Grasshopper Optimization Algorithm: Theory, Variants, and Applications

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ABSTRACT Grasshopper Optimization Algorithm (GOA) is a recent swarm intelligence algorithm inspired by the foraging and swarming behavior of grasshoppers in nature. The GOA algorithm has been successfully applied to solve various optimization problems in several domains and demonstrated its merits in the literature. This paper proposes a comprehensive review of GOA based on more than 120 scientific articles published by leading publishers: IEEE, Springer, Elsevier, IET, Hindawi, and others. It provides the GOA variants, including multi-objective and hybrid variants. It also discusses the main applications of GOA in various fields such as scheduling, economic dispatch, feature selection, load frequency control, distributed generation, wind energy system, and other engineering problems. Finally, the paper provides some possible future research directions in this area.

INDEX TERMS Grasshopper optimization algorithm, GOA, meta-heuristics, optimization, population-based algorithm, swarm intelligence.

I. INTRODUCTION

In the last three decades, the area of optimization using meta-heuristics has gained increasing interest from academics and researchers, so several meta-heuristics are being proposed regularly for solving complex and real-world problems in different fields such as engineering, computer, medical, economics, etc. Meta-heuristics are divided into two major categories: single-based and population-based algorithms as shown in Figure 1.

The main principle of single-based meta-heuristic algorithms, also called trajectory algorithms, is the generation of single solution at each run. This solution is enhanced using the neighborhood mechanism. Some of the popular single-based meta-heuristics are: Simulated Annealing (SA) [1], Guided Local Search (GLS) [2], Tabu Search (TS), Variable Neighborhood Search (VNS) [3], Iterated Local Search (ILS) [4], Stochastic Local Search (SLS) [5], and [6], [7] Greedy Randomized Adaptive Search Procedure (GRASP) [8]–[10].

The associate editor coordinating the review of this manuscript and approving it for publication was Amjad Anvari-Moghaddam.

Unlike single-based meta-heuristic algorithms, population-based meta-heuristic algorithms generate a set of multiples solutions (population) at each run. The class of population-based meta-heuristics can be classified into four main categories: evolutionary-based, swarm intelligence-based, event-based, and physics-based.

The first category of population-based algorithms is Evolutionary Algorithms (EA) which is inspired from the evolutionary phenomena in nature using 3 main operators including selection, recombination, and mutation. Some well-known evolutionary algorithms are: Genetic Algorithm (GA) [11], Differential Evolution (DE) [12], Evolutionary Programming (EP) [13], Genetic Programming (GP) [14], Evolution Strategy (ES) [15], and Biogeography-Based Optimizer (BBO) [16], [17].

The second category includes Swarm Intelligence (SI) approaches, in which the source of information is the collective behaviours in nature. (e.g. birds, ants, bees, etc.). Particle Swarm Optimization (PSO) [18], [19] and Artificial Bee Colony (ABC) Algorithm [20] are of the most popular algoirthms in this category. Other rencetly proposed algoirthms in this camily are Cuckoo Search Algorithm (CS) [21], [22], Krill Herd (KH) [23], [24], Fruit Fly Optimization (FFO)
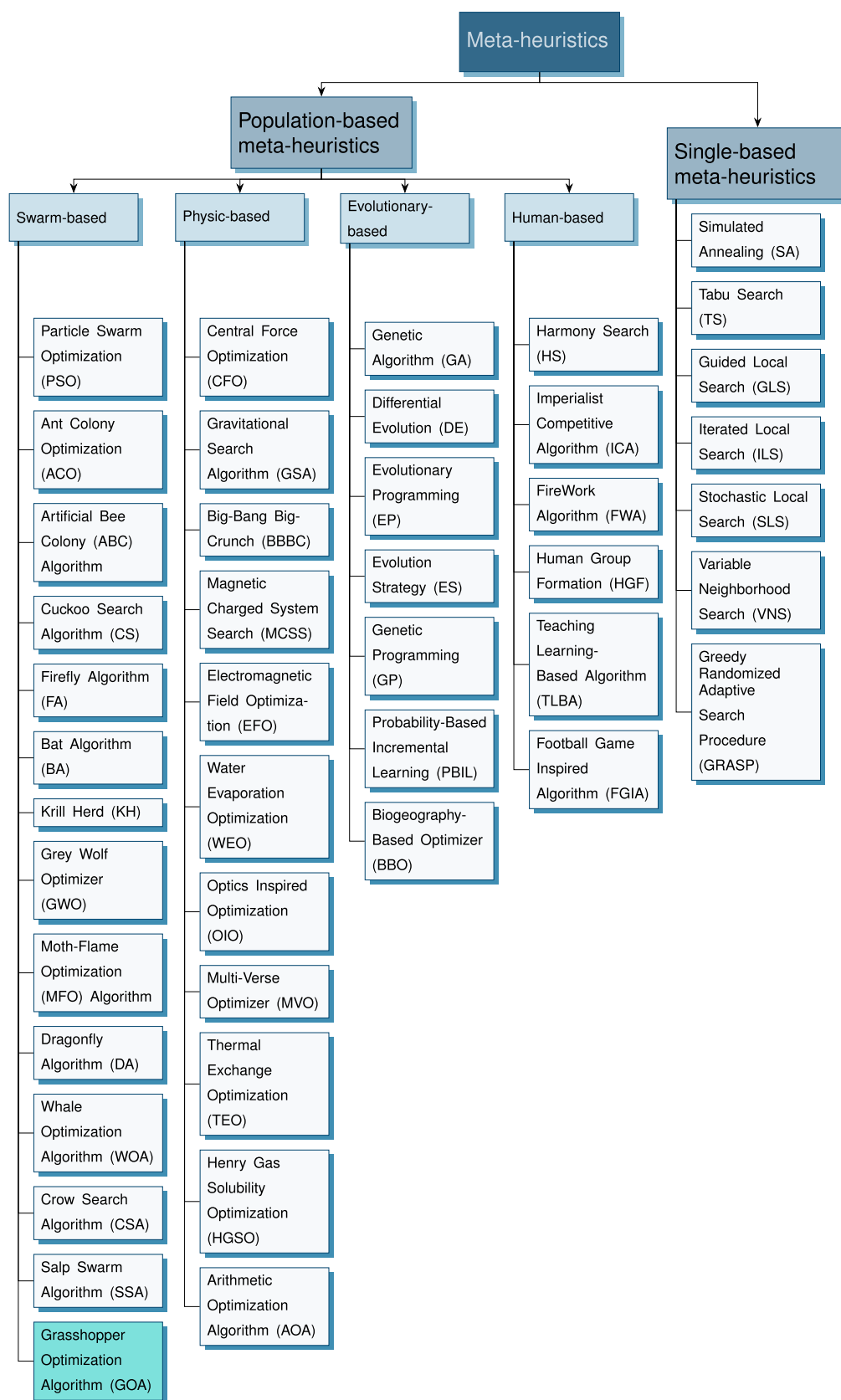
FIGURE 1. Classification of meta-heuristic algorithms.

algorithm [25], Grey Wolf Optimizer (GWO) [26]–[28], Ant Lion Optimizer (ALO) [29], [30], Dragonfly Algorithm (DA) [31], [32], Bat Algorithm (BA) [33], [34], Whale Optimization Algorithm (WOA) [35], [36], Salp Swarm Algorithm (SSA) [37], [38], Crow Search Algorithm (CSA) [39], [40], Firefly Algorithm (FA) [41], [42], and Grasshopper Optimization Algorithm (GOA) [43].

In the third family, the source of inspiration is not nature bur rather from actions related to humans. For example, Teaching Learning-Based Algorithm (TLBA) [44] mimics the teaching and learning process in classrooms, Imperialist Competitive Algorithm (ICA) [45] is inspired from imperialism in societies, and Harmony Search (HS) [46]–[48] is inspired from musical concepts.

The last family of meta-heuristics are Physics-based Algorithms (PA). For instance, Multi-Verse Optimizer (MVO) is inspired from some of the theories about multiple universes and Gravitational Search Algorithm (GSA) [49]–[51] mimics gravitational forces between masses. Other algorithms in this class are Central Force Optimization (CFO) [52]–[54], Water Evaporation Optimization (WEO) [55], Thermal Exchange Optimization (TEO) [56], Vibrating Particles System Algorithm (VPSA) [57], Optics Inspired Optimization (OIO) [58], Electromagnetic Field Optimization (EFO) [59], Big-Bang Big-Crunch (BBBC) [60], Henry Gas Solubility Optimization (HGSO) [61], Magnetic Charged System Search (MCSS) [62], and Arithmetic Optimization Algorithm (AOA) [63].

As discussed in the abstract, GOA is a recent Swarm Intelligence method inspired from the swarming behaviour of grasshoppers in nature. This algorithm was proposed by Saremi *et al.* in 2017 [43]. The literature shows that it has been employed to solve various optimization problems such as feature selection, scheduling, load frequency control, economic dispatch, engineering, etc. GOA is inspired by the foraging and swarming behavior of grasshoppers in nature and revealed its merits in the literature. In this context, this article proposes a review of GOA, its variants (modified, multi-objective, and hybrid versions), and its applications. We have reviewed a large number of publications coming from several leading publishers: IEEE, Springer, Elsevier, IET, Hindawi, and others. The following search keywords were used in Google Scholar:

- GOA.
- Grasshopper Optimization Algorithm
- Hybrid Grasshopper Optimization Algorithm
- Grasshopper Optimization meta-heuristics
- Improved Grasshopper Optimization Algorithm
- Grasshopper Optimization Algorithm applications
- Multi-objective Grasshopper Optimization Algorithm

To sift the large number of papers found, the following criteria were considered and used:

- Papers published in legitimate academic journals;
- Papers having more than 4 pages;
- Papers dated from 2017 to 2020
- Papers Written in English;

- Paper representing a complete version when several versions of the paper exist.

The statistics resulting from our study are shown in the figures below. Figure 2 presents the number of GOA related papers per scientific publishers where Elsevier and Springer are those who published the most about GOA. Figure 3 shows the number GOA related papers per year. We can see that GOA attracted a lot of interest over the last 4 years with a peak recorded in 2019. Table 1 represents the top 10 countries in terms of the number of the publication on the GOA algorithm. It can be seen that GOA has been the most popular in India and China. The Top 10 Journals ranked by the number of GOA publications are given in Table 2. Finally, Figure 4 shows the tag cloud of the top 10 GOA-related keywords. The 10 GOA co-cited articles are presented in Table 3.
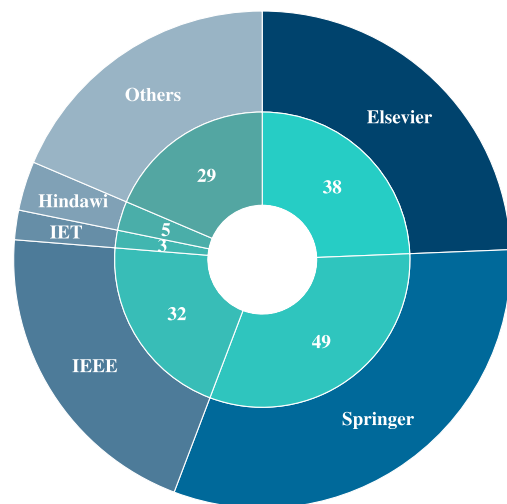

FIGURE 2. Distribution of papers on GOA reviewed in this work based on their publishing vendors.
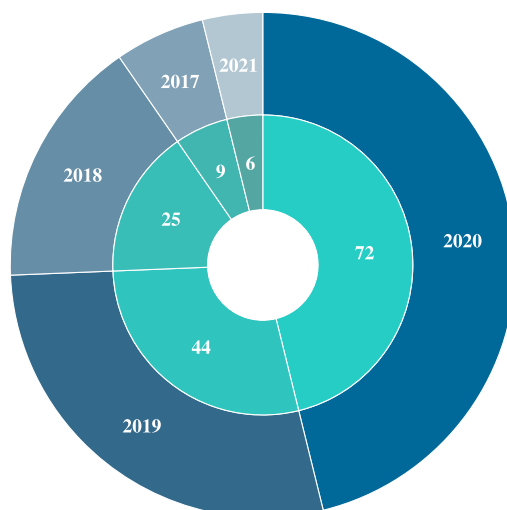

FIGURE 3. Distribution of papers on GOA reviewed in this work based on year of publication.

There is similar survey of GOA which analyzed over 50 research papers (in [64]). What makes this survey different

TABLE 1. Top 10 countries ranked by the number of GOA publications.

Country	Rank	Number of publications
India	1	54
China	2	33
Iran	3	16
Egypt	4	11
Saudi Arabia	5	4
Australia	6	3
Jordan	6	3
Turkey	6	3
Palestine	7	2
Chile	7	2

TABLE 2. Top 10 Journals ranked by the number of GOA publications.

Journals	Rank	Number of GOA publications
IEEE ACCESS	1	13
Expert Systems With Applications	2	5
Soft Computing	3	4
Neural Computing and Applications	4	3
Knowledge-Based Systems	5	2
Energy Conversion and Management	5	2
Multimedia Tools and Applications	5	2
Applied Intelligence	5	2
Energy	5	2
Electrical Engineering	5	2

FIGURE 4. A word cloud of the works we have summarized, reviewed, and analyzed in this paper.

TABLE 3. Top 10 GOA co-cited articles.

Studies	Rank	Number of citations
Saremi et al. [43]	1	803
Mafarja et al. [65]	2	197
Mirjalili et al. [66]	3	182
Mafarja et al. [67]	4	120
Zhang et al. [68]	5	119
Wu et al. [69]	6	114
Luo et al. [70]	7	105
Haidari et al. [71]	8	95
Aljarah et al. [72]	9	94
Barman et al. [73]	10	91

is the collection and analysis of more than 150 GOA articles published between 2017 and the beginning of 2021.

In the rest of this paper, Section 2 first provides the structure of GOA and its pseudo-code. Section 3 the provides an in-depth literature review of GOA's variants and improvements. An extensive overview of GOA applications in various fields is given in section 4. Section 5 provides results and comparisons of GAO with some well-known meta-heuristics. In section 6, GOA is discussed and some possible future research directions for this algorithm are presented. Finally, section 7 concludes the paper.

II. GRASSHOPPER OPTIMIZATION ALGORITHM
The GOA algorithm was proposed by Saremi *et al.* in [43], which is a recent and interesting swarm intelligence algorithm that mimics grasshoppers' natural foraging and swarming behaviors. Grasshoppers are insects well-known as a dangerous pests that affect and damage crop production and agriculture [43], [74]. Their life cycle includes two phases called nymph and adulthood. The nymph phase is characterized by small steps and slow movements, while the adulthood phase is characterized by long-range and abrupt movements [43]. The movements of nymph and adulthood constitute the intensification and diversification phases of GOA. The swarming behavior of grasshoppers is mathematically modeled as follows [43]:

$$P_i = S_i + G_i + A_i \qquad (1)$$

where P_i indicates the *i-th* grasshopper' position, S_i is the social interaction between grasshoppers, G_i denotes the gravity force on the *i-th* grasshopper, and A_i is the wind advection. To produce a random behavior of grasshoppers, Equation 1 can be rewritten as follows:

$$P_i = r_1 S_i + r_2 G_i + r_3 A_i \qquad (2)$$

where r_1, r_2, and r_3 are random numbers in the range [0, 1]
The social interaction S_i is defined as follows:

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s(d_{ij})\hat{d}_{ij} \qquad (3)$$

where N denotes the number of grasshoppers, $d_{ij} = |P_j - P_i|$ defines the Euclidean distance between the *i-th* and the *j-th* grasshopper, $\hat{d}_{ij} = \frac{P_j - P_i}{d_{ij}}$ is a unit vector from the *i-th* to the *j-th* grasshopper, and s represents the social forces designed by the following equation:

$$s(r) = f \exp^{\frac{-r}{l}} - \exp^{-r} \qquad (4)$$

where f and l are the attraction intensity and attraction length scale, respectively. The social interaction between grasshoppers can be defined as attraction and repulsion. The distance is considered in the range [0,15]. The attraction increases in the interval of [2.079, 4] and then decreases gradually. The repulsion occurs in the range [0, 2.079]. When the distance between two grasshoppers is exactly 2.079, there is neither repulsion nor attraction (no force). This area is called comfort zone. Figure shows 5 the interaction between grasshoppers with respect to comfort area.

The gravity force G_i is given by the following equation:

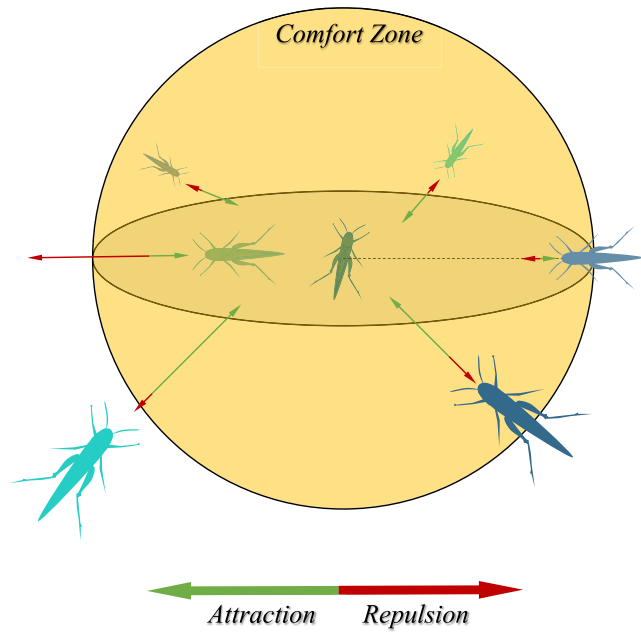$$G_i = -g\hat{e}_g \qquad (5)$$

FIGURE 5. Interaction between grasshoppers with respect to comfort area [43].

where g denotes the gravitational constant and $\hat{e}_g$ represents a unit vector toward the center of earth.

The wind advection A_i is given by the following equation:

$$A_i = u\hat{e}_w \quad (6)$$

where u represents the drift constant and $\hat{e}_w$ is a unit vector in the wind direction.

After replacing the values of S, G, and A, the following equation can be obtained:

$$P_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s(|P_j - P_i|)\frac{P_j - P_i}{d_{ij}} - g\hat{e}_g + u\hat{e}_w \quad (7)$$

Equation 7 cannot be used directly to solve optimization problems, as the grasshoppers reach quickly the comfort zone and the swarm system does not converge to a target location [43], [75]. An enhanced version of this equation is given as:

$$P_i^d = c(\sum_{\substack{j=1 \\ j \neq i}}^{N} c\frac{ub_d - lb_d}{2}s(|P_j^d - P_i^d|)\frac{P_j - P_i}{d_{ij}}) + \hat{T}_d \quad (8)$$

where ub_d and lb_d represent the upper and lower bounds in the d-th dimension, respectively. $\hat{T}_d$ denotes the best solution found so far in the d-th dimension space. Note that S is similar to S component in equation 1, G is equal to zero and A is always toward the best solution $\hat{T}_d$. The parameter c_1 is similar to inertia weight ω in PSO, loudness A_0 in BA, or $\vec{a}$ in GWO [76]. It is used to reduce the grasshoppers movements around the target (food). Thus, it provides a good balance between intensification and diversification. The parameter c_2 is used to reduce the repulsion zone, attraction

zone, and comfort zone between grasshoppers correspondingly to the number of iterations. c_1 and c_2 are considered as a single parameter and it is expressed using the following equation [43]:

$$c = c_{max} - t\frac{c_{max} - c_{min}}{t_{max}} \quad (9)$$

where c_{max} and c_{min} represent the maximum and minimum values of c, respectively, t is the current iteration and t_{max} is the maximum number of iterations.

The position of a grasshopper is updated based on its current position, global best position, and the positions of other grasshoppers within the swarm. This helps GOA to avoid getting trapped in local optima.

The pseudo-code of the standard Grasshopper Optimization Algorithm is given in Algorithm 1 [43]. Its flowchart can be represented in Figure 6. The source code of GOA can be found in: http://www.alimirjalili.com/GOA.html.

Algorithm 1 The Pseudo-Code of the Grasshopper Optimization Algorithm

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1: Generate the initial population of Grasshoppers $P_i(i = 1, 2, \ldots, n)$ randomly
2: Initialize c_{min}, c_{max} and maximum number of iteration t_{max}
3: Evaluate the fitness $f(P_i)$ of each grasshopper P_i
4: $T =$ the best solution
5: **while** $(t < t_{max})$ **do**
6:     Update c_1 and c_2 using equation (9)
7:     **for** i = 1 to N (all N grasshoppers in the population) **do**
8:         Normalize the distance between grasshoppers in the range [1,4]
9:         Update the position of the current grasshopper using equation (8)
10:        Bring the current grasshopper back if it goes outside the boundaries
11:    **end for**
12:    Update T if there is a better solution
13:    $t = t + 1$
14: **end while**
15: Return the best solution T

III. RECENT VARIANTS OF GRASSHOPPER OPTIMIZATION ALGORITHM

Different variants of original GOA categorized into modified and hybrid versions have been suggested in the literature as shown in Figure 7. The realized details of these versions are given in the following subsections.

A. MODIFIED VERSIONS OF GRASSHOPPER OPTIMIZATION ALGORITHM

A summary of some recent modified versions of GOA is given in Figure 8 and Table 4. The details of each modified version are provided below.
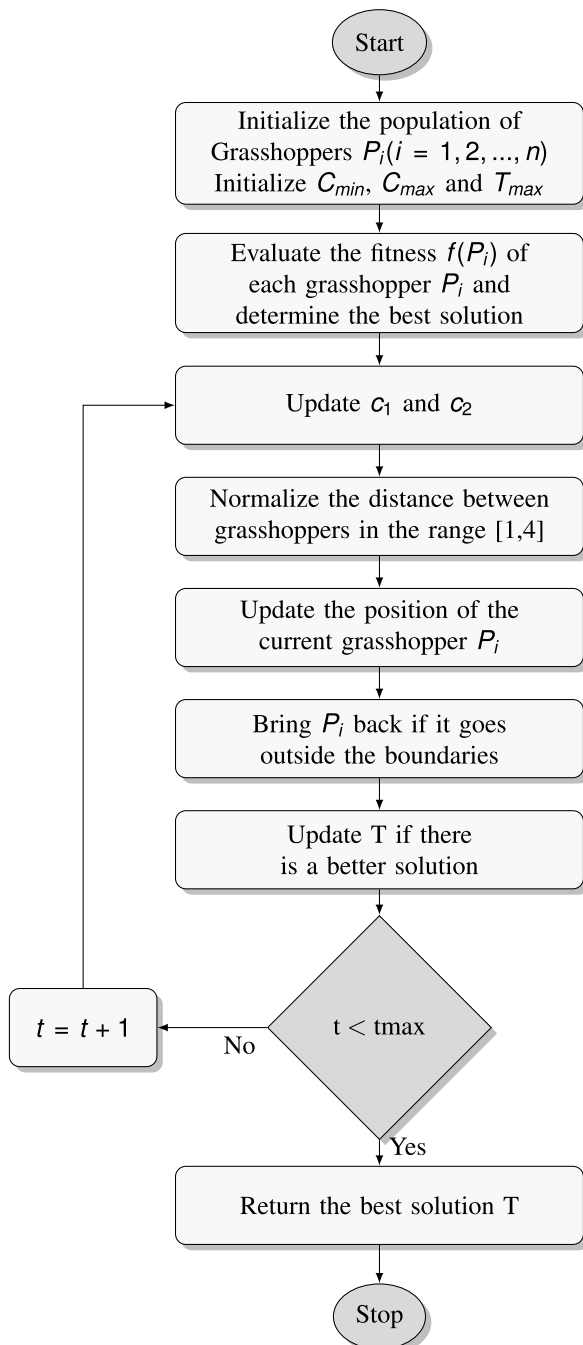
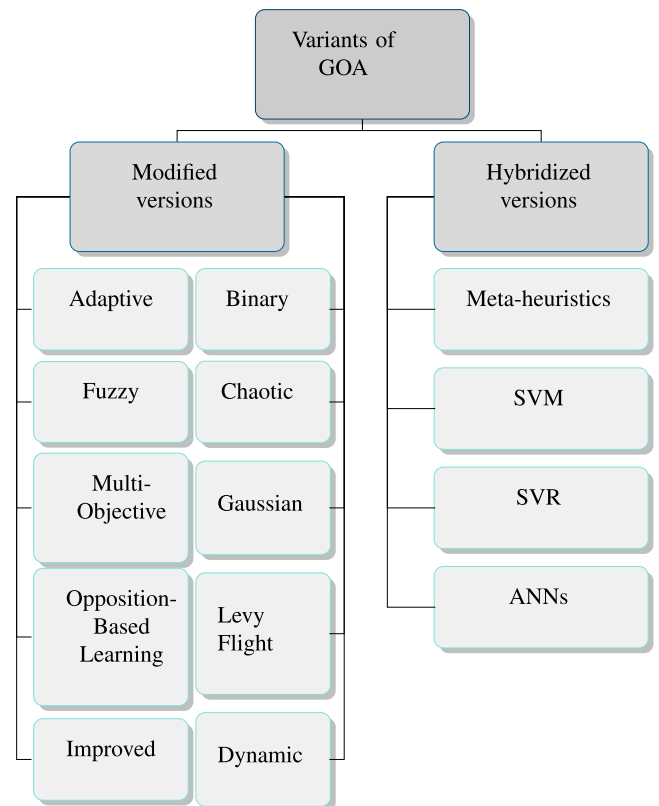**FIGURE 6.** Flowchart of the Grasshopper Optimisation Algorithm.

FIGURE 7. Variants of Grasshopper Optimisation Algorithm.

applied to obtain the binary version of GOA. Simulation results showed that BGOA improves significantly the accuracy and quality of the solutions in solving the SCP.

Hichem *et al.* [79] proposed a Novel Binary GOA (NBGOA) for solving the feature selection problem. The effectiveness of NBGOA was evaluated using 20 datasets with various sizes taken from the UCI datasets repository in comparison with five well-regarded optimization techniques in the feature selection field. Simulation results revealed that NBGOA achieves better results compared to the tested methods in terms of fitness function and average classification accuracy.

Mafarja *et al.* [67] proposed binary variants of GOA for tackling the feature selection problems. Two mechanisms were used to obtain the binary version of GOA. The first mechanism is based on Sigmoid transfer function (BGOA-S) and V-shaped transfer function (BGOA-V). While the second one is based on the mutation operator and best solution found so far (BGOA-M). These techniques were evaluated based on 25 standard UCI datasets in comparison with eight well-known approaches. It was demonstrated that BGOA-M outperforms BGOA-S, BGOA-V, and other existing optimization techniques.

2) CHAOTIC GRASSHOPPER OPTIMIZATION ALGORITHM

Saxena *et al.* [80] proposed ten variants of enhanced chaotic GOA (ECGOAs) for solving the three-bar truss design problem and frequency-modulated sound synthesis parameter
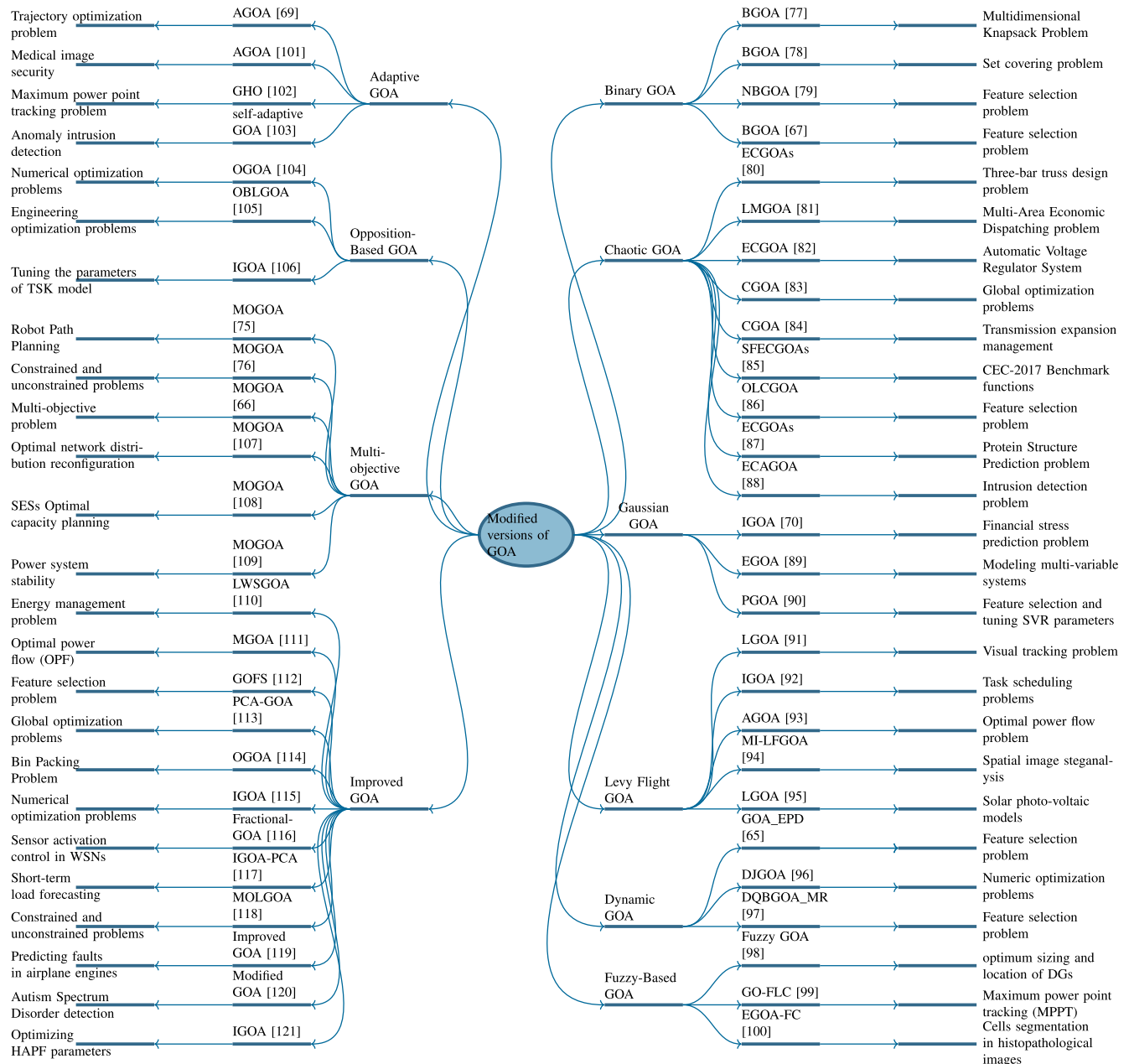
1) BINARY GRASSHOPPER OPTIMIZATION ALGORITHM

Pinto *et al.* [77] developed a Binary GOA (BGOA) based on the percentile concept for solving the Multidimensional Knapsack Problem (MKP). The performance of BGOA was validated using OR-Library benchmarks MKP instances in comparison with Binary Artificial Algae Algorithm (BAAA) and K-Means Transition Ranking (KMTR). Test results showed competitive results of BGOA compared to BAAA and KMTR models.

In [78], a Binary GOA (BGOA) was proposed for tackling the Set Covering Problem (SCP). The percentile concept was

FIGURE 8. Modified versions of GOA.

estimation problem. Ten Chaotic maps were used to enhance the bridging mechanism of GOA and results showed that ECGOA with Singer map outperforms the standard GOA and other 9 variants of ECGOA.

Zhang *et al.* [81] proposed a chaotic GOA (LMGOA) based on Logistic Map for tackling the Multi-Area Economic Dispatching (MAED) problem. The effectiveness of LMGOA was validated in 3 different case studies compared to DE, EP, PSO, and ABC algorithms. Test results illustrated the superiority of LMGOA when compared with GOA and state-of-the-art techniques.

In [82], an enhanced chaotic GOA (ECGOA) based PID controller was proposed for automatic voltage regulator

system. The performance of ECGOA was validated in terms of transient response, robustness, stability, and error. Test results revealed the superiority of ECGOA compared to ABC, BBO, CS, GOA, BFOA, IKA, MBO, SCA, and FPA.

Arora and Anand [83] proposed a Chaotic GOA (CGOA) based on the integration of chaos theory into GOA for solving the global optimization problems. CGOA was evaluated using the thirteen most widely used benchmark functions. According to the experiments, CGOA gave optimal solutions compared to the original GOA. It is proved that the chaotic maps, especially circle map, provide a good balance between intensification/diversification and prevent the GOA from stagnating in local optima.

TABLE 4. Modified versions of GOA.

Variant	Name	Application	Author	Year
Binary GOA	BGOA	Multidimensional Knapsack Problem	Pinto et al. [77]	2018
	BGOA	Set covering problem	Crawford et al. [78]	2018
	NBGOA	Feature selection problem	Hichem et al. [79]	2019
	BGOA	Feature selection problem	Mafarja et al. [67]	2019
Chaotic GOA	ECGOAs	Three-bar truss design problem	Saxena et al. [80]	2018
	LMGOA	Multi-Area Economic Dispatching (MAED) problem	Zhang et al. [81]	2019
	ECGOA	Automatic Voltage Regulator System	Saravanan et al. [82]	2019
	CGOA	Global optimization problems	Arora and Anand [83]	2019
	CGOA	Generation and transmission expansion management	Suriya et al. [84]	2019
	SFECGOAs	CEC-2017 Benchmark functions	Saxena [85]	2019
	OLCGOA	Feature selection problem	Xu et al. [86]	2020
	ECGOAs	Protein Structure Prediction problem	Saxena and Kumar [87]	2020
	ECAGOA	Intrusion detection problem	Dwivedi et al. [88]	2020
Gaussian GOA	IGOA	Financial stress prediction problem	Luo et al. [70]	2018
	EGOA	Modeling multivariable systems	Li et al. [89]	2019
	PGOA	Feature selection and optimizing SVR parameters	Algamal et al. [90]	2020
Levy Flight GOA	LGOA	Visual tracking problem	Zhang et al. [91]	2019
	IGOA	Task scheduling problems	Zhao et al. [92]	2019
	AGOA	Optimal power flow (OPF) problem	Alhejji et al. [93]	2020
	MI-LFGOA	Spatial image steganalysis	Chhikar and Kumar [94]	2020
	LGOA	Parameter extraction of solar photo-voltaic models	Mokeddem [95]	2020
Dynamic GOA	GOA_EPD	Feature selection problem	Mafarja et al. [65]	2018
	DJGOA	Numeric optimization problems	Zhao et al. [96]	2019
	DQBGOA_MR	Feature selection problem	Wang et al. [97]	2020
Adaptive GOA	AGOA	Trajectory optimization problem	Wu et al. [69]	2017
	AGOA	Medical image security	Shankar et al. [101]	2018
	GHO	maximum power point tracking (MPPT) problem	Mansoor et al. [102]	2020
	self-adaptive GOA	Anomaly intrusion detection	Shukla [103]	2020
Fuzzy-Based GOA	Fuzzy GOA	optimum sizing and location of DGs	Gampa et al. [98]	2020
	GO-FLC	Maximum power point tracking (MPPT)	Bhukya and Nandiraju [99]	2020
	EGOA-FC	Cells segmentation in histopathological images	Tiwari and Jain [100]	2020
Opposition-Based GOA	OGOA	Numerical optimization problems	Bairathi and Gopalani [104]	2018
	OBLGOA	benchmark optimization functions and engineering problems	Ewees et al. [105]	2018
	IGOA	Tuning the parameters of Takagi-Sugeno-Kang (TSK) model	Raeesi et al. [106]	2020
Multi-objective GOA	MOGOA	Robot Path Planning	Elmi and Efe [75]	2018
	MOGOA	Constrained and unconstrained problems	Tharwat et al. [76]	2018
	MOGOA	Multi-objective problems	Mirjalili et al. [66]	2018
	MOGOA	Optimal network distribution reconfiguration	Jahani et al. [107]	2019
	MOGOA	Optimal capacity planning of sustainable energy systems (SESs)	Bukar et al. [108]	2020
	MOGOA	Power system stability	Falehi [109]	2020
Improved GOA	LWSGOA	Energy management problem	Liu et al. [110]	2018
	MGOA	Optimal power flow (OPF)	Taher et al. [111]	2019
	GOFS	Feature selection problem	Zakeri and Hokmabadi [112]	2019
	PCA-GOA	Global optimization problems	Yue and Zhang [113]	2019
	OGOA	Bin Packing Problem	Feng et al. [114]	2020
	IGOA	Numerical optimization problems	Mishra et al. [115]	2020
	Fractional-GOA	Sensor activation control in WSNs	Tanwar et al. [116]	2020
	IGOA-PCA	Short-term load forecasting	Salami et al. [117]	2020
	MOLGOA	Constrained and unconstrained problems	Zhou et al. [118]	2020

TABLE 4. *(Continued.)* Modified versions of GOA.

Variant	Name	Application	Author	Year
	Improved GOA	Predicting faults in airplane engines	Bala et al. [119]	2020
	Modified GOA	Autism Spectrum Disorder (ASD) detection	Goel et al. [120]	2020
	IGOA	Optimizing the parameters of power filter (HAPF)	Huang et al. [121]	2020

Suriya *et al.* [84] developed a chaotic GOA (CGOA) based on the incorporation of chaos theory in GOA for optimizing the results of the Generation and Transmission Expansion Plan (GTEP) model. The performance of CGOA was evaluated based on 32 generating units and results showed that CGOA outperforms other tested approaches in terms of peak load reductions and cost of the transmission network expansion.

Saxena [85] proposed eleven different variants of GOA (SFECGOAs) based on the integration of chaos theory and crossover operators into GOA. The robustness of SFECGOAs was validated based on the latest 29 Congress on Evolutionary Computation-2017 (CEC-2017). SFECGOAs were also applied for solving the Model Order Reduction (MOR), Protein Structure Prediction (PSP), and Frequency Modulated (FM) sound wave parameter synthesis problems. Experimental results demonstrated the superiority of SFECGOAs compared to the classical GOA and other state-of-the-art optimization algorithms.

An enhanced GOA (OLCGOA) was proposed by Xu *et al.* [86] for tackling the Feature Selection Problem (FSP). The effectiveness of OLCGOA was tested using 30 IEEE CEC2017 benchmark functions. It was also applied for solving the FSP. According to the experiments, OLCGOA can reach optimal solutions for solving benchmarking and feature selection problem.

Saxena and Kumar [87] proposed 10 enhanced chaotic GOA (ECGOAs) variants for tackling the protein structure prediction problem. The efficiency of ECGOAs was validated using artificial and real protein sequences. Test results revealed the effectiveness of the chaotic variants (ECGOA) compared to the original GOA.

Dwivedi *et al.* [88] suggested an enhanced model (ECAGOA) based on chaotic adaptive GOA with Ensemble of Feature Selection (EFS) for tackling the intrusion detection problem. ECAGOA was assessed using 3 datasets including ISCX 2012, CIC-IDS2017, and NSL-KDD. According to the experiments, ECAGOA provided better performance comparing with state-of-the-art feature selection techniques in terms of accuracy, detection rate, and false alarm rate.

3) GAUSSIAN GRASSHOPPER OPTIMIZATION ALGORITHM

An improved GOA (IGOA) was proposed by Luo *et al.* [70] for solving the financial stress prediction problem. Three strategies including Gaussian mutation, opposition-based learning, and Levy-flight were introduced in GOA to provide a good balance between exploitation and exploration. IGOA was evaluated using datasets collected from some Japanese financial statements from 1995 to 2009 compared to GA, FA, PSO, MFO, DE, SCA, and standard GOA. According to the experiments, IGOA provided good classification accuracy comparing with other existing approaches.

Li *et al.* [89] proposed an enhanced GOA (EGOA) for modeling multivariable systems with support vector regression. Gaussian mutation operator and coevolution strategy were introduced into GOA to enhance the search ability. Experimental results showed the effectiveness and superiority of EGOA compared to standard GOA, GA, PSO, and GSA.

Algamal *et al.* [90] suggested an improved GOA (PGOA) by adding Gaussian function into GOA for feature selection and optimizing SVR parameters. PGOA was tested and assessed using four chemical datasets taking into account three metrics: prediction, number of features, and computational time. According to the simulation, PGOA outperforms other nature-inspired algorithms such as PSO, FA, BA, WOA, and the standard GOA.

4) LEVY-FLIGHT GRASSHOPPER OPTIMIZATION ALGORITHM

Zhang *et al.* [91] developed an enhanced method (LGOA) based on the integration of Levy flight in GOA for visual tracking. The performance of LGOA was evaluated using 8 video sequences in comparison with PSO, CS, ALO, and the standard GOA. Experimental results showed the performance and effectiveness of LGOA compared to the classical GOA, PSO, CS, ALO algorithms.

In [92], an improved GOA (IGOA) was proposed for task scheduling problems. Levy flight mechanism, nonlinear comfort zone parameter, and random jumping strategy were introduced to improve the performance of GOA. IGOA was tested using 29 well-known benchmark functions in comparison with the basic GOA, PSO, DA, Opposition-Based Learning GOA (OBLGOA), WOA, and ALO. According to the results, IGOA obtains competitive results in comparison with the original GOA and other existing optimization algorithms.

Alhejji *et al.* [93] suggested an adaptive GOA (AGOA) by adding a Levy-flight distribution mechanism into the original GOA for tackling the optimal power flow (OPF) problem. The robustness of AGOA was verified using 26-bus and IEEE 30-bus systems as well as 57-bus system. According to the experiments, AGOA gave better results when compared with other optimization approaches reported in the literature.

Chhikar and Kumar [94] developed a Multi-Islands Levy-flight GOA model, named MI-LFGOA, for spatial image steganalysis. MI-LFGOA was tested using SPAM (686-D)

and SRM (34671-D) subsets taken from the BOSS base 1.01 image database. Test results revealed that MI-LFGOA gives promising solutions when comparing with other feature selection approaches.

Mokeddem [95] proposed an improved method (LGOA) by incorporating the Levy-flight mechanism into GOA for parameter extraction of solar photo-voltaic models. LGOA was assessed using Sharp ND-R250A5 module under irradiance and temperature conditions. According to the experiments, LGOA provided high accuracy and good performance compared to the original GOA.

5) DYNAMIC GRASSHOPPER OPTIMIZATION ALGORITHM

An enhanced GOA (GOA_EPD) based on the use of Evolutionary Population Dynamics (EPD) and selection operators was proposed by Mafarja *et al.* [65] for tackling the feature selection problems. GOA_EPD was evaluated based on 22 real benchmark datasets taken from the UCI machine learning repository. Comparative results and analysis showed the robustness of GOA_EPD comparing with GA, PSO, BGSA, BBA, and bGWO.

Zhao *et al.* [96] proposed a Dynamic Improved GOA (DJGOA) by integrating dynamic weight strategy and random jumping concept for tackling the single objective numeric optimization problem. DJGOA was evaluated using 13 benchmark functions in comparison with PSO, DA, and standard GOA. It was demonstrated that DJGOA gives better performance compared to the standard GOA, PSO, and DA.

Wang *et al.* [97] suggested a dynamic quantum binary GOA (DQBGOA_MR) based on quantum computing concept, mutual information strategy, and rough set mechanism for tackling the feature selection problem. DQBGOA_MR was tested using twenty UCI datasets by considering three metrics such as average classification accuracy, average feature subset size, and average fitness value. According to the extensive experiments, DQBGOA_MR provided better solutions comparing with other swarm intelligence techniques.

6) ADAPTIVE GRASSHOPPER OPTIMIZATION ALGORITHM

Wu *et al.* [69] proposed an adaptive GOA (AGOA) for optimizing the trajectory planning of solar-powered Unmanned Aerial Vehicles (SUAVs) in an urban environment. To enhance the performance of AGOA, natural selection, dynamic feedback, and democratic decision-making strategies were incorporated into GOA. Simulation results showed that AGOA gives better performance when compared with standard GOA, PSO, and GWO optimization algorithms.

Shankar *et al.* [101] proposed an adaptive GOA (AGOA) for medical image security with efficient optimal secret and public key. An adaptive process was used to enhance the high-security investigation of GOA.

Mansoor *et al.* [102] proposed an adaptive GOA (GHO) for solving the maximum power point tracking (MPPT) problem fast varying irradiance and partial shading conditions. An adaptive search and skip method were introduced. GHO was tested on five different cases of weather conditions in

comparison with Perturb and Observe (P&O), ABC, PSO, DA, PSO Gravitational Search (PSOGS), and CS algorithms.

Shukla [103] suggested a self-adaptive GOA by adding the concepts of mutation and perceptive into the original GOA for anomaly intrusion detection. To test the performance of self-adaptive GOA, three datasets such as NSL-KDD, CIC-IDS 2017, and AWID were used. According to the experiments, the self-adaptive GOA provided better results comparing with PSO, GA, DE, and ABC in terms of accuracy, detection rate, and false-positive rate.

7) FUZZY-BASED GRASSHOPPER OPTIMIZATION ALGORITHM

Gampa *et al.* [98] developed a Fuzzy GOA model, based on the hybridization of GOA with Fuzzy method for optimum sizing and location of distributed generations, shunt capacitors and electric vehicle charging stations. The performance of Fuzzy GOA was evaluated based on 51-bus and 69-bus distribution networks and results proved the performance and effectiveness of Fuzzy GOA compared to the conventional method, Fuzzy GA, and Fuzzy PSO.

Bhukya and Nandiraju [99] proposed GOA-based Fuzzy Logic Control (GO-FLC) for maximum power point tracking (MPPT). In this method, GOA was used to tune the membership functions (MFs) of FLC. It was demonstrated that the performance and robustness of GO-FLC comparing with other existing methods in terms of accuracy, reliability, and computation time.

Tiwari and Jain [100] suggested a combined model (EGOA-FC) by combining GOA with fuzzy clustering technique for cells segmentation in histopathological images. To test the efficiency of the EGOA-FC model, two histopathological images (i.e TNBC patients cancer and UCSB bio segmentation images datasets) were used in the simulation. According to the experiments, EGOA-FC showed good results compared to K-means and fuzzy c-means techniques in terms of aggregated Jaccard index value and F1-score.

8) OPPOSITION-BASED LEARNING GRASSHOPPER OPTIMIZATION ALGORITHM

Ewees *et al.* [105] proposed an enhanced version of GOA (OBLGOA) by integrating the OBL mechanism into GOA for tackling benchmark optimization functions and engineering problems. The effectiveness of OBLGOA was investigated based on twenty-three benchmark functions and four engineering problems in comparison with standard GOA, GA, BA, DE, DA, PSO, MFO, MVO, ALO, and SCA. Simulation results revealed that OBLGOA outperforms state-of-the-art optimization algorithms in terms of the performance measures.

Raeesi *et al.* [106] suggested an improved GOA (IGOA) by incorporating the opposition-based learning strategy into GOA for tuning the parameters of Takagi-Sugeno-Kang (TSK) model. The efficiency of IGOA was investigated using unimodal and multimodal test functions. According to the

experiments, IGOA gives better solutions compared to the original GOA.

9) MULTI-OBJECTIVE GRASSHOPPER OPTIMIZATION ALGORITHM

Elmi and Efe [75] proposed a multi-objective GOA (MOGOA) for robot path planning in static environments. MOGOA was investigated for optimizing several metrics such as path length, path cost, smoothness, and computational time.

Tharwat *et al.* [76] proposed a novel multi-objective GOA (MOGOA) for tackling constrained and unconstrained optimization problems. MOGOA was validated using 12 testing functions (6 unconstrained functions and 6 constrained functions) in comparison with MOPSO, MOALO, and NSGA-II. It was demonstrated that MOGOA gives competitive results when comparing with other optimization metaheuristics.

In [66], a multi-objective GOA (MOGOA) was proposed for solving multi-objective problems. MOGOA was tested on ZDT and CEC2009 and compared to NSGA-II, MOPSO, MODA, and MOALO. It was demonstrated that MOGOA gives competitive results compared to other multi-objective optimization models by producing accurate Pareto optimal solutions.

Another multi-objective optimization technique (MOGOA) was proposed by Jahani *et al.* [107] for optimal network distribution reconfiguration. The effectiveness of MOGOA was approved based on 33-bus and 69-bus test systems. Test results demonstrated the efficiency and performance of MOGOA to find a Pareto set solution with high-quality results

10) OTHER IMPROVED GRASSHOPPER OPTIMIZATION ALGORITHM

Liu *et al.* [110] proposed a combined approach (LWSGOA) by combining GOA with Linear Weighted Sum (LWS) for solving the energy management problem. LWSGOA was validated by establishing an optimal model of three interconnected heat exchangers (EH) representing Multi-Integrated Energy System (MIES) as the case study. Experimental results proved the scalability and flexibility of LWSGOA by providing lower multi-carrier energy consumption costs, lower peak power, and heat demand for multi-IES compared to other existing methods.

Taher *et al.* [111] proposed a modified GOA (MGOA) by integrating the mutation process in the conventional GOA for tackling the optimal power flow (OPF) problem. MGOA was validated using standard IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus test systems with 13 case studies in comparison with standard GOA, GA, TLBO, and PSO algorithms. It was demonstrated that MGOA gives better results compared to other well-regarded optimization approaches existing in the literature.

In the work of Zakeri and Hokmabadi [112], a real-valued GOA (GOFS) was proposed for tackling the feature selection problem. GOFS was validated using 10 UCI datasets and compared with 12 well-regarded feature selection methods. The effectiveness of GOFS was proved compared with other optimization algorithms by achieving the highest classification accuracy in 7 out of 10 datasets.

Yue and Zhang [113] proposed an enhanced GOA (PCA-GOA) for global optimization problems. Principal Component Analysis (PCA) and novel inertia weight were incorporated into GOA to enhance its search space ability. in a simiar work, Feng *et al.* [114] proposed an enhanced GOA (EGOA) for solving the Bin Packing Problem (BPP). Nonlinear convergence parameter, niche mechanism, and β-hill climbing were introduced to improve the convergence accuracy of GOA. Simulation results showed the efficiency and ability of EGOA to find optimal solutions in different problem sizes compared to the original GOA, DA, ALO, PSO, and OBLGOA algorithms. In a similar work, an improved GOA (IGOA) was proposed by Mishra *et al.* [115], in which random walk theory was leveraged to provide a balanced exploration and exploitation of the search space and avoid premature convergence into local optima.

Tanwar *et al.* [116] proposed a Fractional-GOA model by integrating the fractional calculus into GOA for sensor activation control in Wireless Sensor Networks (WSNs). Experimental results proved the effectiveness of Fractional-GOA comparing with other existing models by obtaining maximal energy, throughput, and alive nodes of 0.111, 0.85, and 11, respectively.

Bala *et al.* [119] suggested an improved GOA by incorporating the Echo State Network (ESN) strategy into GOA for predicting faults in airplane engines. The improved GOA was validated using time-series data collected from the GitHub repository with mean squared error (MSE) as an objective function. According to the experiments, the improved GOA provided accurate solutions comparing with CS, DE, PSO, BPSO, LSTM, ESN, Deep ESN, and the classical GOA.

Goel *et al.* [120] developed a modified GOA by combining GOA with the random forest approach for Autism Spectrum Disorder (ASD) detection. The modified GOA was validated using three ASD screening datasets of different age groups including children, adolescents, and adults. According to the experiments, the modified GOA provides better results when comparing with other state-of-the-art approaches by achieving an accuracy of 100% at all stages of life.

Huang *et al.* [121] suggested an improved GOA (IGOA) by adding the social interaction mechanism and learning strategy into GOA for optimizing the parameters of power filter (HAPF). IGOA was tested using numerical data of three cases of an industrial plant taking into account the parameters of capacitive reactance, inductive reactance, and controllable gain of the active filter. Test results revealed that IGOA provides promising performance when compared with previous optimization techniques.

The analysis of the proportion of published papers that propose a modified version of GOA reveals that most of them focus on improving GOA. In fact, as shown in Figure 9, 23% of approaches improve the performance of the original version of GOA. Chaotic version comes at the second position with a proportion of 17% of the total papers.
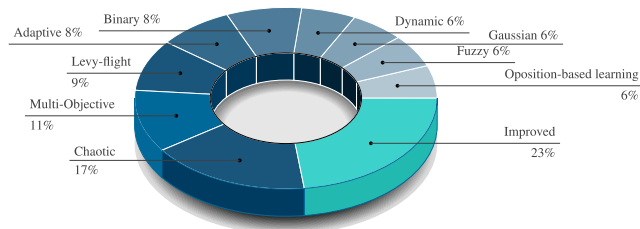

FIGURE 9. Proportions of papers having addressed the different modified versions of GOA.

B. HYBRIDIZED VERSIONS OF GRASSHOPPER OPTIMIZATION ALGORITHM

Various hybridization of GOA with other optimization algorithms such as meta-heuristic and machine learning can be found in the literature. Some of them are given in Figure11 and Table 5. As shown in Figure 10, more than 50% of papers propose hybridization with metaheuristics and 26% of them use Neural Networks (NN) as machine learning technique. The following subsections discuss them in details.

1) HYBRIDIZATION WITH GENETIC ALGORITHM

Alphonsa and MohanaSundaram [122] suggested a hybrid optimization approach (GOAGA) by combining GOA with GA for securing medical data. The performance of GOAGA was examined in 3 different test cases in comparison with GA, ABC, PSO, FA, GSO, GMGW, GWOSEB, and the standard GOA. It was revealed that GOAGA gives better performance for the preservation of sensitive healthcare data compared to GA, ABC, PSO, FA, GSO, GMGW, GWOSEB, and the original GOA.

El-Shorbagy and El-Refaey [123] suggested a combined algorithm (hybrid-GOA-GA) by combining GOA with GA for tackling the non-linear equations system. Eight benchmarks of non-linear equations were used to validate and assess the efficiency of the hybrid-GOA-GA. According to the results, the hybrid-GOA-GA showed its competitiveness and superiority when comparing with other existing methods in terms of accuracy and computational cost.

2) HYBRIDIZATION WITH DIFFERENTIAL EVOLUTION ALGORITHM

In [124], a combined approach (GOA-jDE)integrating GOA with DE was proposed for solving the global optimization problems. GOA-jDE was assessed using 14 optimization test functions and results showed the feasibility of GOA-jDE compared to DE, GOA, Modified GOA (MGOA), PSO,
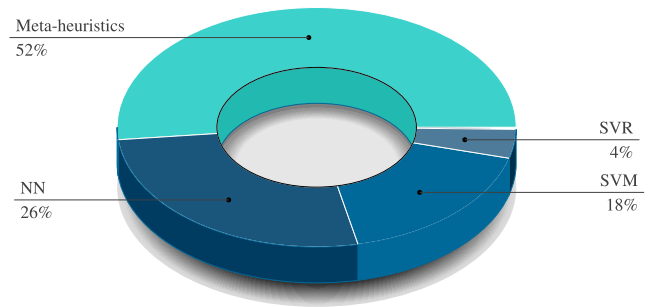

FIGURE 10. Proportions of papers having addressed the different hybridized versions of GOA.

and MVO in terms of convergence speed and calculation precision.

Li *et al.* [125] suggested a novel model (DE-GOA-KELM) by hybridizing GOA with DE and a kernel extreme learning machine (KELM) for color difference detection of dyed fabrics. DE-GOA-KELM was tested using four indicators (i.e average classification accuracy, best classification accuracy, worst classification accuracy, and standard deviation) in comparison with Eleven optimization models. According to the experiments, DE-GOA-KELM provided an impressive stability with an average classification accuracy of 98.89%.

3) HYBRIDIZATION WITH ARTIFICIAL BEE COLONY ALGORITHM

GOA and ABC was hybridized by Dahiya *et al.* [126]. The authors proposed node deployment, cluster leader selection, and optimal route selection in Wireless Sensor Networks (WSNs). HAGOA was examined using metrics such as sensor node lifetime, energy consumption, remaining energy, end to end delay, and maximum number of rounds in comparison with LEACH, ACO, PSO, ABC, ACOPSO, HABCS, and AGOA. It was demonstrated that HAGOA gives better performance compared to other optimization meta-heuristics.

4) HYBRIDIZATION WITH GREY WOLF OPTIMIZER

A hybrid method (GWGHA) based on hybridizing GWO with GOA was proposed by Teng *et al.* [127] for the Cycle Traffic Light Timing Optimization Problem (CTLTOP). The performance of GWGHA was validated based on data taken from Kaohsiung, Taiwan, Bahía Blanca, Argentina, and Malaga, Spain in comparison with PSO, SPSO2011, GWO, and GOA. In [144] a hybrid algorithm (GWO-GOA) was proposed by hybridizing GOA with GWO for tackling the text feature selection problem. GWO-GOA was assessed using eight datasets taking into account five metrics (i.e accuracy, sensitivity, specificity, precision, recall, and F-measure). According to the experiments, GWO-GOA showed better quality when comparing with GOA, GWO, and other techniques.

5) HYBRIDIZATION WITH BAT ALGORITHM

Yue and Zhang [128] suggested a hybrid model (BGOA) by hybridizing GOA with BA for solving global optimization problems. BGOA was assessed using 23 test benchmark test functions comparing with GA, BA, and the standard GOA.

TABLE 5. Hybrid versions of GOA.

Variant	Name	Application	Author	Year
GOA + GA	GOAGA	Cloud computing	Alphonsa and Mohana-Sundaram [122]	2019
	hybrid-GOA-GA	Non-linear equations system	El-Shorbagy and El-Refaey [123]	2020
GOA + SA	SGOA	Global optimization problems	Yu et al. [146]	2021
GOA + DE	GOA-jDE	Global optimization problems	Jia et al. [124]	2019
	DE-GOA-KELM	Color difference detection of dyed fabrics.	Li et al. [125]	2020
GOA + ABC	HAGOA	Node deployment and optimal route selection WSNs	Dahiya et al. [126]	2020
GOA + GWO	GWGHA	Cycle traffic light timing optimization problem	Teng et al. [127]	2019
GOA + BA	BGOA	Global optimization problems	Yue and Zhang [128]	2020
GOA + GSA	HGOA	Benchmark test functions	Guo et al. [129]	2020
GOA + CSO	SM-GNCSOA	Feature selection problem	Bansal et al. [130]	2020
GOA + ALO	GOALO	Circular antenna array	Amaireh et al. [131]	2019
GOA + SSA	HAGOA	Unimodal and multimodal benchmark functions	Dahiya et al. [132]	2019
GOA + TLBO	TLGOA	Abrupt Motion Tracking	Zhang et al. [133]	2019
GOA + IWOA	IWGOA	Global optimization problems	Yue et al. [128]	2020
GOA + SVM	GOA-SVM	Optimization of SVM model parameters	Aljarah et al. [72]	2018
	GOA-SVM	Short-term load forecasting	Barman et al. [73]	2018
	GOA-SVM	Feature selection problem	Ibrahim et al. [135]	2019
	GOA-ImLSTM	Decision-making for Self-Driving Vehicles	Shi et al. [136]	2020
	GOA-MSVM	Fault identification accuracy of rotating machinery	Zhang et al. [137]	2020
	GOA-SVM	Power quality disturbances recognition	Motlagh and Foroud [138]	2021
GOA + SVR	GOA-SVR	Short term load forecasting	Barman and Choudhury [134]	2018
GOA + NN	GOA–RNN	Photovoltaic/wind energy hybrid pumping system	Rufus and Kalaivani [139]	2019
	GOAMLP	Classification of multi-layer perceptrons	Heidari et al. [71]	2019
	MFFNN	Load forecasting	Talaat et al. [140]	2020
	CGOA-NN	Forecasting iron ore price volatility	Ewees et al. [74]	2020
	GOAMLP	Intrusion detection system	Moghanian et al. [141]	2020
	GORNN	Boosting the speed the induction motor	Jape et al. [142]	2020
	DBN-GOA	Liver disease classification	Renukadevi and Karunakaran [143]	2020
	CGOA-ANN	Skin Color Segmentation	Razmjooy et al. [144]	2021

According to the experiments, BGOA provided better solutions compared to GA, BA, and GOA.

6) HYBRIDIZATION WITH GRAVITATIONAL SEARCH ALGORITHM

The GOA algorithm was hybridized with GSA by Guo *et al.* [129]. Gravity search and landmark operators were adopted to enhance the global search capability of GOA. Simulation results demonstrated that HGOA gives competitive results compared to GOA, PSO, SCA, MFO, SSA, and BA.

7) HYBRID GOA AND CAT SWARM OPTIMIZATION ALGORITHM

Bansal *et al.* [130] hybridized the binary variant of GOA known as Simple Matching Binary GOA (SM-BGOA) with a variant of Cat Swarm Optimization Algorithm known as NCSOA for feature selection and optimal design of

multi-layer perceptron. The effectiveness of SM-GNCSOA was evaluated based on 10 data sets selected from the UCI repository and results showed the capability of SM-GNCSOA for solving the optimal design of multi-layer perceptron problem in terms of classification accuracy

8) HYBRIDIZATION WITH ANT LION OPTIMIZATION ALGORITHM

One of the very first hybridization of ALO and GOA was proposed by Amaireh *et al.* [131]. The authors used the hybrid method in sidelobe-level (SLL) suppression for circular antenna array.

9) HYBRIDIZATION WITH SALP SWARM ALGORITHM

Dahiya *et al.* [132] combined GOA with SSA for discovering the global optimum in a given search space. The performance of HAGOA was assessed using unimodal and multimodal benchmark functions.
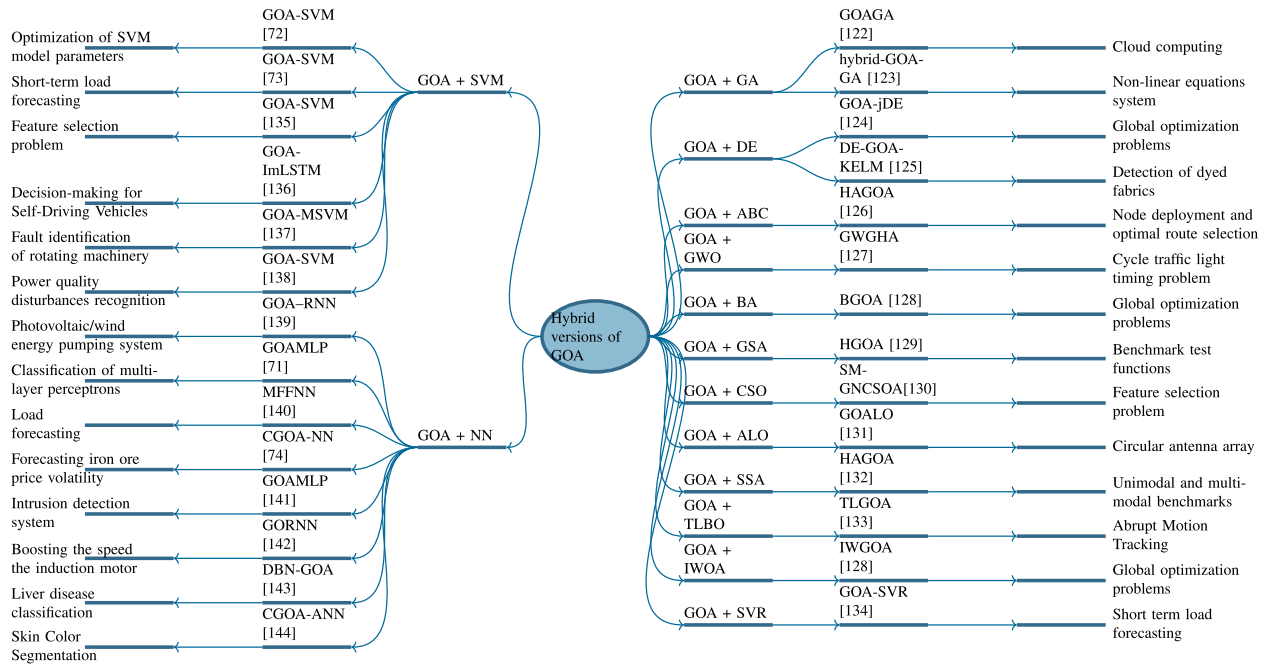
FIGURE 11. Hybrid versions of GOA.

10) HYBRIDIZATION WITH TEACHING-LEARNING-BASED OPTIMIZATION

Zhang *et al.* [133] combined Adaptive GOA with Teaching-Learning-Based Optimization (TLBO) algorithm (TLGOA) and utilizes it for abrupt motion tracking.

11) HYBRIDIZATION WITH INVASIVE WEED OPTIMIZATION ALGORITHM

Yue *et al.* [128] proposed a combined method (IWGOA) based on the hybridization of GOA with invasive weed optimization (IWO) for global optimization problems.

12) GRASSHOPPER OPTIMIZATION ALGORITHM WITH SUPPORT VECTOR MACHINE

Aljarah *et al.* [72] proposed a combined method (GOA-SVM) based on the hybridization of GOA with SVM for optimizing the parameters of SVM model and the location of the best features subset simultaneously. The efficiency of GOA-SVM was evaluated based on 18 low and high-dimensional benchmark datasets in comparison with 7 well-regarded algorithms. Another similar work was done by Barman *et al.* [73] and Ibrahim *et al.* [135].

Shi *et al.* [136] suggested an improved long short-term memory GOA (GOA-ImLSTM) by hybridizing GOA with SVM and LSTM for decision-making for Self-Driving Vehicles. GOA-ImLSTM was assessed using Vehicle trajectory data collected from Roads of Los Angeles and California. According to the experiments, GOA-ImLSTM enhanced the accuracy of solutions when compared with other decision-making techniques.

Zhang *et al.* [137] suggested a novel model (GOA-MSVM) by combining GOA with SVM for fault identification accuracy of rotating machinery. GOA-MSVM was assessed in two

case studies: rolling bearing faults and gear faults. According to the experiments, GOA-MSVM provided promising results compared to five other SVM-based approaches.

13) GRASSHOPPER OPTIMIZATION ALGORITHM WITH SUPPORT VECTOR REGRESSION

Barman and Choudhury [134] hybridized GOA and Support Vector Regression (SVR) for Short Term Load Forecasting (STLF) during periods with substantial weather changes in North-East India. The performance of GOA-SVR was evaluated based on the data of the load dispatch center of Assam state in 3 case studies under 3 typical weather conditions. Experimental results demonstrated that GOA-SVR outperforms the conventional methods in all cases.

14) GRASSHOPPER OPTIMIZATION ALGORITHM WITH NEURAL NETWORK

Talaat *et al.* [140] proposed a hybrid approach(MFFNN-GOA) based on the combination of multi-layer feed-forward neural network (MFFNN) and GOA for load forecasting. The effectiveness of MFFNN-GOA was tested based on different training functions taking into account three parameters: RMSE, MAE, and Mean Absolute Percentage Error (MAPE). The effectiveness of MFFNN-GOA method was demonstrated compared to MFFNN, MFFNN-GA, and MFFNN-GWO optimization methods.

Moghanian *et al.* [141] suggested a novel model (GOAMLP) by combining GOA with multi-layer perceptron neural network for tackling the intrusion detection problem. KDD and UNSW datasets were used to validate the robustness of GOAMLP. Experimental results demonstrated that GOAMLP is more accurate and outperforms other existing

techniques such as RF, XGBooston, HHO, BWO, and ANN with BOA.

A hybrid model (GORNN) by combining GOA with RNN was proposed by Jape *et al.* [142] for boosting the speed of the induction motor. The viability and effectiveness of GORNN was validated using two scenarios: step demand torque with constant demand speed and ramp demand torque with constant demand speed. According to the experiments, GORNN provided good solutions when compared with other existing techniques.

Renukadevi and Karunakaran [143] proposed hybridized GOA with Deep Belief Network(DBN) for liver disease classification. The performance of DBN-GOA was evaluated based on real-time and open-source computed tomography (CT) image datasets. It was demonstrated that DBN-GOA provide 98%, 95.82%, 97.52%, 98.53% and 96.8% for the accuracy, sensitivity, specificity, precision, and F-1 score, respectively.

IV. APPLICATIONS OF GRASSHOPPER OPTIMIZATION ALGORITHM

GOA has been applied for tackling various optimization problems in different domains such as feature selection, load frequency control, distributed generation, scheduling, wind energy system, and economic dispatch. Table 6 provides some of the applications of GOA in continuous, constrained, and combinatorial optimization sub-fields. The details are provided below.

A. GOA FOR CONTINUOUS OPTIMIZATION
1) CLUSTERING
Łukasik *et al.* [147] used GOA for generating accurate data clusterings. GOA was validated using benchmark datasets based on real-world examples taken from the UCI machine learning repository. Test results revealed that GOA outperforms the standard K-means algorithm by obtaining high accuracy.

2) OPTIMAL LINEAR ANTENNA ARRAY
Amaireh *et al.* [149] employed GOA and Antlion optimization (ALO) for optimal design of Linear Antenna Arrays (LAA). GOA was tested on three different case studies: 10, 16, and 24 elements of linear antenna arrays in comparison with Taguchi Algorithm (TA), PSO, and BBO.

3) STABILIZATION OF POWER SYSTEMS
Sahu *et al.* [151] employed GOA for optimizing the parameters of Static Synchronous Series Compensator (SSSC) controller. The performance of GOA was assessed under a single-machine infinite bus system in three scenarios: nominal loading, light loading, and heavy loading.

Hekimo lu [152] used GOA for optimizing the power system stabilizer (PSS) parameters with fractional-order proportional-integral-derivative (FOPID) controller. The performance of GAO was evaluated under three configurations (light, nominal, and heavy loading cases). The merits of GOA in such problems was demonstrated in this study.

4) RECONFIGURABLE HF BROADBAND WHIP ANTENNA
Wang *et al.* [154] used GOA for solving the problems of low gain, low efficiency, and pattern warping in the high-frequency band of the existing 10-meter HF broadband whip antenna. Simulation results showed that GOA improves the gain and efficiency of antenna in low and high-frequency bands and avoids the problem of warping in antenna patterns.

5) HAND POSTURE ESTIMATION
Mirjalili *et al.* [155] estimated hand postures USN the GOA algorithm. The effectiveness of GOA was evaluated using 20-Degree-of-Freedom (DoF) hand model and results showed the reliability of GOA to find a reasonable solution for the problem.

6) BLDC MOTOR DRIVE CONTROLLER
Potnuru and Tummala [156] applied GOA for Controlling a BrushLess Direct Current (BLDC) motor drive. The performance of GOA was validated using Integral Speed Error (ISE) as an objective function and results showed the effectiveness of GOA in reducing the speed error and the time of gain tuning.

7) OPTIMAL ESTIMATION OF SINGLE DIODE MODEL PARAMETERS
Montano *et al.* [157] used GOA for estimating the optimal Single Diode Model (SDM) parameters of a photo-voltaic (PV) module. GOA was tested using four different types of PV modules in comparison with GA and PSO algorithms.

8) GRID-CONNECTED WIND GENERATOR
Amin *et al.* [158] used GOA-based Proportional-Integral (PI) controller for optimizing and improving the grid-connected wind generator. The effectiveness of GOA was tested using wind speed data extracted from Zafarana wind farm in Egypt.

B. GOA FOR CONSTRAINED OPTIMIZATION
1) ECONOMIC DISPATCH PROBLEMS
Rajput *et al.* [159] used GOA for tackling the Economic Load Dispatch Problem (ELDP). The robustness of GOA was validated using 3 power generators test cases consisting of 6 generation units with loss, 13 generation units with valve point loading, and 38 generation units.

2) CONGESTION MANAGEMENT
Kaur and Kumar [160] used GOA for Congestion Management Problem (CMP) in a pool-based electricity market. The effectiveness of GOA was evaluated using IEEE 30 Bus system and results showed the performance of GOA compared to SA, PSO, and Random Search (RS) optimization algorithms.

TABLE 6. Applications of GOA.

Class	Problem	Research Works
Continuous Optimization	Clustering	Łukasik et al. [147]
	Digital Fractional Order Integrator	Guha et al. [148]
	Optimal Linear Antenna Array	Amaireh et al. [149]
	Automatic Voltage Regulator System	Hekimoğlu and Ekinci [150]
	Power System Stabilizer	Sahu et al. [151], Hekimoğlu [152], Nayak et al. [153]
	Reconfigurable HF Broadband Whip Antenna	Wang et al. [154]
	Hand Posture Estimation	Mirjalili et al. [155]
	BLDC Motor Drive Controller	Potnuru and Tummala [156]
	Optimal Estimation of Single Diode Model Parameters	Montano et al. [157]
	Grid-Connected Wind Generator	Amin et al. [158]
Constrained Optimization	Economic Dispatch Problem	Rajput et al. [159]
	Congestion Management	Kaur and Kumar [160]
	Distributed Generator	Asasi et al. [161], Shishupal and Manglani [162], Sambaiah and Jayabarathi [163], Elsayed et al. [164], Rani et al. [165], Sudabattula et al. [166]
	Optimal Reactive Power Planning	Juhari et al. [167]
	Wind Energy System	Fathy and El-baksawi [168]
	Optimal Distribution Network System Reconfiguration	Hamour et al. [169]
	Optimal Snubber Spring	Neve et al. [170]
	FLood Routing Problem	Khalifeh et al. [171]
	Optimal placement of multiple Optical Network Units	Singh and Prakash [172]
	Nonlinear constrained optimization problem	Xiang et al. [173]
	Optimal Proton Exchange Membrane Fuel cells Stack Parameters	El-Fergany [174]
	Load frequency Control	Nosratabadi et al. [175], Lal et al. [176], Barik and Das [177], Annamraju and Nandiraju [178], Tripathy et al. [179],
	Smart Load Management System	Talaat et al. [180]
	Ontology alignment problem	Lv and Peng [181]
	Task assignment in cloud logistics	Xu et al. [182]
	Tuning the parameters of the PID controller hybrid microgrid system	Bhuyan et al. [183]
	Channel assignment for cognitive radio networks	Raju et al. [184]
	Finite impulse response filter design	Dutta et al. [185]
	Optimal short-term hydrothermal scheduling	Zeng et al. [186]
	Antenna array synthesis problem	Chakravarthy et al. [187]
Combinatorial Optimization	Feature Selection	Shukla and Kanungo [188]
	Optimal Resource Allocation	Vahidi and Rahmati [189]

3) DISTRIBUTED GENERATOR
Shishupal and Manglani [162] employed GOA for determining the optimal size and placement of shunt capacitors at suitable bus locations in radial distribution system. The performance of GOA was tested based on 15-bus radial distribution system with main feeder and four lateral feeders. According to the simulation, GOA gives better results compared to the Improved Harmony Algorithm (IHA) in minimizing the system loss and system cost of capacitor placement. Another similar work was done by Sambaiah and Jayabarathi [163], in which GOA was used for the optimal allocation of distributed generation in distribution networks.

4) OPTIMAL REACTIVE POWER PLANNING
Juhari *et al.* [167] applied GOA for tackling the reactive power planning problem. The robustness of GOA was evaluated based on the standard IEEE-30 bus test system with minimization of real power loss as an objective function. According to the simulation, GOA gives good results in minimizing the power transmission loss.

5) WIND ENERGY SYSTEM
Fathy and El-baksawi [168] used GOA to extract the maximum power from the wind energy system. The performance of GOA was evaluated using collected data for wind speed

in 4 different sites in northern Saudi Arabia (Qurayyat, Sakaka, Tabarjal, and Dumat Al-Jandal).

6) OPTIMAL DISTRIBUTION NETWORK SYSTEM RECONFIGURATION
Hamour *et al.* [169] used GOA for solving the Distribution Network System Reconfiguration (DNSR) to minimize the real power loss. GOA was tested on IEEE 33-bus radial distribution systems in comparisons with Enhanced GA (EGA), Selective PSO (SPSO), and Fuzzy Adaptation of EP (FEP). Simulation results demonstrated that GOA gives reasonable computing time and high performance when compared to other optimization methods.

7) OPTIMAL VARIATIONAL MODE DECOMPOSITION (VMD) PARAMETERS
Zhang *et al.* [68] proposed a parameter-adaptive VMD based on GOA for optimizing the Variational Mode Decomposition (VMD) parameters. The proposed adaptive VMD method was used for analyzing the vibration signals from rotating machinery. According to the experiments, the proposed method showed better results compared to the conventional fixed-parameter VMD method on this problem area.

8) OPTIMAL SNUBBER SPRING
Neve *et al.* [170] used GOA for optimizing the snubber spring for weight minimization in railway bogie. The

performance of GOA was validated according to bounds, loading, and boundary conditions and results showed the efficiency of GOA for solving real engineering design problems.

9) FLood ROUTING PROBLEM
Khalifeh *et al.* [171] used GOA for solving the non-linear Muskingum flood routing river problem. The performance of GOA was tested using time-series datasets of the outflow of the Kardeh River with minimizing the Sum of Squares of Residuals (SSQ) as the objective function.

10) OPTIMAL PROTON EXCHANGE MEMBRANE FUEL CELLS STACK PARAMETERS
El-Fergany [174] proposed a GOA-based method for optimizing the parameters of proton exchange membrane fuel cells (PEMFCs) stack. The performance of the GOA-based method was tested using four test studies.

11) OPTIMAL LOAD FREQUENCY CONTROL
Nosratabadi *et al.* [175] used GOA for optimizing the parameters of Predictive Functional Modified PID (PFMPID) controller LFC. The performance of GOA was validated using ITSE as objective function.

Lal *et al.* [176] proposed a GOA-based Fuzzy proportional-integral-derivative (PID) controller of LFC of multi-area interconnected microgrid power system. The efficiency of the proposed algorithm was validated taken into account 3 metrics such as minimum settling time, minimum undershoot, and overshoot.

Barik and Das [177] used GOA for optimal LFC of solar photovoltaic/biogas/biodiesel generator based isolated renewable microgrid. The effectiveness of GOA was evaluated in different scenarios of source and load variations by comparing it with GA, PSO, and GWO and results revealed its robustness and efficiency compared to the three studied algorithms.

Annamraju and Nandiraju [178] applied GOA for tuning the parameters of the PID controller for LFC of an autonomous two-area hybrid MicroGrid (MG). The robustness of GOA was tested using three critical scenarios in comparison with GA and Social-Spider Optimiser (SSO) algorithms.

12) SMART LOAD MANAGEMENT SYSTEM
Talaat *et al.* [180] employed GOA-based Under-Frequency Load Shedding (UFLS) for smart load management system. The performance of GOA was validated using IEEE 9-bus and 39-bus test systems in comparison with GA and PSO.

C. GOA FOR COMBINATORIAL OPTIMIZATION
1) FEATURE SELECTION
Shukla and Kanungo [188] used GOA based feature selection method for face identification in a Content-Based Image Retrieval (CBIR).

2) OPTIMAL RESOURCE ALLOCATION
Vahidi and Rahmati [189] used GOA for optimizing the resource allocation in a cloud computing environment. The effectiveness of GOA was evaluated using 3 sets of small-scale, 3 sets of medium-scale, and 2 sets of large-scale resource allocation standard examples in comparison with GA and SEIRA algorithms.

Yadav *et al.* [190] applied GOA for designing a digital finite impulse response (FIR) filters. The consistency of GOA was done using an absolute error difference objective function comparing with ABC, PSO, and CSA algorithms. According to the experiments, GOA obtains better solutions compared to ABC, PSO, and CSA approaches in terms of minimum stop-band ripple, minimum pass-band ripple, and higher attenuation in stop-band.

V. RESULTS AND COMPARISONS
In this section, the performance of the GOA algorithm is investigated, evaluated, and confirmed based on three sets of mathematical test functions (i.e. unimodal, mutlimodal, and composite). They are compared with some well-regarded optimization algorithms such as GA, PSO, FA, PFA, BA, and GSA. 30 search agents and 500 iterations are employed in the experiments. Results are normalized in the range of [0,1] for all the functions due to their different ranges/domains. The experimental results are provided in Table 7. Firstly, for unimodal test functions, it is clearly shown that GOA algorithm gives superior results on 5 out of 7 test functions (F1, F4, F5, F6, and F7). Due to the proprieties and characteristics of the unimodal functions, these results revealed that GOA has high exploitation ability and convergence. Secondly, according to Table 7, it can be observed that GOA provides better performance on 4 out of 6 multimodal test functions (F9, F11, F12, and F13). These results reveal the performance of GOA in preventing from local optima stagnation. Finally, GOA algorithm gives excellent results on 3 out of 6 composite test functions (F14, F16, and F18). It can be confirmed that GOA algorithm provides good balance between exploration and exploitation.

To confirm the significance of the results, Friedman statistical test is used and the results are given in Table 8. It is clearly observed that GOA algorithm obtains the first rank. These results revealed strongly the effectiveness and performance of GAO compared to other optimization algorithms.

VI. DISCUSSION AND FUTURE WORKS
As discussed above, GOA is a recent and popular optimization algorithm. The wide range of applications is an indication of its merits, and this algorithm benefits from high exploration and exploitation. Some of the advantages of this algorithm are listed in Table 9. However, GOA has some restrictions and disadvantages. It surely requires tuning, adaptation, and modification to solve new optimization problems.

Just like any other meta-heuristics, the performance of this algorithm substantially degrade proportional to the size of a problems (e.g. number of decision variables) due to the

TABLE 7. The average results for solving benchmark functions.

Function	GA	PSO	FA	PFA	BA	GSA	GOA
F1	0.4121	0.2391	0.1581	0.0329	0.9882	0.0002	0.0000
F2	0.0100	0.0097	0.0076	0.0131	1.0000	0.0000	0.0020
F3	0.2022	0.2613	0.0617	0.0000	1.0000	0.0328	0.0010
F4	0.7245	0.4767	0.3796	0.3219	0.9148	0.3244	0.0000
F5	0.0746	0.0386	0.0068	0.0060	1.0000	0.0000	0.0000
F6	0.1933	0.7786	0.0414	0.0088	1.0000	0.3825	0.0000
F7	0.4416	0.1349	0.0590	0.0386	1.0000	0.0226	0.0000
F8	0.0000	0.7425	0.6140	0.0381	0.0148	0.8473	1.0000
F9	1.0000	0.6520	0.8377	0.6568	0.7022	0.1361	0.0000
F10	0.8628	0.6140	0.7078	0.7170	0.9665	0.0000	0.0975
F11	0.1941	0.8184	0.0548	0.0124	0.9912	1.0000	0.0000
F12	1.0000	0.4689	0.2442	0.0237	0.6892	0.0577	0.0000
F13	0.4446	0.0973	0.1119	0.3766	1.0000	0.1603	0.0000
F14	0.3799	0.6083	0.5035	0.0008	1.0000	0.0840	0.0000
F15	0.1338	0.4236	0.5730	0.0000	1.0000	0.0672	0.4892
F16	0.6820	0.4651	0.4921	0.3381	1.0000	0.4799	0.0000
F17	0.3660	0.3241	0.3264	0.1395	1.0000	0.0000	0.8169
F18	0.1347	0.3122	0.3160	0.3249	1.0000	0.0581	0.0000
F19	0.0211	1.0000	0.7068	0.0000	0.9097	0.9391	0.7863

TABLE 8. The Friedman Statistical test.

Function	GA	PSO	FA	PFA	BA	GSA	GOA
F1	6	5	4	3	7	2	1
F2	5	4	3	6	7	1	2
F3	5	6	4	1	7	3	2
F4	6	5	4	2	7	3	1
F5	6	5	4	3	7	1	1
F6	4	6	3	2	7	5	1
F7	6	5	4	3	7	2	1
F8	1	5	4	3	2	6	7
F9	7	3	6	4	5	2	1
F10	6	3	4	5	7	1	2
F11	4	5	3	2	6	7	1
F12	7	5	4	2	6	3	1
F13	6	2	3	5	7	4	1
F14	4	6	5	1	7	3	1
F15	3	4	6	1	7	2	5
F16	6	3	5	2	7	4	1
F17	5	3	4	2	7	1	6
F18	3	4	5	6	7	2	1
F19	2	7	3	1	5	6	4
SUM	92	86	78	54	122	58	40
AVG	4.84	4.53	4.11	2.84	6.42	3.05	2.11
RANK	6	5	4	2	7	3	1

TABLE 9. Advantages and disadvantages of GOA.

Advantages	Disadvantages
- Strong capability of exploration the search space	- Premature convergence in some complex optimization techniques
- Simplicity, robustness, flexibility, and scalability	- Drawbacks in exploiting the search space
- Hybridization with other metaheuristics and techniques	- No theoretical convergence property
- Reasonable execution time	
- Good solutions	
- Easy to implement	

premature convergence. To overcome that, many variants of GOA were proposed as summarized in Tables 4 and 5.

Some of the most interesting research directions around the GOA algorithm are as follows:

- Development of enhanced versions of GOA to handle some hard and challenging, large-scale optimization problems.
- Comparison of the robustness of GOA with other population-based algorithms such as AOA, CSA, FPA, KH, WEO, CFO, and CSO algorithms.
- Hybridization of GOA with other swarm intelligence algorithms like ACO, CS, PSO, FA, DA, CSA, and MFO to improve the balance between exploration/exploitation and prevent premature convergence.
- Application of GOA for handling other optimization problems in different domains such as Multicast Routing, Intrusion Detection, UAV planning, Image segmentation, Travel salesman, Virtual Machine Placement,

Photo-electronic detection, parameter calibration, and other real-world complex optimization problems.

VII. CONCLUSION

This work was an attempt to present, discuss, and analyze the state-of-the-art of the GOA algorithm. We started with first discussing the methodology of this survey. It was discussed that several relevant keywords were used and the best publications were selected using a number of criteria to ensure reviewing high-quality research outputs. Then, the inspirations and mathematical models of GOA were presented. The main part of this work was the discussion and critisim of variants, hybrids, and applications of the GOA in the literature. The application areas investigated were mainly feature selection, scheduling, distributed generation, economic dispatch, and flood routing.

Despite the success of GOA, several areas are worthy of exploration for future works. Firstly, The modification of the standard GOA requires more research. In addition to three main mechanism of swarming (an individual's position, social interaction, and gravity), alignment, separation, and cohesion can be used as well. Secondly. GOA variants by hybridizing GOA with other meta-heuristics and defining new operators and strategies to improve the exploitation and exploration of GOA are recommended. Finally, another interesting area for future research is the application of GOA to solve other practical optimization problems, especially complex, dynamic, and large scale optimization problems.

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