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Recent advances in Grey Wolf Optimizer, its versions and applications: Review

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ABSTRACT

The Grey Wolf Optimizer (GWO) has emerged as one of the most captivating swarm intelligence methods, drawing inspiration from the hunting behavior of wolf packs. GWO's appeal lies in its remarkable characteristics: it is parameter-free, derivative-free, conceptually simple, user-friendly, adaptable, flexible, and robust. Its efficacy has been demonstrated across a wide range of optimization problems in diverse domains, including engineering, bioinformatics, biomedical, scheduling and planning, and business. Given the substantial growth and effectiveness of GWO, it is essential to conduct a recent review to provide updated insights. This review delves into the GWO-related research conducted between 2019 and 2022, encompassing over 200 research articles. It explores the growth of GWO in terms of publications, citations, and the domains that leverage its potential. The review thoroughly examines the latest versions of GWO, categorizing them based on their contributions. Additionally, it highlights the primary applications of GWO, with computer science and engineering emerging as the dominant research domains. A critical analysis of the accomplishments and limitations of GWO is presented, offering valuable insights. Finally, the review concludes with a brief summary and outlines potential future developments in GWO theory and applications. Researchers seeking to employ GWO as a problem-solving tool will find this comprehensive review immensely beneficial in advancing their research endeavors.

INDEX TERMS Grey wolf Optimizer, Swarm Intelligence, Optimization, Evolutionary Computation

I. INTRODUCTION

Metaheuristics are strategic-based techniques capable of intelligently exploring the search space of optimization problems to discover near-optimal solutions [1]. These metaheuristic-based algorithms can be categorized into two main types: local search-based algorithms and population-based algorithms [2], [3]. Furthermore, they can be further classified into evolutionary-based algorithms, physical-based algorithms, chemical-based algorithms, human-based algorithms, and Swarm intelligence algorithms [4], [5].

Local search-based algorithms initiate with an initial solution and iteratively improve it by exploring neighbouring solutions. This iterative process persists until either the maximum number of iterations is reached or the algorithm converges to a local optimum. simulated annealing [6], tabu search [7], greedy randomized adaptive search procedure (GRASP) [8], variable neighborhood search [9], iterated local search [10], β-hill climbing [11], and vortex search algorithm [12] are a few examples of local search-based algorithms [13].

Evolutionary-based algorithms represent a traditional form of population-based algorithms, where a population of solutions is initially generated. Through iterative steps involving recombination, mutation, and natural selection, these solutions are progressively improved. These algorithms like genetic algorithm [14], evolutionary programming [15], genetic programming [16], differential evolution [17], biogeography-based optimization [18], and probability-based incremental learning (PBIL) [19].

Physical-based and chemical-based algorithms draw inspiration from the principles governing physical laws and chemical interactions among components. These algorithms like plasma generation optimization [20], ray optimization [21], solar system algorithm [22], equilibrium optimizer [23], gravitational search algorithm [24], billiards-inspired optimization [25], henry gas solubility optimization [26], simulated annealing [6], vortex search algorithm [12], and chemical reaction optimization [27].

Social or human-based algorithms predominantly derive inspiration from social or human behavior. These algorithms like harmony search [28], brain storm optimization [29], heap-based optimizer [30], teaching-learning-based optimization [31], political optimizer [32], ali baba and the forty thieves [33], group teaching optimization algorithm [34], ebola optimization search algorithm [35], football game inspired algorithm [36], coronavirus herd immunity optimizer [37], arithmetic Optimization Algorithm [38], stock exchange trading optimization [39], and poor and rich optimization algorithm [40].

Swarm intelligence (SI) algorithms often find their inspiration in the collective behavior observed in various animal species, including birds, frogs, bats, rats, bees, ants, and others.[4]. The SI's algorithms normally emulate the prey hunting process, searching for food based on the local interactions between the swarm members or based on their environment (stigmergy) [41]. Therefore, swarm groups are self-organized. It is normally initiated with a swarm of candidate solutions. Usually, the swarm can be divided into two main groups: the leaders and followers, where the interactions occur by attracting the follower to the leaders; thus, converging to the optimal solution.

The most popular SI algorithms are ant colony optimization [42], particle swarm optimization [43], krill herd optimization [44], cuckoo search [45], firefly algorithm [46], white shark optimizer [47], artificial bee colony [48], chicken swarm optimization [49], snake optimizer [50], ant lion optimizer [51], elephant herding optimisation [52], sparrow search algorithm [53], horse herd optimization [54], dragonfly algorithm [55], rat swarm optimizer [56], moth-flame optimization [57], whale optimization algorithm [58], komodo mlipir algorithm [59], Salp Swarm Optimizer [60], chimp optimization algorithm [61], coronavirus herd immunity optimizer [37], dwarf mongoose optimization algorithm [62], lemurs optimizer [63], grey wolf optimizer (GWO) [64], and many others.

The GWO is the fastest-grown SI algorithm introduced by Mirjalili et al. [64] to imitate the hunting behaviour of the grey packs in nature. The GWO is a powerful optimizer due to its impressive features over others, such as it can be easily adapted, parameter-free, derivative-free, memory-less, computational-less, flexible, and sound-and-complete. In the initial searching stage, the GWO starts with high intensity on the exploration stage, while in the last course of runs, the GWO provides more attention to the exploitation phase through the gradual changes in the positions of the three-best leaders. Therefore, GWO is able to tackle a plethora of optimization problems from a wide range of research fields, such as engineering, networking and communication, image processing, robotics, mathematics, bioinformatics, biomedical, and others [65].

To tackle the complex search space characteristics of real-world and combinatorial optimization problems, particularly those with non-convex, nonlinear, and highly constrained features, significant adjustments have been made to the fundamental structure of the Grey Wolf Optimizer (GWO). These modifications have enabled it to handle multi-objective problems and highly constrained scenarios effectively. Moreover, GWO has been enriched by incorporating elements from other optimization algorithms to enhance its performance. Additionally, hybridization with other optimization algorithms has been employed to strike a balance between exploration and exploitation capabilities, thereby improving the quality of solutions generated by GWO. Indeed, many instances of GWO are proposed in the literature, each of which is suitable for specific research applications [66], [67], [68], [65].

The Grey Wolf Optimizer (GWO) starts by initializing a random swarm of grey wolves. These wolves are then organized into four groups: Alpha, Beta, Delta, and Omega. Each group is sequentially ranked based on its role in the hunting process, with Alpha being the best solution, followed by Beta and Delta in the swarm. The Omega group consists of follower wolves that are attracted by the three best wolves. During the collaborative loop, the GWO assesses the distance between the Omega group and the third-best wolves (Alpha, Beta, Delta). It then updates the positions of these wolves using intelligent mechanisms, such as chasing, encircling, and attacking prey. Two predefined parameters are utilized to strike a balance between exploration and exploitation, ensuring an effective optimization process. [64].

The GWO has been spread across many research topics. In our previous review article [69], the growth of GWO rapidly increased from 2014 to 2018 period of time. Many GWO applications and variants have been reviewed and summarized. However, from 2019 to 2021, the growing slop is exponentially increased, where GWO is adopted as the main optimizer to tackle other optimization applications. Interestingly, during this short period, more than 700 articles with the GWO in the title have been published in high-quality journals held by high-prestigious publishers as recorded in the Scopus index dataset, as presented in Section III. The main contributions of this review are summarized as follows:

- Conduct a comprehensive investigation of the GWO studies in a specific period to draw a map for the scientists and researchers planning to work in the related domains by guiding them to apply the GWO to different problems.

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- Conduct an encyclopedic study of all GWO aspects and prove its robustness and effectiveness in addressing various kinds of single and multi-objective optimization problems.
- Conduct a new theoretical analysis to highlight the main and most prominent drawbacks of the GWO and suggest several solutions to address such drawbacks.
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In order to review the GWO growth in the last three years (i.e., 2019-2021), this review can be considered as an extension to the previous GWO paper, which covers the following GWO advances:

- The basics theory of GWO is discussed to show its leading operators and functions, as shown in Section II.
- The growth of GWO is reviewed in terms of the total number of articles, citations, topics, authors, institutions, and countries. This growth review is conducted to prove the viability and efficiency of the GWO and why it is heavily used (See Section III).
- The recent variations of GWO that were proposed over the last three years are also summarized in Section IV.
- The applications tackled by GWO over the last three years are illustrated and tabulated, as shown in the section V.
- A critical analysis is presented to reveal the main pros and cons of GWO, thus suggesting research directions to fill these gaps, as shown in Section VII.
- Finally, the main GWO theoretical foundations and possible future directions of GWO concluded this review.

II. BASIC CONCEPTS OF GREY WOLF OPTIMIZER

GWO is a nature-inspired optimization method introduced in 2014 [64]. It is considered one of the essential SI algorithms that estimate the global optimum for optimization problems. Just like other SI algorithms, the GWO considers the optimization problems as a black box without the needing for gradient information to perform optimization.

GWO's primary inspirations are twofold: social hierarchy and hunting technique in a wolf pack. In the former case, a wolf pack's leadership is divided into three hierarchical categories: Alpha, Beta, and Delta. The remainder of the members in a pack are considered to be Omega, as shown in Fig. 1. Different decision-making around hunting, migration, mating, etc., in a pack are made through this social leadership. In the latter case, the critical mechanism of search in GWO mimics the hunting process of grey wolves in nature. The mathematical models for these processes are presented and discussed below.

Grey wolves tend to encircle prey to exhaust and slow them down. In nature, it happens on a landscape, so this can be modeled on a 2D plane. The encircle mechanism can be formulated as follows:

$$\tau = \mid \mu \cdot X(z) - Y(z) \mid \tag{1}$$

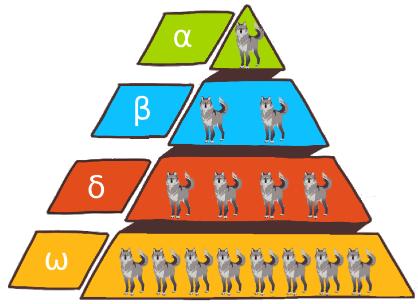

FIGURE 1: GWO hierarchical categories

where $X(z)$ shows the position of prey in z-th unit of time (e.g. iteration), $Y(z)$ indicates the position of a wolf in z-th unit of time, and $\mu = 2 \cdot rand_1$ where $rand_1$ is a random number between 0 to 1.

In the above equations, the vector can be of any dimension. This allows space definition around artificial wolves and preys in any n-dimensional search space.

Encircling prey is done via chasing prey by grey wolves. This is mathematically modeled using the following equations in GWO:

$$Y(z+1) = X(z) - \nu \cdot \tau \tag{2}$$

$$\nu = 2\varkappa \cdot rand_2 - \varkappa \tag{3}$$

where $\varkappa$ is a variable that is usually changed from 2 to 0, and $rand_2$ is a random number between 0 to 1.

The decision-making using alpha, beta, and delta is modeled using the following equations:

$$\tau_\alpha = \mid \mu_1 \cdot Y_\alpha - Y \mid, \quad \tau_\beta = \mid \mu_2 \cdot Y_\beta - Y \mid, \quad \tau_\delta = \mid \mu_3 \cdot Y_\delta - Y \mid \tag{4}$$

$$Y_1 = Y_\alpha - \nu_1 \cdot \tau_\alpha, \quad Y_2 = Y_\beta - \nu_2 \cdot \tau_\beta, \quad Y_3 = Y_\delta - \nu_3 \cdot \tau_\delta \tag{5}$$

$$Y(z+1) = \frac{Y_1 + Y_2 + Y_3}{3} \tag{6}$$

where $Y_\alpha(z)$ shows the position of the alpha wolf (first best solution) in z-th unit of time, $Y_\beta(z)$ is the position of the beta (second best solution) in z-th unit of time, and $Y_\delta(z)$ indicates the position of delta wolf (third best solution) in z-th unit of time.

Eqs. 4 and 5 create three position vectors for alpha, beta, and delta wolves considering the position of an omega wolf ($Y_\omega(z)$). These three vectors will be then used in Eq. 6 to update the position using averaging.

The GWO pseudo-code is given in Algorithm 1.

Algorithm 1 The GWO pseudo-code

```
Create a random population of artificial wolves Y_i (i = 1, 2, ..., n)
Assign initial values to the main controlling parameters: ϰ, ν, and μ
while (end condition is not met) do
    Evaluate and rank wolves by calculating their objective values Choose (or update if needed) Y_α(z), Y_β(z), and Y_δ(z)
    for each wolf (Y_i) do
        Update the main controlling parameters: ϰ, ν, and μ
        Update the position of the current search agent by Eq. (6)
    end for
end while
return Y_α
```

III. THE GROWTH OF GREY WOLF OPTIMIZER IN THE LITERATURE

The GWO has gained substantial consideration from significant research communities to tackle a wide variety of optimization problems. The primary purpose of this section is to provide a comprehensive review of the GWO growth from different aspects, including the number of GWO yearly publications, the number of citations acquired for GWO publications, the leading publishers and journals concerned with GWO publications, the main authors, institutions, and countries used GWO to tackle their optimization problems. The data analyzed in this section are extracted from the Scopus database.

Since the GWO foundation, its number of published articles is more than 800, as shown in Fig. 2. It is a fantastic algorithm that is substantially grown and used for a wide range of optimization problems. The majority of the publications were Journal articles that indicate their high maturity and robustness. Year by year, the researchers' attention to GWO is significantly increased. Although it is not considered the most recent swam-based algorithm, it is still attracting the attention of the optimization research communities due to its superb features.

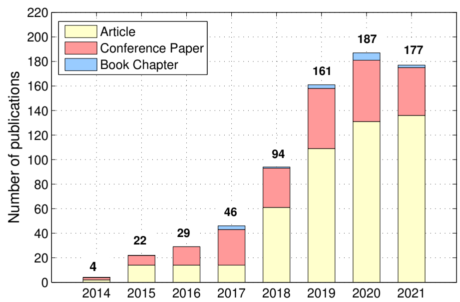

FIGURE 2: The number of GWO publications per year

Due to the GWO solid theory, its related research articles are accepted by highly-prestigious publishers, such as IEEE, Elsevier, Springer-Nature, MDPI, Hindawi, Taylor & Francis, Wiley, Hindawi, and others. As shown in Fig. 3, IEEE, Elsevier, and Springer-Nature are the publishers with the largest portion of GWO-related articles. The IEEE publisher accepted more than 200 articles, most of which are engineering-related optimization problems.

The high-reputed journals that are specialists in the optimization research domains have also published significant GWO research works. In Fig. 4, the top scientific journals that accepted GWO articles to solve different optimization problems are presented. Notably, the IEEE Access journal has accepted more than 40 articles. Applied soft computing journal, which is from top journals of the optimization domain, has also accepted more than 35 GWO-related articles. Other top journals have also accepted more than 10 GWO-related articles on average. This proves the stagnated theory of the GWO.

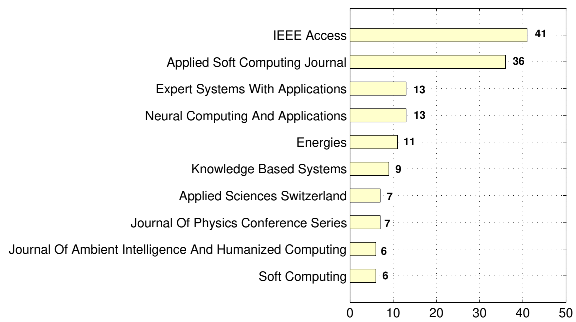

FIGURE 4: The number of GWO publications per Journals

The idea of GWO is stemmed by Seyedali Mirjalili in 2014 [64]. The same author has utilized the GWO to tackle several optimization problems. Deep K followed by Shubham Gupta and Mohammed Al-Betar, conducted the highest publications of GWO-based research articles, as presented in Fig. 5.

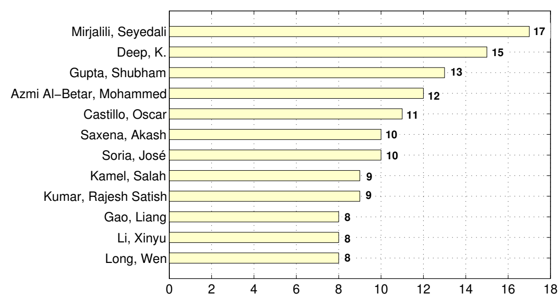

FIGURE 5: The number of GWO publications per author

After a deeper look at Fig. 6, the researchers from China, India, Iran, and Egypt have intensively utilized the GWO in their research work. Researchers from other countries, as highlighted in the Map, also used the GWO to some extent. The GWO has proven its viability through its considerations by many scholars worldwide.

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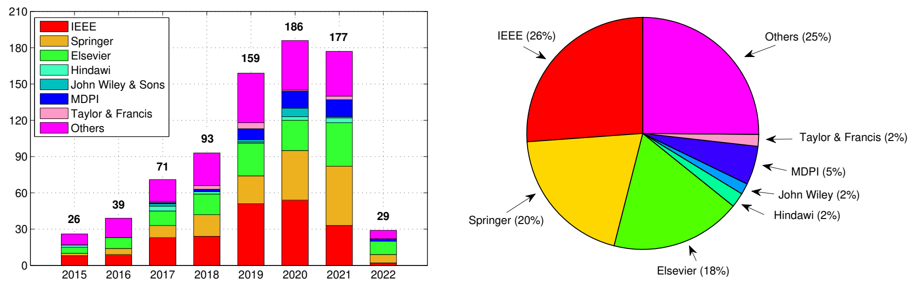

(a) (b)

FIGURE 3: The number of GWO publications per publisher

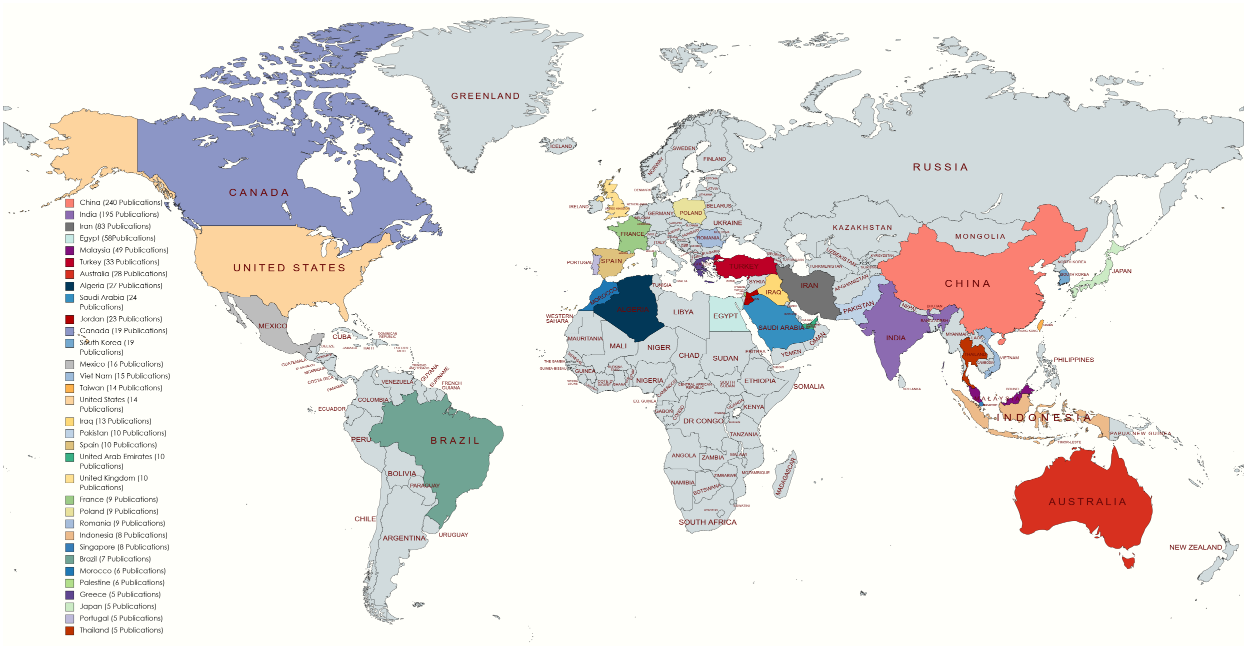

FIGURE 6: The number of GWO publications per country

In terms of GWO publication per affiliation, more than twenty GWO-based research were developed by researchers at Huazhong University of Science and Technology, as shown in Fig. 7. The Indian Institute of Technology Roorkee researchers published more than eighteen GWO research papers. We believe the GWO is a powerful method that lightens the spot for many research works.

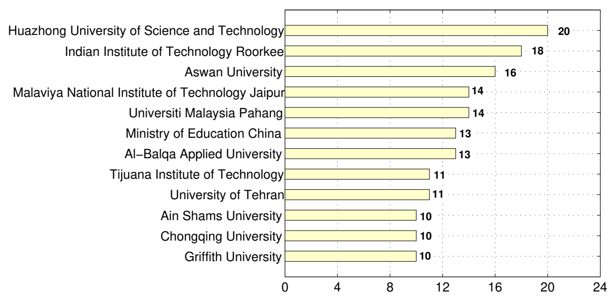

FIGURE 7: The number of GWO publications per Affiliations

Citation is another indication of the viability and applicability of the GWO. Amazingly, the GWO research has gained more than 6200 accumulative citations based on the Scopus citation report, as shown in Fig. 8. Indeed, the GWO is the most cited swarm-based intelligence method grown rapidly and gained high interest from several researchers due to its efficient performance.

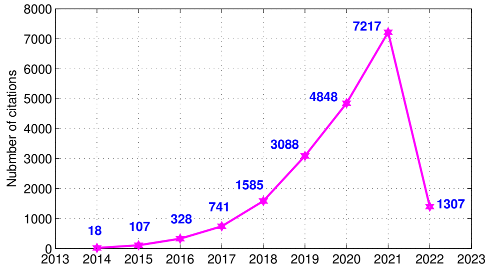

FIGURE 8: The number of citations per year

GWO addressed a wide range of optimization problems from multidisciplinary topics. As can be noticed by the pie chart in Fig. 9, the GWO has been intensively used to tackle computer science problems with more than 500 publications. Engineering problems are the second-largest research topic addressed by GWO, where more than 450 publications tackled engineering problems. The GWO showed its high performance in addressing other optimization problems in other research fields, such as mathematics, energy, physics and astronomy, environmental science, and business and accounting.

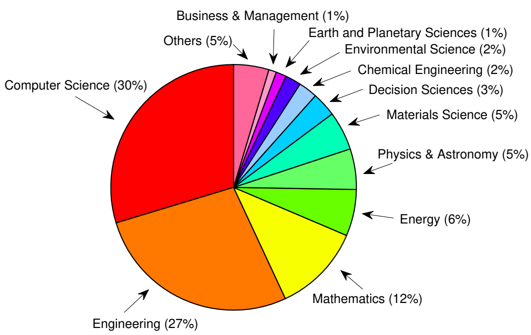

FIGURE 9: The number of GWO publications per Subject

IV. RECENT VARIANTS OF GREY WOLF OPTIMIZER

The GWO is an optimization method that is easy to use and produces high-quality results. It was initially designed for solving continuous optimization problems but has since been adapted for other types of optimization problems. Researchers have also made modifications to the GWO to improve its performance, including improved and hybridized. In addition, several studies change the algorithm optimization processes to address multiobjective optimization problems. These variations have been studied and applied to a variety of different applications and optimization problems in the following sections.

A. MODIFIED VERSIONS OF GREY WOLF OPTIMIZER

Like other algorithms, the GWO has weaknesses in obtaining optimal solutions during the search processes in some cases. Thus, several investigations were presented to enhance the GWO optimization processes and handle the disadvantages, such as local optima stagnation, low convergence speed, low exploration capabilities, and imbalance between exploration and exploitation [66], [70], [71], [72]. Besides, the GWO searching behaviour was modified to deal with various search spaces, such as discrete and binary search spaces [73], [74], [75]. Fig. 10 shows the studies that belong to each modified version.

1) Random Walk Grey Wolf Optimizer

In the original GWO, each wolf in the group is updating their position according to the position of the leader wolves. This updating mechanism can be modified and enhanced by changing its behaviour to randomly update the positions in some cases to avoid local optimal stagnation, either for a part of the pack or all the wolves [66].

Gupta and Deep [66] presented an innovative approach, termed random walk GWO, as a modified version of the Grey Wolf Optimizer (GWO) algorithm. This modification aimed to overcome the challenge of premature convergence and prevent getting stuck in local optima. In their GWO algorithm, the leaders take on an exploratory role by engaging in random walks throughout the search space. Meanwhile, the remaining wolves update their positions based on the leaders' positions. To evaluate the performance of the proposed method, the authors conducted experiments using 30 test functions from the CEC 2014 collection, as well as four real-world engineering problems. The experimental results highlighted the efficiency of the random walk GWO approach when compared to both the original version of GWO and other comparative algorithms.

In another study, the same method was adopted by the same authors for solving the optimal coordination of the overcurrent relays problem with satisfactory results against the original version of GWO and other competitors [76].

A novel modified version of GWO was specifically designed for synchronizing chaotic satellite systems [77]. The proposed method introduced the concept of random searching positions and incorporated memoization of the best solution at each iteration to enhance the searchability of the algorithm. The effectiveness of the proposed method was demonstrated through numerical experiments, comparing it to other state-of-the-art methods. The results highlighted the utility and superiority of the modified GWO algorithm, surpassing the performance of the compared methods in terms of optimization quality and convergence speed.

Heidari et al. (2019) made significant advancements to enhance the performance of the basic GWO by incorporating various innovative components. These components included random leaders, opposition-based learning, levy combat patterns, random spiral-form movements, and a greedy selection strategy. These components were used to strengthen the global research and local exploiting capabilities, as well as to deepen GWO's searching benefits in dealing with increasingly complicated situations. The effectiveness of the enhanced GWO algorithm against a wide range of state-of-the-art optimizers across 23 benchmark testing functions and 30 well-known CEC problems is studied. Additionally,

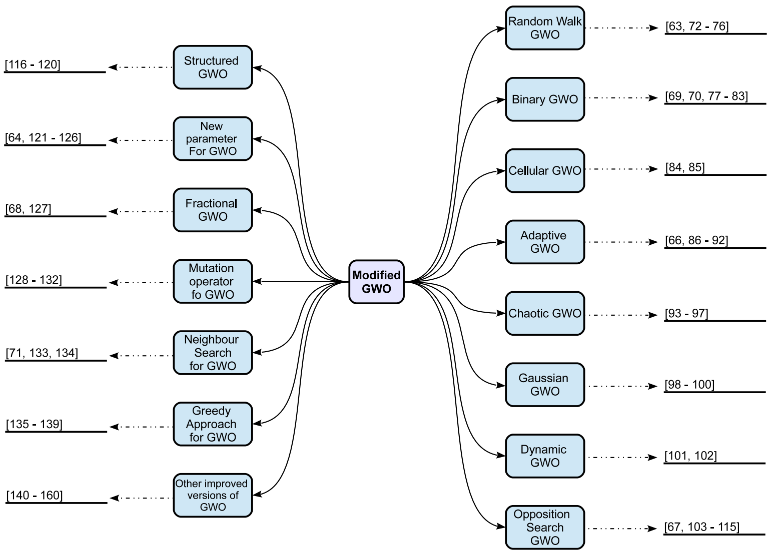

FIGURE 10: Studies for each modified version

the proposed method was utilized for fine-tuning the kernel extreme learning machine in addressing two real-world problems. The experimental findings and analyses demonstrate that the enhanced GWO outperformed the classical GWO and some other well-established methods. Notably, the suggested method exhibited faster convergence rates and consistently delivered higher solution quality across the evaluated problems.

Adhikary and Acharyya [78] introduced an advanced variant of the GWO algorithm called Randomized Balanced GWO. This algorithm enhances the search capabilities by incorporating three successive enhancement strategies, along with a social hierarchy mechanism and random walk. The algorithm is evaluated using a diverse range of benchmark functions from the CEC-2014, spanning various scales. Furthermore, both constrained and unconstrained real-life problems were employed to assess the algorithm's performance. The obtained results against state-of-the-art methods show the superiority of the proposed algorithm.

Liu et al. [79] tackle the flaws in the algorithm by using a dimensional learning strategy (DLS). In addition, the Levy flying technique is also used to explore the abilities of the algorithm. To instruct the grey wolves in the swarm, the proposed approach uses three dominant wolves to create an exemplar wolf using the DLS. The proposed method evaluation process goes through 23 standard functions and some engineering problems. The practical findings demonstrate that the DLGWO performs well in tackling global optimization issues.

2) Binary Grey Wolf Optimizer

The pure version of the GWO was introduced to tackle continuous optimization problems. Other versions of GWO were introduced to deal with other search spaces, such as binary search spaces. Usually, to deal with binary search spaces, the transfer functions like the S-Shaped, V-Shaped, and U-Shaped are combined within the original GWO.

Hu et al. [73] introduced an enhanced binary variant of the Grey Wolf Optimizer (GWO) algorithm specifically designed for feature selection problems. In their approach, they utilized S-shaped and V-shaped transfer functions to transform the continuous GWO into a binary form. Additionally, they modified the equation for updating the parameter a to improve the balance between exploration and exploitation capabilities. To assess the effectiveness of their method, the researchers conducted experiments on 29 well-known test functions and utilized 12 datasets sourced from the UCI repository. The experimental results clearly demonstrated the superiority of the proposed method over other binary versions of GWO, as evidenced by the enhanced fitness values and improved optimization of classification accuracy.

Al-Tashi et al. [74] presented a binary multi-objective Grey Wolf Optimizer (GWO) tailored for feature selection problems. Two distinct versions of their algorithm based on S-shape and V-shape transfer functions are designed to deal with the binary nature of the feature selection. The primary objective of their proposed method was to optimize both the number of selected features and classification accuracy. To evaluate the performance of the proposed versions, the authors conducted experiments using 15 datasets obtained from the UCI repository. The experimental results showcased the effectiveness of the proposed methods when compared to other well-established optimization techniques, demonstrating superior performance in terms of classification accuracy, the number of selected features, and computational efficiency.

Safaldin et al. (2021) introduced an integrated approach that combines a binary Grey Wolf Optimizer (GWO) and Support Vector Machine (SVM) for intrusion detection in wireless sensor networks. Intrusion detection, a feature selection problem within the wireless network domain, was the focus of their study. To convert the GWO algorithm from a continuous to a binary version, the researchers utilized a sigmoidal transfer function. The SVM was employed for classification purposes. The proposed method's performance was assessed using the NSL-KDD'99 dataset. Experimental results demonstrated that the proposed approach outperformed the binary version of particle swarm optimization in terms of intrusion detection accuracy and computational time.

Chantar et al. [80] introduced an alternative binary GWO specifically tailored for Arabic text classification. Their proposed method incorporated an elite-based crossover as a wrapper feature selection technique for this classification task. To convert the original continuous GWO into a binary version, the researchers utilized an S-shaped transfer function. The integration of the elite-based crossover ensured a more flexible balance between exploration and exploitation capabilities. The study investigated various learning models, including decision trees, K-nearest neighbor, Naive Bayes, and SVM classifiers, to determine which classifier yielded the best performance for Arabic text classification. The evaluation utilized three Arabic datasets, namely Alwatan, Akhbar-Alkhaleej, and Al-Jazeera-News. The experimental results demonstrated that the proposed method outperformed other approaches in terms of accuracy and the number of selected features, establishing its superiority in Arabic text classification tasks.

Luo and Zhao [81] introduced an enhanced binary version of the GWO specifically designed for solving the multidimensional knapsack problem. Their proposed method incorporated several key modifications to improve the algorithm's performance. First, they utilized an elite population generator to construct the initial population, ensuring that the search process begins with good-quality solutions rather than random ones. This strategy enhances the algorithm's ability to converge toward optimal solutions more efficiently. Next, a repair procedure was implemented to maintain the feasibility of solutions throughout the search process. To enhance the exploration ability of the GWO algorithm, the equation for updating the position of each wolf in the group was modified. This modification enables the algorithm to explore the search space more comprehensively, facilitating the discovery of diverse and potentially superior solutions. In addition, the S-shape and V-shape were employed to convert the continuous values of the algorithm to binary values. The performance of the proposed method was evaluated using two datasets of varying sizes and complexity obtained from the online OR library. Numerical results demonstrated the superiority of the proposed method compared to other binary comparative algorithms, affirming its effectiveness in solving the multidimensional knapsack problem.

An advanced binary version of GWO is introduced for the profit-based unit commitment of price-taking GENCO in the electricity market [82]. The primary objective of GENCO is to efficiently schedule available units to maximize profit in the competitive electricity market sector. To convert the original continuous GWO algorithm into a binary version, the researchers introduced three different versions, each incorporating a distinct transfer function. These transfer functions included crossover sigmoidal, conventional sigmoidal, and tangent hyperbolic functions. This transformation enabled the GWO algorithm to operate in the binary domain, suitable for solving the profit-based unit commitment problem. Three algorithms were evaluated using two test systems, one with three units and another with ten units. Numerical results clearly demonstrated the superiority of their algorithms over other comparative algorithms found in the literature that was used to solve the same problem in terms of average profit convergence.

Abdel-Basset et al. [83] addressed the feature selection problem by utilizing two improvements for the original GWO. Firstly, the GWO was modified to deal with the binary search spaces using the sigmoid function. Secondly, a mutation operator was utilized in two phases to improve the exploitation capability and increase its accuracy. Several comparisons with well-known methods were conducted to investigate the proposed method's performance. The experiments proved the significance of the proposed method compared with the other methods.

The authors in [84] introduced a novel binary modified variant of GWO, called BIGWO, specifically designed for feature selection in Parkinson's Disease Diagnosis. The researchers incorporated mutation operators into the BIGWO algorithm to enhance its exploration capability, enabling a more comprehensive search for optimal FS solutions. To address FS problems, the continuous GWO algorithm was transformed into a binary version using S-shaped and V-shaped transfer functions. The BIGWO was evaluated using four datasets related to Parkinson's Disease Diagnosis sourced from the UCI repository. The experimental results provided compelling evidence of the superiority of BIGWO when compared to four other algorithms commonly used for FS tasks.

Alyasseri et al. [85] conducted research on the challenging problem of electroencephalogram (EEG) signal channel selection, which was formulated as a binary optimization problem. To tackle this problem, the researchers employed the binary version of the GWO (BGWO) to locate the optimal solution. Furthermore, for EEG-based biometric person identification, they considered the use of a support vector machine (SVM) classifier with a radial basis function (SVM-RBF). Three alternative autoregressive coefficients were investigated for feature extraction. The developed technique is assessed using the accuracy, f-score, recall, and specificity criteria on a common EEG motor picture dataset. The results of the evaluation revealed that the BGWO-SVM approach outperformed other methods in terms of competitive classification accuracy and the number of selected channels.

3) Cellular Grey Wolf optimizer

The incorporation of cellular automata (CA) principles into evolutionary algorithms has gained popularity in the field of optimization. This integration aims to enhance exploration capabilities and mitigate the issue of getting trapped in local optima. In line with this trend, researchers working on the Grey Wolf Optimizer (GWO) have also recognized the potential benefits of integrating CA into the GWO framework to address its limitations [86], [87]. By incorporating CA principles, the GWO algorithm can benefit from improved exploration and a reduced risk of converging to local optimum solutions.

Lu et al. [86] introduced an enhanced version of the GWO for addressing hybrid flow shop scheduling problems with a focus on mitigating noise pollution. In the proposed method, the CA concept is integrated with the multi-objective GWO to empower its exploration ability. The key modification involved updating each solution in the population based on the positions of its neighboring solutions. The neighbours of each solution are determined according to cellular topological structures. Additionally, the authors incorporated a variable neighborhood search into the framework of their method to enhance its exploitation capability. These modifications were introduced to achieve an optimal balance between exploration and exploitation during the search process. Such modifications were introduced to find the optimal balance between the exploration and exploitation abilities during the search process. To evaluate the performance of the proposed method, the researchers conducted experiments using a well-known benchmark dataset. The experimental results demonstrated the effectiveness of the proposed method, as it achieved satisfactory results when compared to other optimization methods commonly used for similar problems.

Cao et al. [87] introduced a novel approach, referred to as cellular GWO, specifically tailored for simulating and optimizing urban growth. In this method, the GWO is triggered to optimize the urban growth rules within a cellular automata (CA) framework. The urban growth rules in the CA framework capture the relationships between spatial variables and the land-use status of each cell, providing a mechanism to simulate the dynamic changes in urban areas. To assess the efficiency of the proposed method, a real-world dataset from Nanjing City, China, spanning the period from 2005 to 2013, was utilized. The simulation results demonstrated the superior performance of the proposed method compared to a well-known alternative method in terms of accuracy for the urban cells and the kappa coefficient.

4) Adaptive Grey Wolf Optimizer

The GWO is a multipurpose metaheuristic search algorithm that uses the minimum number of adjustable parameters. The GWO proved its efficiency in many benchmarks and industrial applications. However, the researchers are always imperative to improve the performance of the GWO by self-tuning or problem by the dependent adaptation for its parameters. Enhancing performance and ensuring efficient convergence are crucial aspects of avoiding the limitations of local minima. This necessitates a delicate equilibrium between exploration and exploitation. Traditionally, achieving this balance involves employing nonlinear operators that inherently adjust the parameters of the GWO algorithm. The following papers provide noteworthy examples in this domain, illustrating the application of such operators to enhance GWO performance.

Yildirim and Alatas [70] introduced a novel approach that combines automatic data mining with the GWO algorithm for multi-objective optimizations. The proposed method was extensively tested on diverse datasets, aiming to identify optimal classification rules and assess the effectiveness of the proposed enhancements. Their GWO method was compared against several comparative techniques, including naive Bayes, k-NN, support vector machines, and decision trees. Additionally, the approach was applied to five real-world datasets. The obtained results convincingly demonstrated the efficiency and accuracy of their GWO algorithm, showcasing its superiority over the alternative methods in terms of achieving optimal solutions.

Rashid et al. [88] proposed an adaptive GWO to train recurrent neural networks. The application was to discover the students' weaknesses and apply better learning methods in the future. The proposed method presented much better accuracy in forecasting the students' performance than the compared methods.

Optimal placement and sizing of active power filters considering the distribution of photovoltaic generation were investigated by Lakum and Mahajan [89] proposing a new adaptive GWO. The optimal placement achieved by the proposed method was tested in 3 different cases. The proposed method was compared with the original GWO. The proposed method showed a significant performance compared with the original GWO.

Liu et al. [90] proposed an adaptive GWO and self-adapted GWO to optimize the problem of optimal cascaded daily pumping of water. The proposed methods used exploitation operators to support the exploration operators of the standard GWO. They also used dynamically adjusting operators in the proposed algorithms. The proposed methods were tested on 23 benchmark functions, and both showed competitive results. They also used them to optimize the operations of six cascaded pumping stations. The proposed methods proved to be more efficient and economical than other methods.

Fu et al. [91] introduced an adaptive mutation GWO to build a forecasting model for the vibrations tendency of hydro-power generators. The authors used the multi-scale chaotic ingredient analysis method and tested their method on six predictive models. During the evaluation phase, the proposed method underwent rigorous testing using several datasets and was subjected to a thorough comparative analysis with other existing approaches. Notably, the results obtained from these experiments clearly showcased the superiority of the proposed method over all the compared alternatives.

Li et al. [92] introduced another variant of adaptive GWO with the objective of optimizing thermal comfort values within an HVAC system. To accurately predict the thermal level, a backpropagation neural network was integrated into the proposed method. Through a comprehensive comparative analysis, the obtained results were contrasted against well-established techniques in the field. The findings from this study demonstrated the exceptional performance of the proposed GWO method, showcasing significantly elevated levels of thermal comfort. Furthermore, it effectively achieved additional energy savings, further emphasizing its superiority when compared to other established methods.

In a similar vein, Dhar et al. [93] presented an innovative and improved version of the GWO algorithm, referred to as cmaGWO. Their objective was to apply this enhanced algorithm for global optimization and parameter tuning of the Forward and Backward mapping models in the context of direct metal deposition processes. To enhance the balance between exploration and exploitation abilities, the authors incorporated the covariance matrix adaptation technique to update the initial perspective prey location in their cmaGWO algorithm. To evaluate its performance, the cmaGWO was rigorously tested on a set of 23 classical test functions as well as 5 additional test functions from CEC-2017. The numerical results obtained from these experiments provided compelling evidence for the effectiveness of the cmaGWO approach when compared to both the original GWO algorithm and other comparative methods. Notably, when employed to tune both the forward and backward mappings, the cmaGWO algorithm showcased superior performance in terms of mean absolute percentage error.

In their work, Meidani et al. [94] introduced an innovative approach to enhance the Grey Wolf Optimizer (GWO) by incorporating adaptive mechanisms. The proposed method dynamically tunes the searching and neighboring parameters based on the fitness history of candidate solutions throughout the search process. This intelligent adaptation enables the algorithm to automatically converge towards a promising optimum within the shortest possible time. Moreover, the authors extended their adaptive GWO by integrating a three-point fitness history, which further refines the convergence parameters. The experimental results obtained from applying the adaptive GWO approach showcased its superior ability to achieve improved solutions when compared to the original GWO algorithm.

5) Chaotic Grey Wolf Optimizer

The chaotic mapping mechanism is a random technique normally integrated with the optimization algorithms to enhance diversity control. In chaotic optimization algorithms, the solution contains chaotic variables rather than random variables. There are different chaotic map functions, each with a different mathematical formulation to convert from the original version to the chaotic version. Many chaotic GWO algorithms are introduced in the literature, as summarized below.

Lu et al. [95] introduced an advanced version of the GWO algorithm by incorporating principles from chaos theory. This integration aimed to address the inherent limitation of GWO by being trapped in local optima. The authors proposed eleven versions of chaotic GWO, each utilizing a different chaotic map function, in order to determine the most effective performance behavior. To assess the algorithm's capabilities, the researchers conducted extensive evaluations using the CEC 2005 dataset and four engineering problems. Through these experiments, the GWO algorithm employing the Chebyshev map function exhibited superior performance compared to the other versions of chaotic GWO. Moreover, simulation results demonstrated the remarkable superiority of the proposed chaotic GWO approach over other comparative algorithms when applied to the same problems.

Saxena et al. [96] presented an innovative approach by introducing a chaotic variant of the GWO algorithm for unconstrained numerical optimization. In their method, the β-chaotic sequence was seamlessly integrated with GWO to adaptively control the exploration and exploitation capabilities. This integration aimed to strike the ideal balance between exploration and exploitation throughout all stages of the search process. The researchers conducted extensive evaluations using a set of test functions derived from the CEC 2017 collection, as well as two real-world engineering problems. The simulation results revealed that the proposed chaotic GWO algorithm consistently outperformed other versions of GWO, as well as other comparative algorithms from the existing literature when applied to the same problem set.

Another chaotic GWO was proposed by Zhang and Hong [97] for forecasting electric loads. The authors combined the variational mode decomposition and the chaotic GWO to enhance the search experience and identify optimal parameter settings for the support vector regression model. The utilization of the Tent chaotic mapping function within their model aimed to augment the diversity of the search process, facilitating improved solution exploration. The proposed model was evaluated using two real-world datasets sampled from New South Wales (Australia) and National Grid (UK). The experimental results demonstrated that the proposed model outperformed other comparative models in terms of forecasting accuracy, showcasing its superior performance and effectiveness in electric load forecasting.

The multi-robot task allocation problem was addressed by Li and Yang [98] proposing a new improved GWO utilizing the chaotic approach to enhance the initial population and its diversity, thus, enhancing the solutions' quality. Furthermore, to further enhance the optimization process, an adaptive strategy was employed to refine the best solution while ensuring a balance between exploration and exploitation. Through rigorous testing on diverse datasets, the proposed method consistently outperformed the compared approaches in terms of solution quality.

Similarly, Hu et al. [99] proposed a modified variant of the GWO called SCGWO, specifically tailored for global optimization and feature selection (FS) problems. The SCGWO method incorporates two key enhancements: an improved spread strategy and a chaotic local search mechanism, aimed at enhancing the performance of GWO. The improved spread strategy is designed to bolster the algorithm's global search capabilities, enabling it to effectively navigate potential local optima. Meanwhile, the chaotic local search mechanism accelerates the convergence speed, allowing for faster and more efficient optimization. To assess its performance, SCGWO was rigorously evaluated using a diverse range of classical test functions and 32 FS datasets sourced from the UCI repository. The simulation results showcased the remarkable effectiveness of SCGWO compared to other comparative methods, both in terms of convergence speed and solution quality.

6) Gaussian Grey Wolf Optimizer

Wang et al. [100] proposed a new modified version of the GWO to address the premature convergence problem. The proposed method was introduced to enhance the GWO exploration capability by combining its searching parameters with the gaussian estimation of distribution approach. In addition, the Gaussian distribution-based inferior solutions repair method was proposed to modify the ill-shaped distribution of the GWO population. In the experimental results, the performance of the proposed method was compared with that of other state-of-the-art methods using the CEC 2014 benchmarking function. The obtained results proved the high performance of the proposed method compared to the other methods.

A new version of the GWO was proposed by Khalilpourazari et al. [101] to address well-known complex benchmark functions optimally. The authors utilized the gradient information on the original GWO to accelerate its convergence into the optimal solution. In addition, the Lévy flight and Gaussian approaches were used to enhance the exploration and exploitation capabilities of the GWO, as well as avoid local optimal stagnation. The proposed method was evaluated using different benchmark functions. The proposed method demonstrated all compared methods in optimizing the problems.

Similarly, the authors in [102] combined the GWO and the Gaussian kernel function in a new algorithm called kernel-based Picture Fuzzy C-Means clustering with GWO (KPFCM-GWO). In their algorithm, the Gaussian kernel function is utilized as a symmetrical measure of distance between data points and cluster centers, while the GWO is used to tune the best settings of PFCM. The simulation results demonstrate the effectiveness of the KPFCM-GWO against other clustering methods.

7) Dynamic Grey Wolf Optimizer

Dynamical GWO is used to provide more flexibility and search capability for the algorithm by modifying the population size when needed or enhancing information exchange among the best wolves. It also uses nonlinear operators to balance the search strategy by either focusing on local or global search strategies. The papers below show several applications using the concepts of the dynamic GWO.

Luo [103] proposed a dynamic GWO to change the wolves' positions dynamically. In this version, the leader wolves always keep estimating the location of the prey. That gives more flexibility and tracking ability to the algorithm. The proposed method outperformed the original GWO based on the CEC2017 testing suite. The proposed method was also used in solving engineering problems at lower computation costs. It showed more convergence speed and quality of the solutions.

A dynamically dimension-ed GWO was proposed by Yan et al. [104]. This dynamical GWO used an interaction strategy between the best three wolves to exchange location information. It also used a nonlinear control parameter to balance exploration with exploitation searches. Experiments were done on 23 benchmark functions and three well-known engineering applications. The proposed method showed a fast convergence and high robustness compared to other compared methods.

8) Opposition Grey Wolf Optimizer

Opposition-based GWO is introduced to solve the stagnation and lack of diversity problems the standard GWO may have. The GWO uses a nonlinear operator to introduce jumping and escaping local minima. This implies more exploitation of search space areas around the best solutions found. Many applications were efficiently solved based on the opposition-learning theory-based GWO. The papers below present some of the applications that used such a concept.

An opposition-based competitive GWO was used by Too and Abdullah [71] to find the optimal feature selection and classification of EMGs. The authors accessed the publicly available EMG database for training and testing. They use the binary version of the GWO and convert it into a continuous version of GWO in order to perform a search in continuous space. The proposed method proved its high capabilities in optimizing the problem and achieving the best results compared with the compared methods.

Yu et al. [105] proposed an opposition-based GWO to optimize complex and multi-modal functions. The authors used a jumping rate for the opposition dynamically adjusted by a nonlinear function to balance exploitation with exploration. Several experiments were conducted, and the proposed method proved to be much better than conventional techniques.

A random opposition-based GWO was used by Long et al. [106]. This method was used to avoid the GWO from getting stuck in local minima. In addition, the proposed method aims to obtain a better balance between exploration and exploitation. The proposed method was evaluated on 23 benchmark test functions and 30 benchmarks from IEEE CEC 2014. The results obtained were competitive with other optimization techniques.

Feng et al. [107] improved GWO to optimize 12 classical test functions in addition to the two cascaded hydropower

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constraint optimization problems. The goal was to smooth the peak loads of the power system. Quasi-oppositional learning and an elite mutation operator were employed in this improved GWO version. Elastic ball strategy and heuristic constraint handling were used. The results showed that the proposed method outperformed several existing classical techniques.

Long et al. [108] used a new version of oppositional GWO based on the process of the refraction of lights in physics. Theoretical proof for convergence is provided. Testing for the RL-GWO was done on 23 benchmark functions and the other 30 test functions from CEC 2014. It has been shown that the proposed method is efficient and reliable in solving optimization problems.

Another opposition-based GWO version was proposed by Guttula and Nandanavanam [109] to find the optimal design of a microstrip patch antenna. The authors used a nonlinear model based on the antenna parameters. The proposed model proved its high optimization capabilities by obtaining better performance than other conventional methods. The resulting design was superior, with higher values of antenna gains.

The training of an echo state network was implemented by Chen et al. [110] using selective opposition GWO. The main aim of such a model is to predict nonlinear and chaotic time series. The proposed method was applied to typical chaotic time series such as Mackey-Glass and Lorenz. Simulations showed that the proposed method has better prediction performance than other state-of-the-art methods.

Gupta and Deep [111] introduced an enhanced GWO called the opposition-based chaotic GWO. The proposed methods mitigate the stagnation problem that the standard GWO may suffer from by introducing more exploitation searches and applying opposition-based learning. The method was applied to three standard engineering problems and 23 standard benchmark tests. Experiments showed the new method's reliability and superiority over the standard GWO.

The opposition-based learning approach and explorative equation were combined with the GWO to enhance its exploration and exploitation abilities, thus, improving the solutions' quality [112]. The validation of the proposed method was tested using 23 standard benchmark test problems. The obtained results showed the high performance of the proposed method in addressing the optimization problems.

The authors in [113] introduced another modified version of GWO, called EOCSGWO, for global optimization and to optimize the parameter of an auto drum-fashioned brake. In EOCSGWO, the elite opposition-based learning strategy and k-best gravitational search strategy are combined with the GWO to enhance its performance. The elite opposition-based learning strategy is introduced to take advantage of the best wolves in the next generations, while the k-best gravitational search strategy is used to enhance the global search ability. The performance of the EOCSGWO is evaluated using 10 classical test functions and compared to the seven other variants of GWO. The simulation results illustrated the superiority of the EOCSGWO against others. Finally, the EOCSGWO is applied to find the best parameter settings of an auto drum-fashioned brake with satisfactory results compared to the initial design.

The new quasi-opposition-based learning was combined with the GWO in [114] to emphasize its exploitation and exploration capabilities, as well as escape the stagnation in local optima. The proposed method was tested by finding the best factors for adaptive model predictive control. The obtained results by the proposed method proved its high performance in achieving the optimal factors compared to other methods.

Another modified GWO version was proposed in [115] based on the dynamic opposite learning to improve the local and global search behaviour and find better results for the CEC2014 23 benchmark functions. In the experimental phase, the proposed method was compared with ten original and improved optimization methods. The proposed method almost outperformed all compared methods.

Rezaei et al.[116] develop a novel version of the GWO to address the lack of a velocity operator in the technique of position-updating that leads to a limitation in exploration capability. So, this modification enhances the algorithm's capabilities for exploration and exploitation by controlling the step size in both early iterations and later iterations, making them large and then small, respectively. The experimental findings show that the VAGWO technique is a computationally efficient one that produces incredibly precise results when used to optimize highly dimensional and complicated issues.

Sun et al. [117] developed a new version of the GWO in order to improve optimization performance. The modification was made to address falling into the local optimal problem by incorporating a refraction opposite learning (REL) technique. The proposed method resolves the problem of low swarm population variation in the late iteration of GWO by effectively utilizing the REL. Additionally, the equilibrium pool technique also lessens the possibility of wolves migrating to the local extremum areas. IEEE CEC 2019 test functions as well as 21 commonly used benchmark functions are utilized to evaluate the performance of a modified algorithm.

9) Structured population Grey Wolf Optimizer

The GWO can be enhanced by structuring the population into different groups depending on the rank or quality of every sub-group. Different learning strategies could be used for different sub-groups based on some decision mechanism. The primary aim of such enhancement is to improve the efficiency and capability of the GWO to solve large-scale and complex optimization problems with the best performance. Several related studies have been proposed and summarized below.

Tu et al. [118] proposed a hierarchy-strengthened GWO to optimize a 50-dimensional problem based on the CEC 2014. The proposed method was tested with large-scale optimization problems with 100 decision variables. Finally, the feature selection problem was used for further testing. The proposed method divides the population into dominant wolves and omega wolves. Dominant wolves were trained with an elite learning strategy. The omega wolves were trained with differential evolution and enhanced GWO. This is all done to balance the exploitation and exploration strategies of the proposed method. Testing proved the efficiency of the proposed method and the speed of convergence.

Ezhilsabareesh et al. [119] used grouped GWO to optimize PID controllers. This is done to achieve maximum efficiency tracking for the generators of different axial velocities. The generator's work was introduced based on the oscillating water column wave energy converters. The obtained results of optimization showed an increase in the system's efficiency.

A synchronous-asynchronous processing scheme was adapted for the GWO using a set of nonlinear functions and operations to increase diversity by Rodríguez et al. [120]. In that sense, a better balance between exploration and exploitation was achieved. More accuracy and local minimum avoidance were obtained. Evaluation of the proposed method was implemented with the 2017 benchmark set of functions and real-world problems. The results prove the effectiveness and quality of the new method.

A multi-group GWO was proposed by AlShabi et al. [121]. The new method consists of several packs or clans, each consisting of 4 levels of wolves. That resulted in a higher speed of convergence and more efficient reach to the solutions. The technique was used to extract the parameters of a single-diode photovoltaic solar cell. The results obtained for the proposed method were much better than those of other comparative techniques. The achieved results were even better than those for standard GWO.

The authors in [122] introduced a new modified variant of GWO for global optimization. Their algorithm is called adult-pup teaching–learning based interactive grey wolf optimization (AP-TLB-IGWO). In AP-TLB-IGWO, the adult wolves and pup wolves act as search agents. The search agents between the two subpopulations concurrently and independently explore the entire search space for optimal results. In addition, Information sharing takes place between adult and pup wolves to enhance diversification and to make the right balance between the exploration and exploitation abilities during all stages of the search process. The performance of the AP-TLB-IGWO was evaluated using 23 classical test functions, 30 test functions from CEC2014, 30 test functions from CEC2017, and five classical engineering problems. The simulation results demonstrated the effectiveness of the AP-TLB-IGWO compared to the original GWO and other modified versions of GWO and other comparative methods.

10) New parameter for Grey Wolf Optimizer

The searching behaviour of GWO can also be modified by integrating its components with new optimization parameters to address different drawbacks based on the added parameter.

The selection behaviour of the best solutions in GWO was modified to enhance its searching capabilities and find better solutions in the search space by utilizing a new adaptive parameter to assign an appropriate weight for the solutions [67]. The proposed method tested a feature selection problem in the medical science domain. In the evaluation phase, the proposed method was evaluated and compared with well-known methods. The proposed method outperformed the compared method in achieving the best solutions.

The GWO searchability was improved by utilizing a crossover operation and adaptive control parameter by Liu et al. [123]. The crossover operation was used to increase the population diversity of the GWO and the adaptive parameter to maintain balance the exploration and exploitation. The proposed method was evaluated using benchmark optimization functions. The obtained results proved the high performance of the proposed method compared to six well-known methods.

A modified GWO was introduced to address the supplier selection and order quantity allocation problems [124]. In the proposed method, a new weighted coefficient parameter and a displacement vector were utilized to enhance the exploration capabilities and avoid unfeasible solutions. In the evaluation phase, the proposed method was tested, evaluated, and compared with other optimization methods. The proposed method proved its high capability to optimize such problems efficiently.

The GWO was improved by Miao et al. [125] to overcome its drawbacks and enhance its search performance in addressing global optimization problems. The enhancement of the GWO starts by utilizing a new adaptive coefficients parameter to achieve better convergence speed. Subsequently, a new position-updating equation is used to emphasize the exploration capabilities and find better solutions. The experimental results proved the high performance of the proposed method in optimizing well-known global functions and outperforming the compared methods.

Komijani et al. [126] proposed an extended GWO by utilizing a new coefficient parameter to optimize the fractional-order proportional derivative sliding mode controller. In the evaluation results, the proposed method was compared with the original GWO. The obtained results proved the high capability of the proposed method in optimizing the controller and achieving better solutions.

An extended GWO was proposed by utilizing a new coefficients parameter to enhance the algorithm searchability and obtain better solutions [127]. The proposed method was evaluated by testing its performance in optimizing a novel control approach sliding mode control. The proposed method exhibited better results than all compared results in the evaluation stage.

New dynamic inertia weights were proposed to control the grey wolf social hierarchy and make the wolf more adaptable for better exploring and exploiting the search space [128]. The proposed method was mainly used to optimize the support vector machine parameters and find the best accuracy of traditional coal spontaneous combustion temperature prediction. In the evaluation stage, the proposed method was tested on different datasets and constraints. The proposed method showed high performance in finding the best accuracy.

11) Fractional Grey Wolf Optimizer

A further alterations method that can impact how well the GWO searches is the functional method. In searching space, the functional technique is mostly employed to alter the wolves' movements [72], [129].

Deshmukh and Rani [72] used an upgraded release of the GWO to solve the resolution issue for multi-view facial video super-resolution. To significantly improve the performance of the GWO search agents and achieve the optimal exploitation and exploration balance, a particular GWO release is suggested based on the fractional technique and GWO elements. The suggested method's outcomes were contrasted with those of other widely used approaches. In solving such a problem, the suggested solution performed better than all those that were compared.

Ma et al. [129] suggested a unique fractional GWO to improve the GWO's accuracy and produce better outcomes. The advanced model was also used to improve the planned fractional GWO searching functionality. Utilizing four optimization issues, the suggested approach was assessed and contrasted with the other eight GWO methods. The findings collected demonstrated the suggested method's superior performance compared to existing approaches.

12) Mutation operator for Grey Wolf Optimizer

The GWO search agents can be paired with an evolutionary element known as a mutation operator to improve their searching powers and produce superior outcomes [130].

Niu et al. [130] suggested an enhanced GWO approach to expand diversity utilizing the adaptive mutation method, boost local search capacity using the hyperbolic acceleration strategy, and maximize convergence speed using the elitist selection strategy. By modifying the suggested method's parameters for water resource systems, it was put to the test. In comparison to the compared methodologies, the suggested method provided superior schedules, according to the simulations.

In [131], an alpha-guided GWO approach was put up as a way to speed up the original GWO's convergence and produce better results. The suggested strategy was also enhanced to prevent stagnation in local optima by using a mutation operator to alter the seeking agents' location-updating behavior and enhance exploration. Utilizing well-known optimization functions, the suggested technique was evaluated. In comparison to all other ways, the suggested method produced better outcomes.

To solve scheduling issues in the electricity industry, Sidea et al. [132] presented an improved GWO based on the elements of the mutation technique. The suggested modification's primary goal is to prioritize exploration and exploitation while striking the ideal balance between the two. Along with the scheduling issues, the effectiveness of the suggested strategy was examined using 23 conventional benchmark functions. The suggested strategy fared better at maximizing the search spaces and producing the best results than all other strategies that were examined.

A mutation-driven modified grey wolf optimizer was suggested by Singh and ChandBansal [133]. The improved algorithm uses a mutation-driven approach and a greedy way to choose the grey wolf, which changes the control value. Four actual engineering design challenges from the real world and 23 well-known standard benchmark functions are used to assess the suggested approach. The outcomes demonstrate that the suggested algorithm beats other comparable approaches by delivering the best outcomes and achieving a faster convergence to the ideal solution.

The GWO was combined, involving uniform as well as nonuniform mutation agents, by the developers of [134] to improve its exploration capabilities for sizing optimization of truss design issues with continuous and discrete decision variables. Their algorithm's effectiveness was evaluated using four issues and ten distinct situations. The simulation findings proved the suggested GWO's efficacy by producing an optimal design with the fewest weights that was on par with or superior to the other comparison algorithms described in the literature.

13) Neighbour Search for Grey Wolf Optimizer

In order to improve local search abilities and prevent stasis in local optima, optimization approaches primarily use the neighborhood searching approach [135].

In order to overcome issues with engineering and general optimization, Nadimi-Shahraki et al. [135] presented an updated GWO. The suggested approach was developed to overcome the original GWO flaws, such as the unequal distribution of exploitation and exploration, the absence of population variety, and the sluggish convergence pace. The improvement in GWO is accomplished by applying the movement strategy, also known as the level of learning-based hunting strategy, to boost neighboring search behavior and exchange data among the solutions. Six cutting-edge approaches were compared to the performance of the suggested method. The collected findings demonstrated the excellent performance of the suggested approach, showing that it outperformed the strategies that were being evaluated in terms of results.

In order to best handle the welding shop inverse scheduling issue, Wang et al. [75] suggested a new GWO version. The suggested version was developed to improve the GWO's local search capabilities by utilizing the neighborhood searching strategy while modifying the GWO's searching behavior to handle discrete optimization challenges. The efficacy of the suggested approach was examined by contrasting it with numerous cutting-edge approaches in the simulation findings. The suggested approach demonstrated its efficacy by surpassing all other methods that were compared.

In order to solve the welding shop inverse scheduling problem specifically for welding shop settings, Wang et al. [136]

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offer an improved version of the GWO that adds dynamic incidents in addition to minimizing parameter modification. First, for typical discrete optimization problems, encoding based on a matrix and initiation by the crucial path are proposed. These methods can shorten the duration of searches and improve search efficiency. The second step is to implement a variable neighborhood search strategy to enhance the presented method's local search functionality. In order to minimize parameter alterations, the performance of the suggested algorithm is then evaluated in three distinct types of cases. Comparisons with cutting-edge methodologies are also done. The results in practice show how successful the proposed strategy is in handling WSISIP.

14) Greedy Approach for Grey Wolf Optimizer

The GWO was altered by utilizing the greedy technique to improve hunting operations and the horizontal crossover operator to improve and refine the best three wolves' capacity to search, according to [137]. A modification was made to the GWO in order to handle the multiobjective optimal power flow optimization issue and maximize all of its goals. On IEEE 30- and 118-bus systems, the suggested technique was verified. The outcomes showed that the suggested approach performed superiorly to the approaches that were evaluated.

To preserve the balance among exploitation and exploration, Gupta et al. [138] suggested an upgraded variant of the GWO that utilized the memory method. The crossover, greedy choosing, and individual ideal history techniques of the solutions are all used in the suggested approach to carry out its intended function. Utilizing well-known benchmark functions, the suggested technique was assessed. The suggested strategy fared better at optimizing the functions than all the strategies that were compared.

Gupta et al. [139] suggested an enhanced leadership-based GWO to increase the wolves' capacity for searching and the precision of their searches by employing greedy selecting and the Levy-flight strategy. The suggested technique was validated using industry benchmarks like IEEE CEC 2006 and IEEE CEC 2014. The obtained results demonstrated the recommended method's reliable effectiveness in solving the challenges.

A novel hybrid GWO model using integer coding and greedy techniques was presented by Huang et al. [140] to improve the GWO's ability to effectively handle discrete search spaces. Additionally, in order to improve the exploration and exploitation capabilities, the GWO searching behavior was altered by using a central location and two-opt with Azimut techniques. The proposed strategy was put to the test during the experimental phase by utilizing the task distribution for the unmanned aerial vehicle challenge. The acquired findings were contrasted with those of the original GWO and additional approaches in order to effectively assess the suggested approach. The outcomes demonstrated the great effectiveness of the suggested approach in solving the issue.

Another modified version of GWO, known as G-SCNHGWO, was presented by the authors in [141] to address issues with economic load dispatch. In G-SCNHGWO, sine and cosine functions are used in the GWO's architecture to improve exploration and prevent the local optimum issue. Additionally, G-SCNHGWO makes use of the greedy non-hierarchical idea to strengthen the algorithm's searchability and balance the capabilities of exploitation and exploration at all phases of the search procedure. Four real-world datasets are used to assess the G-SCNHGWO's performance, and the comparison with other rivals yields promising findings.

15) Other improved versions of Grey Wolf Optimizer

Other improvements to the GWO searching behavior have been suggested in various research studies to develop it and solve its shortcomings in order to find better answers to a variety of optimization challenges.

In order to increase the GWO's capacities for exploration and exploitation and overcome the GWO's searching limitations, Khanum et al. [142] developed two improvements. Initially, a novel parameter that alters the equations of surrounding and location updates for search agents was proposed, which changed the encircling, updating locations, and hunting procedures. Second, the GWO components were merged with the Minkowski technique. Using well-known test functions, the suggested strategy was evaluated and contrasted with alternative approaches. The outcomes demonstrated the suggested method's effectiveness by outperforming all other approaches that were compared.

By balancing exploration and exploitation functionally and boosting the sensitivity factor of the fuzzy clustering iterative method, Zou et al. [143] proposed an improved version of the GWO based on the immune clone selection approach to increase the GWO's searchability. The simulation's results showed that all of the compared outcomes were successful in accomplishing and optimizing the goals.

To locate and retrieve the earthquake catalog based on the idea of ergodicity, Vijay et al. developed and handled the cluster event optimization issue [144]. In order to increase the exploration and exploitation capabilities of the GWO and achieve optimal balance, the defined problem was handled and improved utilizing a new modified GWO that was developed based on the quantum method. 24 benchmark functions were used to assess the suggested technique. The collected findings demonstrated the suggested technique's solid efficacy by exceeding all other approaches that were examined.

To improve its searching efficiency and capacities in dealing with the design membership problem and optimizing seismic structure damage, Azizi et al. [145] suggested an improved GWO. Twenty benchmark datasets with nonlinear behavior involving up to 400 design variables were used to evaluate the suggested methodology. When contrasted with all other state-of-the-art approaches, the suggested method performed better.

The capabilities of the technique were improved, and local optima were avoided by using a new variation of the GWO that was suggested in [146]. In order to overcome issues

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with global optimization, the proposed approach was created. Three popular engineering challenges were employed together with 23 commonly used benchmark test functions to evaluate the strategy. It turns out that the suggested algorithm is both highly competitive and frequently superior.

Le et al. [147] suggested an improved GWO to overcome the learning rate determination issue in the multilayer type-2 asymmetric fuzzy controller. Two phases were suggested for improving the GWO: remembering the swarm's optimal location and enhancing the ability of the agents to search. When compared to alternative ways, the suggested solution demonstrated superior effectiveness in managing the issue and maximizing its goal.

In order to improve the convergence behavior of the classic GWO, Guo et al. [148] presented a new GWO edition by mixing its elements along with the nonlinear tangent trigonometric function. By changing its settings to remedy the power point tracking issue, the suggested solution was put to the test. The suggested approach, along with other widely used optimization techniques, has been compared with the results of the experiment. In most instances, the suggested technique produced superior outcomes compared to the comparative methods.

Guo et al. [149] used both tracking and searching techniques to improve preliminary GWO optimization efficiency, broaden the population, and keep the ratio of exploration to exploitation in check. Using test functions and traditional engineering issues, the suggested technique was evaluated. A sizable amount of comparative research was carried out to demonstrate the offered approaches' reliable performance. In terms of issue optimization, the outcomes achieved exceeded all examined strategies.

Wang and Xie [150] used an improved edition of the GWO to solve the deployment issue for wireless sensor networks. It was suggested that the GWO be improved in order to increase the population's capacity for exploitation and exploration. The first component is for encircling the outside layer, while the second part is for encircling the internal layer. Employing popular test functions, the suggested technique was evaluated. The outcomes demonstrated the great performance of the suggested approach.

In order to effectively solve global optimization issues, Seyyedabbasi et al. [151] proposed two updated variants of the GWO. In the initial update, a larger version of the GWO's model was used to increase the number of search agents in charge of the searching process. The second change enhanced the position updating strategies and raised the standard of the answers by using an incremental framework. 33 test functions were utilized to assess the suggested technique in the evaluation findings. The outcomes demonstrated that the suggested strategy outperformed all other strategies that were examined.

To improve the GWO's ability to search and find superior options for global functions, a multi-strategy ensemble GWO was suggested [152]. The suggested approach was presented in three steps: enhance global-best solutions to improve local search capabilities; employ adaptable cooperative tactics to boost population variation and global search capabilities; and implement dispersed foraging methods to equalize exploitation and exploration. The suggested technique evaluated well-known functions against various optimization techniques. The suggested approach produced the best outcomes when compared to all other methods.

By suggesting an integer-encoding GWO approach, Xing et al. [153] improve the simulated network function location optimization issue. The integer encoding strategy and a novel updating mechanism for the wolves in the search space are used in the suggested method to highlight exploitation and exploration skills and achieve the optimal balance. Twenty test examples were used to evaluate the performance of the suggested technique. The outcomes were contrasted with those of other cutting-edge techniques. The results demonstrated the outstanding efficacy of the suggested approach.

To increase the classification performance and resilience of the probabilistic neural network, an upgraded GWO was put out in [154]. The suggested approach was put forth to enhance the GWO's convergence and exploration capabilities. When compared to other ways, the suggested strategy performed well in the assessment findings for optimizing the issue and finding the best answers.

By adopting an entirely improved variation on GWO, the disassembly sequence planning issue was handled by Xie et al[155]. Three coefficients, the viable solution generator, the neighborhood search operator, and the directed search coefficient, were included in the suggested technique to verify the viability of the solutions. On the basis of two engineering situations, the suggested technique was evaluated. The outcomes demonstrated the great efficiency of the suggested approach to solving the issue.

Yang et al. [156] used an upgraded GWO to optimize an energy-aware approach, ensuring the precision of the discovered solution. The suggested approach was put forward to improve exploration and exploitation skills and preserve equilibrium. To assess its effectiveness, the effectiveness of the suggested approach has been contrasted with a number of cutting-edge techniques. The suggested approach outperformed every strategy that was compared.

In order to effectively optimize the gene picking issue, Alomari et al. [157] proposed a new, improved GWO version. The TRIZ-inventive approach's components were used to introduce the suggested improvement in order to broaden the population's variety and raise the caliber of the answers. During the assessment stage, nine popular datasets were used to evaluate the proposed technique. Seven cutting-edge approaches were examined, and their effectiveness was contrasted to that of the suggested approach. In terms of achieving the ideal answer, the suggested technique outperformed the comparative method.

The fuzzy technique [158] helped the GWO better balance convergence and variation in populations. In order to highlight local and global optimization, mutation and crossover operators were also modified for the suggested approach.

Five technical optimization tasks and CEC-2014 were used to assess the performance of the suggested technique. Additionally, the outcomes of the suggested strategy were evaluated against a number of popular optimization techniques. When compared to various optimization techniques, the suggested strategy produced the best outcomes.

To increase the GWO population variety and convergence to ideal agents, the Cross-Dimensional Coordination GWO was suggested in [159]. The best answer is updated using all previous best information acquired by honest agents in the suggested approach, which employs a revolutionary learning mechanism. CEC06-2019 and 12 engineering issues were used in the assessment step to assess the effectiveness of the suggested strategy. The proposed strategy was also contrasted with a number of cutting-edge techniques. Most of the compared approaches were outperformed by the suggested strategy.

A strengthened exploitation and exploration GWO (REEGWO) was proposed by Yu et al. [160]. By giving the highest three wolves varying weights based on their understanding of the position of the prey, the methodology is changed. Also used to enhance method exploration is tournament choice. The data collected demonstrates that REEGWO performs better than the other four new GWO versions. The suggested method also performs better than other heuristic algorithms.

The grey wolf optimizer was created by Nadimi-Shahraki et al. [161] using a gaze cues learning framework. The suggested method uses neighbor gaze cues learning (NGCL) and random gaze cues learning (RGCL) to lessen the GWO algorithm's strong selection pressure and heterogeneity. The method is assessed using two optimum power flow issues, four genuine engineering layout issues, and the CEC'18 test functions. The suggested approach outperformed nine metaheuristic methods in the evaluation.

The Parallel Cooperative Coevolutionary Grey Wolf Optimizer (PCCGWO) was introduced by Jarray et al. [162] to address the issue of route design for unmanned aerial vehicles (UAVs). The suggested method uses several smaller-dimensional subspaces. In order to search for an agent in a portion of the search area, it produces several swarms from the initial population. Then, to shorten the calculation time needed to address the issue, a parallel master-slave architecture is employed. The outcomes demonstrate the suggested algorithm's effectiveness in terms of output and nonparametric statistical findings.

B. HYBRIDIZED VERSIONS OF GREY WOLF OPTIMIZER

Another improvement technique utilized for the GWO is hybridization. Such an approach is proposed by combining the GWO with components from another optimization method. Several studies utilized the hybridization approach, which is summarized below.

1) Local Search with Grey Wolf Optimizer

Makhadmeh et al. [163] introduced a novel hybrid GWO with an efficient local search method to enhance its exploitation capabilities and avoid local search stagnation, thus, improving its searchability. The utilized local search method for the GWO is called the min-conflict algorithm. Furthermore, the proposed method was formulated as a multi-objective optimization method to address optimization problems with multiple objectives. The proposed method was tested and evaluated using a well-known multi-objective engineering optimization problem called the power scheduling problem in a smart home. The performance of the method was investigated through several scenarios. The acquired results presented the performance of the proposed method, where it exceeded almost all other methods.

Guo et al. [164] integrated the simulated annealing and a stochastic simulation approach with multi-objective GWO for line balancing scheduling in disassembling numerous products. Three conflicting objectives were considered by the proposed method, where objectives are: maximizing the minimizing energy consumption and disassembly profit and minimizing carbon emission. The method's performance was evaluated using real-world datasets. Simulation outcomes demonstrated the proposed method's efficiency against three other multi-objective methods.

Hoballah et al. [165] used hybrid GWO to develop a code matrix depending on dissolved gas percentages for reliable defect identification while accounting for measurement errors. The criteria that map the boundaries of gas ratios for various fault kinds were created using a fuzzy approach. Each percentile range of gas was separated into three zones, each with three fuzzy memberships. After that, a fuzzy system is created to link the gas percentages to the fault category. Thus order to improve the accuracy, the membership limitations were then optimized via heuristic techniques. The suggested code reduces the effect of measurement errors on output fault diagnostics. The proposed approach demonstrated its ease of use in diagnosing transformer faults and its reliability against error margins.

El-Kenawy et al. [166] developed a modified binary GWO depending on the stochastic fractal search to discover the important characteristics by attaining search locally and globally and make a balance between them. To begin, the proposed GWO was created by using an exponential form of the iterations number of the original GWO to expand the search area for global search and crossover/mutation operations to boost population variety and improve local search capabilities. Then, the Gaussian distribution approach was utilized for walk randomly in a growth process; the stochastic fractal search diffusion procedure was used to find the best solution for the modified GWO. The proposed method's continuous values are then transformed into binary values to deal with feature selection problems. Nineteen UCI datasets were examined to ensure the stability and effectiveness of the proposed method. For classification tasks, the K-Nearest Neighbor method was used to assess the quality of a subset of characteristics. The results showed that the proposed method beat binary versions of state-of-the-art optimization techniques.

Helmi et al. [167] introduced a new lightweight feature selection approach. The GWO was hybridized with the gradient-based optimizer to address such an optimization problem. The support vector machine was employed to identify the features selected by the proposed method. Extensive tests were done to examine the proposed method's performance. Overall, the obtained results from the method proved its high performance.

Al-Betar et al. [168] increased the convergence qualities of the GWO by hybridizing it with the hill-climbing optimizer. GWO is quite effective in a broad search, but hill-climbing is highly effective in a deep search. The balance between exploration and exploitation is properly managed by integrating wide and deep search capabilities in a single optimization framework. The suggested hybrid algorithm was assessed utilizing five distinct test cases. The proposed method was assessed utilizing 49 different comparison methods. In most test instances, the results the proposed method gained surpass those others obtained.

Sun et al. [169] used the GWO and gradient algorithm to present a sub-pixel displacement measuring approach. The correlation between the reference image and distorted image subsets was first investigated using the zero-mean normalization cross-correlation function. Second, the beginning integer pixel value was acquired and is seen as the initial displacement by utilizing the GWO global searching capability. Finally, a Barron gradient method was used to acquire the final sub-pixel displacement. The presented approach can successfully assess the deformation and displacement of rigid structures compared to the state-of-the-arts using synthetic speckle pictures.

Qin et al. [170] reduced total delivery delay and production cost using a multi-objective casting production scheduling framework. In this method model, a hybridization discrete multi-objective GWO is proposed. To improve the quality of the initial population, an initialization method focused on minimizing work transit time and process time was developed. To avoid the GWO's premature convergence, an improved tabu search method was combined with the GWO. To evaluate the effectiveness of the proposed method, a case study of a genuine foundry enterprise was presented. Experimental findings showed that the suggested method outperformed five other multi-objective algorithms in terms of classification accuracy. The implementation of the proposed scheduling model was verified utilizing a real-world testing system.

Xu et al. [171] suggested a novel hybrid GWO with local search to tackle engineering problems. The presented method was introduced to improve the local search strategy of the GWO. The experimental results showed that the presented approach could handle the problem more efficiently and with relatively high solutions.

The authors in [172] introduced another hybrid GWO algorithm for disassembly sequencing and line-balancing scheduling problem. In their hybrid algorithm, the simulated annealing is injected within the framework of the GWO to improve its performance and balance the exploration and exploitation abilities. The simulation results displayed the significance of the hybrid method in terms of solution quality and computational time.

Alomari et al. [173] use the GWO and combine it with the Triz operator as a wrapper approach to address the problem of text classification by hybridizing the filter-wrapper technique based Principal Component Analysis to develop a filter to choose an informative and suitable subset of traits, which in turn decreases the data dimensionality. The experiment employs three datasets of Arabic-language text to evaluate the proposed method's performance. The findings confirm the proposed method's efficiency in terms of classification accuracy.

2) Swarm Intelligence with Grey Wolf Optimizer

The GWO can be hybridized with swarm intelligence methods to enhance its capabilities in addressing complex, multi-objective, and large-scale search spaces. The integration of two or more meta-heuristics forms a synergy that is needed to enhance the capabilities of the search algorithm. Some of these algorithms are more exploitation-oriented, and others are more exploration-oriented. Some are more appropriate for binary search spaces or mixed-integer optimization. Hybridized techniques can be considered to avoid stagnation in local optima or speed up convergence. When mixing two or more hybridization algorithms, more richness and versatility in solutions can be discovered. The following papers show examples of using swarm intelligence with GWO in solving complex optimization problems.

Goudos et al. [174] addressed antenna design and fabrication problems for the 5G mobile devices proposing a new hybrid optimization method based on the GWO and the components of the Jaya optimizer. In the proposed method, the components and features of the two algorithms were combined to emphasize exploration and exploitation with maintaining the balance between them. The proposed approach was evaluated using different well-known benchmark functions. The proposed method showed better performance in addressing the problem than the compared methods.

Another hybrid approach on the basis of the GWO components and symbiotic organisms search was introduced by Qu et al. [175] to handle the same problem. The symbiotic organism's search was utilized to improve the exploitation abilities and the convergence rate of the original GWO, thus, finding better solutions. The achieved outcomes by the proposed approach were compared with that achieved by the GWO, symbiotic organisms search, and simulated annealing algorithms. The proposed approach exceeded all compared approaches in handling the problem.

Al-Wajih et al. [176] proposed a new binary GWO and harris hawks optimization mimetic approach to solving the optimum feature selection problem. The proposed method provided a balance between exploration and exploitation and used sigmoid transfer functions to convert the continuous values of search space into binary. The testing was done on 18 standard UCI problems, and the results were compared with other comparable binary optimization methods. The proposed method showed more accuracy and lowered computational cost than the other techniques.

A hybrid crow search algorithm with GWO was proposed by Rizk-Allah et al. [177] to solve large-scale optimization problems. The GWO operates more on exploration, while the crow search algorithm focuses more on local search. The proposed method was introduced to avoid getting stuck in local minima and achieve fast convergence. A dynamic fuzzy learning mechanism was used to search for the best solution areas. The method was tested using 15 CEC 2015 benchmark suites and four large-scale engineering problems. Comparisons with competitive techniques proved the effectiveness of the proposed method.

Chen et al. [178] used the hybridization of chaotic GWO with the dragonfly algorithm to solve the complex and highly nonlinear problem of short-term hydrothermal scheduling. The GWO can provide local solutions, while the dragonfly algorithm is more into global solutions with premature convergence. The combination of the two algorithms provided a more capable technique. Three systems were used for testing and compared to the outcomes of other methods. The new method showed superiority over the other techniques in obtaining better scheduling schemes.

The hybrid of the GWO with the Cuckoo search algorithm was proposed by Mouhou and Badr [179] to find a low-order model with a good fit for the ideal transfer function applied to fractional order functions. Comparisons are made between the two techniques. Different numerical examples were used. The results confirmed the effectiveness of the proposed method compared to the other methods.

A nonlinear PI controller of a voltage source converter for an HVDC offshore system was optimized by Mahmoud et al. [180]. A hybrid version of the GWO and the cuckoo search algorithm was utilized in obtaining the controller parameters. The performance of the controller was tested in dynamic and transient conditions. Real wind speed patterns were used in the evaluation stage. The proposed method outperformed results obtained by other competitive methods, especially during different faults.

A new hybrid approach based on GWO and cuckoo search algorithm was proposed to extract PV cell parameters by Long et al. [181]. The proposed method used a learning strategy that utilizes opposition learning to maintain diversity in the population. The introduced approach provided a great balance between exploration and exploitation search. The introduced approach was experimented on ten benchmark test functions and then applied to PV models under different conditions. Results showed a promising approach for the PV cell parameters extraction.

Karakoyun et al. [182] proposed a GWO hybridized with the shuffled frog leaping algorithm. Some modifications were also applied to the proposed method to enhance its performance based on the cases handled. The proposed method was tested on 36 benchmark problems. Four comparison metrics were used for comparisons in addition to several statistical tests. The results were competitive and better than the existing methods.

A hybrid between the sine-cosine search algorithm and the GWO was proposed by Gupta et al. [183]. The goal was to strike a balance between exploitation and exploration, as the two algorithms vary in nature and search mechanism. The GWO has social and collective behaviour that helps in reaching un-visited areas in the search space. The hybridization of both algorithms offers a synergy between the two algorithms resulting in additional positive characteristics. Testing was done on large dimension problems with sizes 30-100 in addition to a set of benchmark engineering problems. Results proved the superiority of the proposed method over other methods.

The authors in [184] integrated two swarm-baed algorithms, called HGEOGWO, for 3D path scheduling of multiple unmanned aerial vehicles in power inspection. The learning strategy is combined with the golden eagle optimizer, PELGEO, to enhance the search process capability and avoid trapping in local optima. Next, the GWO algorithm is combined with the differential mutation strategy, called DMSGWO, to empower its exploration ability. Finally, the HGEOGWO and PELGEO are integrated using an adaptive hybridization strategy to take advantage of the two algorithms. The performance of the HGEOGWO is tested using CEC 2013 test functions and compared to other comparative methods used to solve the same problems. The numerical results illustrated the power of the HGEOGWO in terms of solution quality and stability of the algorithm. Furthermore, the HGEOGWO is applied to solve 3D path planning of multiple unmanned aerial vehicles in power inspection with satisfactory results.

Makhadmeh et al. [185] proposed a grey wolf optimizer hybridized with a multi-verse optimizer (MVO) to solve the problem of the power scheduling. The new method is called MVOG. The technique updates the worst solution generated by MVO using the GWO. The technique is applied to the other four optimization methods. The results show that the MVOG outperformed the compared state-of-the-art methods.

3) Evolutionary Algorithms with Grey Wolf Optimizer

Saxena et al. [186] combined the components of the evolutionary algorithm, including the selection operator and crossover and mutation operation, and the GWO search agents to efficiently update the positions of the search agents and balance global and local search; thus, finding better solutions. The introduced method performance was validated using benchmarked functions and real-world optimization problems. The suggested strategy exhibited and achieved more satisfactory outcomes than the compared method.

Similarly, the authors in [187] integrated the deep learning convolutional neural networks with the enhanced version of

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GWO, called EGWO-GA, for early COVID-19 discovery by precise diagnosis. In EGWO-GA, the operators of the genetic algorithm, including crossover and mutation, were integrated within the framework of the GWO to improve the population variety and exploitation ability. The EGWO-GA was evaluated using two benchmark CXR image datasets. The simulation outcomes dementated the usefulness and robustness of the EGWO-GA against other comparative algorithms.

Wang and Li [188] presented a hybrid GWO with differential evolution to prove a good global and local search balance, speed up convergence, and enhance GWO's accuracy. The proposed method was proposed for featuring evolution and elimination mechanisms. In the simulation tests, the results were carried out using 12 common benchmark functions. The results of the experiments revealed that the proposed method had a faster convergence rate and higher optimization accuracy.

Tawhid and Ibrahim [189] developed a novel technique for solving systems of complicated nonlinear equations utilizing a hybridization method that combined the GWO with differential evolution. A new improved encircling and crossover approaches are applied. The introduced approach performance was estimated using numerical experiments involving 13 optimization problems across 100 dimensions and seven benchmark equations. Empirical results revealed that the suggested approach beat competing approaches throughout the literature by finding the best candidate solutions for most nonlinear equation systems and optimization problems, demonstrating its efficiency in contrast to other methods.

Davahli et al. [190] presented an IoT intrusion detection system with great performance for resource-constrained IoT wireless networks. The genetic algorithm and the GWO were combined to address such a problem. The testing findings showed that the proposed method has the best performance compared to all compared methods.

Lei and Ouyang [191] introduced a kernel-based fuzzy clustering strategy combining an upgraded GWO with a kernel-based intuitionistic fuzzy C-means clustering method competent for image segmentation differential mutations. The hybrid approach was examined based on a comparison study. The proposed method exceeded all methods in handling the problem.

Mohsin et al. [192] proposed a hybrid optimization technique based on differential evolution and GWO. In terms of balancing exploration and exploitation, the proposed method outperformed the compared versions.

Bouzary and Frank Chen [193] presented a novel hybrid strategy based on the genetic algorithm's evolutionary operators and GWO. The incorporated crossover and mutation operators serve two purposes. Several tests were devised and carried out to illustrate the efficiency of the suggested algorithm, and the results showed that the new algorithm outperformed both the current discrete varieties of GWO and the genetic algorithm.

A new GWO version was proposed in [194] to explore and search deeply in the search space and efficiently address the job shop scheduling problem. The method was proposed utilizing four crossover operators and a local search strategy. The presented approach was tested using 69 famous benchmarks and compared with six approaches. The acquired results confirmed the approach's high performance compared to the compared methods.

The GWO was hybridized with the genetic algorithm in [195] to enhance the exploration and exploitation capabilities of the GWO to track the global peak for the energy sector problem. The introduced approach was tested and assessed by comparing its GWO and genetic algorithm performance. The approach achieved better results than the compared approaches.

4) Other Grey Wolf Optimizer hybridization

Chen et al. [196] developed a novel method that applies support vector regression and GWO address the proton life problem. The support vector regression is utilized to develop the degradation model. While the GWO is utilized to tune the hyperparameters of support vector regression to have a better prediction using the model. The proposed method is able to predict fuel cell degradation with a low mean absolute percentage error when compared to other methods.

Yang et al. [197] developed GWO-feature weighted-multiple kernel-support vector regression to forecast Full-face tunnel boring machine penetration rate. A tunnel in China is chosen to evaluate the algorithm's performance. The introduced approach is compared against three other models. The obtained results showed that the new hybrid model is producing accurate prediction results.

Zamfirache et al.[198] propose the GWO in combination with a reinforcement learning (RL)-based control approach to train the neural networks using policy iteration. This method is contrasted with the traditional PI RL-based control method that employs gradient descent and RL-based control methods as well as the particle swarm optimization algorithm. The analyses are carried out with the use of nonlinear servo scheme laboratory apparatus, and each strategy is assessed according to how effectively it handles the best reference following supervision for an empirical servo scheme location control mechanism. According to the experimental findings, the GWO algorithm provides a superior solution to the control objective taken into account in this work when compared to the GD and PSO algorithms.

Shariati et al. [199] combine extreme learning machine and GWO to develop a new hybrid ELM-GWO model for estimating concrete compressive strength parameters. The introduced approach was compared with several approaches, including support vector regression with radial basis function, adaptive neuro-fuzzy inference system, extreme learning machine, SVR with a polynomial kernel, and artificial neural network. Findings show that incorporating the ELM model into GWO may effectively enhance this model's performance, and it is inferred that the ELM-GWO model can achieve higher performance indices than other methods.

C. MULTIOBJECTIVE VERSIONS OF GREY WOLF OPTIMIZATION

Multi-objective Optimization Problems (MOPs) optimize problems that have multiple objectives [200]. Most engineering problems and real-world applications are considered to be multi-objective. Usually, these multiple objectives are conflicting. For example, when solving the assembly line problem one of the goals can be maximizing production and minimizing power consumption. Hence, one objective optimal solution may not produce other objectives' best solution [201].

Design space exploration procedure during architectural synthesis has two conflicting objectives power performance and the occupied area by resources. GWO is used to tackle this multi-objective problem [202]. Utility coefficients and utility ranking techniques are introduced to develop a unique solution. The results showed that the proposed algorithm has a better exploration and less exploration time when compared to other comparative methods on the evaluated datasets.

Multi-objective GWO (MOGWO) was developed by Dash et al. [203] for effective speech enhancement. The best set of values for different noise levels to increase the quality of speech is selected. The noisy speech was then categorized into four levels using predefined audio features. These values were then used to enhance an unknown noisy speech signal. The algorithm was evaluated on two speech datasets, and the results showed the superiority of the proposed technique compared to other comparative methods.

Li et al. [204] proposed a MOGWO for solving multi-objective complementary scheduling of hydro-thermal-RE power systems. The proposed method was utilized with real and integral variables. The proposed algorithm was tested using a hybrid system consisting of cascade hydropower stations, thermal power units, and renewable energy power plants with superior results against the other competitors.

A MOGWO with the Lévy technique was developed by Mahmoud et al. [205] to solve the voltage rise/drop by controlling the optimal voltage in distribution systems. The number of tap movements of transformers and the PV units' active power curtailment was considered when developing the solution. The proposed method was evaluated using 24-h simulation with different load types and with a 119-bus PV distribution system. The results demonstrated the efficiency of the proposed solution when compared with three other optimizers in terms of curtailed power of PV and tap movement rate of transformers.

The single document text summarization problem was tackled using a multi-objective framework that utilizes multi-objective differential evolution, MOGWO, and multi-objective water cycle algorithm [206]. The document sentences were clustered, then using the proposed multi-objective, the solution fitness was measured using the two conflicting objective compactness and separation of the sentence clusters. After that, a scoring feature was used to develop the summary. Two datasets were used to evaluate the proposed method. The comparison against other comparative methods showed the competitiveness of the proposed technique.

A MOGWO that utilized k-Nearest Neighbor was proposed to classify power quality disturbances by 2D-Riesz transform by Karasu and Saraç [207]. The power quality disturbances events are collected. Then the 1D signals are transformed into 2D signals to develop the 2D-Riesz transform. A set of statistical and image-based features was determined. The evaluation with multiple events and noisy data showed that the proposed method produced efficient results when compared to other comparative methods.

A MOGWO based on decomposition was proposed by Zapotecas-Martinez et al. [208]. It estimated the Pareto solutions cooperatively by determining the neighbourhood relation between the scalarizing sub-problems. The proposed algorithm was evaluated using two real engineering problems and a set of well-known benchmark problems. The obtained results showed the superiority of the proposed method when compared to six comparative bio-inspired methods.

The optimal mapping of cloud tasks to the set of resources is called the task schedule problem. This problem was tackled by Alsadie [209] using a MOGWO by satisfying high computing and storage requirements while reducing makespan and resource utilization. The GoCJ, HCSP, and Synthetic datasets were used to evaluate the proposed algorithm. The obtained results showed that the proposed algorithm outperformed the other comparative methods.

The generated power by the PV array is highly affected by the shadow phenomenon. A MOGWO was proposed by Yousri et al. [210] to reconfigure the shaded PV array optimally. The objective is to reduce the row current difference and increase the output power. The proposed solution was validated using six shade patterns 9-9 PV array. The obtained results revealed the efficiency of the proposed algorithm.

The voltage quality problem requires the pulse width modulation to utilize the scission-style harmonic elimination to enhance the voltage quality of the asymmetrical multi-level inverter. The MOGWO was developed by Darvish Falehi [211] to solve this problem. It was then compared against the non-dominated sorting genetic algorithm II. The experimental results showed the effectiveness of the proposed algorithm in solving this problem as it optimized the ameliorated voltage quality of the odd-nary multi-level structure.

Thresholding was utilized as a MOP by using the Otsu and Kapur techniques by Karakoyun et al. [212]. The goal is to develop a better image segmentation algorithm. A discrete MOGWO to tackle multi-level thresholding segmentation was proposed. The obtained results showed the superiority of the proposed algorithm when compared with other comparative methods.

The flexible job shop scheduling problem with job precedence constraints was tackled by Zhu and Zhou [213] using a MOGWO that utilized a mixed-integer programming mathematical model. A repair technique using a binary tree was applied to fix the job precedence constraint. The proposed algorithm was evaluated on well-known test instances. The evaluation results showed the efficiency of the proposed algorithm when compared to other techniques in terms of diversity metrics, cardinality, and convergence.

The problem of multi-objective service composition and optimal selection in cloud manufacturing was tackled in [214] by developing an enhanced MOGWO. The proposed technique used backward learning to improve the exploration capabilities of the algorithm. After that, a nonlinear adjustment strategy was used to improve the algorithm's global exploration. The proposed algorithm was compared against other comparative algorithms using a set of benchmark problems. The results proved the proposed method's performance in outperforming other comparative techniques.

In order to overcome information overload and browse answers more efficiently, it is vital to provide a set of core answers which cover most topics questioned. Li et al. [215] proposed a MOGWO to solve this problem. It started by using the bi-term topic model for texts of different sizes. After that, the core answers coverage, quality, number, and redundancy were defined. The algorithm was then used to get a predefined number of core answers. Real datasets were used to evaluate the proposed algorithm. The results showed the feasibility of the proposed algorithm.

The problem of maximizing the transmission in microwave power transmission applications requires another conflicting objective which was reducing the peak radiation level. A MOGWO was proposed in [216] to tackle this problem. The algorithm generated a new antenna design that satisfies the problem constraints. The proposed algorithm was evaluated on continuous aperture with different Fresnel parameters, space solar power satellite models, and array antennas. The obtained results showed the feasibility of the proposed algorithm.

To improve the transmission capacity of fiber optics, the optimal design of orbital angular momentum of light was proposed using the MOGWO [217]. The goal is to identify the optimal fiber cross-section refractive index profile. The proposed algorithm was compared against single-objective GWO. The results showed the proposed algorithm's effectiveness in producing 20 OAM modes supportive of optimal designs.

Predicting an offshore wind farm's short-term wind power using a two-stage hybrid model was proposed by Lu et al. [218]. The ensemble empirical mode decomposition with adaptive noise was utilized to make smoother raw data. Then, to ensure prediction stability and accuracy, a MOGWO was used to optimize the kernel-based nonlinear extension of the Arps decline model. The offshore wind farms in Belgium historical data were used to evaluate the proposed method. The results showed that the multi-objective optimizer improves the prediction performance.

The problem of choosing a set of requirements to develop in the next release of the software was tackled by Ghasemi et al. [219] using MOGWO and whale optimization algorithm. To satisfy the problem constraints, the cost-to-score ratio and the roulette wheel techniques are applied. The MOGWO, whale optimization algorithm, and other three evolutionary algorithms were used to solve such a problem. The proposed algorithms were evaluated using four datasets. The results showed the high performance of the proposed methods in addressing such a MOP.

The assembly line balancing considering preventive maintenance of machines problem was solved in [137] using an enhanced MOGWO. The algorithm applies variable step-size decoding mechanisms and tailored specific neighbour operators to improve the algorithm convergence. The proposed algorithm was compared against three other variants and six evolutionary algorithms. The obtained results showed that the proposed algorithm outperformed other comparative methods.

A novel MOGWO that applied the search strategies: boundary mutation strategy, sorting and crowding distance-based elitism strategy, and adaptive chaotic mutation strategy was proposed by Liu et al. [220]. The algorithm utilized a fixed-sized external archive to maintain the discovered non-dominated solutions. The proposed algorithm was evaluated on a set of well-known MOPs. The experimental results with other comparative multi-objective optimization algorithms showed the efficiency of the proposed algorithm. The algorithm was then evaluated on the multi-objective real-world scheduling problem of the cascade hydropower stations problem. The proposed algorithm produced good quality solutions, and it is a competitive method compared to other comparable methods.

The resource allocation problem was addressed by Kishor and Niyog [221] considering multiobjective function containing optimizing response time and imbalance between resources. A modified GWO was proposed based on the concept of the best response approach to increase the searching capabilities of the GWO. In addition, the GWO was modeled as a MOGWO to deal with the two objectives of the problem. The experimental results proved the high performance of the proposed method in optimizing the two objectives compared with the other methods.

The MOGWO was adapted and hybridized in [222] to enhance its optimization performance in addressing an enterprise service composition problem. The proposed hybridization was introduced on the bases of the components of evolutionary optimization, including crossover and mutation. The experiments were conducted in different stages and comparisons. The proposed hybrid MOGWO showed its high performance in addressing the problem by outperforming all compared multi-objective methods.

An improved MOGWO version was proposed in [223] to address the multi-objective energy scheduling problem in smart homes and optimize four objectives together. The proposed method was introduced on the basis of the neighbourhood selection strategy to emphasize the exploitation capabilities. The proposed method was tested using 30 different smart home scenarios and compared with different well-known optimization methods in several stages. The proposed method proved its robust performance compared to the other methods.

Cao et al. [224] developed a nondominated-sorting grey wolf optimizer algorithm (NSGWO) to solve the multiobjective problem of load dispatch of coal-fired power plants. The proposed technique applies a reference-point selection and a simulated binary crossover. The proposed algorithm outperforms other techniques in terms of economy, environmental protection, and speediness.

Yin and Sun [225] proposed distributed multi-objective grey wolf optimizer to solve economic dispatch optimization. The technique solves the optimization of large-scale multi-area interconnected power systems by sharing bus information between areas. The algorithm is evaluated using IEEE 39-bus and 118-bus systems. The obtained results show that the proposed algorithm outperforms other centralized optimization techniques with a better performance.

V. APPLICATIONS OF GREY WOLF OPTIMIZER

The effectiveness of GWO and its variants enables it to successfully tackle a wide range of real-world applications. This include electrical and electronic engineering [147], [148], [185], renewable energy [226], [181], [195], networking and communication [214], [186], mechanical engineering [220], [130], medical applications [227], [67], classification [228], [157], [229], [173], [85], chemical engineering [230], [231], petroleum engineering [129], [215], industrial engineering [232], [219], software engineering [65], civil engineering [233], [234], geotechnical & geoenvironmental Engineering [235], [236], planing & scheduling [170], [110], robotics [237], [127], image processing [238], [239], [240], and mathematical functions [123], [241], and others [242], [243], [244].

Table 1 presents the applications of the GWO and its variations. The applications are categorized according to the domain, the problem name, the GWO variant (i.e., original, modified, hybrid, and multi-objective), and the dataset used.

A summary of some of the main applications tackled by the GWO and its variations is demonstrated next. Electrical and electronic engineering problems are solved by variations of the GWO. This includes developing a new controller [147], maximize power point tracking for PV system [148], optimal charging pattern of Li-ion batteries [110], [245], optimizing electrical power system with distributed power generating stations [76], [246], [247], [163], [248], fractional-order proportional-integral controller [249], optimal placement of Distributed Generation (DG) units in radial distribution system [250], and economic load dispatch problem [168], [141].

The renewable energy optimization problem is tackled by GWO and its modifications. The following are some of these applications predicting solar diffuse fraction [226], parameter extraction of solar photovoltaic models [181], [195], prediction of offshore wind farm power [218], estimating photovoltaic solar cell model [121], parameter extraction of photovoltaic cells and modules [251], and optimal configuration of photovoltaic power plant [252], [253].

The networking and communication domain is another area that has been tackled by GWO and its variations, including service composition in cloud manufacturing [214], virtual network function placement [153], wireless sensor network coverage optimization [125], energy-efficient load balancing [254], energy-efficient routing in wireless sensor networks [255], antenna aperture illuminations [216], design optimization of orbital angular momentum fibers [217], and optimize the enterprise service composition problem [222].

Mechanical engineering has optimization problems of diverse types, which are solved using GWO, such as the optimal operation of cascade hydropower stations [220], transformer fault diagnosis [154], predictive torque control for electric buses [256], design of highly uniform magnetic field cylinder coils in atomic sensors [257], and fault diagnosis of rolling bearing [258].

Medical applications are another domain that utilizes the GWO. This includes applying the algorithm to solve compressive sensing MRI reconstruction [227], predicting diabetes complications [67], COVID-19 pandemic modeling and prediction [101], and breast cancer classification [259], [173].

Classification is an important machine learning problem that is applied to solve several real-world problems such as extractive single document summarization [228], gene selection [157], feature selection [83], [152], [118], [166], [74], [73], [99], [84], Arabic text classification [80], and classification of power quality disturbances [207]. On the other hand, the integration between the GWO and machine learning techniques was applied to the forecasting domain such as streamflow forecasting [260], [261], short-term load forecasting [262], and navigation technology [263].

Similarly, the GWO is investigated for tackling chemical engineering problems like modeling and optimization of lead and cobalt biosorption from water with Rafsanjan pistachio shell [230], and reference evapotranspiration estimating [231]. Furthermore, the GWO was successfully utilized for solving problems in the petroleum industry, such as forecasting the natural gas and coal consumption in Chongqing China [129], prediction for the favorable reservoir of oil based on data sampled from the Niuzhuang area (China) [215], optimizing cetane improver concentration in the biodiesel-diesel blend [264], optimizing biodiesel production from abundant waste oils [265], forecasting fuel combustion-related CO2 emissions [266], and traditional coal spontaneous combustion temperature prediction [128].

The GWO is successfully adopted for various problems from the industry domain using real-world or simulation datasets such as assembly line balancing problem [137], disassembly sequence planning [155], [164], bi-objective next release problem [219], degree reduction of SG-Bezier surfaces [232], supplier selection and order quantity allocation problem [192], daily optimal operation of cascade pumping stations [90], optimization of thermal efficiency and unburned carbon in fly ash of coal-fired utility boiler [267], optimal QoS-aware service composition and optimal selection in cloud manufacturing [193], pattern recognition method for mixture control charts [226], enhancement of an impulse turbine for oscillating water column [119], design of the spur gear pairs with minimum weight [268], forecasting of automobile sales [269], optimization of an auto drum fashioned brake [113], multi-objective disassembly sequencing and line balancing planning in disassembling multiple products [172], and optimal control parameters and design of the output filter of a grid-tied three-phase inverter [270].

In the same way, the GWO-based algorithms are applied for solving optimization problems in the civil engineering domains, like control of the nonlinear building using an optimum inverse Takagi-Sugeno-Kang model of magnetorheological damper [271], predicting the compressive strength of normal and High-Performance Concretes [233], the equipment detection and localization of large-scale construction Jobsite by far-field construction surveillance video [234], estimation of soil moisture content using a dataset from Dehgolan plain - Iran [68], predicting the dynamic modulus of asphalt mixture [272], optimization of construction duration and schedule robustness [273], and predict the compressive strength of concrete with partial replacements for cement [274].

Geotechnical & Geoenvironmental Engineering has diverse kinds of optimization problems that are tackled by the GWO-based algorithms such as groundwater remediation [235], predicting soil electrical conductivity [236], urban growth simulation and optimization using dataset sampled from Nanjing city - China [87], spatial prediction of landslide susceptibility using real-world dataset sampled from Tehri Garhwal, State of Uttarakhand - India [275], and water resources management using a real-world dataset from Shangjingyou station and Fenhe reservoir station of Fenhe River [276], estimates of greenhouse gas emission in Turkey [277].

The Planning & scheduling is another area that has been tackled by the GWO-based algorithms like casting production scheduling problem [170], flow shop scheduling problems with multi-machine collaboration [110], [136], hybrid flow shop scheduling problem considering noise pollution [86], flexible job shop scheduling problem with hierarchical job precedence constraints [213], [194], task scheduling for cloud data centers [209], short-Term hydrothermal scheduling [178], knapsack problem [81], and welding shop inverse scheduling problem [75].

Furthermore, the GWO-based algorithms are introduced to enhance the performance of robotics from various perspectives such as the path planning for Unmanned Aerial Vehicle (UAV) [278], [175], [114], multi-UAV Path Planning [140], 3D path planning of multiple UAVs in power inspection [184], multi-robot exploration & Hybrid & ordinary and complex maps [237], sliding mode control of 2-DOF robot manipulator [127], [126].

The GWO is introduced different optimization problems in the image processing domain like joint denoising and unmixing of multispectral images [238], camera calibration method [239], multi-level image thresholding [212], multi-modal image registration [279], classification of magnetic resonance brain images [280], image segmentation [191], non-blind RGB watermarking [281], sub-pixel displacement measurement [169], and key points selected to simplify the point cloud [282].

Finally, the performance of the GWO-based algorithms was evaluated using different benchmark test functions such as the classical test functions [111], [183], [192], [104], CEC 2006 [139], CEC 2014 [108], [283], [122], [115], [158], CEC 2017 [123], [96], [103], [122], CEC 2018 [135], CEC 2019 [115], classical engineering problems [96], [103], [111], [183], [122], multi-objective test functions (i.e., LZ09F, WFG, and ZDT) [208], [182]. Other problems were tackled by GWO like designing convolutional neural network-long short-term memory networks for time series analysis [242], stock selection [123], extracting core answers in community question answering [215], and automatic speech emotion detection [243].

VI. COMPARISON BETWEEN GREY WOLF OPTIMIZER VARIANTS

This section discusses the effectiveness and robustness of three GWO variants, including original, modified, and hybridized. The original version is the GWO [64], the modified is the link-based grey wolf optimizer (LBGWO) [223], and the hybrid is GWO with β-hill climbing optimizer (β-GWO) [168]. The CEC-2017 test functions are utilized to conduct such a comparison. The same GWO parameters configuration is used for the three methods to ensure a fair comparison. The number of iterations is 5000, and the population size is 30 with 30 independent runs. The achieved results by the three algorithms are compared in terms of the mean (AVG) and standard deviation (STD).

The CEC-2017 benchmark test set features 30 test functions, with 29 of them being stable and one being unstable. These tests provide a highly demanding evaluation environment. These functions imitate the intricate nature of real search spaces, which contain numerous local optimums with various shaped functions across different areas. The 30 functions are categorized into: (1) Unimodal functions, represented by functions 1 to 3, (2) Basic multimodal functions, represented by functions 4 to 10, (3) Hybrid functions, represented by functions 11 to f20, and (4) Composite functions, represented by functions 21 to 30.

The obtained results by the three algorithms are presented in Table 2, where the best results are presented in bold.

According to the results of the unimodal test functions (i.e., C-17-f1 to C-17-f3), it can be seen that the BGWO obtained the best results in the three test functions, whereas the GWO achieved the second best for the same functions. In addition, the BGWO obtained the best STD among all compared algorithms. This proves that the BGWO has superior search characteristics against the other optimization algorithms in unimodal functions.

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TABLE 1: Application of GWO on different domains

Domain	Problem	Variant	Dataset source	Ref.
Electrical and Electronic Engineering	Developed a new controller	Modified	Numerical simulation	[147]
	Optimize the model parameters of clean coal power generation	Original	Numerical simulation	[284]
	Optimize PV system with boost full-bridge isolated converter (BFBIC)	Modified	Numerical simulation	[148]
	Optimal charging pattern of Li-ion batteries	Original	Numerical simulation	[110]
	Optimizing coordinating of protective devices in electrical power system	Modified	Numerical simulation	[76]
	Fractional order proportional integral (FOPI) controller for power factor correction (PFC)	Original	Numerical simulation	[249]
	Optimal placement of Distributed Generation (DG) units in radial distribution system	Multi-objective	IEEE-33 bus radial distribution system	[249]
	Direction overcurrent relays coordination	Multi-objective	8-bus system and IEEE-30 bus system	[285]
	Predict the remaining useful life for fuel cell under different load currents	Original	Numerical simulation	[110]
	Optimal power flow (OPF) problem	Modified	IEEE 30-bus system and IEEE 118-bus system	[137]
	Economic load dispatch problem	Hybrid	five different test cases of ELD problems	[168]
	Economic load dispatch problem	Modified	four different test cases of ELD problems	[141]
	Optimal placement and sizing of active power filters in radial distribution system	Modified	IEEE-69 bus test system	[89]
	Forecasting electric loads	Modified	Numerical simulation	[97]
	Vibration tendency forecasting of hydropower generator	Modified	Ertan Hydropower Station in China	[91]
	Photovoltaic-Wind-Battery Energy System Design Considering Outage Concept	Original	Ahvaz city in Iran	[286]
	Thermal comfort and energy consumption prediction	Modified	Simulation dataset	[92]
	Complementary scheduling of hydro-thermal-RE power system	Hybrid	Simulation dataset	[204]
	Optimal placement and sizing of multiple active power filters in radial distribution system	Original	IEEE 519	[287]
	Forecasting energy production and conversion of China	Original	China Statistical Yearbook 2019, and IRENA Renewable Capacity Statistics 2020	[288]
	Energy-Aware Service Composition in Cloud Manufacturing	Modified	Simulated dataset	[156]
	Ameliorate voltage quality of odd-nary multi-level structure	Multi-objective	Simulation dataset	[211]
	Energy mix optimization in Polish	Original	Polityka Energetyczna Polski 2040	[289]
	An optimal power allocation scheme of microgrid	Original	Simulation dataset	[290]
	Approximation of Fractional-Order Systems	Hybrid	Simulation dataset	[179]
	Predict the remaining useful life of fuel cell	Hybrid	Simulation dataset	[196]
	Distributed economic dispatch optimization	Multi-objective	Simulation dataset	[225]
Renewable energy	Predicting Solar Diffuse Fraction	Hybrid	Simulation dataset	[226], [195], [253]
	Parameter extraction of solar photovoltaic models	Hybrid	Simulation dataset	[181]
	Prediction of offshore wind farm power	Multi-objective	http://www.elia.be/en	[218]
	Estimating photovoltaic solar cell model	Modified	Simulation dataset	[121]
	Parameter extraction of photovoltaic cells and modules	Modified	Simulation dataset	[251]
	Optimal configuration of photovoltaic power plant	Original	Simulation dataset	[252]
	Optimal Operation of Hydropower System	Modified	Numerical simulation	[107]
	Load dispatch of coal-fired power plants	Multi-objective	Simulation dataset	[224]
Networking and Communication	Multi-objective service composition and optimal selection (MO-SCOS) problem in cloud manufacturing	Multi-Objective	MO-SCOS problems	[214]
	Harmonic estimator design	Modified	Numerical simulation	[186]
	Virtual network function placement (VNF-P) problem	Modified	http://userweb.swjtu.edu.cn/Userweb/hxx/research.htm	[153]
	Wireless sensor network coverage optimization problem	Modified	Simulation dataset	[125]
	Energy efficient load balancing approach for avoiding energy hole problem in WSN	Modified	Simulation dataset	[254]
	Electromagnetics	Modified	Numerical simulation	[291]
	Antenna aperture illuminations for microwave power transmission	Multi-objective	Numerical simulation	[216]
	Design optimization of orbital angular momentum fibers	Multi-objective	Numerical simulation	[217]
	Peak-to-average power ratio reduction technique in OFDM scheme for high-speed wireless applications	Original	Simulation dataset	[292]
	Wireless Sensor Network Deployment of 3D Surface	Modified	Numerical simulation	[150]
	Energy-Efficient Routing in Wireless Sensor Networks	Modified	Simulation dataset	[255]
	Self-Organizing Interval Type-2 Fuzzy Asymmetric CMAC Design to Synchronize Chaotic Satellite Systems	Modified	Simulation dataset	[77]
	Estimating modal amplitude and phase of multimode near field patterns	Hybrid	Numerical simulation	[293]
	Chaotic time series prediction using echo state network	Modified	Numerical simulation	[110]
	enterprise service composition problem	Hybrid	Simulation dataset	[222]

TABLE 1: Continue...

Domain	Problem	Variant	Dataset source	Ref.
Mechanical engineering	Optimal operation of cascade hydropower stations	Multi-objective	Jinsha River CHSs in China	[220]
	Multiple Hydropower Reservoirs Operation	Hybrid	Wu River in southwest China	[130]
	Transformer fault diagnosis	Hybrid	Jiangxi Power Company dataset	[154]
	Predictive Torque Control for Electric Buses	Original	Simulation dataset	[256]
	Transformer Fault Diagnosis Using Dissolved Gases Considering Uncertainty in Measurements	Hybrid	Egyptian Electricity Utility	[165]
	Design of Highly Uniform Magnetic Field Cylinder Coils in Atomic Sensors	Original	Simulation dataset	[257]
	Robust Control of Underwater Vehicle-Manipulator System	Hybrid	Vehicle-6DOF manipulator	[294]
	Predicate full-face tunnel boring machine performance	Hybrid	Simulation dataset	[214]
	Fault diagnosis of rolling bearing	Hybrid	NSF I/UCR Center on Intelligent Maintenance Systems dataset	[258]
Medical applications	Compressive sensing MRI reconstruction	Original	https://ranger.uta.edu/ huang/Downloads.htm	[227]
	Predict diabetes complications	Modified	UCI Repository of Machine Learning Databases	[67]
	COVID-19 pandemic modelling and prediction	Modified	https://data.humdata.org/dataset/novel-coronavirus-2019-ncov-cases	[101]
	Breast cancer classification	Hybrid	GLCM dataset	[259], [173]
Classification	Extractive single document summarization	Multi-objective	DUC2001 and DUC2002 dataset	[228]
	Gene selection	Hybrid	Microarray benchmark datasets	[157]
	Feature Selection	Modified	UCI repository	[83], [152], [118], [166], [74], [73], [99], [84]
	Feature Selection	Hybrid	UCI repository	[295], [296], [176]
	Hyperspectral feature selection	Modified	Indian Pines, Pavia University, and Salinas	[297]
	Feature selection for inconsistent heterogeneous information systems	Hybrid	IHIS dataset	[298]
	Feature selection method for human activity recognition using smartphone sensors	Hybrid	UCI-HAR	[167]
	Arabic text classification	Hybrid	Akhbar-Alkhaleej dataset	[80]
	Classification of power quality disturbances	Multi-objective	LV-25P/LA-55P, and NI-cDAQ datasets	[207]
	Streamflow forecasting	Modified	Shangjingyou station and , Fenhe reservoir station	[260], [261]
	Short-term load forecasting	Hybrid	Simulation dataset	[262]
	Navigation technology	Hybrid	North University of China	[263]
Chemical engineering	Modeling and optimization of lead and cobalt biosorption from water with Rafsanjan pistachio shell	Hybrid	NA	[230]
	Reference evapotranspiration estimating	Hybrid	Simulation dataset	[231]
Petroleum Engineering	Forecasting the natural gas and coal consumption in Chongqing China	Hybrid	Chongqing dataset	[129]
	Prediction for favorable reservoir of oil	Hybrid	3D seismic data of Niuzhuang area	[215]
	Optimizing cetane improver concentration in the biodiesel-diesel blend	Original	Simulation dataset	[264]
	Optimizing biodiesel production from abundant waste oils	Hybrid	Simulation dataset	[265]
	Forecasting fuel combustion-related CO2 emissions	Hybrid	Simulation dataset	[266]
Geotechnical & Geoenvironmental Engineering	Groundwater Remediation	Hybrid	NA	[235]
	Predicting soil electrical conductivity	Hybrid	Simulation dataset	[236]
	Urban growth simulation and optimization	Modified	Nanjing City, China	[87]
	Spatial prediction of landslide susceptibility	Hybrid	Tehri Garhwal, State of Uttarakhand, India	[275]
	Water resources management	Modified	Shangjingyou station and Fenhe reservoir station of Fenhe River	[276]
	Estimates of greenhouse gas emission in Turkey	Hybrid	TURKSTAT, other Turkish datasets	[277]
Civil Engineering	Predicting the compressive strength of normal and High-Performance Concretes	Hybrid	NA	[233]
	The equipment detection and localization of large-scale construction job site by far-field construction surveillance video	Hybrid	PASCAL Visual Object Classes (VOC) 2007, 2012 and MS COCO	[234]
	Estimation of soil moisture content	Hybrid	Agricultural lands of Dehgolan plain, Iran	[68]
	Predicting the dynamic modulus of asphalt mixture	Hybrid	XXX	[272]
	Optimization of construction duration and schedule robustness	Hybrid	PSPLIB dataset	[273]
	Predict the compressive strength of concrete with partial replacements for cement	Hybrid	NA	[274]
	Control of the nonlinear building using an optimum inverse Takagi-Sugeno-Kang model of magnetorheological damper	Modified	Numerical simulation	[271]
Robotics	Multi-robot exploration	Hybrid	ordinary and complex maps	[237]
	Sliding Mode Control of 2-DOF Robot Manipulator	Modified	Simulation dataset	[127]
	Sliding Mode Control of 2-DOF Robot Manipulator	Hybrid	Simulation dataset	[126]
	The path planning for 3D multi-Unmanned Aerial Vehicle (UAV)	Modified	Simulation dataset	[278], [175], [114]
	The path planning for Unmanned Aerial Vehicle (UAV)	Hybrid	Simulation dataset	[175]
	Multi-UAV Path Planning	Hybrid	Simulation dataset	[140]
	3D path planning of multiple UAVs in power inspection	Hybrid	Simulation dataset	[184]

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TABLE 1: Continue...

Domain	Problem	Variant	Dataset source	Ref.
Industrial Engineering	Degree reduction of SG-Bezier surfaces	Hybrid	4×4, and 6×6 SG-Bezier surfaces	[232]
	Bi-Objective next release problem	Multi-objective	http:// researchers.lille.inria.fr/ xuan/-page/ project/nrp	[219]
	Disassembly sequence planning	Modified	vise, ball valve, azimuth thruster propeller, robot arm	[155]
	Assembly line balancing problem considering preventive maintenance scenarios	Modified	https://assembly-line-balancing.de/	[137]
	Supplier selection and order quantity allocation problem	Modified	Simulation dataset	[192]
	Daily optimal operation of cascade pumping stations	Hybrid	Simulation dataset	[90]
	Optimization of thermal efficiency and unburned carbon in fly ash of coal-fired utility boiler	Original	DCS dataset	[267]
	Optimal QoS-aware service composition and optimal selection in cloud manufacturing	Hybrid	Simulation dataset	[193]
	Pattern recognition method for mixture control charts	Modified	Numerical simulation	[226]
	Multi-UAV multi-target urban tracking path planning problems	Modified	Numerical simulation	[100]
	Enhancement of an impulse turbine for oscillating water column	Modified	Numerical simulation	[119]
	Design of the spur gear pairs with minimum weight	Original	Numerical simulation	[268]
	Disassembly sequencing and line balancing problem	Multi-Objective	Numerical simulation	[164]
	Forecasting of automobile sales	Original	Suteng and Kaluola	[269]
	Optimization of an auto drum fashioned brake	Modified	Numerical simulation	[113]
	Optimal control parameters and design of the output filter of a grid-tied three-phase inverter	Original	Numerical simulation	[270]
	multi-objective disassembly sequencing and line balancing planning in disassembling multiple products	Hybrid	Numerical simulation	[172]
Planing & scheduling	Casting production scheduling problem	Multi-objective	Simulation dataset	[170]
	Flow Shop Scheduling Problem with Multi-machine Collaboration	Modified	FSSP-MC instances	[110]
	Flexible job shop scheduling problem with hierarchical job precedence constraints	Hybrid	https://github.com/zzw95/FJSP_JPC/tree/master/test_instances	[213], [194]
	Hybrid flowshop scheduling problem considering noise pollution	Multi-objective	HFSP benchmarks	[86]
	Task schedule for cloud data centers	Multi-objective	GoCJ, HCSP and Synthetic dataset	[209]
	Short-Term Hydrothermal Scheduling	Hybrid	Three STHS systems	[178]
	knapsack problem	Binary	http://people.brunel.ac.uk/mastjjb/jeb/orlib/mknapinfo.html	[81]
	Welding shop inverse scheduling problem (WSISP)	Modified	WSISP problems	[75], [136]
	Power scheduling problem in smart home	Hybrid	seven consumption scenarios	[185]
	Path planning of Unmanned Aerial Vehicles	Modified	Simulation dataset	[162]
Image processing	Joint denoising and unmixing of multispectral images	Modified	tensor	[238]
	Camera calibration method	Modified	Simulation dataset	[239]
	Multi-level image thresholding	Modified	Berkeley dataset	[212]
	Multimodal image registration	Hybrid	Synthetic dataset	[279]
	Classification of magnetic resonance brain images	Hybrid	Harvard Medical School, and BRATS	[280]
	Image Segmentation	hybrid	Iris, and UCI	[191]
	Non-blind RGB watermarking	Modified	RGB images and Watermarked images	[281]
	Sub-pixel displacement measurement	Hybrid	Synthetic speckle images	[169]
	Key points selected to simplify the point cloud	Modified	The Stanford 3D Scanning Repository	[282]
Others	Designing Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) networks for time series analysis	Modified	Cbenchmark problems	[242]
	Software Engineering	Hybrid	UCI repository	[65]
	Stock selection	Hybrid	http://choice.eastmoney.com/	[123]
	Extracting core answers in community question answering	Original	Zhihu and Yahoo!Answers QA dataset	[215]
	Automatic speech emotion detection	Hybrid	SAVEE and TESS datasets	[243]
	Test functions	Hybrid	CEC 2017	[123]
		Modified	CEC 2017 and engineering problems	[96], [103], [120]
		Multi-objective	DTLZ	[208]
		Hybrid	DTLZ, LZ09F, WFG and ZDT	[182]
		Modified	CEC 2018	[135]
		Hybrid	Integer and mixed-integer problems	[241]
		Hybrid	classical test functions, and engineering problems	[111], [183]
		Hybrid	classical test functions	[192]
		Modified	classical test functions, and engineering problems	[104], [198], [116], [117], [79]
		Modified	classical test functions, and CEC 2014	[108], [115], [158]
		Hybrid	classical test functions, and CEC 2014	[283]
		Modified	classical test functions	[142], [151], [105]
		Modified	CEC 2006 and CEC 2014	[139]
		Modified	classical test functions, CEC 2014, and KELM	[299]
		Modified	classical test functions, CEC 2014, and engineering problems	[106]
		Modified	CEC 2014, CEC 2017, and engineering problems	[138], [122]
		Modified	CEC 2014, CEC 2017, and large-scale numerical optimization problems	[300]
		Modified	test functions and real-world problems	[105]
		Modified	CEC 2019 and real-world problems	[105]
		Modified	CEC 2018 and real-world problems	[78]

TABLE 2: Comparison between GWO, LGWO, and BGWO

Function	Measure	GWO	LGWO	BGWO
Fun 1	AVG	11564013.83	277635737.77	**3013.85**
	STD	77129790.73	398464430.50	**690.91**
Fun 2	AVG	4019015.57	1334283570.97	**7534.64**
	STD	16277161.73	4535252236.03	**690.91**
Fun 3	AVG	1107.81	3706.89	**300.43**
	STD	1601.53	2452.92	**1.05**
Fun 4	AVG	409.46	440.52	**400.00**
	STD	9.04	34.80	**0.00**
Fun 5	AVG	509.31	528.47	**500.00**
	STD	4.91	5.68	**0.01**
Fun 6	AVG	600.36	610.32	**600.01**
	STD	1.81	5.90	**0.00**
Fun 7	AVG	723.82	747.59	**704.37**
	STD	6.11	7.89	**5.99**
Fun 8	AVG	810.34	821.34	**800.00**
	STD	5.45	6.76	**0.01**
Fun 9	AVG	917.91	964.09	**900.00**
	STD	60.13	77.23	**0.00**
Fun 10	AVG	1456.41	1959.39	**1000.05**
	STD	296.43	313.45	**0.06**
Fun 11	AVG	1130.59	1328.03	**1100.00**
	STD	39.19	801.00	**0.01**
Fun 12	AVG	124550.98	920846.21	**1233.12**
	STD	945659.94	754327.14	**12.94**
Fun 13	AVG	4534.84	8876.58	**1304.09**
	STD	5894.38	3425.20	**0.94**
Fun 14	AVG	1815.34	3291.46	**1400.46**
	STD	1378.90	1828.60	**0.52**
Fun 15	AVG	2024.14	3905.45	**1500.22**
	STD	1107.76	2259.67	**0.29**
Fun 16	AVG	1680.12	1834.81	**1600.04**
	STD	72.64	156.33	**0.01**
Fun 17	AVG	1737.13	1774.27	**1700.05**
	STD	16.98	36.50	**0.02**
Fun 18	AVG	20934.37	27568.68	**1802.23**
	STD	13635.92	9917.83	**0.87**
Fun 19	AVG	2664.92	7554.32	**1900.27**
	STD	46814.38	5407.43	**0.16**
Fun 20	AVG	2076.49	2097.00	**2000.05**
	STD	50.30	59.35	**0.01**
Fun 21	AVG	2301.76	2311.70	**2108.34**
	STD	29.41	41.47	**28.87**
Fun 22	AVG	2322.78	2330.89	**2222.47**
	STD	117.39	**30.18**	40.82
Fun 23	AVG	2613.13	2640.10	**2300.01**
	STD	6.25	11.11	**0.00**
Fun 24	AVG	2732.55	2748.79	**2500.02**
	STD	3.97	61.86	**0.00**
Fun 25	AVG	2925.58	2935.87	**2808.55**
	STD	**19.45**	22.48	143.62
Fun 26	AVG	3150.69	3316.66	**2622.37**
	STD	419.32	395.55	**66.67**
Fun 27	AVG	3095.30	3130.37	**3086.89**
	STD	9.42	35.79	**0.00**
Fun 28	AVG	3361.30	3410.47	**2900.28**
	STD	**83.36**	122.38	149.82
Fun 29	AVG	3169.45	3217.27	**3045.58**
	STD	42.26	42.51	**0.08**
Fun 30	AVG	289160.55	1477449.27	**3426.58**
	STD	677985.04	2134784.53	**17.46**

In terms of multimodal test functions, it can be observed that the BGWO was ranked first by obtaining the best results in all test functions, including the fourth to the tenth functions, while the GWO was ranked second. The LGWO was reported third by achieving the worst results in all test functions. Furthermore, the BGWO outperformed the compared algorithms in achieving the best STD. Based on the above discussion, we can conclude that the BGWO is superior in searching for optimal solutions compared to GWO and LGWO.

For the Hybrid test functions, also the BGWO obtained the best outcomes compared with the GWO and LBGWO, where it achieved the best AVG and STD results in all test functions. Accordingly, the BGWO outperformed the competing algorithms in optimizing the Hybrid test functions. According to Composite functions, the BGWO also outperformed the compared algorithms by obtaining the best AVG and STD in all and seven functions, respectively.

VII. CRITICAL ANALYSIS OF GREY WOLF OPTIMIZER THEORY

The critical analysis section will provide the research gaps in the optimization framework of GWO when dealing with some non-convex, nonlinear, multimodal, and constrained optimization problems. During our theoretical review, different GWO versions have been proposed by either combining efficient operators from other optimization algorithms or hybridizing GWO with other algorithms to improve the balance between the exploration and exploitation search process when dealing with rugged and deep search spaces.

Based on the optimization behaviour of GWO, it has two groups which are the follower (i.e., omega) and three leaders (i.e., alpha, beta, and delta). The leaders represent the best three solutions so far found (i.e., first-best, second-best, and third-best). The members of omega groups are attracted by the leader groups and their base values. This structure reveals very efficient outcomes when dealing with "free optimization problem (FOP)" [1]. However, when the "constrained optimization problem (COP)" is subject to be addressed, the ruggedness and the shape of the search space will be substantially increased. Therefore, the process of focusing on the leaders to attract followers might drive the search toward premature convergence. Thus, the search shall also be injected with random elements to improve the diversity of the search space. For example, the GWO has been combined with a random walk to improve the exploration process [76], [77]. Furthermore, the Chaotic concepts as exploiter engines have been incorporated inside GWO [96], [97], [98]. Also, in the Opposition GWO, the diversity behaviour is improved [71], [105]

Another issue that has been tackled in the theory of GWO is the definition of the search space based on the nature of the problem decision variables. In its base article published in 2014, GWO was proposed to deal with the continuous domains (or real values decision variables). However, there are different encoding systems in the genotype space for the different types of optimization problems, such as binary, discrete, permutation, graph structure, and network. To deal with these genotype spaces, the theory of GWO has to be adjusted. For example, different binary GWO instances have been proposed to deal with binary search space [74], [301], [80], [81], [82]. These instances are different in terms of the to-binary transfer function, the recombination process, and the randomness process. Also, the discrete search space has been well-defined and the GWO operators have adjusted

[1]this refers to the problems with only objective function not restricted by any constraints

accordingly [75], [140], [164]. In dealing with permutation search space like the traveling salesman problem where the decision variables are not duplicated and not missed, the operator of GWO has been also modified to preserve the integrity of the solution during the inheritance process [302].

In any evolutionary algorithm (EA) like GWO, the losing diversity dilemma can be dealt with either implicitly or explicitly. The implicit approach is normally injected with problem encoding by adding restricted values to the solution to define a forbidding area. In the explicit approaches, the structured population algorithms such as island model [303], Cellular automata [86], [87] and Gaussian theory [100], [101] are used to improve the diversity power of GWO.

The parameter values in evolutionary algorithms play important role in the convergence behaviour and ensure the right balance between the exploration and exploitation of the search space. Although the initial version of GWO has been established without any parameter settings, there are three control parameters that are initialized randomly within specific ranges (i.e., a, A, and C). However, these control parameters have a great impact on the performance of GWO. Therefore, several trials to improve the convergence behaviour of GWO have been conducted, such as adaptive GWO [70], [88], [91], and Dynamic GWO [103], [104].

Indeed, the convergence strength of any evolutionary algorithm, such as GWO is proved when dealing with large-scale optimization problems. This is because the complexity is increased and the search space will be huge. Therefore, to deal with a large-scale optimization problem, the structured GWO is proposed in many pieces of research [118], [119], [120]. To empower the research behaviour, the hybrid mechanism with local search has also revealed very successful outcomes such as Neighbour GWO [135], [75] and memetic GWO [163], [164]. Finally, the exploration and exploitation process is balanced during the search using Fractional GWO [72], [129].

The main limitation of the GWO is connected to the NFL optimization theorem, which is also a challenge faced by other optimization algorithms. The NFL theorem asserts that no single optimization algorithm can outperform all others for every type of optimization problem or every instance of the same problem [304]. Consequently, the convergence of the GWO heavily depends on the properties of the problem's search space. Therefore, in an unfamiliar search space, it is essential to adapt or combine the GWO with other techniques to tackle the optimization task.

VIII. CONCLUSION AND FUTURE WORK

Grey wolf optimizer (GWO) gains substantial attention from a wide range of research communities due to its superb features. The strengths of GWO lie in its ability to synergy the trade-off between exploration and exploitation during the search process. Accomplishing an outstanding review for GWO is not a trivial task due to the fact that it is growing rapidly over the last three years where more than 750 articles (Journal paper, conference, book chapter, book, review, etc.) have been published. Therefore, in this review paper, we have only focused on the Scopus journal papers published in the last four years (2019-2022).

Although GWO behaves perfectly when dealing with mathematical or free optimization problems. Its performance is degraded when addressing non-convex, multimodal, non-linear, highly-constrained optimization problems with deep and rugged search space. Therefore, different versions of GWO have been proposed in the literature to deal with such problems. In some state-of-the-art, the GWO is hybridized with other optimization algorithms especially the algorithm is empowered using local search (i.e., memetic strategy) to enhance its search capability. Also, GWO has been adjusted to deal with multi-objective optimization problems.

Due to its proven efficiency, researchers from different research backgrounds have been encouraged to utilize GWO for their optimization problems. Therefore, GWO has been used to solve different kinds of optimization problems from different research domains such as electrical and electronic engineering, renewable energy, networking and communication, mechanical engineering, and many others. Indeed, researchers nowadays like to start with GWO to tackle their problems because it has an efficient and simple optimization framework. We believe that GWO will gain much interest in the future.

The main limitations of GWO are reviewed in previous sections which are related to losing diversity due to its focus on the three best solutions to adjust other solutions. Additionally, its degraded performance when dealing with large-scale optimization problems and the parameter settings dilemma to boost its performance. The discrete, binary, permutation genotype space required tweaking in the GWO optimization structure to deal with the genotype space shape.

Several future research directions can be tackled by researchers. The following are some of these possible future research directions:

Structured population: A Structured population means dividing the population into several parts. It can be in different forms such as island models, cellular automata, hierarchical models, etc. [305]. This population organization can improve the diversity of the developed solutions. The GWO is modified using island models to tackle specific problems (e.g., [306]). In the future, other structured population models can be utilized and evaluated.

Adaptive Parameters: The performance of GWO depends on the chosen values of its control parameters. Considerable research work is proposed to develop parameter-free GWO [70], [88], [90]. Developing a black box robust parameter-free GWO can be a future direction.

Hybrid Strategy: The complexity of real-world problems requires improving GWO capabilities as it requires dealing with a deep and rugged problem search space [223]. The exploration and exploitation processes of GWO can be improved by hybridizing the technique with other techniques as a possible path for future investigation for optimization problems that are non-linear, non-convex, highly constrained, combinatorial, and multimodal.

Tackling multi-objective problems : A number of research works is applied to apply GWO to tackle multi-objective problems (e.g., [217], [216], [214]). The GWO can utilize popular multi-objective optimization frameworks such as NSGA II and MOEA/D [307]. The multi-objective stopping criterion influences the final solution quality. Another future direction can be choosing the proper multi-objective stopping technique [308].

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest

DATA AVAILABILITY

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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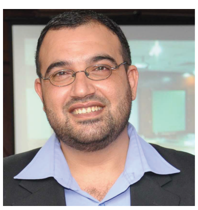

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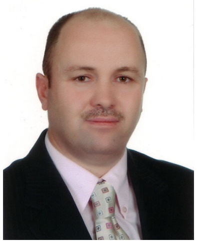

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