity of these algorithms, which is a large part of the reason why they are able to mimic natural notions in the form of new meta-heuristic algorithms, update existing algorithms to improve their performance, or hybridise many algorithms to harness the strengths of the individual algorithms when addressing additional problems. In addition, the simplicity of these methodologies, both in terms of learning them and putting them into practise, makes them valuable tools for researchers and scientists working in a wide range of disciplines.

- Since meta-heuristics treat the problem as a black box, they can be applied to a wide variety of problems with little need for structural changes to the underlying algorithm. In most cases, just the problem's creator is required to know its inputs and outputs in order to use meta-heuristics. how to apply meta-heuristics to an issue, you need to know how to formulate the problem. The vast majority of existing Meta-heuristic Unlike methods like gradient-based optimizations, which require computing the derivative of the problem space in order to obtain optimal values, meta-heuristic techniques use a stochastic approach to optimization by starting with randomly initialized agents. These agents then evolve and cooperate to find the best possible solution to the problem at hand. This feature expands the scope in which meta-heuristics can be used to a difficult and unexplored search space.
- Since meta-heuristics use a stochastic strategy to solve problems, they are better able to solve real-world problems with complex and unknown problem search spaces than traditional techniques because they are less likely to get stuck in local sub-regions and more likely to diverge as a result.
- There are a few main categories that the algorithms for meta-heuristic optimisation can be placed into. The number of different solutions that optimisation algorithms use and the method(s) that served as an inspiration for those algorithms are two common approaches that may be found in the relevant research. According to the aforementioned framework, optimisation algorithms are classified into one of four categories, depending on the origins of their respective ideas. These categories are swarm intelligence, evolutionary algorithms, physical algorithms, and human algorithms.

The cooperative behaviour of swarms (animals, birds, and insects) in their quest for prey, food, and the location of individual swarm members is imitated by swarm intelligence (SI) algorithms [2–5]. The Cuckoo Search CS [6], the Dragonfly Algorithm DA [8], and the Particle Swarm Optimisation (PSO) [7] are a few examples of such algorithms. Computer programmes that solve problems by utilising tactics that are akin to biological processes such as mutation, recombination, and selection are referred to as evolutionary based algorithms (abbreviated as EA). The process of biological evolution is the source of inspiration for these projects. In order to arrive at the optimal solution, EA algorithms start by generating a random population, evaluating that population, and then choosing and evolving the most successful individuals from within that population. Genetic techniques GA [9], Differential evolution DE [10] and Genetic Programming GP [11] are the three forms of evolutionary analysis that are used most frequently nowadays. Several examples of algorithms that take their cues from the laws of physics and apply them to real-world settings include the Gravitational Search Algorithm (GSA) [12], the Heat Transfer Search [13], and the Lévy flight distribution [14].

The Archimedes Optimisation Algorithm [15] and the Henry Gas Solubility Optimisation Algorithm [16]. Tabu Search (TS) [17], which uses short and long-term memory to improve search space exploration and diversity, and Teaching Learning Based Optimisation (TLBO) [18], which mimics the human learning approach used by a teacher and a student, are both instances of human-based algorithms. Tabu Search (TS) [17] utilises short and long-term memory to increase search space exploration and diversity, and TLBO [18] simulates the human learning approach used by a teacher and a student. Tabu Search (TS) [17] makes use of both short-term and long-term memory in order to enhance search space exploration and diversity.

The number of solutions that each meta-heuristic utilises in the course of its optimisation process constitutes the second method for classifying meta-heuristics. Individual-based algorithms include Hill Climbing [19] and Simulated Annealing (SA) [20], whereas population-based algorithms include GAs [9], ES [21], PSO [6], ABC [22], GSA [12], GWO [23], and TLBO [24]. Hill Climbing [19] and Simulated Annealing (SA) [20] are examples of algorithms that belong to the individual-based group. An algorithm that is based on a single solution or individual solution focuses entirely on that solution, which develops as a consequence of the optimisation process, in order to arrive at an ideal state.

On the other hand, population-based algorithms need the creation of a population of agents, which are then initialised in a random manner, evolve through time, and collaborate with one another to

obtain the best possible outcomes. In contrast to population-based algorithms, which can perform up to NT function evaluations (where N denotes the number of population agents used by the algorithm), this approach can only perform up to T function evaluations.

In single-solution algorithms, the evaluation of the objective function is only required to take place a limited number of times during the course of a set number T of iterations $1T$ of times. Single-solution algorithms have a greater propensity to get stuck in local optima as compared to multiple-solution algorithms. Multiple-solution algorithms allow sets of solutions to work together, share and collect information about the problem search space, and ultimately improve the exploration of the problem space and the ability to escape from local sub-regions through more complex problem spaces. Metaheuristic optimization has many applications as in [25-28]

This study provides an approach to feature selection that can be used to find the ideal parameters for support vector machines (SVMs) and the input data for classifiers. The approach may be used to determine the optimal parameters for support vector machines (SVMs). The values of two different kinds of parameters can have a significant impact on the performance of support vector machines (SVMs) [29, 30]. The penalty constant C parameter and the kernel functions parameters. If these criteria are chosen correctly, then the classification accuracy will be as high as it can possibly be. As a result, the authors of this study make use of GOA in order to present a novel GOA-SVM hybrid optimised classification system for tagging ECG signals that are symptomatic of epilepsy [31]. The acquired experimental findings demonstrate very clearly that the suggested GOA-SVMs classification system performs better in terms of classification accuracy than the usual SVMs classification algorithm and the Particle Swarm Optimisation with SVM (PSO-SVM).

The following is the structure of this paper: In the next section, we will provide a concise explanation of the many types of optimisation problems. In Section 3, we go over applications, feature selection, and the use of single objective meta-heuristic algorithms to solve engineering design difficulties. All of this is done in an effort to improve engineering design.

2. Types of Optimization Problems

A. Single Object Optimization

There is just one optimal solution in single-objective optimization. This is because there is only ever one correct answer to a single-objective problem. When focusing on a single criterion, a comparison of possible outcomes can be performed with relative ease using the relational operators $>$, or $=$. Because of how they are structured, optimization issues make quick work of contrasting potential solutions and selecting the optimal one. A generic formulation of the single objective optimization problem looks like this:

One should try to

$$\text{minimize the function } f(x_1, x_2, x_3, \dots, x_{n-1}, x_n) \quad (1)$$

$$\text{subject to : } g_i(x_1, x_2, x_3, \dots, x_{n-1}, x_n) \geq 0, \quad i = 1, 2, \dots, m \quad (2)$$

$$h_i(x_1, x_2, x_3, \dots, x_{n-1}, x_n) = 0 \quad i = 1, 2, \dots, p \quad (3)$$

$$lb_i \leq x_i \leq ub_i \quad i = 1, 2, \dots, n \quad (4)$$

The search space of a single objective optimization problem is made up of the problem variables, the constraints (equality, and inequality constraints), and the objective, where n is the number of problem variables, p is the number of equality constraints, and m shows the number of inequality constraints.

B. Multi-objective Optimization

For optimal judgements in multi-objective optimization situations, it is necessary to take into account trade-offs between the several objective functions that must be optimized at the same time. Many disciplines, including engineering and economics, regularly face multi-objective optimization challenges. There is no unique answer to a multi-objective optimization problem; rather, there is a collection of answers—the Pareto optimal solutions—that maximize each objective function in turn. Pareto optimum dominance is used by multi-objective optimization methods to evaluate competing approaches to a given issue with multiple objectives. Since a multi-objective problem can have multiple optimal solutions, most multi-objective algorithms use some sort of storage to keep track of the optimal solutions they've found so far (called Pareto optimum solutions) and then refine this set as they optimize [32].

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For maximum generality, consider the following formulation of the multi-objective optimization problem as a minimization issue:

$$\text{Minimize } F(\mathbf{x}) = \{ f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_o(\mathbf{x}) \} \quad (5)$$

$$\text{Subject to: } g_i(\mathbf{x}) \geq 0, \quad i = 1, 2, \dots, m \quad (6)$$

$$h_i(\mathbf{x}) = 0, \quad i = 1, 2, \dots, p \quad (7)$$

$$L_i \leq U_i \quad , i = 1, 2, \dots, n \quad (8)$$

where n is the total number of variables in the problem, p is the total number of equality constraints, m is the total number of inequality constraints, o is the total number of objective functions, $[h_i, g_i]$ is the i th equality and i th inequality constraints, and $[L_i, U_i]$ are the i th variable's bounds. Defining superior solutions typically necessitates a shared operator known as Pareto dominance because objectives in a multi-objective search space can be at odds with one another and relational operators cannot be used to compare them because there are multiple criteria at play in the problem at hand.

$$\forall i \in \{1, 2, \dots, o\} : f_i(\mathbf{x}) \leq f_i(\mathbf{y}) \wedge \exists i \in \{1, 2, \dots, k\} : f_i(\mathbf{x}) < f_i(\mathbf{y}) \quad (9)$$

where $\bar{x} = (x_1, x_2, \dots, x_k)$ and $\bar{y} = (y_1, y_2, \dots, y_k)$ and a solution (represented by vector \mathbf{x}) is preferable to another solution (represented by vector \mathbf{y}) if it has the same or a higher value for all objectives. To indicate that \mathbf{x} is more important than \mathbf{y} , we write $\mathbf{x} \succ \mathbf{y}$.

C. Combinatorial Optimization Problems

Finding the optimal answer among a limited number of choices is the goal of the class of mathematical optimization issues known as combinatorial optimization problems. One defining feature of this class of issues is the requirement to optimize some discrete functions within some bounds. Scheduling, routing, and resource allocation are just a few examples of the many real-world applications that might give birth to combinatorial optimization challenges. Computer science, mathematics, and operations research have all been actively investigating combinatorial optimization problems due to their complexity.

The branch and bound algorithm is an iterative method for addressing combinatorial optimization issues; it narrows the search space by applying rules based on the best answer found so far. In addition to these methods, simulated annealing, genetic algorithms, and ant colony optimization are also widely used. The traveling salesman problem, the knapsack problem, and the graph colouring problem are just some of the many problems that have benefited from these methods.

In this day and age of huge data and complicated systems, combinatorial optimization problems remain a formidable obstacle. Researchers used to struggle with solving issues of growing complexity, but now, because of advancements in algorithm design, parallel computing, and machine learning, they can do it with better efficiency and precision. Combinatorial optimization is an active area of study that has great potential for illuminating and solving a wide variety of practical issues.

D. Continuous Optimization Problems

Mathematical optimization problems that have a continuous collection of feasible solutions are called continuous optimization problems. The optimization of a continuous function within a given set of constraints is the defining feature of this class of problems. Engineering design, finance, and data analysis are only few of the many real-world contexts in which challenges of continuous optimization arise. Research in mathematics, computer science, and operations research has focused on continuous optimization issues because of their complexity.

Gradient-based methods, which include iteratively refining the solution by moving in the direction of steepest descent of the objective function, are one of the most popular strategies for tackling continuous optimization issues. Interior point methods, evolutionary algorithms, and simulated annealing are among other well-liked approaches. Linear programming, quadratic programming, and nonlinear programming are only few of the many problem types that have benefited from these methods.

Even in the age of enormous data and complicated systems, problems of continuous optimization remain difficult. However, researchers are now able to solve more difficult issues with more efficiency and precision thanks to developments in algorithm design, numerical analysis, and high-

performance computing. Insights and answers to many practical issues will likely emerge from the ongoing study of continuous optimization.

3. Metaheuristic optimization applications

A. Engineering Problems

Metaheuristic optimization algorithms have shown great potential in solving complex engineering problems that are difficult to solve using traditional optimization techniques. One of the most significant applications of metaheuristic algorithms is in the optimization of mechanical systems. For example, metaheuristic algorithms have been used in the design of gearboxes, where the optimization problem is non-linear and multi-objective. Recent studies have shown that metaheuristic algorithms are effective in finding optimal solutions to complex mechanical design problems [33].

Furthermore, metaheuristic optimization techniques have been employed to enhance the performance of control systems. Control systems play a pivotal role in numerous technical applications, including but not limited to the aerospace and automotive industries, as well as robotics. Metaheuristic algorithmic approaches have been implemented in the development of control systems, such as model predictive controllers (MPCs). According to recent studies, metaheuristic algorithms have proven to be a successful approach in identifying optimal solutions for complex control system design problems [34].

The utilization of metaheuristic optimization algorithms in engineering challenges has proven to be a noteworthy approach in optimizing manufacturing processes. Various technical domains, including aerospace, automotive, and electronics, employ manufacturing methods to produce their products. Metaheuristic algorithms have been utilized to optimize manufacturing processes, including turning and milling. According to recent research, metaheuristic algorithms have proven to be an effective approach for identifying optimal solutions to complex problems related to the optimization of manufacturing processes [35].

Furthermore, metaheuristic optimization algorithms have been employed for the purpose of optimizing delivery systems for renewable energy. The field of engineering is increasingly prioritizing the advancement of renewable energy systems, owing to their capacity to offer a sustainable and environmentally-friendly source of energy. Metaheuristic algorithms have been employed in the development of renewable energy systems such as wind turbines and solar photovoltaic systems. According to recent research, metaheuristic algorithms have proven to be a highly effective approach in identifying optimal solutions for intricate design problems related to renewable energy systems [36].

To sum up, metaheuristic optimization algorithms have been applied to address a diverse range of technical problems, such as chemical process design and water resource management, among others. Metaheuristic algorithms have been employed to optimize chemical processes, including the design of distillation columns, as an example. According to recent studies, metaheuristic algorithms have proven to be a viable approach in identifying optimal solutions for intricate chemical process design problems [37]. Table 1 presents the latest endeavors in the domain of engineering metaheuristic optimization, along with the corresponding techniques employed in these pursuits.

Table 1: 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
[38]	Genetic Algorithm (GA)	Circuit Design, Machine Learning
[39]	Particle Swarm Optimization (PSO)	Power System Optimization, Image Processing, Robotics
[40]	Ant Colony Optimization (ACO)	Routing and Scheduling, Telecommunications, Transportation Planning
[41]	Simulated Annealing (SA)	VLSI Design, Protein Folding
[42]	Tabu Search (TS)	Resource Allocation, Network Design
[43]	Harmony Search (HS)	Water Resources Management, Structural Optimization
[44]	Differential Evolution (DE)	Chemical Process Optimization, Power System Control
[45]	Firefly Algorithm (FA)	Wireless Sensor Networks, Image Segmentation
[46]	Artificial Bee Colony (ABC)	Economic Load Dispatch, Image Compression, Feature

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		Selection
[47]	Grey Wolf Optimizer (GWO)	Portfolio Optimization, Control Systems

B. Feature Selection

In machine learning, one of the most important steps is called "feature selection." This phase entails choosing a smaller subset of pertinent features from a larger set of potential features in order to increase the accuracy and effectiveness of a model. A reduction in overfitting, an increase in the interpretability of the model, and a decrease in the computing burden can all result from careful feature selection. The selection of features can be accomplished in a number of ways, some of which are referred to as filter methods, wrapper methods, or embedded methods. The significance of a feature's inclusion is determined by filter methods regardless of the model's presence. These methods rank characteristics according to their statistical traits, such as their correlation or mutual information with the variable that is being studied. A recent study that was conducted by Li et al. (2021) introduced a new filter approach that is based on a probabilistic interpretation of mutual information [48]. It was demonstrated that the method performed better than previous filtering methods on a variety of datasets. Wrapper approaches make feature selections based on the model's overall performance. These methods analyze various subsets of features by training and testing a model, and then select the subset that gives the greatest performance based on the results of those evaluations. Zhang et al. (2021), authors of a recent study, suggested a new wrapper approach that is based on a convolutional neural network (CNN) and a genetic algorithm [49]. On a number of datasets, it was demonstrated that this strategy performed better than other wrapper methods.

Methods that are embedded integrate the process of selecting features into the construction of the model. These methods make use of a model during the training phase that is capable of selecting pertinent features, such as the Lasso or Elastic Net regression. Wang et al. (2021) published a work not too long ago in which they offered a novel embedded technique that is based on a quantum-inspired evolutionary algorithm [50]. It was demonstrated that the approach is efficient in lessening the dimensionality of high-dimensional datasets while either preserving or enhancing the accuracy of the model. In order to improve the consistency and robustness of the picked features, ensemble approaches combine many feature selection algorithms into a single process. In a recent work, Li et al. (2021) suggested an ensemble feature selection approach [51]. This method selects the ideal subset of features by combining numerous filter, wrapper, and embedded methods. It was demonstrated that the approach is efficient in lessening the dimensionality of high-dimensional datasets while either preserving or enhancing the accuracy of the model.

Recent investigations have been conducted to investigate the possible applications of deep learning for feature selection. In their work [52], Zhang et al. (2020) presented a proposal for a feature selection technique that was based on deep learning. For the purpose of extracting features, a convolutional neural network (CNN) is utilized, and a genetic algorithm is utilized for the purpose of selecting the most optimal subset of features. On a number of datasets, the performance of the strategy was demonstrated to be superior to that of conventional feature selection methods. In a more recent paper, Wang et al. (2021) proposed a method for feature selection that was based on a quantum-inspired evolutionary algorithm [50]. Encoding the qualities as qubits is one of the steps that this technique takes to select the most useful subset of features. Quantum-inspired operators and a hybrid encoding scheme are the two components that make up this method. It has been demonstrated that the method is efficient in lessening the dimensionality of high-dimensional datasets while maintaining or enhancing the accuracy of the model.

Recent research has investigated the use of feature selection in conjunction with other methods, such as data augmentation and transfer learning, in addition to the standard methods of feature selection that have been used in the past. Gao et al. (2021) came up with a strategy for feature selection that improves the accuracy of a model for image classification by combining data augmentation, transfer learning, and feature selection [53]. This method was proposed in their work. It was demonstrated that the strategy was superior to conventional methods of feature selection and improved the accuracy of the model on a number of different datasets. The selection of relevant features can help enhance the accuracy and interpretability of a model, which is especially significant in healthcare applications, which might have a very high number of features. Feature selection is very crucial in these applications because of the high number of features. Khan et al. (2021) recently conducted a review in which they analyzed numerous feature selection approaches and their applications in the healthcare industry [54]. In the review, a variety of feature selection approaches, such as filter,

wrapper, and embedding methods, were examined, along with their applications in healthcare domains such as medical image analysis, clinical decision-making, and disease diagnosis.

The merit of the features themselves will determine how fruitful the process of feature selection will be. Recent studies have investigated the application of feature engineering to the process of developing more informative features. The process of changing the raw data into a set of features that are able to more accurately reflect the underlying patterns in the data is known as feature engineering. Das et al. (2021) published a paper in which they offered a feature engineering strategy that is based on the use of a generative adversarial network (GAN) to produce synthetic features that have the potential to increase the model's accuracy [55]. In the most recent research, the usage of hybrid feature selection approaches, which integrate several different feature selection strategies, has been investigated. [51] Li et al. (2021) conducted research in which they developed a hybrid feature selection approach. This method combines filter, wrapper, and embedding methods in order to pick the best possible subset of features. It was demonstrated that the approach is efficient in lessening the dimensionality of high-dimensional datasets while either preserving or enhancing the accuracy of the model. In addition to this, it was demonstrated that the hybrid method is more resistant to noise and outliers than individual feature selection methods.

In conclusion, the selection of features is an essential component of machine learning that has the potential to enhance the precision and effectiveness of models [56-57]. The selection of features can be accomplished in a number of ways, some of which are referred to as filter methods, wrapper methods, or embedded methods. Recent studies have investigated the application of feature selection based on deep learning, evolutionary algorithms inspired by quantum mechanics, ensemble approaches, feature selection in combination with other methods such as data augmentation and transfer learning, and hybrid feature selection methods. The quality of the features is critical to the success of the feature selection process, and in recent years, researchers have investigated the possibility of using feature engineering to develop characteristics that are inherently more informative. The selection of relevant features can increase the accuracy and interpretability of the model, making feature selection a very significant consideration in healthcare applications.

4. Conclusion

This article provides an overview of how metaheuristics may be used to a range of optimization problems, as well as an introduction to meta-heuristic algorithms and some of the main elements that distinguish them from other types of optimization methods. Additionally, the article includes an overview of how metaheuristics can be applied to a number of optimization problems. The investigation of a wide variety of optimization issues is carried out with the goals of educating newly minted researchers on metaheuristics and assisting them in gaining their foothold in the field. the use of a feature selection process to boost classification accuracy, in addition to other real-world applications of metaheuristics, is also covered in this article.

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