Using Grasshopper Optimization in Big Data

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Abstract. From algorithms that have been popular and presently used in meta-heuristic is the grasshopper optimization method, which has made many theoretical breakthroughs and is widely applied in numerous optimization issues across different fields such as image processing, machine learning, engineering design, control over wireless networking, power systems, and other things. In this study, we review the literature that is currently accessible on the grasshopper optimization technique and its extensions to the chaotic, binary, multi-objective scenarios and hybrid. Finally, the grasshopper optimization algorithm has proven superior to other optimization algorithms in most literature.

Keywords: Grasshopper Optimization · Data Mining · Meta-heuristic Optimization

1 Introduction

Optimization determines the optimal value of a specific problem variable to reduce or increase the target function. There are optimal problems in all areas of the study. There are several steps you can take to resolve an optimization problem. First, the problem's parameters must be determined. The problems can be categorized as either discrete or continuous depending on the type of parameters. Second, it's important to understand the restrictions placed on the parameters. Restrictions separate unrestricted and restricted optimization problems. Third, it is necessary to look through and consider the supplied problem's objectives. In this instance, optimization issues are separated into issues with many objectives and issues with a single target. An appropriate optimizer should be chosen and used to solve the problem based on the number of targets identified, the types of parameters, and the limitations [1]. Examples of optimization are all areas such as business, personnel management, sophisticated engineering planning, transportation problems, winning proposals and industrial applications [2]. Before humans existed on this planet, nature used evolution to solve difficult problems all the time. In the field of optimization, the Netherlands proposed a revolutionary idea in 1977 when simulating evolutionary concepts in nature on a computer to solve optimization problems [3].

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Many optimization mechanisms have been used to solve many complicated problems in various fields, including engineering applications, machine learning, data mining, text mining, networks, economics, medicine, energy, and others. Optimization algorithms are mostly used to find the best solution by combining different ideal values to provide a candidate solution that solves the underlying problem. Typically, meta-heuristic optimization algorithms work by minimizing or maximizing the objective function to arrive at the ideal value and arrive at the optimum choice. Finding the best choice value from a range of feasible options is the main objective of decision-making. The ultimate objective of optimization methods is to identify the best decision value among all potential solutions.

Many research topics in optimization fields have recently remained interesting. They require promising solutions owing to their realism in life and nature, like problems with an industrial nature, problems with mathematics, problems with the real world, and other problems. These problems are referred to as hard optimization problems. [4]. Typically, utilizing the various optimization techniques available, the main purpose is to maximize or minimize the fitness function or objective function of a problem to find the optimum solution. Four categories can be used to classify optimization problems: the first group includes multi-objective or single problems, and the second category contains constrained and unconstrained problems. The third category contains dynamic or static problems. The fourth category explores discrete and continuous problems. The following steps describe steps for solving optimization problems.

1. Describe each variable separately. Create a diagram with all variables labeled, if applicable.
2. Determine the range of values for the other variables and the quantity that will be minimized or maximized (if at this time this can be set).
3. Making use of the variables, develop an formula to minimize or maximize the quantity. Multiple variables could be used in this formula.
4. The quantity that has to be minimized or maximized as one variable in this function should be written down using any equations find in step 3 in the formula relating the independent variables with these equations.
5. To solve the physical problem, choose the domain of consideration for the function in step 4.
6. From step 4, determine the maximum and lowest values of the function. Typically, this stage entails looking for important places and testing a function at endpoints.

Recently, a number of biologically or naturally inspired algorithms have been developed to locate nearly ideal answers to a variety of challenging optimization issues. These algorithms have demonstrated success in resolving actual optimization issues. Additionally, its superior searchability and ability to handle large instances make it a superior choice over other methods. In general, Optimization algorithms research things that happen in nature, like animals looking for food [3]. The four major categories of optimization algorithms are human-based, swarm-based, evolution-based, and physics-based. Evolutionary algorithms (EAs) use methods like recombination that are inspired by biological evolution, mutation, crossover, and the inheritance of traits in offspring [5]. When solving optimization problems, potential solutions are represented as members of a population, and the answers' quality depends on the fitness function. Differential evolution (DE) [6] and the genetic algorithm [7] are two major EAs inspired by biological evolution.

The swarm optimization algorithms are algorithms that mimic the mass behavior of living creatures. The best mass behaviour is achieved through interaction between living things [8]. An offshoot is particle swarm optimization [9], which mimics the hunting behavior of groups of fish and birds, we use physics in physics-based algorithms to create variables that facilitate the search for the ideal answer within the search scope [10,11]. Some of the most popular categories in this branch are electromagnetism optimization (EMO) [12] and the gravitational search algorithm [13]. Human-based algorithms are inspired by human gregarious demeanor. The main algorithms in this branch are the election campaign algorithm [14], the heap-based optimizer (HBO) [15] and teaching-learning-based optimization.

The main goal of this paper is to survey previously published articles using the GOA. This paper has carried out a comprehensive study of all the perspectives of the GOA as well as the researcher's viewpoints. In addition, we investigate how interesting academics employ grasshopper optimization algorithms to tackle a variety of optimization problems in complicated applications.

2 Grasshopper Optimization Algorithm

The Grasshopper Algorithm (GA), which is inspired by honey badger behavior in nature, is described in this section along with its mathematical model.

A new metaheuristic algorithm called GOA was created by Saremi et al. based on a productive population that was inspired by nature. To promote grasshopper insects' in the wild exhibiting their ideal, polite demeanour in 2017. For global unlimited/unlimited optimization and different practical jobs, this algorithm can deliver enhanced results and scientific understanding. The baseline GOA was utilised to determine the optimal proton exchange (PEMFC) parameters, and the results highlighted the viability of GOA-based rhythm while dealing with steady-state models and dynamic [16]. 2016 Wu et al. [17] a GOA was suggested to streamline the UAV distribution path in an urban environment. They showed that this algorithm could achieve satisfactory satisfaction paths and improved results. The basics GOA are developed with multiple objectives by Tharwat et al. Restricted and Mirjalili et al. [18] and the proposed algorithm can solve multiple reference problems more efficiently and effectively in terms of the optimal distribution and accuracy of individual solutions.

The grasshoppers move slowly and take small steps, which is the most distinguishing feature of the swarm of larvae. On the other hand, the adult swarm's key trait is long-term, abrupt movement. The locusts' quest for a food supply is another significant aspect of them. As was explained in the introduction session, nature-inspired algorithms logically divide the research process into two trends:

exploitation and exploration. During operations, search agents although they often move locally during an operation, sudden movement is encouraged. These two capabilities are incorporated, as well as the trainees' ability to search for a certain part of the course. So, if we can find out a mathematical way to do it, we can come up with a new algorithm inspired by nature. This is exactly what we do. There are three stages in a grasshopper's life cycle: The three stages of development are the egg, the nymph, and the adult. At any time throughout the swarm, you can find a grasshopper. From nymph to adulthood, it goes through all stages of its life cycle [19]. Figure 1 shows The life, in general, is depicted.

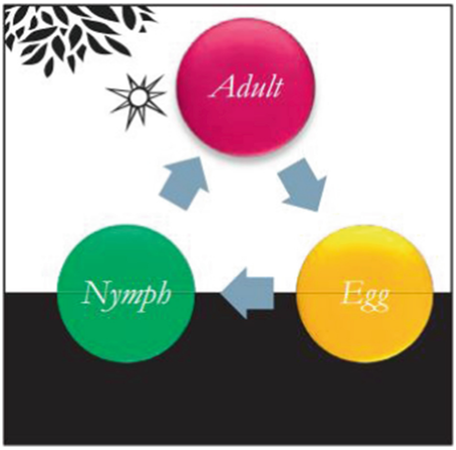

Fig. 1. The grasshopper's life cycle [1].

The mathematical model that was applied to replicate the behavior of a swarm of grasshoppers is as follows: The mathematical model that was utilized to replicate the behavior of swarms of grasshoppers is shown in the table below:

$$\mathrm{X}_i = \mathrm{G}_i + \mathrm{S}_i + \mathrm{A}_i \tag{1}$$

where $X_\mathbf{i}$ determines the position of the i-th grasshopper, $A_\mathbf{i}$ depicts wind addiction, $S_\mathbf{i}$ represents the gravitational pull on it, and $G_\mathbf{i}$ represents social interaction. Be aware that the equation $X_\mathbf{i} = v_\mathbf{1}\ G_\mathbf{i} + v_\mathbf{2}\ S_\mathbf{i} + v_\mathbf{3}$ can be written to produce random behavior. $A_\mathbf{i}$, where [0, 1] random integers $v_\mathbf{1}$, $v_\mathbf{2}$, and $v_\mathbf{3}$ are used.

$$G_i = \sum_{\substack{J=1 \\ J\neq 1}}^{N} g(d_{ij})\widehat{d_{ij}} \tag{2}$$

between the ith and jth grasshoppers, there is a distance of $d_\mathbf{ij}$ and can be calculated as $d_\mathbf{ij} = |X_\mathbf{j} - X_\mathbf{i}|$. In Eq. 1, The social force's strength is denoted by

G and determined by Eq (3) by using

$$\widehat{d_{ij}} = \frac{x_j - x_i}{d_{ij}}$$

The unit vector between the ith and j-th grasshoppers can be calculated The function that calculates the social forces is determined as:

$$g(v) = fe^{\frac{v}{l}} - e^{-v} \tag{3}$$

where the density of attraction is exemplified by f and the attractive length scale is referenced by l. The S component in Eq. (1) is calculated as:

$$S_i = -s\widehat{e_s} \tag{4}$$

Here the gravitational constant is represented by s and and the vector pointing toward the centre of the earth is denoted by the letter $\widehat{e}_{\mathbf{s}}$. (1)'s A component is calculated as:

$$A_i = \widehat{ue_w} \tag{5}$$

In this case, u stands for the continuous drift and $\widehat{e}_{\mathbf{g}}$ is the unity vector for the wind direction. The equation changes when G. S. and A are substituted in Eq. (1).

$$x_i = \sum_{j=1, j\neq i}^{N} s(|x_j - x_i|)\frac{x_j - x_i}{d_{ij}} - g\widehat{e_g} + u\widehat{e_w} \tag{6}$$

N then stands for the number of grasshoppers. Because Eq. (6) inhibits the program from exploring and taking advantage of the search space close to a solution, it is not used in the optimization method. This model of a grasshopper nymph represents an open-air grasshopper swarm. Furthermore, the swarm doesn't congregate at a single location because the grasshoppers reach their comfort zone fast, the optimization issues were not immediately addressed by this mathematical model. In order to address optimization issues, a modified version of Eq. (6) is applied:

$$X_i^d = c_1\Big(\sum_{j=1, j\neq 1}^{N} c_2\frac{ub_d - lb_d}{2}g\big(\big[x_j^d - x_i^d\big]\big)\frac{x_j - x_i}{d_{ij}}\Big) + \widehat{T_d} \tag{7}$$

Here are appeared the lower and upper borders by l$b_{\mathbf{d}}$ and u$b_{\mathbf{d}}$, respectively, the aimed value and the best solution are represented by $T_{\mathbf{d}}$, whereas $c_{\mathbf{2}}$ and $c_{\mathbf{1}}$ are the coefficients to shrivel the repulsion zone, attraction zone, and comfort zone. It is assumed in this equation that the wind always blows in the direction of a target $T_{\mathbf{d}}$ and that the gravity component is not used. The target's position, its present location, and the locations of every other grasshopper are used to determine the grasshopper's subsequent location.

The next position of a grasshopper is determined based on its current position, global best, and the positions of all other search agents, as shown in Eq. (7). In other words, GOA mandates that all search agents participate in determining each grasshopper's future position. It is important to note that the initial part of Eq. (7) decreases the agent's motions around the target. In contrast, the second portion of the equation allows for the direction of the existing grasshopper to other grasshoppers in the area. In particular, the parameter c_1 is in charge of limiting grasshopper moves around the target, which means that c_1 balances the swarm's widespread exploitation and exploration. On the other hand, the parameter c_2 decreases the attraction zone, comfort zone, and repulsion zone between grasshoppers, i.e., c_2 linearly decreases the space to guide the grasshoppers to find the optimal solution in the search space. A related point to consider is that the adaptive parameter c_1 contributes to the reduction in repulsion or attraction forces among grasshoppers proportional to the number of iterations, while the c_2 reduces the search coverage around the target as the number of iteration increases. To maintain a balance between exploration and exploitation, c_1 is dropped proportionally as the amount of iterations rises. With the help of this strategy, GOA was able to carry out efficient exploitation in the optimization's final stages.

Similar to this, the values of c_2 are dropped to reduce the comfort level about a rise in the number of iterations. The arguments c_1 and c_2 are treated as one parameter for the following modification:

$$c = c\max - I\frac{c\max - c\min}{N} \tag{8}$$

where I denotes the number of current iterations and N denotes the total number of iterations. The highest and lowest values of c are denoted by cmax and cmin, respectively. The mature swarm is distinguished by abrupt, distant movements. In contrast, In the nymph phase, the swarm moves slowly and with small cricket steps. A crucial characteristic of grasshoppers is their constant quest for food sources. The two primary stages of nature-inspired algorithms exploitation and exploration are designed to speed up convergence and/or prevent local optima from forming when the algorithm is looking for a target. Search agents frequently move in the search space locally while operating. Nevertheless, during the exploratory process, they are urged to move quickly. Both of these actions are carried out by locusts in a natural manner in search of their prey (food source). The authors conducted in depth tests to examine the behaviour of grasshoppers with various values of the attractive length scale and the intensity of attraction, and they discovered that repulsion occurs between any two grasshoppers if their distances fall within the range [0, 2.079]. Grasshoppers enter their comfort zones when they are 2.079 units apart from one another. The conceptual model of the comfort zone and the forces that draw grasshoppers together and away from each other are shown in Fig. 2. The swarm in the nymph stage is a characteristic of slow movements with small cricket levels. Revenge, the swarm, and a phase maturity characterize the sudden and distant movements. Discover the grasshoppers' unique characteristics and their sources of nourishment. When

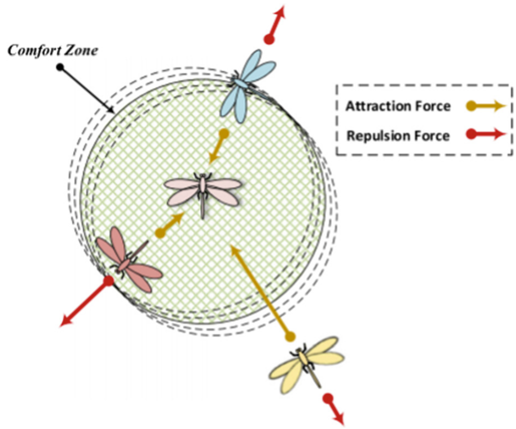

Fig. 2. The comfort zone of grasshopper [20].

searching for a goal, algorithms that are inspired by nature typically go through two stages: exploration and exploitation. These two steps aim to speed up convergence and/or prevent local optimization. During the activation phase, search agents frequently relocate locally inside the search region. While the review is taking place, feel free to move suddenly. Both of these actions are equally carried out by locusts in a natural manner.

Beginning with a sequence of initial random solutions (grasshoppers), GOA determines the applicability of each of these solutions. Locust updates its positions based on the equations many researchers in this field have modified the grasshopper optimization method for numerous distinct alterations to manage and handle different challenging problems of optimization. Modifications are mostly in (binary, hybridized, adjusted, and variants that are listed beneath) will now be covered, nevertheless not comprehensive. A brief overview of all grasshopper optimization algorithm types and vers. The best grasshopper (target) location is updated for each iteration. Additionally, the normalizing of the grasshopper distances from 1 to 4 and the calculation of the current position is done with each iteration. Iteratively updating the grasshopper's location until the stop condition is satisfied. The best estimation of the total optimal is then returned, known as the good goal(target) [20].

When there is a distance of [0, 2.079] between two locusts, there is a repulsive force, and when there is a distance of 2.079 between the two locusts, there is neither an attraction nor a repulsion to create a comfortable area. The gravitational force progressively increases and diminishes by 4 for distances greater than 2.079. To address this issue, the distance between the locusts is specified in [1, 4]. If the distance between the two locusts is larger than 10, the function cannot have force between the locusts. The study shown above demonstrates the grasshopper optimization algorithm's suitability for problems with illogical optimal solutions.

3 Developments on GOA

Many researchers in this field have modified the grasshopper optimization method for numerous distinct alterations to manage and address various challenging optimization problems. The majority of these modifications (binary, hybridized, modified, and other variants listed below) will be covered, but not exhaustively. A brief overview of all grasshopper optimization algorithm types and versions.

3.1 Grasshopper Optimization Algorithm in Binary

A complex machine learning technique known as feature selection (FS) is used to limit the amount of features used while maintaining the best level of classification accuracy. In [20], the authors discuss binary versions of the technique of the Grasshopper optimization for choosing the ideal subset of classification to features for goals inside of an envelope-based framework. The sigmoid model (transfer function) is the first strategy used to produce an algorithm for binary locust optimization, and function of V-shaped (transfer function) is the second technique, which is referred to as BGOA-V and BGOA-S, respectively.

3.2 Grasshopper Optimization Algorithm Modifications

In [21], improved Grasshopper optimization method is presented to handle optimization problems such as financial stress prediction (prediction) problems and continuous optimization. Grasshopper is a recently developed optimization method inspired by the clustering process of the grasshopper in real life. This approach has been proven to be beneficial for solving numerous global problems of optimization (unconstrained and constrained). Nonetheless, The original Grasshopper optimization process has several weaknesses, for example, becoming stuck in optimum, slowing its the velocity of convergence. To overcome these issues, an enhanced Grasshopper optimization method has been presented, three search strategies (operators) are combined to improve the balance of search strategies like exploration and exploitation.

3.3 Chaotic Grasshopper Optimization Algorithm

To accelerate global convergence, chaos theory systems are incorporated into the optimization techniques of the Grasshopper optimization algorithm [22]. Chaotic system maps are employed in optimization procedures to create a fair and efficient balance between exploring and exploiting search techniques, as well as to lessen the operative forces of attraction and repulsion (discord) between grasshoppers. The results revealed that chaotic system mappings are typically beneficial in improving performance. Especially, the circular map is thought to be the optimum map for the best outcomes when running the grasshopper optimization method.

3.4 Grasshopper Optimization Algorithm Hybridizations

In [19], Two main optimization issues are addressed by a hybrid Grasshopper optimization method with opposition-based learning (OBL). Namely technical optimization problems and benchmark test functions. This hybridization is known as OBLGOA. There are two phases in the suggested Grasshopper optimization technique. In the first phase, the opposing learning process is used to produce the initial solution approaches and their opposite. Opposition-based learning is incorporated into the population of the Grasshopper optimization algorithm in the second phase as a new step in each generation. However, opposition-based learning is used in a balanced population to reduce lead times. The GOA-SVM approach was published in [23] as a hybrid classification strategy for computational seizure exposure in EEG that uses a support vector machine and a Grasshopper optimization algorithm. Several fitting parameters are chosen and used as leaders in the radial support function kernel function classification strategy to train support vector machines. To acquire a good EEG classification, The subset of valuable features and the best support vector machine parameter values are chosen using the Grasshopper optimization procedure. The test results showed that the suggested approach is capable of detecting the start of epileptic seizures in healthy individuals, and as a result, it might enhance the study of epilepsy with a high accuracy rate (100%).

4 Applications of Grasshopper Optimization Algorithm

The GOA algorithm is able to outperform other methods and get beyond the challenges of multi-goal research space. Additionally, the computational complexity of this optimization strategy is less difficult than many others described in the literature. Our efforts to develop certain applications and strategies that employed GOA to tackle their challenges were motivated by these potent capabilities.

Data clustering, also known as the division of a huge data set into discrete groups of comparable structure, is a crucial issue in data analysis and study. Several clustering strategies that use either mathematical or heuristic methods can be used to tackle this data clustering challenge. The main components of heuristic approaches often consist of a wide range of instruments that are helpful in nature's active optimizers. The potential application of a novel optimization method, the Grasshopper optimization algorithm, is discussed in [24], to produce more accurate data clustering results is investigated. The Calinski-Harabasz index, which is based on the cluster validation test, is used as a metric to generate solutions. To tackle the data clustering challenge, the researchers used the Grasshopper optimization method and ran experimental testing on several reference data sets. In the context of this investigation, it was found that, in comparison to other conventional k-means approaches, the clustering methodology with the suggested algorithm attained a high accuracy rate.

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder whose late diagnosis has made addressing the severity of patients' problems difficult.

Patients with ASD have difficulty communicating and interacting with others. They also engage in constrained and repetitive behavior patterns. ASD affects roughly 62 million people worldwide. ASD is 3–4 times more common in males than in girls. ASD is statistically detectable between the ages of one and two, Some situations, nevertheless, can take a very long time to be detected. To effectively treat ASD, it is imperative to appropriately and promptly identify it. Used the Modified Grasshopper Optimization Algorithm (MGOA) to identify Autism Spectrum Disorder at all stages of life in the study [25]. By making this change, researchers hoped to improve upon the limitations of the conventional GOA and enable the early diagnosis of sickness. Three ASD screening datasets for distinct age groups adults, adolescents, and children are subjected to the algorithm, and the findings are contrasted with those from cutting-edge methods. The proposed algorithm's Random Forest classifier was able to predict ASD at every stage of life with a specificity and sensitivity that was about equal to 100.

Cloud computing is a novel computing technique that keeps data and apps operating by utilizing the internet and central remote servers. Users can access database resources from anywhere via cloud computing, removing the need to manage physical resources. Almost every industry, including healthcare, can benefit from this notion. Data mining and successful inquiry from the cloud are more difficult in such circumstances due to the privacy involved in data preservation. As a result, security attacks such as the Known Cipher Text Attack (CTA) and the Plain Text Attack (KPA) represent a serious threat to the information system's privacy and security (CPA). To solve these issues and offer a privacy-preserving solution for protecting medical data through data restoration and cleaning. Researchers presented a hybrid system called Grasshopper Optimization with Genetic Algorithm for the data restoration and cleaning procedure (GOAGA) [26]. In addition, the success of the hybrid approach's restoration and sanitization, statistical analysis, convergence, and key sensitivity analysis are compared to those of other traditional ways, validating the advanced approach's governance. Finally, this hybrid approach has proven to be superior to other conventional approaches.

Text mining involves the employment of complex procedures for dealing with multiple text documents, which necessitates the use of text analysis. Text clustering is one of the most successful text mining, pattern recognition, and machine recruitment techniques. Using a suitable text-clustering technique, computers can start to arrange a corpus document into a specific organisational structure of conceptual clusters. Noise, irrelevant, and extraneous elements can be found in both informative and non-informational text documents. Unsupervised text feature selection is the primary method for identifying a brand-new subset of informative feats for each document. Reduce the quantity of uninformative features and increase the dependability of the text clustering algorithm are the two objectives of the functional selection technique. The suggested method is imprisoned in local minima in a low-dimensional space, has a mature convergence rate, and takes little processing effort. The document pre-processes the text data that it receives as input. Then, using a hybrid GWO-GOA algorithm, the text feature selection is completed by first identifying the local optima from the text content. [27], choosing from the local optimum the finest global optimum. The Fuzzy c-means (FCM) clustering algorithm is also used to group the selected optima. With this technique, dependability is improved while computation time is decreased. The proposed algorithm makes use of eight datasets and has proven superior when compared to other algorithms, text clustering evaluation and Text feature selection measures include specificity, precision, sensitivity, F-measure, accuracy, recall, and demonstrate higher quality. The proposed methodology is 87.6% more effective than GOA, the proposed hybrid GWO-GOA algorithm, and GWO.

Using irrelevant features with powerful classifiers can result in over-fitting and models that do not perform as well as when these features are not utilized, hence feature selection strategies are crucial in predictive modeling. It's particularly essential when it comes to sickness datasets because many of the factors in these data may not be related to a disease's diagnosis and a variety of characteristics or traits are accessible through patient medical records. In this circumstance, inaccurate models can be fatal, resulting in misdiagnosis and, in the worst-case scenario, death. We used a wrapper-based feature selection technique to do this. In recent years, the Grasshopper Optimization Algorithm (GOA) has proven to be superior to other optimization algorithms in a range of study areas. Researchers propose (LAGOA) [28], an improved version of GOA that uses Learning Automata (LA) for adaptive adjusting GOA parameters and two-phase mutation to improve the algorithm's exploitation capability. In the swarm, every grasshopper has its parameters individually adjusted using LA. The two-phase mutation's first stage reduces the amount of chosen characteristics while retaining highly accurate results, and the second stage introduces pertinent features that raise classification accuracy. Data from the UCI Repository, including Breast Cancer (Diagnosis), Breast Cancer (Wisconsin), Lung Cancer, Statlog (Heart), Hepatitis, and SpectF Heart, were subjected to the LAGOA method. Results of experiments demonstrate that it performs better than cutting-edge techniques comparison.

Researchers suggest a modified grasshopper optimization technique to handle the optimal power flow (OPF) problem (MGOA). In [29], the traditional GOA is a relatively new optimization technique based on grasshopper movement and migration in their native habitat. The MGOA avoids entrapment in local optima by altering the mutation process in the standard GOA. The suggested optimization method is used to solve various multi-objective and single functions. Active power loss minimization, quadratic fuel cost and active power loss minimization, quadratic fuel cost minimization, voltage profile improvement, emission cost minimization, quadratic fuel cost and voltage stability improvement, quadratic fuel cost and power loss minimization, quadratic fuel cost, quadratic fuel cost and emission minimization, voltage stability improvement and voltage profile, are some of these objective functions. The proposed technique is validated with thirteen case studies using standard IEEE 118-bus, IEEE 57-bus, and IEEE 30-bus test systems. The simulation results present that the proposed technique outperforms and outperforms well-known evolutionary optimization techniques in solving various OPF problems.

4.1 GOA in Medical Domain

There are many diseases in which GOA contributed to obtaining better results, early detection of diseases, and prescribing the appropriate medication, which led to reducing the risk to the patient through early detection and reducing the death rate resulting from various diseases. In [30], through the application of several machine learning approaches, GOA is utilized to develop a better classifier and increase the accuracy of diabetic type II testing. A promising accuracy of 97% was achieved in the study using the Support-Vector Machine (SVM) technique. To show that the grasshopper algorithm is superior at choosing characteristics and improving the accuracy of diabetes testing. [31], the MGOA was influential in identifying Parkinson's disease with a detection rate of 99.4%, a calculated accuracy of 95.37%, and a false alarm rate of 15.78%. The results of the MGOA presented on The sets of data were assessed and compared with the results of the modified squid optimization algorithm and the modified gray wolf optimizer. Experience has shown that the results indicate that modifying the GOA can improve accuracy and reduce the number of selected features. [32], to aid clinicians in the detection of cardiac illness, the algorithms Bi-Hybrid Grasshopper Optimization (BGO) and K-Nearest Neighbors (KNN) were used. Feature selection (FS) is done with the BGO method, and classification is done with the KNN algorithm. The sensitivity was 89.61%, the accuracy was 89.82%, and the specificity was 90.41%, which is acceptable when compared to previous cardiology investigations. [33], the diagnostic model was developed using an upgraded GOA-based support vector machine to discriminate complex appendicitis (CAP) from uncomplicated appendicitis (UAP). The best model has average values for sensitivity, accuracy, Matthews correlation coefficients, and specificity of 81.71%, 83.56%, and 85.33%. The intelligent diagnosis paradigm that has been proposed is quite trustworthy, because it is based on commonly available markers. [34], Grasshopper algorithm improvement aims to provide a new method for diagnosing lung cancer using (GOA) high-dimensional feature identification and uses (KNN) to classify these features. The results indicate that This technique performs wonderfully, with an efficiency of 98.65, a specificity of 96.7, and a sensitivity of 94.10, which indicates the distinction of this method from others. [35], the process of diagnosing breast cancer can be sped up using GOA, a new technique that does so by using fewer features. In the last stage, a classifier is used to choose the best features and optimise the parameters (SVM). For the datasets from the WDBC, WBC, and WPBC, respectively, this technique yields high accuracy values of 99.51, 98.83, and 91.38. The outcomes revealed that the proposed strategy performs better when compared to other methods. [36], improved Linear Factor depend on GOA with Ensemble Learning (ILFGOA with EL) for covid-19 forecasting. The optimal features are then chosen using the Improved Linear Factor-based Grasshopper Optimization Algorithm (ILFGOA) algorithm to improve prediction accuracy. The analysis results show that the introduced method outperforms the previous system in terms of error rate, accuracy, error rate, recall, precision, and f-measure. In [37], the GOA technique is used to analyse the type 1 diabetes mellitus system's performance, and modifying the controller parameters to boost control performance is also covered. The simulation results showed that the suggested approach performed significantly better than other standard controllers like PSO-PID and EHO-PID [38], with better outcomes. Artificial Neural networks are based on error estimations that use the GOA and Gradient Descent. Deep neural networks (DNNs) powered by Grasshopper Optimization-based (GOA-based) are designed to classify cancer more accurately. A 0.0769 FAR, a 0.9666 detection rate, and a 0.9534 accuracy rate are achieved by the suggested classification approach employing gene expression data.

4.2 GOA in Industry Domain

There are many improvements and problems in which the government contributed to obtaining better results and reaching a faster solution at a lower cost to reach a higher benefit, which led to a reduction in industrial risks. IN [39], Using an enhanced grasshopper optimization technique, the hidden units in the bidirectional LSTM (long short-term memory) layer of the AlexNet are selected (IGOA). The accuracy, specificity, sensitivity, recall, and precision of the suggested technique were found to be 2.4%, 0.3%, 1.01%, and 0.97%, respectively. Considering the findings, the proposed algorithm is found to be more efficient than the existing algorithm. [40], ESN based on an IGOA. To improve performance, The new solution representation used by the proposed method has streamlined mechanisms for attraction and repulsion. The RUL (Remaining Useful Life) of turbofan engines The original GOA, conventional ESN, deep ESN, LSTM, Particle Swarm Optimization (PSO), Binary PSO (BPSO), Differential Evolution (DE), Cuckoo Search (CS), Particle Swarm Optimization (PSO), and Binary PSO (BPSO) are all surpassed by this approach. [41], The GOA-ELM is a combination of the GOA and Harris hawks optimization (HHO) for foretelling ground vibrations brought by mine blasting. The error values of the GOA-ELM model were 2.8551and 2.0239 for the testing dataset and training dataset, respectively. And the coefficients of determination for the GOA-ELM model 0.9410 for the training and 0.9105 testing datasets, which produced more accurate ground vibration values. [42], the problems of grain train design and pressure vessel are used to evaluated the performance of original GOA algorithm as benchmark engineering design. To achieve the best feasible economic structures using these structures with the smallest design weights while meeting structural behavior limitations like strength, displacement, stability, and drift derived from the American Institute of Steel Construction-Load and Resistance Factor Design specifications. [43], a novel multi-objective model's optimization to enhance voltage profiles, maximise energy transfer between peak and off-peak hours, and reduce DG and BESS costs. The Multi-Objective Grasshopper Optimization Algorithm (MOGOA) is used to solve. Using two Pareto optimality indices, the other heuristic optimization algorithms is compared to that of

MOGOA algorithm's performance. [44], standard GOA performance has been improved with a new clutter strategy and velocity perturbation mechanism. CV-CAVA outperforms the other variants in terms of accuracy and rate of convergence. The results show that the structural weight is excellently designed. CV-GOA outperforms the other variants in terms of accuracy and rate of convergence. Furthermore, CV-GOA optimizes three structural weight design problems: the cantilever beam design problem, the pressure vessel design problem, and the speed reducer design problem. [45], in the automotive industry, there is a growing interest in designing lightweight, low-cost vehicles to solve shape improvement problems. One of the first experiments used in the literature is the use of HHO, SSA, GOA, and DA to form design optimization problems. The results demonstrate the ability of HHO, SSA, GOA, and DA to design the most optimal components. [46], an automated voltage regulator (AVR) system's optimal controller settings can be determined using a unique approach, which has given. The performance index is called the integral of time-weighted squared error (ITSE). The proposed technique, when compared with the differential evolution (DE), artificial bee colony (ABC) tuning methods, and PID controllers based on Ziegler-Nichols (ZN), is robust and highly effective. [47], the hybrid GA-GOA algorithm does indeed improve performance, with a 1.45% increase in optimum weighted efficiency at a computation cost of 63.7 h. The proposed hybrid GA-GOA algorithm is a useful tool for optimising heliostat field layouts and reducing their land footprint. [48], system that reliably optimizes energy demand based on Power Supply Potential (DPSP) and Cost of Energy (COE). The results show that GOA outperforms its peers, CS and PSO, in terms of system size. The system capital cost is reduced by 14% and 19.3%, respectively.

[49], GOA-based VMD method for analysing vibration signals from rotating machinery. The method works well for analysing machinery vibration signals for fault diagnosis. In comparison to the traditional VMD and fast kurtogram methods. [50], the problem of traffic light optimization to minimise cars' waiting time and maximise the cars arriving at the destination within a specified time period GWGHA performance is evaluated using different data experimental cases. The results show that the algorithm outperforms other optimization algorithms when compared to CTLP. [51], a new approach to predict monthly volatility of iron ore prices. In terms of mean square error, the chaotic grasshopper optimization algorithm (CGOA)-NN model outperforms GOA-NN, PSO-NN, GA-NN, and classic NN models by 38.71 %, 16.49 %, 32.18 %, and 60.82 %, respectively. [52], the problem of big data sonar classification. According to the results, FGOA has the highest accuracy for both training and generalised datasets, with 96.43% and 92.03%, respectively. [53], a novel enhanced version of (GOA) for solving the optimal chiller loading (OCL) problem while minimizing power consumption. The outcomes demonstrated that the shown chaos GOA produces better (or comparable) outcomes than the other methods investigated. [54], the new GOA improves the factors for reducing power loss and voltage stability by optimizing the allocation of (BSS) and distributed generation (DG). GOA outperforms in terms of convergence characteristics and system performance. EV users, BSS

developers, and the power and utility grid benefit from the optimized DG-BSS placement in the system.

4.3 GOA in Agriculture Domain

For many people, agriculture is a key and significant field, and its advancement aids in the progress of the entire population. GOA has aided in the development of several agricultural solutions and enhancements, such as, [55], a classification model for cadmium stress in lettuce leaves was developed using VISA-GOA-SVM. The calibration and forecast accuracies were both 100% and 98.57%, respectively. The most effective techniques were found to be RTD (initial fusion of three data input layers) combined with SVM mixed with grasshopper optimization support vector machine and vis-NIR spectra. In [56], the authors enhanced the GOA to optimize the model of the Non-linear Muskingum flood routing. The results of GOA proved superior compared with HS and GA in the problem of the optimal flood routing river, and values of optimal solutions obtained by the GOA, Harmony search (HS), and Genetic Algorithm (GA) were 3.53, 5.69, and 5.29, respectively. [57], it is proposed to use a hybrid GOA with invasive weed optimization (IWGOA). The grouping strategy improves the IWGOA algorithm's exploration and exploitation capabilities. The optimal solutions obtained by the IWGOA algorithm proved superior in most test functions. [58], the suggested IGOA utilized for optimizing the parameters of HAPF topologies. To replace the target in the original GOA, a learning technique is added, and an exemplar pool is established, which can avoid drop into local optima and enhance global search ability. In [59], the GOA's intelligence is used for optimizing the PI controller parameters. The results produced from compared GOA with WOA and PSO proved that the GOA is fastest and best solution, resulting in less frequency and voltage, less Total Harmonic Distortion (THD), and less output current.

4.4 GOA in Education Domain

Education is the foundation for any society's progress, and one of the most significant aspects is its development, progress, and improvement across all fields. Assisted GOA with this assignment and submitted numerous models, including [60], the genetic algorithm (GA) and GOA are used to solve the nonlinear equations system: GOA-GA-hybrid (SNLEs). The GOA-GA-hybrid algorithm outperforms the other algorithms. GOA-GA-hybrid is efficient in resolving SNLEs in terms of accuracy. [61], the grid search is compared to a hybrid approach based on the GOA, the common technique for tuning SVM parameters. In terms of classification accuracy, it outperforms all compared methods in most databases. In [62], the results of the constrained and unconstrained test functions solved utilizing the GOA can validate that the algorithm produces reliable results. The algorithm can also be utilized for solving various problems of engineering in reality. In [28], the authors enhanced a version of GOA by utilizing Learning Automata (LA) called LAGOA to adjust the parameters of GOA adaptively, and is implemented for Lung Cancer, Breast Cancer disease (Diagnosis or Wisconsin), Starlog (Heart), and Spector Heart, and demonstrates its superiority. GOA algorithm performance is enhanced in [63] by incorporating a novel mutation factor into the standard GOA algorithm. It is the EGOA that seeks to solve the problems in optimization such as trapping in the local optima and slow convergence, by striking a good balance between the exploration phase and exploitation phase, EGOAs is superior to the original GOA algorithm. [64], a strategy for quantifying the quality of work-life through the elimination of human resource hazards. It is carried out using the enhanced GOA. The GOA and the bees algorithm make up this algorithm. The newly proposed method outperforms the traditional method and produces more accurate findings.

5 Conclusion and Future Work

This article provided and summarized the most popular Optimization methods used in machine learning and data mining, as well as examined their applications in various fields. First, we discuss the theoretical foundation's First-class, high-level optimization methods, Derivative-free perspectives, as well as recent research progress. Then, in the supplementary material, we describe the applications of optimization methods in various Machine learning scenarios, data mining, and treatment of many diseases and in the fields of industry, agriculture, and education, as well as approaches to improve their performance. Finally, most Of the previous literature has proven that the optimum grasshopper algorithm is superior to other metaheuristic optimization algorithms in data mining and machine learning problems. Therefore, we expect that if we integrate Archimedes' optimization algorithm using the grasshopper algorithm for reduce national computing time and avoid baiting in the local optima, this hybrid will give more performance than other algorithms, according to previous studies.

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