A COMPREHENSIVE SURVEY OF GREY WOLF OPTIMIZER ALGORITHM AND ITS APPLICATION

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ABSTRACT

This study presents a comprehensive and through summary of the Grey Wolf Optimizer (GWO).The GWO algorithm is a newly-presented meta-heuristic, propelled from the social hunting behavior of grey wolves. The GWO has become a progressively critical device of Swarm Intelligence that has been used in nearly all zones of optimization, and engineering practice. Numerous issues from different regions have been effectively illuminated utilizing the GWO algorithm and its variants. In arrange to utilize the calculation to illuminate assorted issues, the original GWO algorithm required to be modified or hybridized. This study conducts an exhaustive review of this living and advancing area of Swarm Intelligence, so that to show that the GWO algorithm might be connected to each issue emerging in hone. However, it empowers novice researchers and algorithm developers to utilize this straightforward and however exceptionally effective algorithm for issue tackling. It frequently ensures that the gained results about will meet the expectation.

KEYWORDS

Grey Wolf Optimizer; Swarm intelligence; Nature-inspired algorithm; Optimization.

1. INTRODUCTION

Meta-heuristic optimization algorithms have getting to be increasingly well known in engineering applications since they: (I) depend on or maybe basic concepts and has simple to execute; (II) do not need gradient information; (III) can bypass local optima; (IV) can be used in a big range of issues covering diverse disciplines [1-5]. Meta-heuristic algorithms have appeared promising execution for fathoming most real-world optimization issues that has amazingly nonlinear and multimodal. All metaheuristic algorithms utilize a definite tradeoff of randomization and local search [6]. These algorithms can explore best solutions for complicated optimization issues, however, there is no ensure that ideal solutions can be come to. Meta-heuristic algorithms might be appropriate for global optimization [7].

Nature-inspired meta-heuristic algorithms solve optimization issues by imitating organic or physical marvels [6]. They can be gathered in three fundamental categories: evolutionary algorithms (EA), swarm intelligence (SI) and physics-based (PB) algorithms [6]. EAs mimic the evolutionary behavior of creatures existed in nature. The search algorithms begin with generated solutions that has random, that in general termed as population, which further evolves over successive generations. Best individuals have integrated to form new generation, which is the essential benefits of EAs as it increases the performance of population over the course of iterations [8]. Some of the popular evolutionary-based strategies has Genetic Algorithms (GA) [9], Genetic Programming (GP) [10], Evolution Strategy (ES) [11], Differential Evolution (DE)

[12] and Biogeography-Based Optimizer (BBO) [13].The second classification is swarm intelligence-based ones, which imitate the intelligent social behavior of groups of animals. Generally, SI based algorithm collect and use all information about search space with the progress of algorithm, whereas such data is deserted by EAs from generation to generation. Particle Swarm Optimization (PSO) [14], Ant Colony Optimization (ACO) [15], Firefly Algorithm (FA) [16], Bat Algorithm (BA) [17] and Artificial Bee Colony algorithm (ABC) [18]can be depicted as representative algorithms in SIs. Some of the modern SIs has Cuckoo Search (CS) [19], Fruit Fly Optimization Algorithm (FOA) [20], Dragonfly Algorithm (DA) [21] and Farmland Fertility (FF) [22]. The physics-based algorithms have propelled from essential physical laws that exist in universe. A few of the winning strategies of this category has Gravitational Search Algorithm (GSA) [23], Multi-verse Optimizer (MVO) [24], Magnetic Optimization Algorithm (MOA) [25], Electromagnetic Field Optimization (EFO) [26], and Charged System Search (CSS) [27].

In 2014, a capable and recently risen meta-heuristic evolutionary optimization strategy, called grey wolf optimization (GWO) [28] that is according to social hierarchy and hunting behavior of grey wolves, is presented by Mirjalili et al. The GWO approach is inspired by gray wolves (Canis Lupus) owns to the Canidae family. Gray wolves live in a pack and the measure of bunch is between 5 and 12. The pioneer is called alpha and is capable for making the choicearound: hunting, sleeping place, etc. The second one is named beta and assists the alpha in decision making. The beta wolf should respect the alpha. The lowest gray wolf from the rank point of view is omega and it submits the data to all the others prevailingwolves. The rest of gray wolves has named delta and prevail the omega.The essential subcategories of metaheuristic algorithms have exploration and exploitation [29, 30]. Exploration guarantees the algorithm to reach distinctive promising locales of the search space, while exploitation ensures the searching of optimal solutions in the given region [31].

We designed the format of the rest of the paper as follows: in Section 2, we introduce the basic GWO concepts. In section 3, a description general structure of GWO algorithm is provided, while the reviews of GWO algorithm in relation to its hybridizations, multi-objective, and modifications. Section 4, an overview of GWO in Applications in Engineering Optimization Problems is provided.Section 5 discusses the GWO algorithm and the basics and building blocks of GWO is reviewed. Lastly, the conclusion will be presented in Section 6.

2. General Structure of GWO Algorithm

This review paper is completed by considering different publishers such as: ACM, Science Direct, Hindawi, IEEE Explorer, SpringerLink, Taylor& Francis, and others.

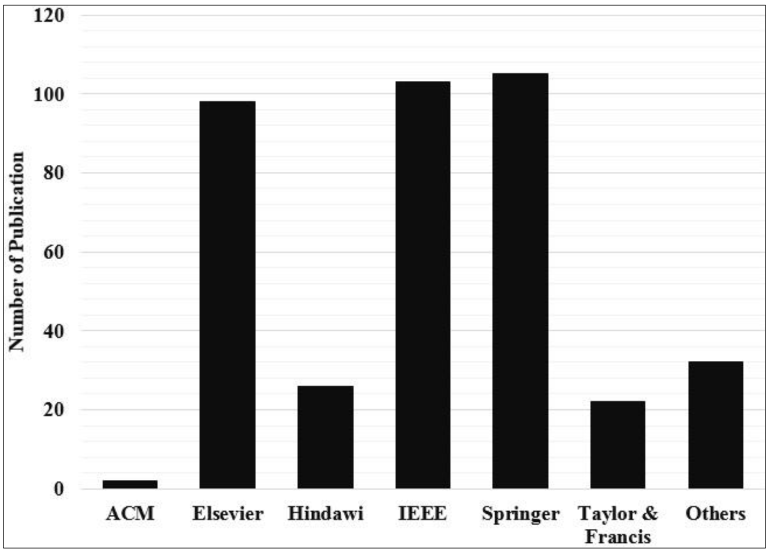

Figure1. Number of publications of GWO algorithm per databases

In population, they have not lenient social hierarchy that can be classified into four layers [28]: alpha (α), beta (β), delta (δ) and omega (ω) (see Figure2). This social hierarchy plays a critical role in hunting process. Leaders, designated as α, often lead the hunting process. In the hunting process, wolves search, track, chase, and approach the prey according to team model. Then, they continue, encircle and harass the prey so that it stops moving. When enclosure is adequatelysmall, wolves' β and δ closest to the prey start attacking, and the rest of wolves serve as supplements. When a prey makes itself free, supplements update the encirclement based on position of the prey. This lets uninterrupted attack on the prey so that the prey is captured.

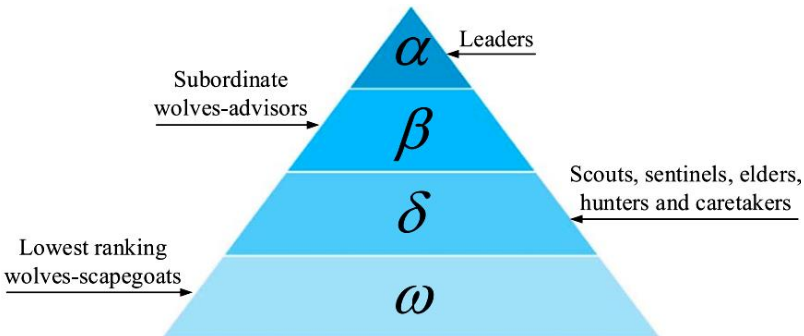

Figure2. Hierarchy of grey wolf population [28]

In GWO algorithm, the best, second and third best search agents has called as α, β and δ respectively. Position of the prey compass to the global optimal solution of the optimization problem. The optimization process of GWO algorithm is as follows. First, it creates a number of gray wolves randomly in a search space. During the course of repetitions, α, β and δ calculates the prey's position, and other wolves update their positions based on positions of α, β and δ. Following this, it encircles and approach the prey, and ends the hunt by attacking the prey at the time that it stops moving. Various comparing definitions in GWO algorithm has described as follows [28].To make similar the group hunting behavior of grey wolves, α, β and δ wolves has supposed to have better knowledge regarding the potential location of prey. They calculate the position of prey in the search space and ω wolves position themselves randomly around the prey.

So, the best three positions (that of α, β and δ wolves) has gained in the population and has used to update the ϖ wolves' positions according.

Definition 1. Distance between grey wolf and the prey based on Eq. (1).

$$D = |\vec{C}.\vec{X}_p(t) - \vec{X}(t)| \quad (1)$$

Where t indicates current iteration, $\vec{X}_p$ and $\vec{X}$has position vectors of the prey and a grey wolf respectively, and$\vec{C}$ is coefficient vector, which is determined by Eq. (2).

$$\vec{C} = 2.\vec{r}_1 \quad (2)$$

In Eq. (2)$\vec{r}_1$ is random vector in interval of [0, 1].

Definition 2. Prey location recognition based on Eq. (3).

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \quad (3)$$

$$\vec{A} = 2.\vec{d}.\vec{r}_2 - \vec{d} \quad (4)$$

Where $\vec{A}$ is a coefficient vector, $\vec{r}_2$ is random vector in interval of [0, 1], and components of $\vec{d}$has linearly decreased from 2 to 0 over the course of iterations.

Definition 3. Grey wolf position updating based on Eq. (5).

$$\begin{cases} \vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right| \\ \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right| \\ \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \end{cases} \quad (5)$$

Distance between each search agent and α, β, δ can be measured by Eq. (5) and Eq. (6). Subsequently, search agents go to the prey based on the Eq. (7).

The grey wolves end the hunt by assaulting the prey when it stops moving. This framework or model is decided by various values of$\vec{A}$. The range of $\vec{A}$ is a random value in the interval [-2a, 2a] and went down by $\vec{a}$ from 2 to 0 over the course of repetitions. The parameter $a$is to focus exploration and exploitation. In the case that the random values of $\vec{A}$has in [-1, 1], the next position of a search agent can be in any positions between its current position and the position of the prey. The wolves have constrained when |A| < 1 to attack towards the prey. The vector $\vec{C}$ is another sub-category of GWO that is interested in exploration. As it is shown in Eq. (2), the $\vec{C}$ vector includes random values in [0, 2]. This sub-categorymakes random weights for prey so that to stochastically emphasize (C > 1) or deemphasize (C < 1) in the impact of prey of defining the distance in Eq. (1).Pseudo code of GWO algorithm is shown in Figure (3) [28].

Initialize the grey wolf population $X_i (i = 1,2, \ldots, n)$
Initialize d, A and C
Generate the Randomly Positions of Search Agent
Calculation the fitness of each search agent
X_α=the best search agent
X_β=the second-best search agent
X_δ=the third best search agent
While (t<max number of iterations)
  for each search agent
    Update the position of the current search agent by $\vec{X}(t+1) = \vec{X}_1 + \vec{X}_2 + \vec{X}_3/3$
  End for
  Update d, A and C
  Calculation the fitness of all search agents
  Update X_α, X_β and X_δ
End while
Return X_α

Figure 3. Pseudo code of GWO algorithm [28]

The structure of GWO is elaborated in Figure (4).

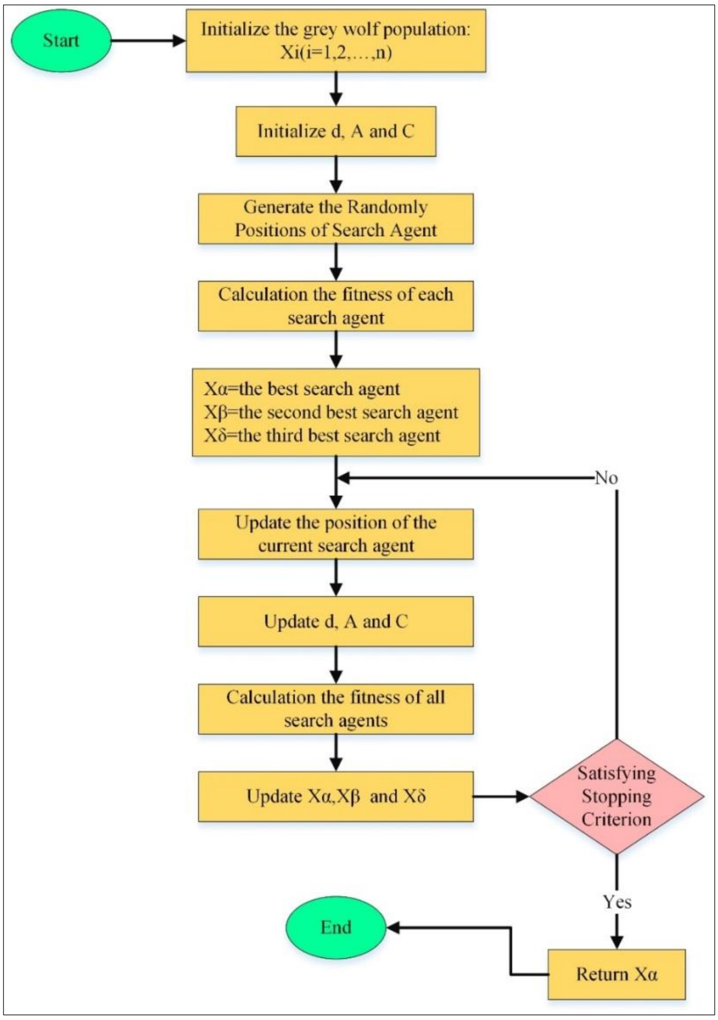

Figure 4. The flowchart of the GWO algorithm [28]

3. STUDIES ON GREY WOLF OPTIMIZER: CLASSIFICATIONS AND ANALYSIS

In this study, the GWO algorithm has analyzed based on Figure (5), where the classical GWO algorithmshas classified into hybrid, multi-objective, and modified. The essential directions of these modifications have gone into the advancement of Opposition-based Learning and Binary GWO algorithms, Chaotic based GWO algorithms, Levy Flight and, the Parallelized GWO algorithms. This means that the following hybridizations have been used to the classical GWO algorithm: GA [9], PSO [14], Flower Pollination Algorithm (FPA) [32], DE [12], Harmony Search Algorithm (HSA) [33], ABC [18], CS [19], BA [17], Sine Cosine Algorithm (SCA) [34], Fireworks Algorithm (FWA) [35], Whale Optimization Algorithm (WOA) [36], Biogeography-Based Optimization (BBO) [37], Ant Lion Optimization (ALO) [38], Pattern Search Algorithm (PSA) [39], FA [16],Artificial Neural Networks (ANNs), and Support Vector Machine (SVM). The accountability of hybrid approach in the hat of optimization is grew in a fast speed and focus is on performing the improvement of classical algorithms in terms of idea of hybridizing the categories from other optimization strategies. Research has shown that the performance of the GWO algorithm have been improved through the incorporations of other operators from meta-heuristic techniques.

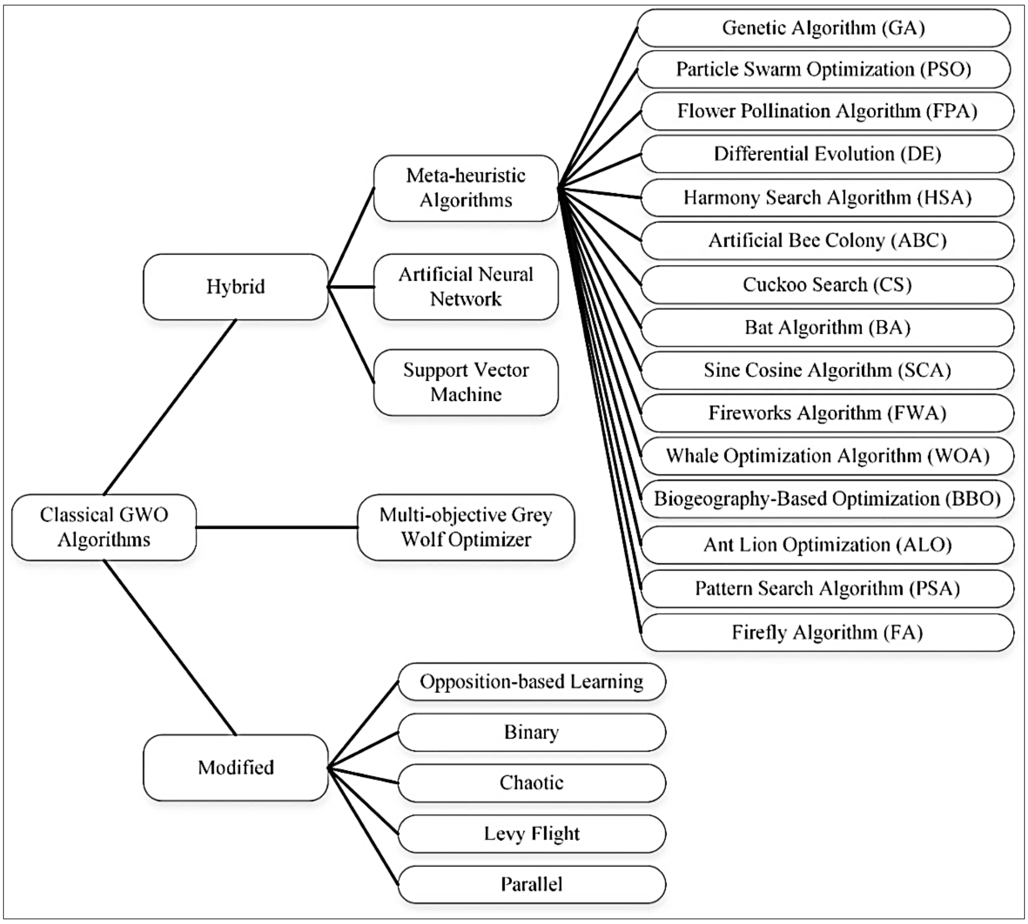

Figure5. Taxonomy of GWO algorithm.

3.1. Hybrid

3.1.1. Hybridization with Meta-Heuristic Algorithm

Table (1) indicates summary of hybridization of GWO with component of meta-heuristic algorithms.

Table 1: summary of hybridization of GWO with component of meta-heuristic algorithms

Algorithm name	Year	hybridization	Topic	References
HGWOGA	2017	Genetic Algorithm	minimizing potential energy function	[40]
GGWO	2017		Channel Estimation in Wireless Communication System	[41]
PSO-GWO	2018	Particle Swarm Optimization	Optimal design of a grid-connected	[42]
PSO-GWO	2018		Filter Optimization	[43]
PSO-GWO	2018		Global optimization	[44]
HPSOGWO	2017		optimization problems	[45]
GWOFPA	2018	Flower Pollination Algorithm	for Optimization Applications	[46]
FGWO	2019		Energy Management in Smart Grid	[47]
DE-GWO	2017	Differential Evolution	Power system stability	[48]
DE-GWO	2016		Economic dispatch	[49]
HSGWO	2019	Harmony Search Algorithm	Home Energy Management	[50]
GWO-ABC	2018	Artificial Bee Colony	Optimum controller design	[51]
HCS-GWO	2017	Cuckoo Search	Optimum wavelet mask based medical image	[52]
CS-GWO	2017		for optimization problems	[53]
GWOBA	2018	Bat Algorithm	for Global Optimization	[54]
GWOSCA	2017	Sine Cosine Algorithm	for optimization problems	[55]
FWA-GWO	2018	Fireworks Algorithm	for optimization problems	[56]
HAGWO	2018	Whale Optimization Algorithm	for Global Optimization	[57]
WGC	2017		for data clustering	[58]
HBBOG	2018	Biogeography-Based Optimization	for optimization problems	[59]
ALO-GWO	2018	Ant Lion Optimization	Feature selection	[60]
ALO-GWO	2018		Annual electricity consumption forecasting	[61]
GWO-PS	2015	Pattern Search Algorithm	Voltage stability	[62]
FA-GWO	2018	Firefly Algorithm	Transfer function	[63]

3.1.2. Hybridization with Artificial Neural Networks

An information processing paradigm named Artificial Neural Network (ANN) is inspired through the method biological nervous systems, such as the brain, process information. The key factor of this paradigm is the new structure of the information processing system. It is consisting of a large number of highly interconnected processing elements (neurons) acting in unison to solve specific issues. ANNs, like individuals, learn by example. A specific application is configured by an

ANN, like pattern recognition or data classification, via a learning process. Learning in biological systems consists adjustments to the synaptic connections that exist between the neurons.Table (2) shows summary of hybridization of GWO with ANNs.

Table 2: summary of hybridization of GWO with ANNs

Topic	Application	References	Year
breast cancer classification	To optimize the weights of the ANN, GWO algorithm is used	[64]	2018
Prediction of siro-spun yarns tensile strength	In the proposed GWNN, a GWO algorithm is applied as a global search method to determine weights of a Multi-Layer Perception (MLP)	[65]	2018
Human Recognition	In this work a GWO has been proposed for the design of modular granular ANN	[66]	2017
classification	FS, finding optimal weights for ANN	[67]	2017
Automatic leaf segmentation	The weight and bias values of ANN model has optimized by GWO	[68]	2017
Short-term Load Forecasting	The GWO has been applied to determine the weight coefficients of the prediction results of RBFNN	[69]	2017
Eye Movement Recognition	GWO is used to reduce the error function of the classifier outcome	[70]	2017
melanoma detection	The GWO algorithm is utilized to optimize an MLP ANN	[71]	2017
Classification	GWO provides the initial solution to a BP ANN	[72]	2016
Wind Speed Forecasting	To optimize the weights of the ANN, GWO algorithm is used	[73]	2016
Design Static Var Compensator Controller	GWO algorithm is used to optimized all the connection of weights and biases for the ANN	[74]	2015

3.1.3. Hybridization with Support Vector Machine

Support vector machines, a set of margin classifier models utilized by Vapnik and his group at AT&T Bell Laboratories in the 1990s, has one sort of the influential models with high generalization ability in practice [75]. Various from experimental risk minimization-based statistical learning methods, SVM purported to decrease structural risk that represents a robust capability in overfitting avoidance [76]. In the SVM model, decision hyperplanes have constructed to form a separation gap to classify two class examples with the high margin.Table (3) shows summary of hybridization of GWO with SVM.

Table 3: summary of hybridization of GWO with SVM

Topic	Application	References	Year
Features selection	Features selection by GWO with SVM	[77]	2018
EEG Signals Classification	GWO was used for selecting the significant feature subset and the optimal parameters of SVM in order to obtain a successful EEG classification.	[78]	2018
Color difference classification	capability of GWO algorithm to compute the best parameter combination of SVM	[79]	2018
Prediction of sulfur solubility in supercritical sour gases	Adjusting the SVM parameters using GWO algorithm	[80]	2018
prediction system	Features selection	[81]	2017
bankruptcy prediction	Adjusting the SVM parameters using GWO algorithm	[82]	2017
The prediction of solute solubility in supercritical carbon dioxide	parameter optimization	[83]	2017
Intrusion Detection Model	Adjusting the SVM parameters using GWO algorithm	[84]	2016
Optimization of Acid Gas Sweetening Plant	parameter optimization	[85]	2016
Time Series Forecasting	parameter optimization	[86]	2015
Classification	GWO-SVMs model has been developed for selecting the optimal SVMs parameters	[87]	2015

3.2. MULTI-OBJECTIVE GREY WOLF OPTIMIZER

Table (4) shows summary of research articles related to MOGWO.

Table 4: summary of papers related to MOGWO

Topic	Application	References	Year
Optimal Power Flow Problem	MOGWO algorithm has been used to find pareto-optimal solution for two different multi-objective cases like Minimization of Fuel cost with Emission value and Minimization of Fuel cost with Active Power loss	[88]	2018
Robot Path Planning Optimization	Two criteria of distance and smooth path of the robot path planning issue has transformed into a minimization one for fitness function	[89]	2017
Congestion management	locating and sizing of series FACTS devices has done with using MOGWO	[90]	2017
dynamic scheduling in a real-world welding industry	This model involves sequence dependent setup time, job dependent transportation times and controllable processing times.	[91]	2017
Optimal Reactive Power Dispatch Problem	objective functions being active power loss minimization and voltage profile improvement (voltage deviation minimization)	[92]	2017
Optimal Integration of Bio refineries	The objective of this problem is to synthesize a sustainable integrated bio refinery with maximum NPV and minimum IMP while considering all the flow rates as variables.	[93]	2016
Optimal Power Flow	Proposed MOGWO is used to generate Pareto-optimal solutions for simultaneous minimization of the environmental pollution emissions along with the economic cost	[94]	2016
Engineering optimization	Minimize Solutions	[95]	2016
Welding scheduling	The solution is encoded as a two-part representation including a permutation vector and a machine assignment matrix. A reduction machine load strategy is used to adjust the number of machines aiming to minimize the machine load	[96]	2016
Classification	This model is able to avoid stagnation in local optima by maintaining a balance between exploration and exploitation	[97]	2016
Attribute Reduction	It has been employed to search the space of features to find optimal feature subset that both achieve data description with minor redundancy and keeps classification performance	[98]	2015

3.3. Modifications of GWO Algorithm

3.3.1. Opposition-based Learning

Table (5) indicates the sum of papers related to OBL.

Table 5: the sum of papers related to OBL

Topic	Application	References	Year
Global Optimization	It has been used a chaotic opposition-based strategy for selecting the suitable initial population, also, in order to improve the exploitation ability of wolves to exploit the has in their neighborhood, the DE operators has used since they work as a local search mechanism.	[99]	2018
stochastic optimization problem	The OGWO encompasses opposition concept with the GWO algorithm to accelerate the convergence rate.	[100]	2018
Machine Scheduling in Cloud Environment	opposition based learning is used with the standard GWO to enhance its computational speed and convergence	[101]	2017
function optimization	To overcome the poor population diversity and slow convergence rate of GWO, this paper introduces the elite opposition-based learning strategy and simplex method into GWO	[102]	2017
economic dispatch problem of power system	opposition based learning is used with the standard GWO to enhance its computational speed and convergence	[103]	2017
Load frequency control of large-scale power system	opposition based learning is used with the standard GWO to enhance its computational speed and convergence	[104]	2016

3.3.2. Binary

Table (6) shows the sum of papers related to BGWO.

Table 6: the sum of papers related to BGWO

Topic	Application	References	Year
FS	BGWO is hired in the FS domain for finding feature subset maximizing the classification accuracy while minimizing the number of selected features	[105]	2015
Instruction Detection	FS	[106]	2016
Optimal Scheduling of Uncertain Wind Energy and Demand Response in Unit Commitment	This model considers the effect of uncertain wind energy in terms of total rescheduling cost, total energy balancing cost and total reserve cost.	[107]	2016
unit commitment problem	BGWO is applied to solve UC problem of different dimensions of 10, 20, 40, 60, 80 and 100 units with associated hourly load and reserve constraints	[108]	2017
large scale unit commitment problem	The first approach includes upfront binarization of wolf update process towards the global best solution (s) followed by crossover operation. While, the second approach estimates continuous valued update of wolves towards global best solution(s) followed by sigmoid transformation	[109]	2017

3.3.3. Chaotic

Table (7) shows summary of papers related to chaotic GWO.

Table 7: summary of papers related to chaotic GWO

Topic	Application	References	Year
Parameters Identification of Fractional Order Permanent Magnet Synchronous Motor Models	estimate the permanent magnet synchronous motor (PMSM) models parameters using chaotic GWO	[110]	2018
optimization problems	The searching operators and hunting patterns has modified in a new method to boost the performance of the basic GWO	[111]	2018
continuous optimization	optimization parameters	[112]	2017
Control optimization for pumped storage unit in micro-grid with wind power penetration	the optimal control parameters of the AFPID controller has selected by an improved stochastic optimization algorithm, namely CGWO	[113]	2017
constrained optimization problems	This chaos helps the controlling parameter to find the optimal solution more quickly and thus refine the convergence rate of the algorithm	[114]	2017
Nonlinear control	optimization parameters	[115]	2017
Distributed Controller Allocation	optimization parameters	[116]	2017
robot motion	Optimization of population sizes and parameters	[117]	2016
small hydro generator cluster	optimization parameters	[118]	2016
continuous optimization	optimization parameters	[119]	2016

3.3.4. Levy Flight

Table (8) shows summary of papers related to Levy Flight.

Table 8: summary of papers related to Levy Flight

Topic	Application	References	Year
FS for image steganalysis	In this paper, a novel levy flight-based grey wolf optimization has been introduced which is used to select the prominent features for steganalysis algorithm from a set of original features	[120]	2018
FS	Learning	[121]	2017
Continuous Problems	Optimization Parameters and Convergence	[122]	2017

3.3.5. Parallel

Table (9) shows summary of papers related to parallel.

Table 9: summary of papers related to parallel

Topic	Application	References	Year
Numerical optimization	In this paper, the population wolves are split into several independent groups based on the original structure of the GWO, and the proposed communication strategy provides the information flow for the wolves to communicate in different groups.	[123]	2016
Numerical optimization	Test functions indicate faster convergence and more precision in final results compared with other algorithms	[124]	2016
Aligning Multiple Molecular Sequences	The main issue in this aligning process is to find a significant alignment in less computation time.	[125]	2015

4. DISCUSSION

The distribution of published research articles on GWO with respect to hybridizations, Multi-objective GWO, and modifications is represented in Figure(6).

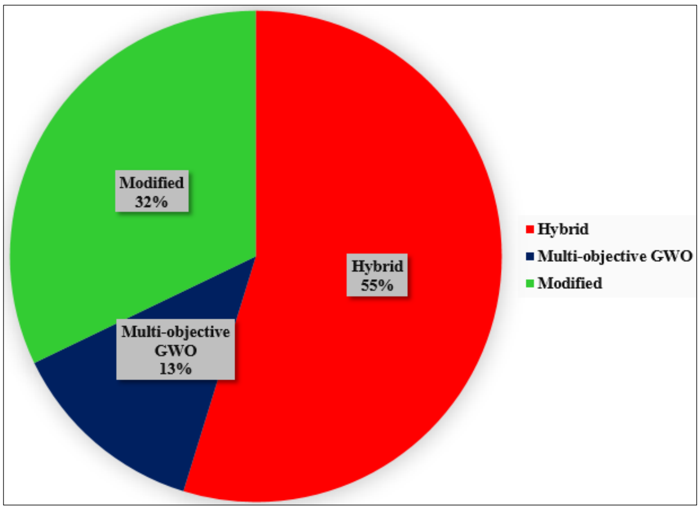

Figure 6. The distribution of published research articles on GWO

The success of GWO most shows upwithin the case of hybridization with other optimization procedures (e.g. metaheuristics, SVM, ANNs, etc.).

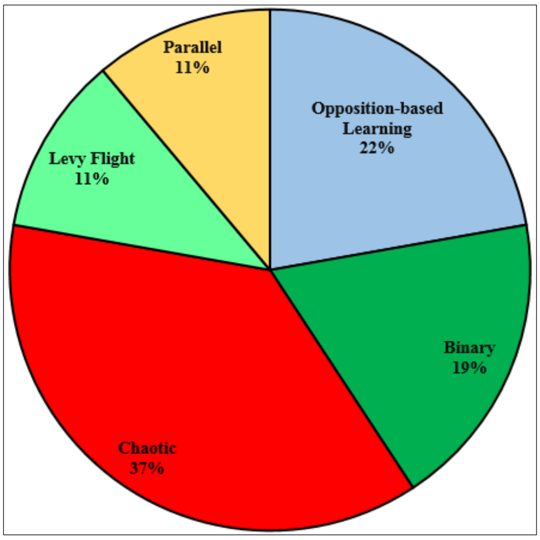

Figure7. Published research papers on GWO with respect to modifications

5. Conclusion

In any case, metaheuristics has not issue particular, choosing the suitable metaheuristic for the given issueought to be considered, that is the more adjustment to the given issue, the more productive metaheuristic. This can, be what characterizes GWO since it owns some parameters that ought to be balanced. Analysts have proposed an expansive difference of strategies to make strides GWO, such as utilizing upgraded administrators, hybridization of GWO with other heuristic algorithms, and parameter adjustment and control plans for GWO. This research conducted a precise, broad (not comprehensive) survey to get the important writing on the hybridizations, alterations, and applications of the GWO algorithm when utilized to illuminate issues of high dimensionality completely different space. In summary, it is believed that this survey-based paper will be valuable to the community and the analysts who has now working or will work in this heading by directing them around how the GWO algorithm can be utilized to handle the issues in these spaces. Conclusively, it can be seen from the papers, there still numerous curiously investigate headings ahead that can be overcome by the utilization of the GWO algorithm.

For future research, there has numerous applications regions hasseldomattacked which has a few issues can be fathomedpossibly by GWO such as Artificial Neural Networks, Medicine, and clustering, etc. furthermore, the modification of standard GWO still prevailing field requires extra research.

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