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Review Article

A comprehensive survey of golden jacal optimization and its applications

Mehdi Hosseinzadeh [a,b,1], Jawad Tanveer [c,1], Amir Masoud Rahmani [d], Abed Alanazi [e], Monji Mohamed Zaidi [f,g], Khursheed Aurangzeb [h], Hamid Alinejad-Rokny [i], Thantrira Porntaveetus [j,*], Sang-Woong Lee [k,*]

[a] *School of Computer Science, Duy Tan University, Da Nang, Vietnam*
[b] *Jadara University Research Center, Jadara University, Irbid, Jordan*
[c] *Department of Computer Science and Engineering, Sejong University, Seoul 05006, South Korea*
[d] *Future Technology Research Center, National Yunlin University of Science and Technology, Yunlin, Taiwan*
[e] *Department of Computer Science, College of Computer Engineering and Sciences in Al-Kharj, Prince Sattam bin Abdulaziz University, P.O. Box 151, Al-Kharj 11942, Saudi Arabia*
[f] *Department of Electrical Engineering, College of Engineering, King Khalid University, Abha, 61421, Saudi Arabia*
[g] *Center for Engineering and Technology Innovations, King Khalid University, Abha 61421, Saudi Arabia*
[h] *Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, P. O. Box 51178, Riyadh, 11543, Saudi Arabia*
[i] *UNSW BioMedical Machine Learning Lab (BML), The Graduate School of Biomedical Engineering, UNSW Sydney, 2052, NSW, Australia*
[j] *Center of Excellence in Genomics and Precision Dentistry, Clinical Research Center, Geriatric Dentistry and Special Patients Care International Program, Department of Physiology, Faculty of Dentistry, Chulalongkorn University, Bangkok, Thailand*
[k] *Pattern Recognition and Machine Learning Lab, School of Computing, Gachon University, Seongnam 13120, South Korea*

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ABSTRACT

In recent decades, there has been an increasing interest from the research community in various scientific and engineering fields, including robotic control, signal processing, image processing, feature selection, classification, clustering, and other issues. Many optimization problems are inherently complicated and complex. They cannot be solved by traditional optimization methods, such as mathematical programming, because most conventional optimization methods focus on evaluating first derivatives. On the other hand, metaheuristic algorithms have high ability and adaptability in finding near-optimal solutions in a reasonable time for different optimization problems due to parallel search and balance between exploration and exploitation. This study discusses the basic principles and mechanisms of the GJO algorithm and its challenges. This review aims to provide valuable insights into the potential of the GJO algorithm for real-world and scientific optimization tasks. In this paper, a complete review of the Golden Jackal Optimization (GJO) algorithm for various optimization problems is done. The GJO algorithm is one of the metaheuristic algorithms invented in 2022 and inspired by the life of natural jackals. This paper's complete classification of GJO in hybrid, improved, binary, multi-objective, and optimization problems is done. The analysis shows that the percentage of studies conducted in the four fields of hybrid, improved variants of GJO (binary, multi-objective), and optimization are 11 %, 44 %, 9 %, and 36 %, respectively. Studies have shown that this algorithm performs well in real-world challenges. GJO is a powerful tool for solving scientific and engineering problems flexibly.

1. Introduction

Constrained nonlinear optimization is concerned with finding the best possible solution from a set of available options by minimizing or maximizing a specific objective function [1]. This area is crucial in various fields, such as engineering, finance, physics, and management, offering numerous practical applications [2]. Depending on the nature of the objective function and the constraints involved, these

* Corresponding authors.
E-mail addresses: mehdihosseinzadeh@duytan.edu.vn (M. Hosseinzadeh), Jawadtanveer@sejong.ac.kr (J. Tanveer), rahmania@yuntech.edu.tw (A.M. Rahmani), ad.alanazi@psau.edu.sa (A. Alanazi), amzaydi@kku.edu.sa (M.M. Zaidi), kaurangzeb@ksu.edu.sa (K. Aurangzeb), h.alinejad@unsw.edu.au (H. Alinejad-Rokny), thantrira.p@chula.ac.th (T. Porntaveetus), slee@gachon.ac.kr (S.-W. Lee).
[1] These authors contributed equally to this work.

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optimization problems are categorized into two primary types: convex and nonconvex. Convex optimization problems, encompassing methods like linear and quadratic programming, represent a specialized subset within the broader realm of nonconvex optimization challenges and have attracted significant research attention. Strategies such as the primal-dual interior point method have been developed to address these problems effectively. In contrast, nonconvex optimization problems are known for their complexity and are typically tackled with gradient descent-based techniques. However, these methods often face challenges in achieving global optimality, representing a common obstacle in the optimization process [3].

Current optimization methods include well-established techniques such as linear programming, mixed-integer programming, nonlinear programming, and integer programming. These are complemented by newer methods such as Newton's method, the conjugate gradient method, and the gradient descent method [4]. While these approaches are practical for globally optimizing certain types of problems, they typically require conditions like the convexity of the solution space, continuity in the objective function, or specific additional constraints to be met [5]. However, complex optimization challenges often present characteristics such as non-differentiability, non-convexity, or multimodality, which complicate their resolution within traditional frameworks [6]. Consequently, conventional optimization strategies can encounter significant difficulties when faced with large-scale and intricate problems.

In light of the challenges faced, there is an increasing demand for optimization algorithms that are accurate, efficient, and robust enough to tackle complex problems. Metaheuristic (MH) algorithms have become a key solution, gaining widespread acceptance for their ability to approach optimal solutions in diverse optimization contexts. These algorithms often incorporate stochastic elements and are capable of delivering near-optimal outcomes in various scenarios [7,8]. Drawing inspiration from the collective behaviors observed in nature, such as those of ants, bees, and birds, MH algorithms are marked by their collaborative and competitive dynamics, along with their self-organizing and adaptive qualities [9]. The strengths of MH algorithms lie in their integration of swarm intelligence principles with optimization theories, offering notable advantages such as ease of implementation, exceptional stability and resilience, and effective scalability [10]. High-dimensional solution spaces, nonlinear relationships, and the existence of multiple local optima lead to the failure to find a global optimum in optimal computational time [11]. MH algorithms are effective as powerful tools for optimizing complex and nonlinear problems. Optimization problems often involve constraints that make it difficult to find practical solutions [12]. MH algorithms use intelligent strategies such as balancing and optimal exploitation to handle the constraints flexibly.

The superiority of MH algorithms compared to conventional methods stems from their gradient-free approach and their ability to circumvent local optima [13]. Traditional optimization methods often struggle with the issue of getting trapped in local optima, resulting in slow convergence rates and hindering their ability to identify global optimal solutions. In contrast, MH algorithms offer greater flexibility and adaptability, making them applicable across a wide range of problems without requiring a deep understanding of the specific optimization landscape [14]. In contrast to traditional methods, MH algorithms explore many potential solutions, increasing the likelihood of discovering excellent solutions with fewer computational resources. Over time, MH algorithms, endowed with unparalleled advantages over traditional methods, have evolved into iterative adaptive heuristic probabilistic search algorithms [15,16]. With their adaptability, capacity for global optimality, and inherent parallelism in addressing diverse nonlinear problems, metaheuristic algorithms hold unique appeal and offer expanded application prospects in engineering design.

Researchers have, researchers, have introduced a range of optimization techniques: physics-based, evolution-based, swarm-based, nature-based physics-based algorithms, evolution-based algorithms, swarm-based algorithms, nature-based algorithms, and human-based algorithms. Physics-based algorithms include Gradient-based Optimizer (GBO) [17], Golden Sine Algorithm (GSA) [18], Charged System Search (CSS) [19], Sine Cosine Algorithm (SCA) [20], etc. Evolution-based algorithms include Biogeography-based optimization [21], biology migration algorithm (BMA) [22], Barnacles Mating Optimizer (BMO) [23], etc. Swarm-based algorithms include Particle swarm optimization (PSO) [24], Seagull Optimization Algorithm (SOA) [25], Emperor Penguin Optimizer (EPO) [26], Sparrow Search Algorithm (SSA) [27], etc. Nature-based algorithms include Golden Jackal Optimization (GJO) [28], Farmland Fertility Algorithm (FFA) [29], Grey Wolf Optimizer (GWO) [30], Electric Eel Foraging Optimization (EEFO) [31], Dung Beetle Optimizer (DBO), Manta Ray Foraging Optimization (MRFO), Capuchin Search Algorithm (CapSA) [32], Greylag Goose Optimization (GGO) [33]Forty Thievesbased algorithms include Ali Baba and the forty thieves (AFT) [34], Gaining Sharing Knowledge based Algorithm (GSK) [35], coronavirus herd immunity optimizer (CHIO) [36], etc.

Each of these algorithms surpasses traditional ones in their respective contexts and continues to develop. The primary objective of all generated algorithms is to locate an optimal solution (global optimum) from the pool of available solutions within the search space. MH algorithms function through two key phases: exploration and exploitation. Exploration involves traversing the entire search space to identify the global optimum, while exploitation entails focusing on previously identified potential subspaces to converge toward the optimal solution [37,38]. A successful MH algorithm balances exploration and exploitation, ultimately achieving the finest optimal solution [39]. Traditional optimization methods, such as gradient-based and exhaustive search methods, often face many challenges when dealing with complex, multidimensional, or nonlinear problems. These methods usually get stuck in local optima, require significant computational resources, and are highly dependent on the mathematical formulation of the problem [40]. In real-world applications, these limitations can significantly reduce the efficiency of these methods, especially in dynamic and multi-objective problems. In contrast, metaheuristic algorithms inspired by nature can explore the search space more efficiently. For example, the GJO algorithm has overcome the limitations of traditional methods by utilizing various strategies and providing powerful solutions to optimization challenges.

The Golden Jackal Optimization (GJO) [28] algorithm, unveiled by Chopra and Ansari in 2022, introduces a novel, nature-inspired approach to optimization, aligning with the broader family of MH algorithms. This technique is specifically designed to tackle complex engineering problems by emulating the cooperative hunting strategies of Golden Jackals. These animals are known for their group hunting tactics, employing a systematic process that includes locating, encircling, and ultimately overpowering their prey. The GJO algorithm encapsulates this behavior into two primary phases: the exploration phase, which focuses on detecting, following, and closing in on the prey, and the exploitation phase, which involves the strategic encirclement and final assault on the prey. The GJO algorithm stands out for its global optimization capabilities, requiring only a few control parameters to simplify its application. Furthermore, it is characterized by its high level of stability and the ease with which it can be implemented. The significant contributions of this research include the introduction of the GJO algorithm itself, an in-depth exploration of its theoretical underpinnings, and its practical implications for solving real-world engineering problems.

- A comprehensive review of the GJO algorithm is done. This review includes changes and improvements to the GJO algorithm. The limitations and advantages of GJO compared to other algorithms are investigated

- All hybrid models of the GJO algorithm have been thoroughly investigated and analyzed
- This study has investigated the binary and multi-objective models of the GJO algorithm.
- All problems and areas that have used the GJO algorithm have been examined using formulas and results.
- Advantages and disadvantages of GJO compared to other algorithms are investigated.
- Applied concepts and methods of solving optimization problems are proposed as future works.

The structure of this paper is as follows: Section 2 describes the growth of GJO. Section 3 states the definition of GJO and its mathematical model. In Section 4, all versions and modifications of GJO are reviewed. GJO methods are classified into four categories: hybridization, improvement, GJO variations, and optimization problems. Section 5 describes convergence behavior analysis. This section compares the GJO algorithm with other algorithms based on convergence. Section 6 will discuss GJO, including its capabilities, advantages, and disadvantages. In Section 7, we discuss the final summary and future works.

2. The growth of GJO

This section examines the growth trend of GJO-related research from various angles. These aspects include the number of citations to GJO-related articles and the number of articles published in multiple journals. It also examines the leading countries that publish GJO-related research, prominent academic institutions and organizations, and authors focused on the GJO field.

Table 1 shows the most cited GJO articles from 2022 to 2024. The article "Golden Jackal Optimization: A Novel nature-inspired Optimizer for Engineering Applications" had the most impact, with 519 citations. This indicates that this article pioneered this algorithm's introduction and initial application. The reviewed articles were published in various countries, including India, Egypt, China, Iran, Saudi Arabia, and Turkey. This geographical diversity indicates the importance and widespread application of the GJO algorithm in various scientific and industrial

Table 1
GJO articles with the most citations (Source: https://scholar.google.com).

Title	Authors	Journal	Publisher	Country	Year	Cited
Golden jackal optimization: A novel nature-inspired optimizer for engineering applications [28]	Nitish Chopra, Muhammad Mohsin Ansari	Expert Systems with Applications	Elsevier	India, Pakistan	2022	519
An efficient image segmentation method for skin cancer imaging using an improved golden jackal optimization algorithm [41]	Essam H. Houssein, Doaa A. Abdelkareem, Marwa M. Emam, Mohamed Abdel Hameed, Mina Younan	Computers in Biology and Medicine	Elsevier	Egypt	2022	119
Model parameters estimation of the proton exchange membrane fuel cell by a Modified Golden Jackal Optimization [42]	Mehrdad Rezaie, Keyvan karamnejadi azar, Armin kardan sani, Ehsan Akbari, Noradin Ghadimi, Navid Razmjooy, Mojtaba Ghadamyari	Sustainable Energy Technologies and Assessments	Elsevier	Iran, Iraq	2022	104
Prediction of tribological properties of alumina-coated, silver-reinforced copper nanocomposites using extended short-term model combined with golden jackal optimization [43]	Ismail R. Najjar, Ayman M. Sadoun, Adel Fathy, Ahmed W. Abdallah, Mohamed Abd Elaziz and Marwa Elmahdy	Lubricants	MDPI	Saudi Arabia, Egypt	2022	69
A multi-objective optimization (MOO) solution for distributed generation energy management in microgrids with hybrid energy sources and battery storage systems [44]	R. Praveen Kumar, G. Karthikeyan	Journal of Energy Storage	Elsevier	India	2024	58
Performance prediction of aluminum and polycarbonate solar stills with air cavity using an optimized neural network model by golden jackal optimizer [45]	Emad Ghandourah, Y.S. Prasanna, Ammar H. Elsheikh, Essam B. Moustafa, Manabu Fujii, Sandip S. Deshmukh	Case Studies in Thermal Engineering	Elsevier	Saudi Arabia, India, Japan, Egypt	2023	45
Fast random opposition-based learning Golden Jackal Optimization algorithm[46]	Sarada Mohapatra, Prabhujit Mohapatra	Knowledge-Based Systems	Elsevier	India	2023	43
A Hybrid Golden Jackal Optimization and Golden Sine Algorithm with Dynamic Lens-Imaging Learning for Global Optimization Problems [47]	Panliang Yuan, Taihua Zhang, Liguo Yao, Yao Lu, and Weibin Zhuang	Applied Sciences	MDPI	China	2022	32
A novel deep learning ensemble model based on two-stage feature selection and intelligent optimization for water quality prediction [48]	Wenli Liu, Tianxiang Liu, Zihan Liu, Hanbin Luo, Hanmin Pei	Environmental Research	Elsevier	China	2023	30
Copula entropy-based golden jackal optimization algorithm for high-dimensional feature selection problems [49]	Heba Askr, Mahmoud Abdel-Salam, Aboul Ella Hassanien	Expert Systems with Applications	Elsevier	Egypt	2024	29
Adaptive infinite impulse response system identification using an enhanced golden jackal optimization [50]	Jinzhong Zhang, Gang Zhang, Min Kong & Tan Zhang	The Journal of Supercomputing	Springer	China	2023	28
IGJO: an improved golden Jackel optimization algorithm using a local escaping operator for feature selection problems [51]	R. Manjula Devi, M. Premkumar, G. Kiruthiga & R. Sowmya	Neural Processing Letters	Springer	India	2023	27
Intrusion detection in the Internet of Things using improved binary golden jackal optimization algorithm and LSTM [52]	Amir Vafid Hanafi, Ali Ghaffari, Hesam Rezaei, Aida Valipour & Bahman Arasteh	Cluster Computing	Springer	Iran, Turkey	2024	20
Golden jackal optimization algorithm with deep learning assisted intrusion detection system for network security [53]	Nojood O. Aljehane, Hanan Abdullah Mengash, Majdy M. Eltahir, Faiz Abdullah Alotaibi, Sumayh S. Aljameel, Ayman Yafoz, Raed Alsini, Mohammed Assiri	Alexandria Engineering Journal	Elsevier	Saudi Arabia	2024	19
A hybrid strategy-based GJO algorithm for robot path planning [54]	Tai-shan Lou, Zhe-peng Yue, Yu-Zhao Jiao, Zhen-dong He	Expert Systems with Applications	Elsevier	China	2024	18
IBGJO: Improved Binary Golden Jackal Optimization with Chaotic Tent Map and Cosine Similarity for Feature Selection[55]	Kunpeng Zhang, Yanheng Liu, Fang Mei, Geng Sun and Jingyi Jin	Entropy	MDPI	China	2023	12

problems. Most GJO articles have been published in Elsevier journals, which means the prestigious position of this publication in accepting and publishing-related research.

Fig. 1 shows the relationship between the GJO algorithm and the keywords. In the center of the graph, the GJO algorithm is located and is connected with dotted lines to concepts such as Optimization, Metaheuristics, and Global Optimization. These concepts include algorithm applications in Machine Learning, Deep Learning, and Engineering Problems. Feature Selection, Benchmark Function, and Multi-Objective can be mentioned. Also, concepts such as Adaptive Strategy, Internet of Things, and Image Segmentation indicate the algorithm's capabilities in solving complex problems. The relationship between Opposition-based Learning and Chaotic Mapping is also clearly shown. This graph emphasizes that GJO is a metaheuristic algorithm with broad applications in mathematics, computing, and optimization of complex problems. This algorithm is designed to solve complex problems with a creative and adaptive approach and can be generalized to many practical problems.

Table 2 lists the most recent published papers based on the GJO. According to the documents published in 2025, the GJO continues to be recognized as a powerful and practical tool in solving complex problems and various engineering and computer science optimizations. This shows that GJO, as a reliable and effective algorithm, will continue to be used in the coming years and will be able to solve new challenges in various fields, such as energy management, cloud computing, dynamic modeling, and complex data analysis. The GJO has been effectively used in multiple fields such as energy, cloud computing, resource management, and modeling due to its features, such as optimizing complex and challenging spaces, and its learning and information processing capabilities with limited data. GJO applications usually involve complex optimization problems that require accurate modeling and complex decision-making. The GJO has explicitly been used with a progressive conditional generative adversarial network (PCGAN) to optimize energy mix in microgrids and electric vehicle charging. This optimization is suitable for managing energy resources, reducing costs, and increasing efficiency. Using a recurrent autoencoder, the GJO has also been used to schedule tasks in cloud environments. This research shows that GJO can be effectively used for task scheduling in cloud computing with various conditions and constraints. Since cloud tasks may face latency, network traffic, and limited resources, using the GJO for scheduling optimization is very effective.

Fig. 2 plots the number of articles published in Elsevier journals based on the GJO algorithm. The vertical axis shows the names of the different journals, and the horizontal axis indicates the number of articles published in each journal. Clearly, "Expert Systems with Applications" has the highest number of publications, with 17 articles. Other journals have published fewer articles. The graph shows that some specialized journals, such as "Knowledge-Based Systems" and "Applied Soft Computing," have published more articles than others.

Fig. 3 plots the distribution of GJO articles with the highest number in different journals. These journals belong to the three leading publishers: Elsevier, Springer, and IEEE. The highest number of articles is related to journals such as "Expert Systems with Applications," "Knowledge-Based Systems," and "Applied Soft Computing," which indicates the high focus of this algorithm in the fields of expert systems, soft computing, and knowledge-based systems. Also, reputable journals such as "Scientific Reports" from Springer and "Access and IEEE" from IEEE indicate that the GJO algorithm has been used in various scientific fields, including applied mechanical engineering, bioengineering, and software engineering. The distribution of these articles in prominent journals of different publishers indicates the impact and scope of GJO application in research and industrial issues.

Fig. 4 plots the distribution of GJO papers in Springer based on different topics between 2022 and 2025. The most significant number of articles is in the optimization field, with 111 articles indicating the widespread use of this algorithm in solving optimization problems. Topics related to continuous optimization (93 articles) and learning algorithms (73 articles) are in the following positions. Other widely used areas include discrete algorithms (64 articles) and variational and optimization calculations (37). Also, topics such as machine learning (16 articles), computational intelligence (15 articles), and image processing (9 articles) indicate more specialized applications of GJO in various sciences. This distribution shows that the GJO algorithm has been used

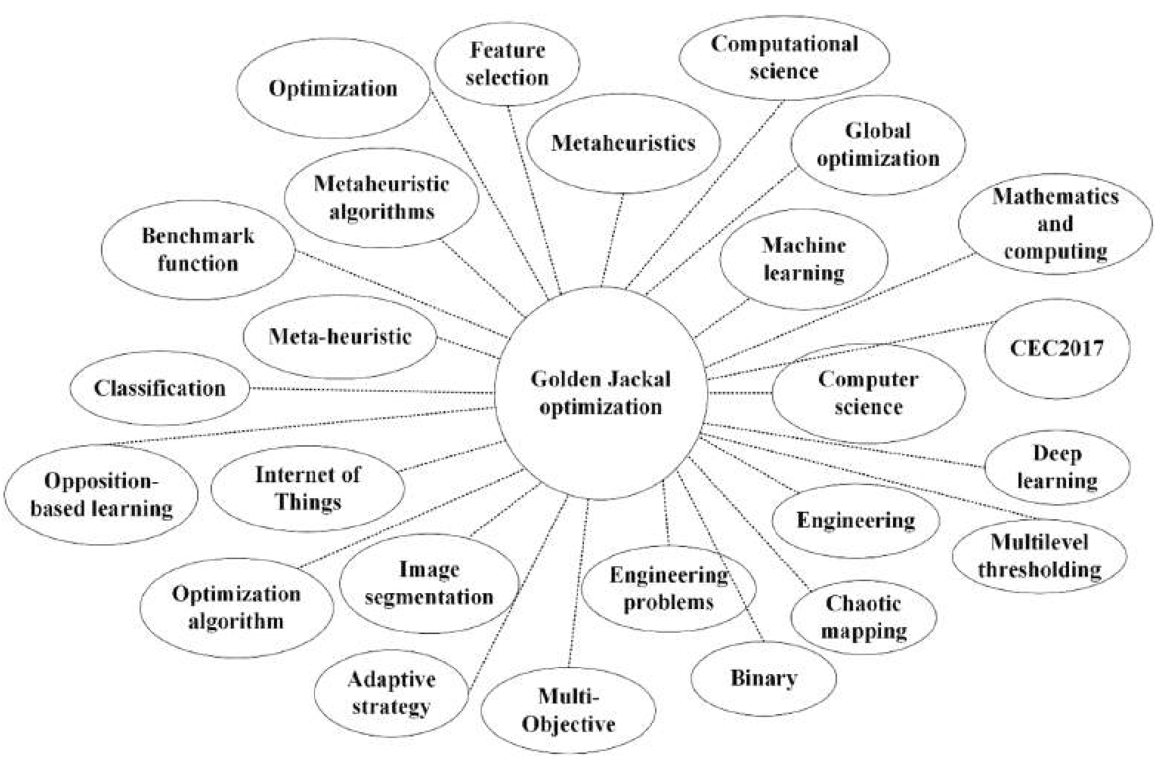

Fig. 1. Relationship between GJO algorithm and keywords (Source: https://journals.scholarsportal.info).

Table 2
Latest published papers based on GJO (Source: https://www.scopus.com).

Title	Authors	Journal	Publisher	Country	Year
A battery SOH estimation method based on entropy domain features and semi-supervised learning under limited sample conditions [56]	Yaming Liu, Jiaxin Ding, Yingjie Cai, Biaolin Luo, Ligang Yao, Zhenya Wang	Journal of Energy Storage	Elsevier	China	2025
Multiple microgrids with electric vehicle charging in a hybrid GJO-PCGAN approach for energy management [57]	Sankar Rangasamy, S. Arun Prakash, Nitin Nandkumar Sakhare & U. Arun Kumar	Electrical Engineering	Springer	India	2025
An Efficient Workflow Scheduling Using Genetically Modified Golden Jackal Optimization with Recurrent Autoencoder in Cloud Computing [58]	Saurav Tripathi and Sarsij Tripathi	International Journal of Network Management	CoLab	India	2025
Golden jackal optimization-based regression analysis application on volume expansion estimation of cement pastes with MgO expansive additive [59]	Yuqing Tian, Lina Zhang & Guozhi Wang	Multiscale and Multidisciplinary Modeling, Experiments and Design	Springer	China	2025
Investigation of Lamb wave modes recognition and acoustic emission source localization for steel plate based on golden jackal optimization VMD parameters and CWT [60]	Shishang Dong, Jun You, Mohamed El-attaboy, Ming Li, Li Guo, Zian Cheng, Xin Zhang, Shi Gong, Yong Wang	Measurement	Elsevier	China	2025
Optimization-based control of overcurrent relays in distribution network considering real-time measurements: A case study [61]	Ali Unluturk, Ishak Ozer	Applied Energy	Elsevier	Turkey	2025
Dynamics and analog circuit of a class of new Hénon maps and its application in the welded beam optimal design [62]	Yao Lu, Xu Wang, Xianming Wu, Shaobo He, Longxiang Fu & Huihai Wang	Nonlinear Dynamics	Springer	China	2025

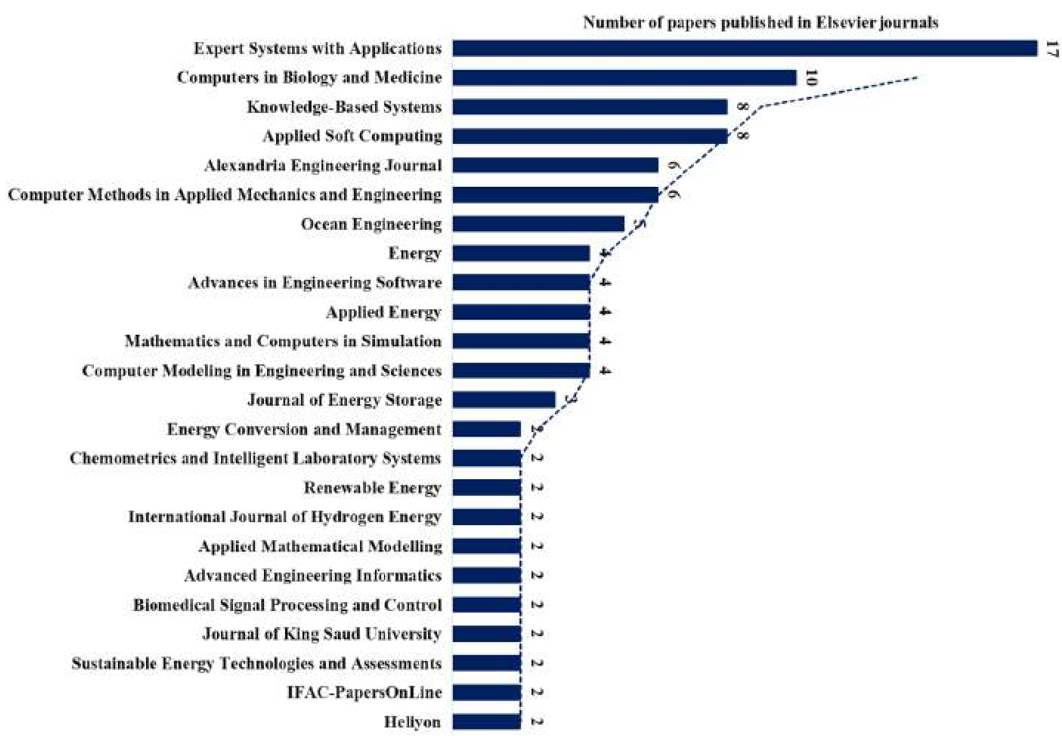

Fig. 2. Number of articles published in Elsevier journals.

in multiple scientific and engineering fields.

Fig. 5 plots the distribution of GJO articles in Elsevier based on different subjects between 2022 and 2025. The largest share is related to engineering, with 28 %, which indicates the importance of many articles in this field. Then, computer science is in second place with 18 %, which accounts for a significant share of articles. Energy, with 11 %, and agricultural and life sciences, with 9 %, are the following places and have a considerable share. Mathematics comprises 8 % of the articles, while environmental sciences constitute 7 %. Medicine and dentistry are next with 6 % and materials sciences with 5 %. Finally, the two fields of immunology and microbiology and molecular biology and genetics cover 4 % of the articles. This distribution reflects the thematic diversity of GJO articles and highly focuses on engineering and computer science topics. Other areas have also received a reasonable share of research. By taking advantage of the flexibility in defining search functions and updating positions, the GJO algorithm can adapt and connect to optimization problems.

Fig. 6 plots the distribution of GJO papers in Scopus based on different subjects between 2022 and 2025. The largest share is from the engineering field with 26 % (116 papers), followed by computer science with 23 % (102 papers). Mathematics accounts for 12 % of the articles, while energy and other subjects have a 7 % share. Physics and astronomy are next with 6 %, materials science with 5 %, and environmental science with 4 %. Other fields include decision sciences (3 %), multidisciplinary (2 %), chemical engineering (2 %), medicine (2 %), molecular biology and genetics (2 %), and agriculture and life sciences (1 %). This distribution shows that the main focus of GJO articles in Scopus is on technical and engineering topics, likely due to industrial needs and advanced scientific research in these areas. The low share of subjects such as arts and humanities indicates a lower focus on the humanities.

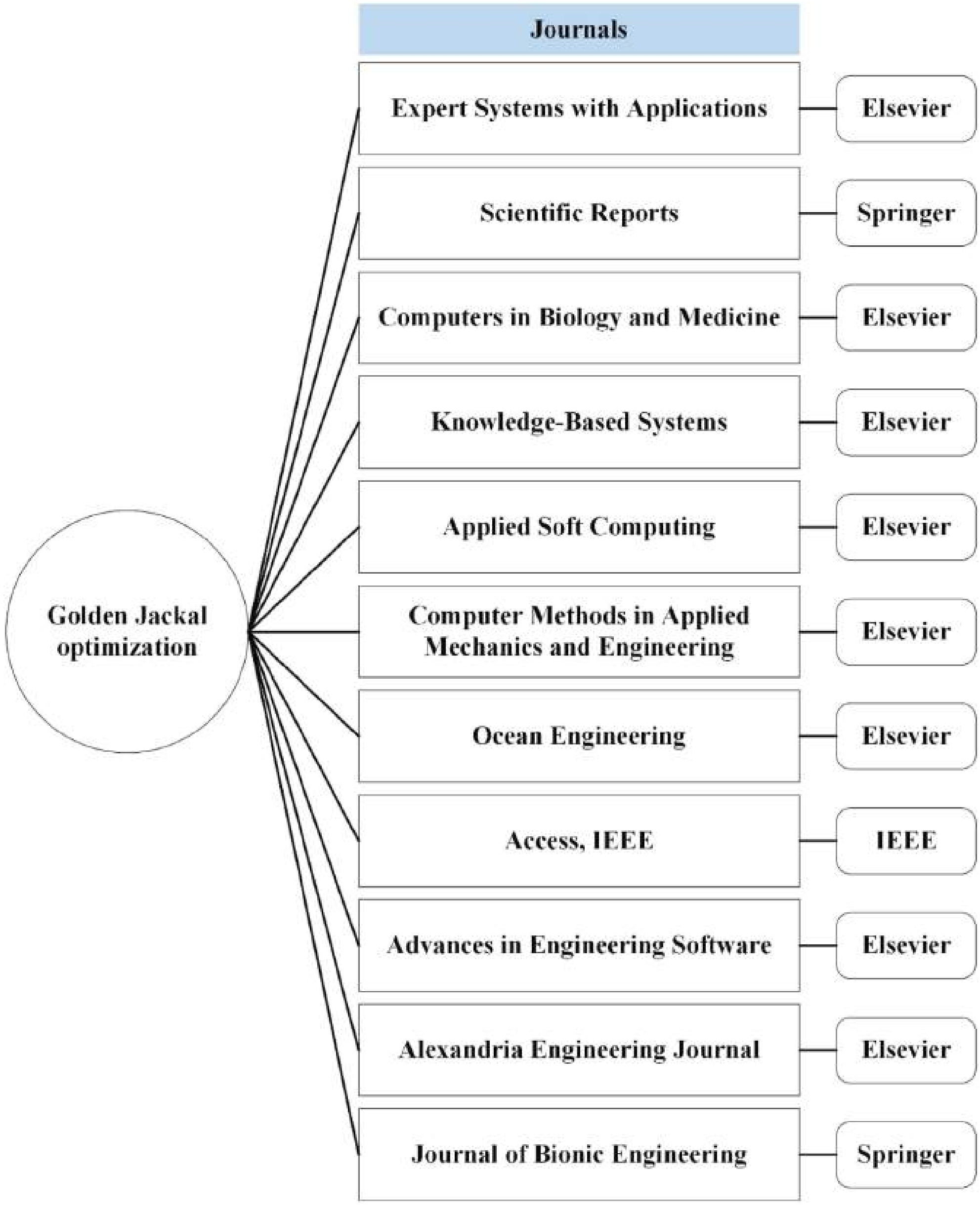

Fig. 3. Distribution of GJO articles published with the highest number in different journals (Source: https://journals.scholarsportal.info).

The papers were collected by scrutinizing titles, keywords, and abstracts, ensuring a meticulous review process. All reputable and widely recognized databases were meticulously searched to gather relevant literature. Each paper underwent a comprehensive evaluation, focusing on both content and the type of algorithm employed. Duplicate papers were identified and eliminated during the initial screening phase. Subsequently, papers about the GJO algorithm were categorized and grouped accordingly. Fig. 7 visually represents the sequential search steps and the corresponding number of articles at each stage.

In this section, first a comprehensive and general analysis of the GJO algorithm was conducted. Then, the articles related to this algorithm were manually analyzed and monitored. Only articles that directly and practically belong to the GJO algorithm were selected. It is worth noting that in some articles, the name of the GJO algorithm was only mentioned and it was not used in solving problems or functions. For this reason, all articles were carefully and in full detail reviewed, and only articles that had practical application and scientific value related to the GJO algorithm were selected for the final analysis. Fig. 8 shows the number of GJO papers published per year. The number of GJO papers published in 2023 was equal to 51.

Since 2022, there has been a surge in research focused on employing the GJO method to tackle optimization problems. To gauge the volume of research output on GJO, a comprehensive collection of papers employing this method was assembled. Subsequently, an analysis was conducted to categorize these papers based on their distribution across various publications and the yearly output of GJO-related articles. Fig. 9 illustrates the distribution of GJO papers across different publication platforms. The graph in Fig. 9 was drawn manually based on expert analysis of the articles. To draw this graph, all important and main sources were reviewed using the keywords optimization and GJO and their articles were extracted. The majority of publications were found in Elsevier (33 %), followed by IEEE (22 %), Springer (24 %), MDPI (10 %), Tandfonline (4 %), and Other (7 %) journals.

3. Golden jackal optimization

The GJO technique was proposed in 2022 [28]. This approach is inspired by the hunting habits of the golden jackal in its natural habitat.

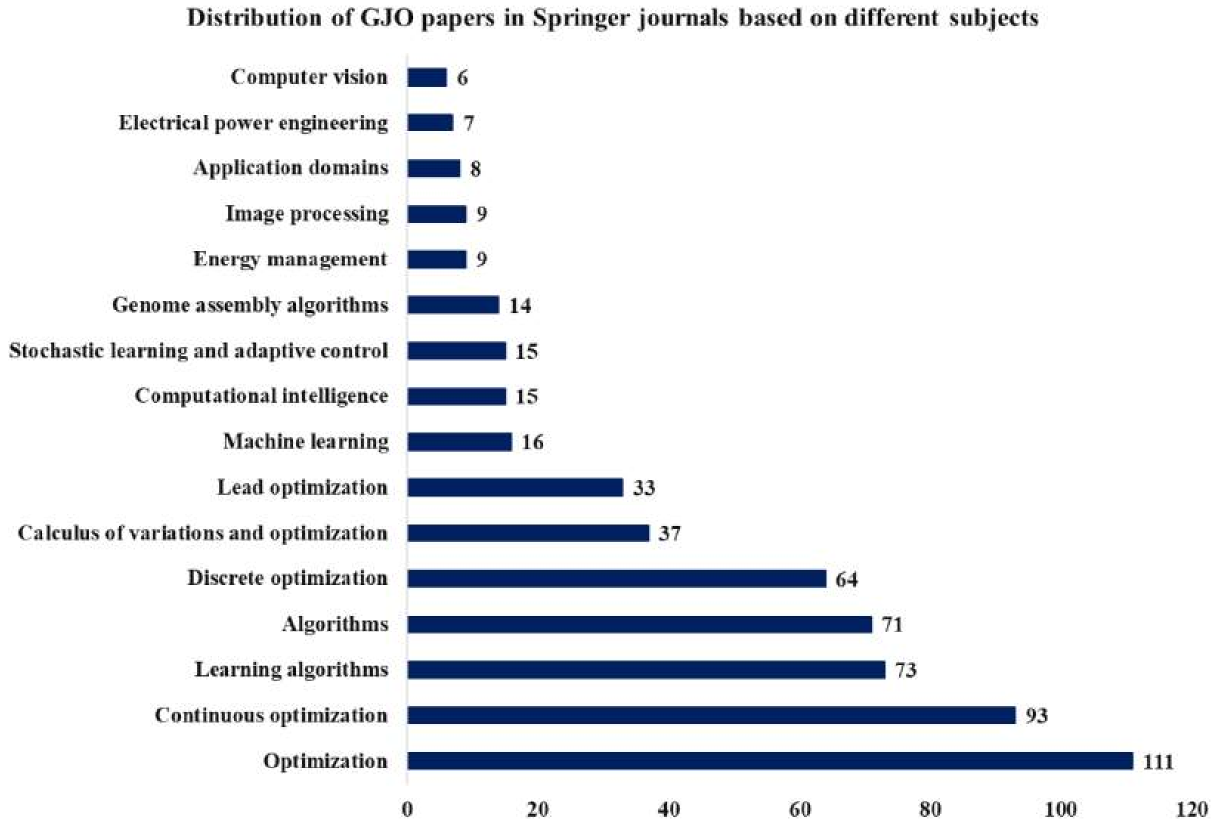

Fig. 4. Distribution of GJO articles in Springer based on different topics.

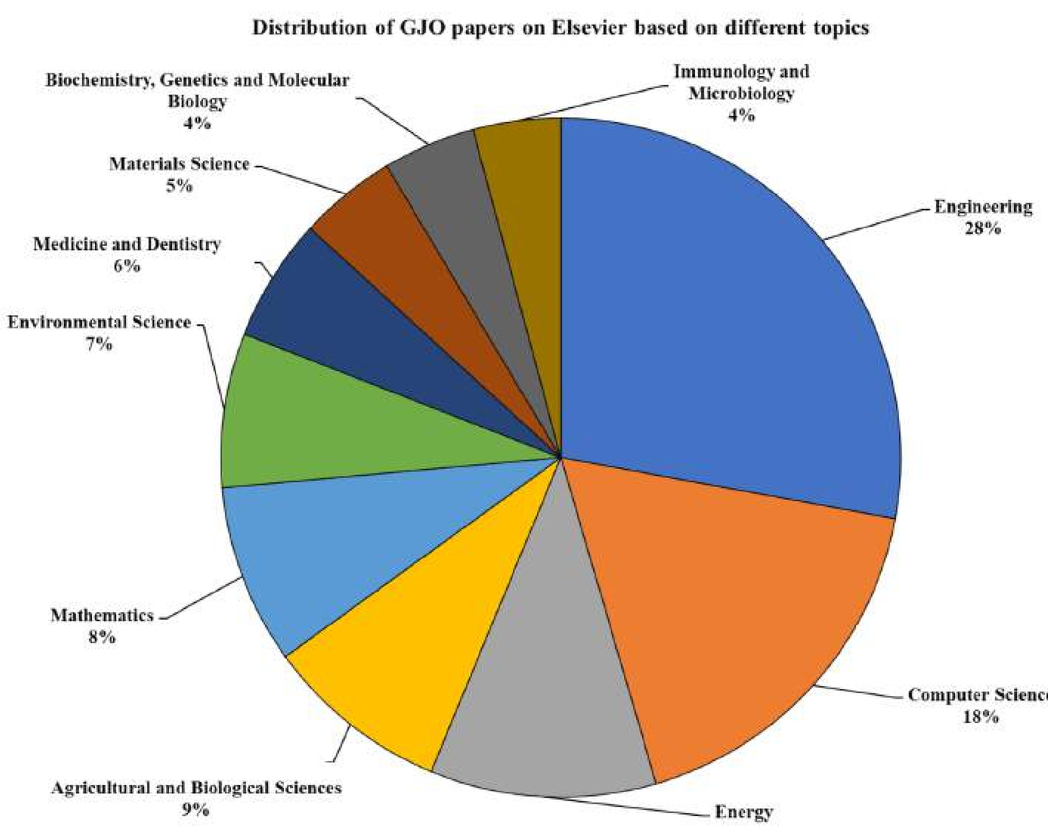

Fig. 5. Distribution of GJO papers in Elsevier based on different topics (Source: https://www.sciencedirect.com/).

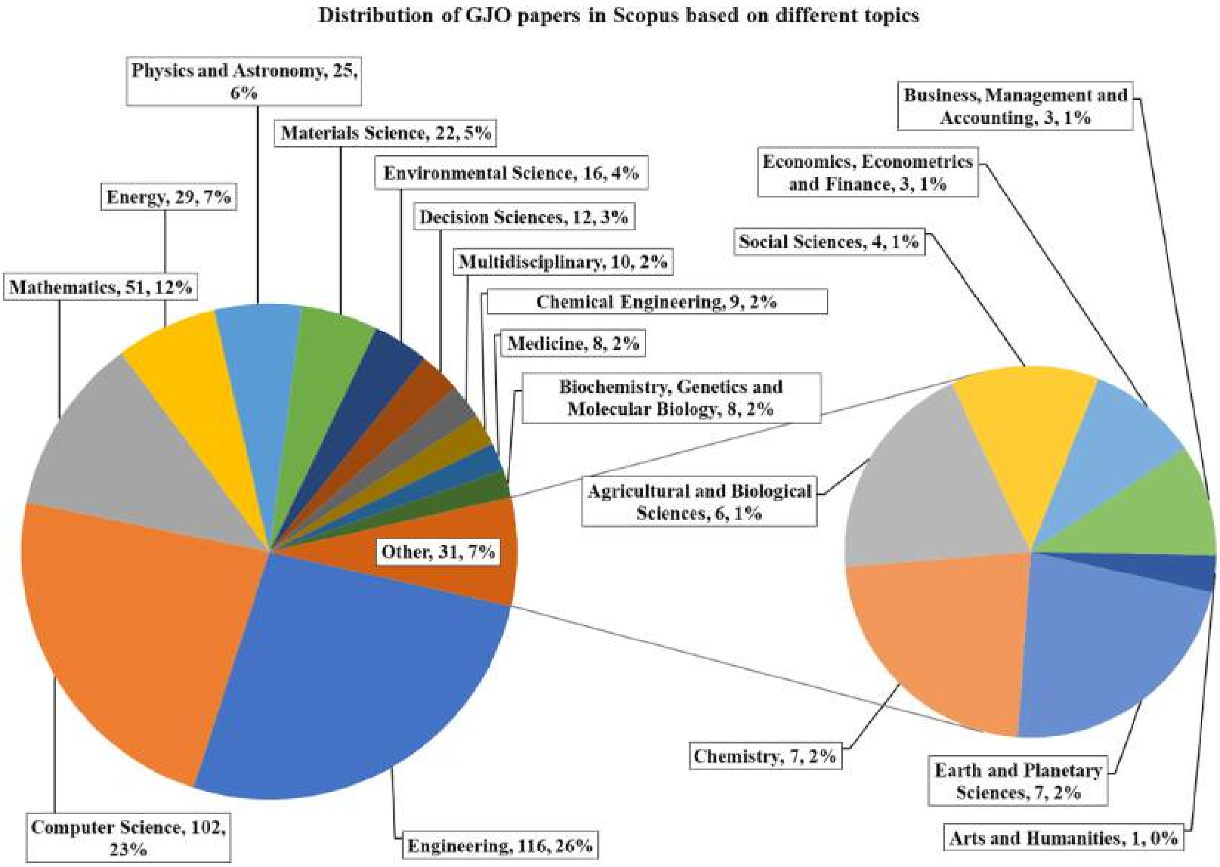

Fig. 6. Distribution of GJO papers in Scopus based on different topics (Source: https://www.scopus.com).

The golden jackal, a terrestrial predator of moderate size belonging to the canine family, inhabits various regions in the world. With its compact build and long legs, the jackal can cover great distances while pursuing prey. Jackals usually form pairs and engage in cooperative activities with their mates. Their actions are highly coordinated, with pairs hunting, foraging, and resting together. Cooperative hunting is vital for jackals, as hunting in pairs can be significantly more effective than solitary hunting, potentially yielding three times the success rate. Golden jackals communicate through various calls and utilize various howls to locate each other.

The primary steps involved in the hunting process of a golden jackal pair (illustrated in Fig. 10) are outlined as follows:

➢ Searching for and advancing towards the prey.
➢ Surrounding and provoking the prey until it ceases movement.
➢ Launching an attack on the prey.

3.1. Search space formulation

Like numerous other metaheuristic approaches, GJO follows a population-based methodology, wherein the initial solution is evenly spread across the search space for the initial trial.

$$Y_0 = Y_{min} + \mathrm{rand}(Y_{max} - Y_{min}) \tag{1}$$

Where Y_{max} and Y_{min} represent the upper and lower bounds for variables, respectively, and "rand" denotes a random vector uniformly distributed within the range of 0 to 1.

The initialization process generates the initial Prey matrix, wherein the first and second-fittest members constitute the jackal pair. The *Prey* matrix is represented as shown in Eq. (2).

$$\text{Prey} = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,d} \\ Y_{2,1} & Y_{2,1} & \cdots & Y_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ Y_{n,1} & Y_{n,2} & \cdots & Y_{n,d} \end{bmatrix} \tag{2}$$

In this context, Y_{ij} represents the j^{th} dimension of the i^{th} prey. There are n preys and d variables. The position of a prey pertains to the parameters defining a particular solution. A fitness function is then utilized to evaluate the fitness value of each prey during the optimization process, followed by the assembly of a matrix to collect the fitness values of all prey.

$$F_{OA} = \begin{bmatrix} f(Y_{1,1}; Y_{1,2}; \cdots; Y_{1,d}) \\ f(Y_{2,1}; Y_{2,1}; \cdots; Y_{2,d}) \\ \vdots \\ f(Y_{n,1}; Y_{n,2}; \cdots; Y_{n,d}) \end{bmatrix} \tag{3}$$

In this setup, FOA represents the matrix used to store the fitness of each prey, while Y_{ij} indicates the value of the j^{th} dimension of the i^{th} prey. Here, n is the number of preys, and f denotes the objective function. The most fit individual is referred to as the Male Jackal, and the second most fit is the Female Jackal. The jackal pair then assumes the corresponding positions of their respective prey.

3.2. Exploration stage or searching the prey

The sophisticated exploration strategies deployed by GJO are delved into in this segment. These strategies are remarkably reminiscent of the innate behaviors of jackals in the wild, characterized by their acute ability to sense and actively chase down potential prey. However, it is worth noting that prey can sometimes outmaneuver their pursuers, successfully evading capture. When this occurs, jackals must pause their chase momentarily and reassess their surroundings for new hunting

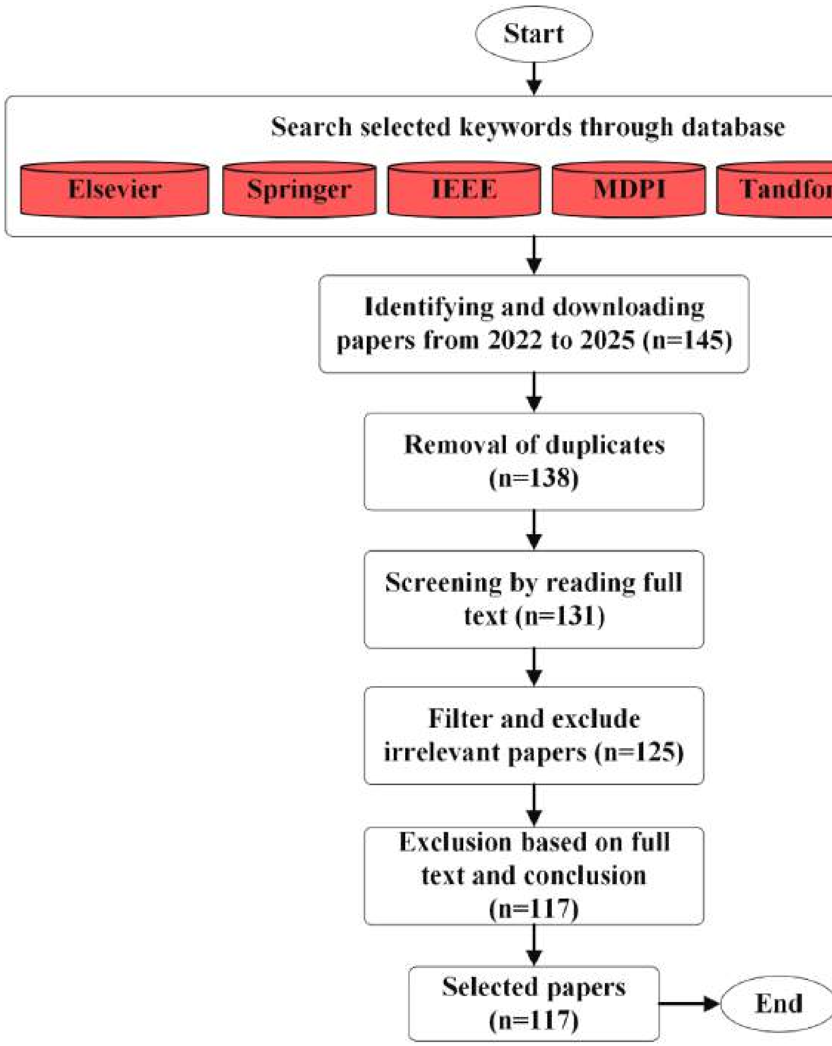

Fig. 7. The Procedure for extracting papers belongs to the GJO algorithm.

opportunities. It is typically observed that the male jackal assumes the lead role, spearheading the pursuit with keen determination. In contrast, the female jackal adopts a more supportive stance, closely following the male and contributing to the hunting efforts from behind. This coordinated approach underscores the adaptability and teamwork inherent in their survival tactics.

$$Y_1(t) = Y_M(t) - E\cdot|Y_M(t) - rl.Prey(t)| \tag{4}$$

$$Y_2(t) = Y_{FM}(t) - E\cdot|Y_{FM}(t) - rl.Prey(t)| \tag{5}$$

Here, the symbol "t" denotes the ongoing iteration, while $Prey(t)$ represents the position vector of the prey. Furthermore, $Y_M(t)$ and $Y_{FM}(t)$ signify the locations of the male and female jackals, respectively. Furthermore, $Y_1(t)$ and $Y_2(t)$ denote the updated locations of the male and female jackals relative to the prey. The variable E represents the prey's evading energy, which is computed using Eq. (6).

$$E = E_1 * E_0 \tag{6}$$

E_1 represents the diminishing energy level of the prey, while E_0 signifies its initial energy state.

$$E_0 = 2^* r - 1 \tag{7}$$

r is any random value selected uniformly from 0 to 1.

$$E_1 = c_1 * (1 - (t / T)) \tag{8}$$

In Eq. (8), T represents the maximum number of iterations, where c_1 is a constant set to 1.5, and t signifies the current iteration. The variable E_1 decreases linearly from 1.5 to 0 throughout iterations. The term rl Eqs. (4) and (5) represent a vector of random numbers generated according to the Lévy distribution, miming the Lévy movement. In Eqs. (4) and (5), $|Y(t) - rl.Prey(t)|$ calculates the distance between the jackal and the prey. This distance is subtracted from or added to the jackal's current position based on the prey's evading energy. The multiplication of rl and prey simulates the prey's movement in a Lévy-like manner and is computed as follows.

$$rl = 0.05^* LF(y) \tag{9}$$

LF represents the levy flight (LF) function, computed using the following formula. This function is utilized to model characteristic *movements* similar to *LF*.

$$LF(y) = 0.01 \times (\mu \times \sigma) \Big/ \left(\left|v^{(1/\beta)}\right|\right); \sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times \left(2^{\frac{\beta-1}{2}}\right)}\right)^{1/\beta} \tag{10}$$

In Eq. (10), u and v represent random values ranging between 0 and 1, while β is a preset constant value, typically set to 1.5. Ultimately, the positions of the jackals are adjusted by averaging the results obtained from Eqs. (4) and (5).

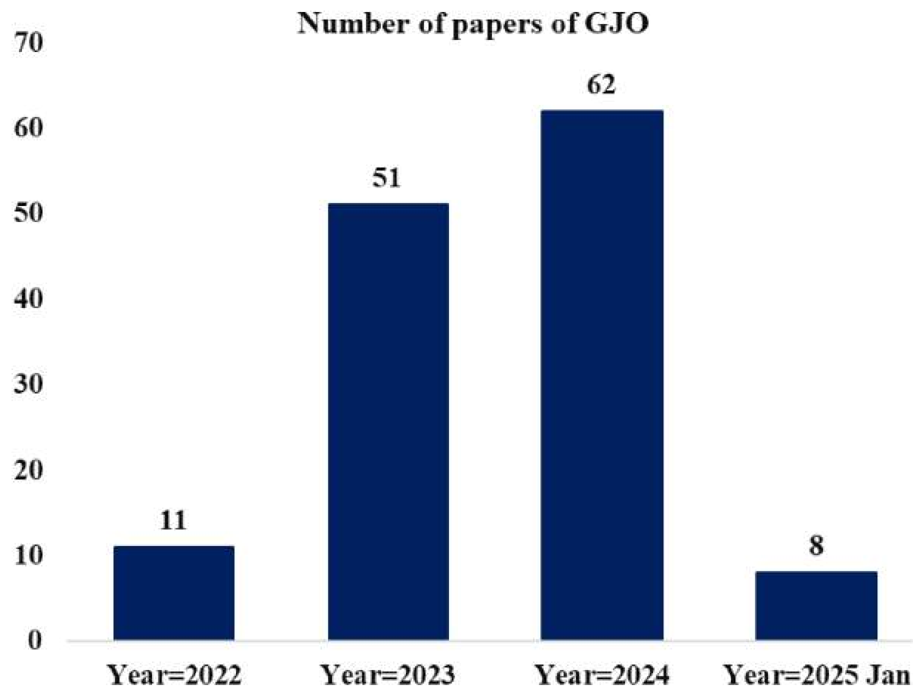

Fig. 8. Number of GJO papers published per year.

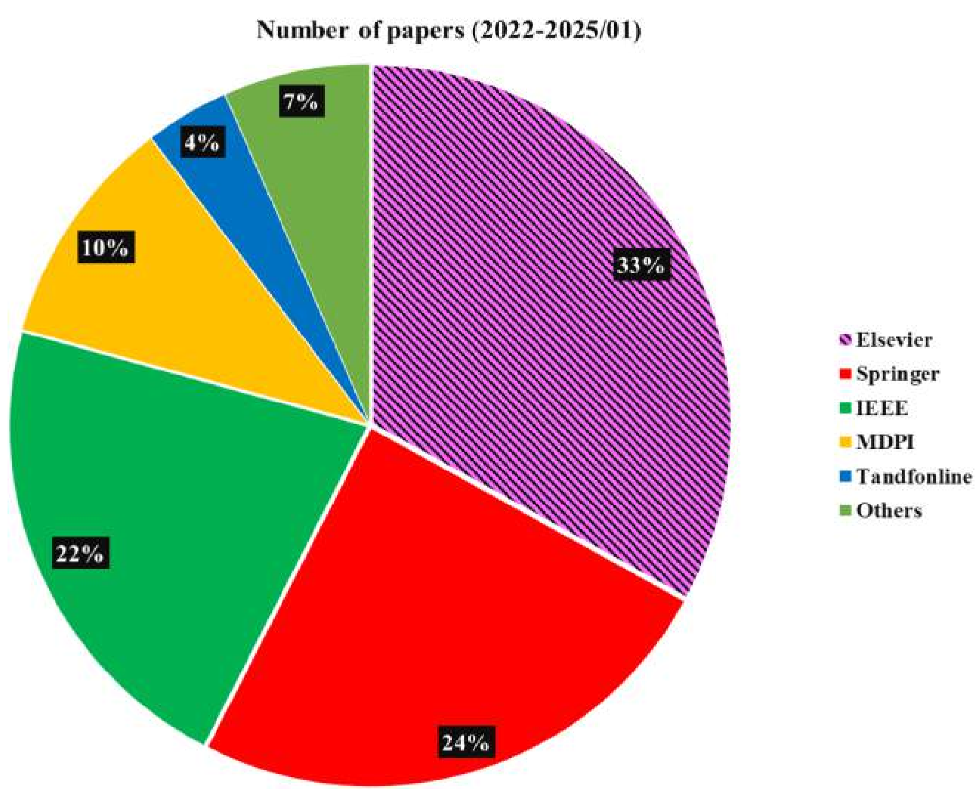

Fig. 9. Percentage of papers published with GJO in different publications.

$$Y(t+1) = \frac{Y_1(t) + Y_2(t)}{2} \tag{11}$$

3.3. Exploitation stage or enclosing and pouncing the prey

When subjected to persistent harassment by the jackals, the prey's capacity to evade gradually depletes, leading to a scenario where the prey, previously singled out, becomes encircled by the jackals. At this juncture, the encirclement strategy allows them to initiate an attack, ultimately leading to prey consumption. This methodical approach to hunting, characterized by a joint effort between the male and female jackals, is encapsulated within the mathematical frameworks outlined in Eqs. (12) and (13). This passive strategy highlights the systematic and collaborative nature of the jackals' hunting tactics, emphasizing the role

Fig. 10. A) Duo of Golden Jackals B) Golden Jackal on the hunt C) Ambushing and surrounding the prey D) & E) Leaping at the prey [28].

of endurance and strategic encirclement in their success.

$$Y_1(t) = Y_M(t) - E.|rl.Y_M(t) - Prey(t)| \quad (12)$$

$$Y_2(t) = Y_{FM}(t) - E\cdot|rl.Y_{FM}(t) - Prey(t)| \quad (13)$$

In this context, t denotes the current iteration, while Prey(t) signifies the location vector of the prey. $Y_M(t)$ and $Y_{FM}(t)$ represent the locations of the male and female jackals, respectively. $Y_1(t)$ and $Y_2(t)$ denote the updated locations of the male and female jackals relative to the prey. The prey's evading energy, denoted as E, is computed according to Eq. (6). Ultimately, the locations of the jackals are adjusted based on Eq. (11).

In Eqs. (12) and (13), the role of *rl* is to introduce random behavior during the exploitation phase, promoting exploration and avoiding local optima. The *rl* calculation follows the procedure outlined in Eq. (9). This component circumvents the sluggishness associated with local optima, especially during the final iterations. This element can be seen as a result of obstacles that hinder the approach to the prey. Typically, challenges in nature manifest along the pursuit routes of jackals, impeding their efficient and swift advancement toward their prey. This is the function of *rl* during the exploitation phase.

3.4. Switching from exploration to exploitation

In the GJO algorithm, the prey's diminishing energy is a mechanism for transitioning from exploration to exploitation phases. As the prey engages in evasion maneuvers, its energy diminishes considerably. To represent this, the prey's evading energy is formulated according to Eq. (6). The initial energy, denoted as E_0, exhibits random variations within the range of -1 to 1 during each iteration. A decrease in the E_0 value

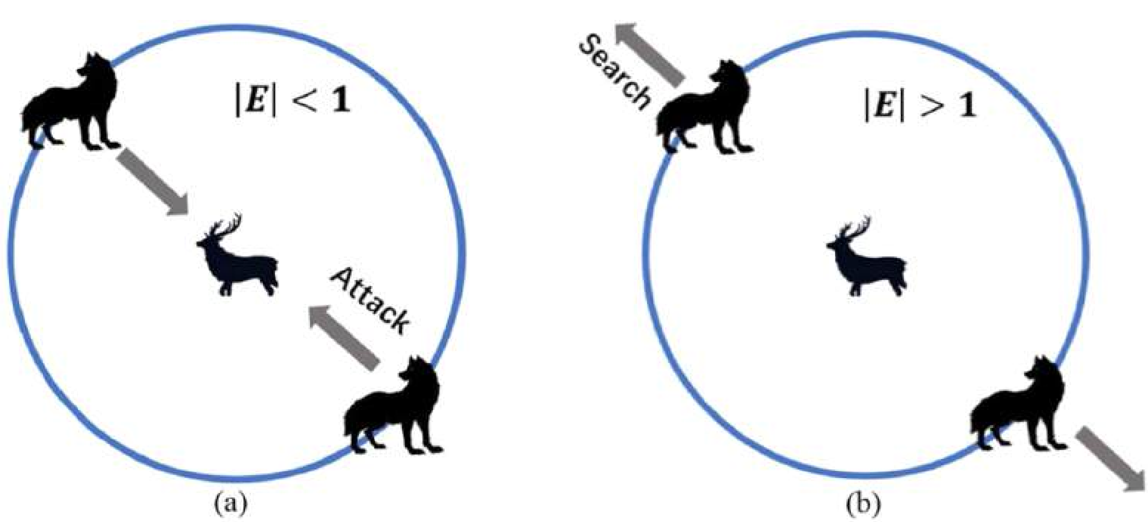

Fig. 11. Attacking vs searching for prey [28].

from 0 to −1 signifies a weakening of the prey, whereas an increase from 0 to 1 indicates an enhancement in its vigor. When the absolute value of E exceeds 1, the jackal pairs venture into distinct regions to explore potential prey. Conversely, when the absolute value of E falls below 1, the GJO algorithm switches to attacking the prey and engaging in exploitation, as depicted in Fig. 11. This transition between the exploration and exploitation phases is crucial for optimizing the hunting strategy.

In the GJO algorithm, the initiation of the search process is marked by forming a diverse, randomly generated group of prey, each

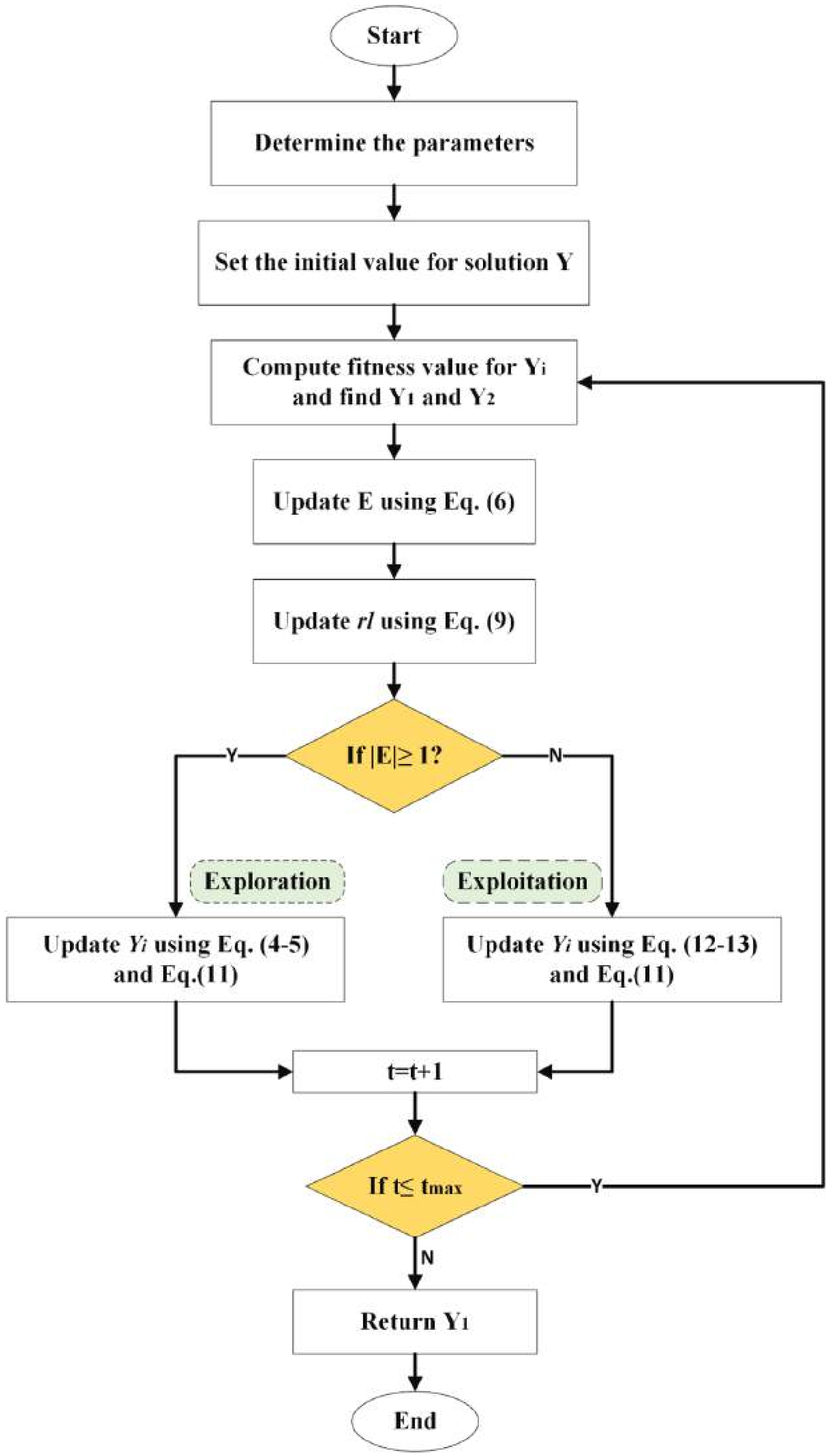

Fig. 12. The flowchart of the GJO algorithm [28].

symbolizing a potential solution. As the algorithm progresses through various iterations, the positions where the prey is likely to be found are deduced by a team comprising a male and female jackal. Subsequently, every member within this group of potential solutions adjusts its proximity to the jackal duo based on their movements. A key parameter, denoted as E_1, is methodically reduced from an initial value of 1.5 to 0. This gradual transition shifts the focus from exploring the search space to exploiting the discovered solutions. The value of E influences the behavior of the golden jackal pair; they distance themselves from the prey when E exceeds the threshold of 1 and move closer as E drops below this critical value. Completing the GJO algorithm signifies fulfilling a predetermined termination condition, marking the end of the search process.

Fig. 12 shows the flowchart of the GJO algorithm.

The pseudo-code of the GJO algorithm is presented in Algorithm 1.

4. Methods of GJO

Fig. 13 presents the categorization of GJO methodologies, which is structured around four main classifications: Hybridization, Improved Techniques, Variants of GJO, and Optimization Problem Domains. Under Hybridization, MH algorithms are incorporated. In the Improved category, various sub-categories are explored to enhance solution quality. Variants of GJO encompass Binary and Multi-objective approaches. Lastly, within the Optimization Problem domain, GJO is applied to address a diverse range of optimization challenges, aiming to identify optimal solutions.

4.1. Hybridization with other metaheuristics

The hybridization approach is a technique developed to deal with the drawbacks of MH algorithms, where two or more MH algorithms are synergistic. Each base algorithm exploits the weakness of the other algorithm.

4.1.1. GJO-SCA

Multilevel thresholding is an essential technique that has gained significant attention and acceptance in recent years due to its effectiveness and utility. However, as threshold levels increase, the computational complexity also grows, presenting a challenge. To address the limitations of traditional GJO, such as its tendency for premature convergence, less precise computation results, and slow convergence speed, a novel approach combining GJO with the sine cosine algorithm, termed Sine Cosine-GJO (SCGJO) [63], has been introduced. SCGJO is a suitable method for solving complex problems due to its exceptional consistency and reliability, and it effectively uses the advantages of synergy to achieve high convergence accuracy. Therefore, the exploration and exploitation stages are skillfully balanced, and the risk of search stagnation is minimized. Experimental results show that SCGJO outperforms competing algorithms regarding faster convergence rate, high computational accuracy, improved segmentation performance, and strong stability. This makes the SCGJO a reliable and consistent method for addressing challenges in image segmentation tasks. During the exploration phase of SCGJO, it generates positions based on specific mathematical equations, referred to as Equations 14 and 15 [63], which plays a crucial role in its operational mechanism.

$$Y_1^{'}(t) = \begin{cases} Y_1(t) + r_1 \times sin(r_2) \times |r_3 \text{ prey } - Y_1(t)|, & r_4 < 0.5 \\ Y_1(t) + r_1 \times cos(r_2) \times |r_3 \text{ prey } - Y_1(t)|, & r_4 \geq 0.5 \end{cases} \tag{14}$$

$$Y_2^{'}(t) = \begin{cases} Y_2(t) + r_1 \times sin(r_2) \times |r_3 \text{ prey } - Y_2(t)|, & r_4 < 0.5 \\ Y_2(t) + r_1 \times cos(r_2) \times |r_3 \text{ prey } - Y_2(t)|, & r_4 \geq 0.5 \end{cases} \tag{15}$$

$$Y(t+1) = \frac{Y_1^{'}(t) + Y_2^{'}(t)}{2} \tag{16}$$

In Eq. (14), Prey(t) represents the location vector of the prey, while $Y_1(t)$ and $Y_2(t)$ indicate the most recent positions of the pair of jackals. The terms $Y_1^{'}(t)$ and $Y_2^{'}(t)$ refer to the positions of the jackal pair after being adjusted by the Sine-Cosine. The variables r_2, r_3, and r_4 fall within the ranges [0, 2π], [-2, 2], and [0, 1], respectively, with r1 gradually reducing from 2 to 0 over time. Y signifies the revised location of the jackal following these updates. During the exploitation stage of the SCGJO, the positions are determined according to Eqs. (17) and (18) [63].

$$Y_1^{''}(t) = \begin{cases} Y_1(t) + r_1 \times sin(r_2) \times |r_3 \text{ prey } - Y_1(t)|, & r_4 < 0.5 \\ Y_1(t) + r_1 \times cos(r_2) \times |r_3 \text{ prey } - Y_1(t)|, & r_4 \geq 0.5 \end{cases} \tag{17}$$

$$Y_2^{''}(t) = \begin{cases} Y_2(t) + r_1 \times sin(r_2) \times |r_3 \text{ prey } - Y_2(t)|, & r_4 < 0.5 \\ Y_2(t) + r_1 \times cos(r_2) \times |r_3 \text{ prey } - Y_2(t)|, & r_4 \geq 0.5 \end{cases} \tag{18}$$

$$Y(t+1) = \frac{Y_1^{''}(t) + Y_2^{''}(t)}{2} \tag{19}$$

Prey(t) refers to the vector indicating the prey's location in this context. $Y_1(t)$ and $Y_2(t)$ represent the most recent positions of the two jackals, while $Y_1^{''}(t)$ and $Y_2^{''}(t)$ stand for the positions of the jackals after being updated through the Sine Cosine Algorithm (SCA). The parameters r_2, r_3, and r_4 have specified ranges: r_2 falls between 0 and 2π, r_3 between -2 and 2, and r_4 between 0 and 1. The value of r1 decreases linearly from 2 to 0. Y signifies the revised position of the jackal after these adjustments.

In [54], the authors introduced a new method called the Hybrid Strategy-based GJO (HGJO) algorithm, designed for planning the paths of mobile robots. This improved algorithm version blends a unique

Algorithm 1
Pseudo code of the GJO algorithm [28].

```
Inputs: The size of the population N and the highest number of cycles T
  Outputs: The position of the prey and its corresponding fitness level
  Initialize the random agent population Yi(i = 1, 2, ..., N)
  While (t < T)
      Compute the fitness values of prey
      Y1 = best agent (Male Jackal position)
      Y2 = second best agent (Female Jackal Position)
  For (each prey)
      Upgrade the evading energy E using Eq. (6), Eqs. (7) and (8)
      Upgrade rl using Eqs. (9) and (10)
      IF (|E| is greater than or equal to 1) (Exploration phase)
      Update the prey location using Eq. (4), Eq. (5), and Eq. (11)
      IF (|E| is <1) (Exploitation phase)
      Upgrade the prey location using Eq. (12), Eq. (13), and Eq. (11)
  End For
  t = t + 1
  End While
  Return Y1
```

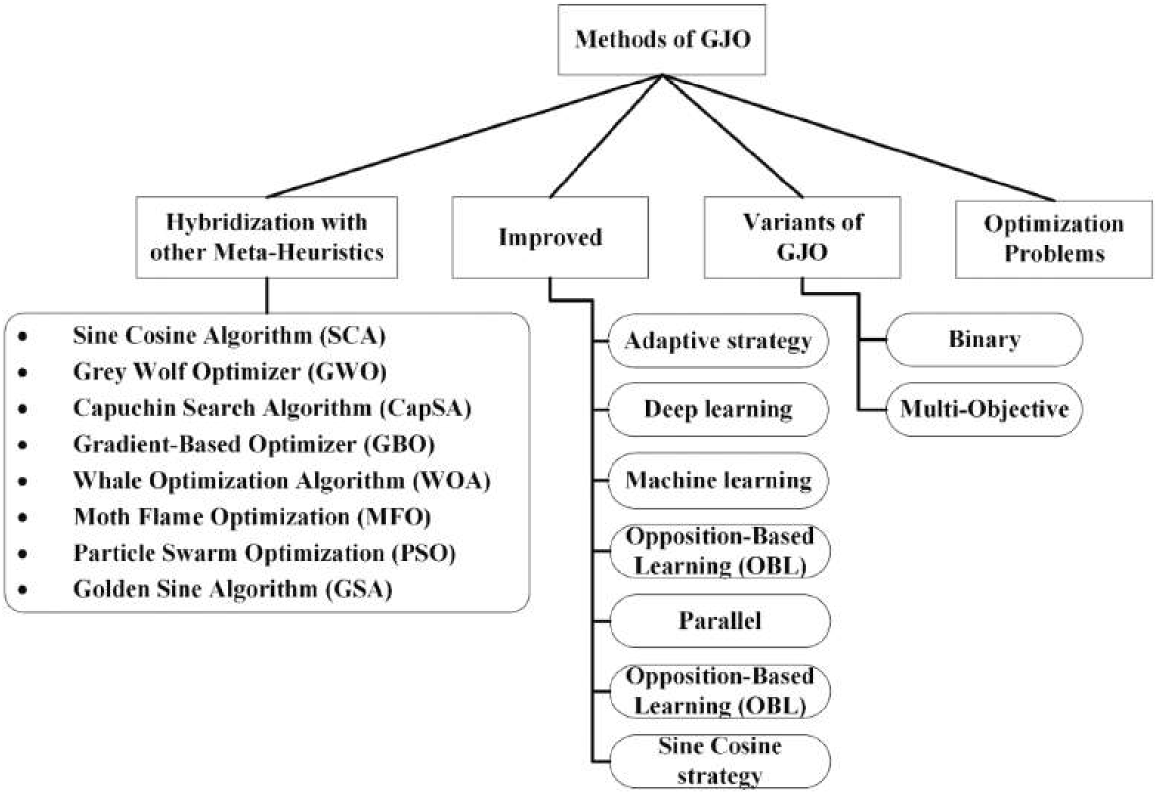

Fig. 13. Classification of GJO methods.

strategy that reduces energy nonlinearly, ensuring a good mix of broad and precise search capabilities. The HGJO algorithm adds a roulette wheel selection method and Lévy flight technique to the GJO's updating process to boost its effectiveness and avoid getting stuck in less optimal solutions. The performance of the HGJO algorithm was thoroughly evaluated against leading optimization algorithms using 23 standard tests and the CEC2021 benchmark. Additionally, it was assessed in detailed studies focused on planning paths for mobile robots. The outcomes were encouraging, showing that the HGJO algorithm could surpass the original in minimizing the average path length for mobile robots. In particular, based on 30 separate tests, enhancements of 0.21 %, 82.4 %, and 7.9 % were shown in three different settings. A key new feature of the HGJO algorithm is using a roulette wheel selection approach when exploiting resources, which significantly improves the search effectiveness of the GJO algorithm. The adjustments made to the algorithm are explained in detail in Eqs. (20) and (21) [54], highlighting the advanced formulas that help achieve better results.

$$Y_1(t) = (Y_M(t) - E \cdot |rl \cdot Y_M(t) - Prey(t)|) \cdot \cos(\theta) \tag{20}$$

$$Y_2(t) = (Y_{FM}(t) - E \cdot |rl \cdot Y_{FM}(t) - Prey(t)|) \cdot \cos(\theta) \tag{21}$$

In this context, θ represents a randomly chosen angle ranging from 0 to 360°, and the term $cos(\theta)$ is used to denote the application of a roulette wheel selection algorithm, producing values within the range of -1 to 1. Using random angles prevents the algorithm from becoming stuck in local optima, offering a significant advantage. Moreover, this approach positively influences the hunting behavior, enhancing the algorithm's effectiveness in exploring and exploiting the search space.

In the GJO algorithm, the simulation of hunting behavior mirrors that of actual golden jackals, where the hunt is typically led by male jackals and followed by their female counterparts. While effective in specific scenarios, this method can sometimes cause the algorithm to prematurely converge to local optima, limiting its ability to effectively explore the broader search space. This study integrates the Lévy flight strategy into the GJO's position updating mechanism to overcome this limitation and enhance the algorithm's exploration capabilities. Lévy flights, characterized by long jumps interspersed with short, random movements, are known for their efficiency in exploring complex landscapes. By integrating this strategy, the position update formula within the GJO algorithm is significantly improved to promote a more extensive search of the optimization landscape. The enhancements made to the algorithm are encapsulated in the revised formulae, which are detailed in Equations 22 and 23 [54]. These modifications aim to enhance the GJO algorithm's ability to avoid premature convergence and improve its overall performance in finding global optima.

$$Y(t+1) = Y_M(t) - [0.5 \times (Y_1(t) + Y_2(t))] \cdot \cos(\theta)|A| < 0.5 \tag{22}$$

$$Y(t+1) = Y_M(t) - \text{rand} \times Y(t) + Z \times LF(\beta)|A| > 0.5 \tag{23}$$

$$Z = 0.01 \times (Y(t) - Y_M(t)) \tag{24}$$

The text describes a process where *rand* represents a random number from 0 to 1; *A* also signifies a random value within the same range, and its role is to boost the capability to escape local optima; *Z* stands for the control step weight and signifies Lévy motion. During each cycle, the golden jackal adjusts its location by considering both the position of the male jackal and its existing location. This enhancement allows the golden jackal's subsequent location to be positioned somewhere between its current spot and the location of the prey.

4.1.2. GJO-GWO

A hybrid optimization technique that blends the GJO and Grey Wolf Optimizer (GWO) to form a novel method aimed at reducing the dimensions of data effectively [64]. This method removes unnecessary, irrelevant, and noisy attributes from datasets with many dimensions. In one scenario, this combined GJO-GWO approach was applied to eight intricate benchmark functions, and in another, it was used for ten feature selection challenges. The experimental results consistently demonstrated that the GJO-GWO strategy outperforms in terms of lower average values, reduced variability, improved classification precision, and faster processing times across both types of tasks. These results highlight the method's exceptional ability in optimization, accuracy in classification, and stability. A standout characteristic of this proposed approach is its adeptness at balancing the exploration and exploitation phases within the search process. This helps prevent the algorithm from getting stuck in local optimums and enables it to identify the most optimal global solutions. This balance makes the algorithm particularly effective for complex optimization problems with multiple local optimums.

4.1.3. GJO- CapSA

A combined method to evaluate the efficiency of buck converters controlled by fractional-order proportional integral derivative (FOPID) controllers has been designed. This hybrid method merges the Capuchin Search Algorithm (CapSA) with the GJO, resulting in an enhanced version of GJO, termed the Improved GJO (IGJO) [65]. Power converters are challenging to control due to their nonlinear characteristics; searching for practical and intelligent control solutions is an ongoing endeavor. In recent years, fractional-order controllers have shown superior performance in managing power electronic systems. The IGJO approach is used to optimize the design of a FOPID controller for buck converters and minimize various performance indicators, particularly the integral squared error (ISE). This method is implemented and tested in MATLAB, comparing its effectiveness against existing approaches. The simulation results indicate that the proposed IGJO method achieves a more significant reduction in error than current techniques.

4.1.4. GJO- Gradient-based optimizer

In [51] an enhanced version of the GJO, the Improved GJO (IGJO), incorporates a local escaping operator to tackle feature selection issues more effectively. The standard GJO algorithm gets stuck in local optima, especially when dealing with high-dimensional feature selection tasks. To overcome this limitation, the IGJO integrates mechanisms from gradient-based optimizers, specifically focusing on a local escaping operator and the direction of population movement. These additions aim to boost the algorithm's capability to explore and exploit the search space more efficiently. The efficacy of the IGJO algorithm was rigorously tested across a wide array of problems, including 23 standard numerical benchmarks, 29 optimization challenges from the CEC2017 suite, and 33 constrained real-world engineering design problems from CEC2020. Furthermore, to address feature selection specifically, the IGJO was adapted into a binary version employing a novel nonlinear time-varying sigmoid function. This binary variant was assessed on various feature selection tasks using benchmark datasets. A comparative analysis with other well-known algorithms was conducted to establish the effectiveness of the IGJO. The results from these comparisons highlighted the IGJO as a dependable and superior option for both numerical optimization and feature selection challenges.

4.1.5. GJO-WOA

In [66] discusses an adaptive algorithm known as GJO-Whale (GJOW), designed to enhance the accuracy of detecting bone cancer in bone scans by focusing on feature extraction and selection. This method aims to identify the presence or absence of tumors in bone scans that are preliminarily categorized as normal or abnormal. The study introduces a novel approach using machine learning techniques to detect bone metastasis through gamma camera scans. It improves the GJO algorithm by integrating elements from the Whale Optimization Algorithm (WOA), and it assesses a new feature selection technique using actual datasets related to bone metastasis. The effectiveness of the GJOW algorithm is demonstrated through experimental results, which show a significant improvement in classification accuracy. The method surpasses other approaches in all tested datasets, achieving an impressive average accuracy rate of 97 % in one set of experiments and the highest accuracy rate of 73 % in another. The study plans to expand its evaluation using a more extensive dataset and investigate other feature selection techniques to enhance further the model's performance in detecting bone cancer.

The fitness function is recalculated for every updated solution within the cycle in the process described. This procedure continues to repeat until a predefined stopping criterion is met. In the context of the described GJOW algorithm, this criterion is set as reaching the maximum number of iterations. Fig. 14 illustrates the core framework of the combined GJO and GJO-WOA, detailing this iterative process and how solutions are updated and evaluated in each cycle until the algorithm concludes.

4.1.6. GJO-MFO

To improve upon the limitations of the GJO algorithm, a novel hybrid approach combining Moth Flame Optimization (MFO) with GJO, named the Opposition-based Moth Flame GJO (OMGJO), is introduced [67]. This model integrates the concept of opposition learning with the spiral path search mechanism from MFO, aiming to boost the algorithm's efficiency and speed of convergence. The performance of the OMGJO algorithm is assessed by comparing it against 10 different metaheuristic algorithms across 30 benchmark functions, followed by statistical analysis of the results. The findings from these experiments highlight the competitive advantage of the OMGJO algorithm, demonstrating its ability to achieve superior outcomes. Compared to the conventional GJO and other optimization techniques, the enhanced algorithm excels with faster convergence rates and more efficient search capabilities. Furthermore, the algorithm's effectiveness and versatility are validated through its application to various engineering challenges, underlining its potential for practical implementation.

4.1.7. GJO-PSO

A novel enhanced metaheuristic algorithm named PSO-based GJO was explicitly designed to optimize the parameter estimation of Proton Exchange Membrane Fuel Cells (PEMFC) to achieve minimal error values [42]. The core concept behind this method is to utilize the PSO-enhanced GJO technique to minimize the Sum of Squared Errors (SSE) between the actual output voltage and the modeled output voltage of the PEMFC stack. To demonstrate the effectiveness of the proposed methodology, it was applied to two test cases, and the results were benchmarked against various contemporary optimization algorithms. The comparison findings showed that the proposed implicitly referring to the improved algorithm (ICSO) consistently outperformed the other evaluated methods in accurately estimating the PEMFC model parameters. A significant aspect of this approach is incorporating PSO's swarm behavior to enhance the exploration capabilities of the GJO algorithm. In updating the PSO equation, two key elements are considered: the position and velocity of each candidate solution. Specifically, the velocity component, crucial for the PSO's efficiency, is computed as per Eq. (25) [42], underscoring its importance in optimization.

$$V(t+1) = c_1\left(Y_{\text{best}}^{\text{local}}\ (t) - Y(t)\right) + c_2\left(Y_{\text{best}}^{\text{global}}\ (t) - Y(t)\right) + wV(t) \tag{25}$$

In the context of the PSO algorithm, $V(t)$ and $V(t+1)$ denote the velocities of a particle at consecutive time steps, where $V(t)$ is the velocity at the current time step, and $V(t+1)$ is the velocity at the next time step. The velocity update equation in PSO is crucial for guiding the particles toward optimal solutions by incorporating both their best-found positions (local best) and the best position found by any particle in the swarm (global best). The parameters c_1 and c_2 in the velocity update equation are critical constants known as acceleration coefficients. By adjusting these parameters, one can control the extent to which individual particles are influenced by their past successes versus the successes of their neighbors, thereby affecting the exploration and exploitation capabilities of the PSO algorithm. This balance is crucial for the effectiveness of PSO in finding optimal solutions across a wide range

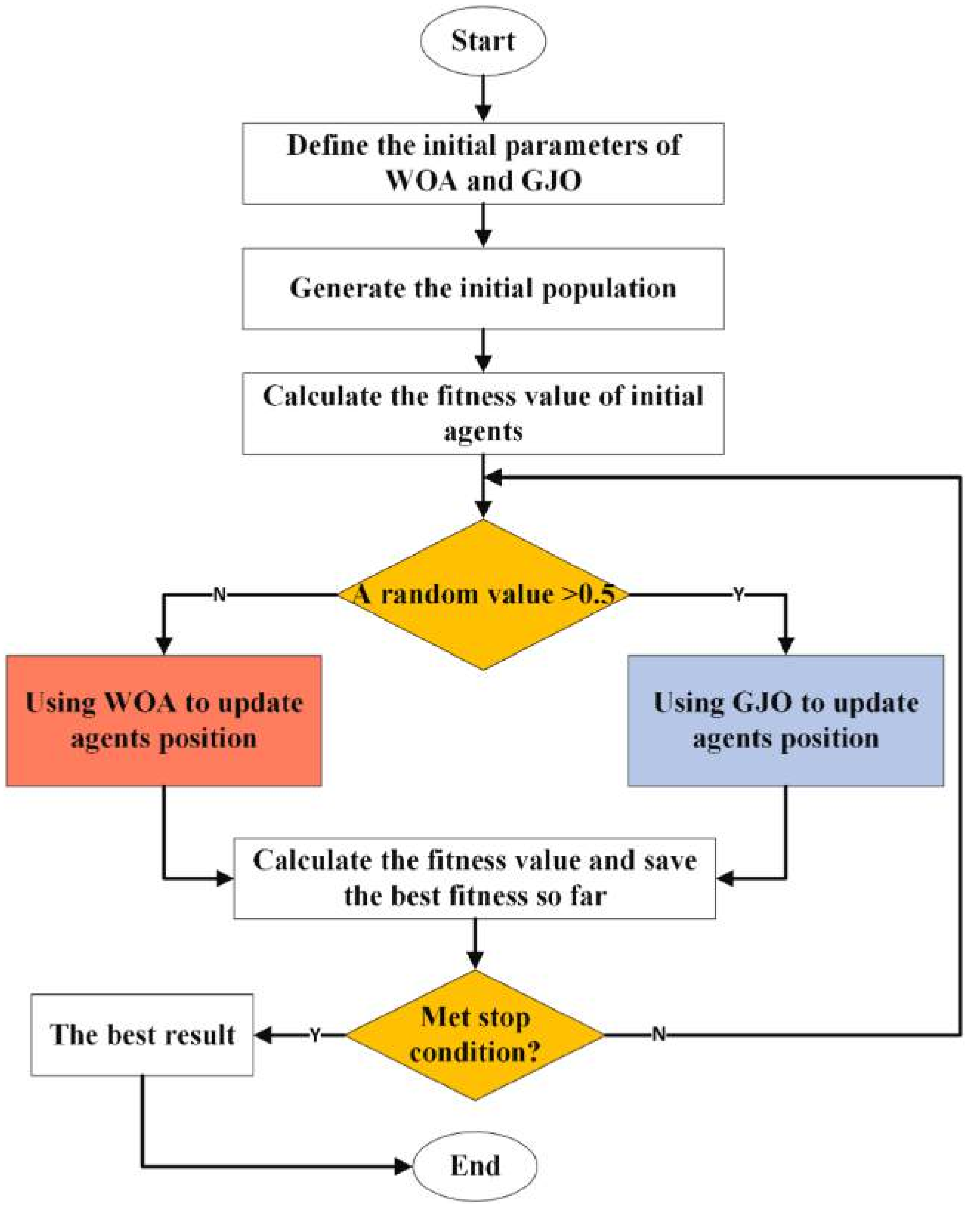

Fig. 14. The main structure of the GJO-WOA [66].

of optimization problems.

In this formula, $Y_{\text{best}}^{\text{local}}(t)$ represents both the best positions found individually and by the swarm. Eqs determine the updated position. (26 and 27) [42], with the coefficients α and β set to 0.6 and 0.4, respectively.

$$\mathrm{Y}_1^{\text{new}}(\mathrm{t}) = \mathrm{Y_M}(\mathrm{t}) - \alpha \times E.|\mathrm{Y_M}(\mathrm{t}) - \mathrm{rl.Prey}(\mathrm{t})| - \beta \times V(t+1) \tag{26}$$

$$\mathrm{Y}_2^{\text{new}}(\mathrm{t}) = \mathrm{Y_{FM}}(\mathrm{t}) - \alpha \times E.|\mathrm{Y_{FM}}(\mathrm{t}) - \mathrm{rl.Prey}(\mathrm{t})| - \beta \times V(t+1) \tag{27}$$

4.1.8. GJO- Golden Sine algorithm

The GJO algorithm, inspired by the collaborative hunting strategy of golden jackals, is a potent metaheuristic approach. However, its reliance on the leading male jackal for updating prey positions and the occasional lack of variety among the jackals can lead to premature convergence at local optima. To overcome these limitations, this study introduces an enhanced version called the Golden Sine Algorithm (GSA) integrated Dynamic Lens-Imaging Learning (LSGJO) with GJO [47]. First, this approach can enhance GJO with dual update mechanisms inspired by GSA. Then, it enhances the intelligence of search agents and the overall optimization power. In addition, a unique nonlinear dynamic scaling factor is used to maintain diversity among the population. The efficacy of LSGJO is confirmed through tests on 23 standard benchmarks and three intricate real-world design challenges. The findings indicate that LSGJO outpaces 11 cutting-edge algorithms in terms of convergence speed and precision, showcasing notable enhancements in global and local search capabilities, and excels particularly in handling constrained optimization tasks.

Fig. 15 shows the advantages of combining GJO with other algorithms.

Fig. 16 illustrates the disadvantages of combining GJO with other methods. Combining algorithms has many advantages, but it also creates disadvantages in reaching the final solution. Increased computational complexity is one of the main problems because combining algorithms requires more time and resources to execute. Another problem is convergence instability because some algorithms, such as SCA or MFO, tend to have oscillatory behavior, and this behavior can interfere with GJO for local optimization. In addition, the need for precise parameter tuning in combined algorithms is a serious challenge because a lack of proper tuning can lead to reduced effectiveness and get

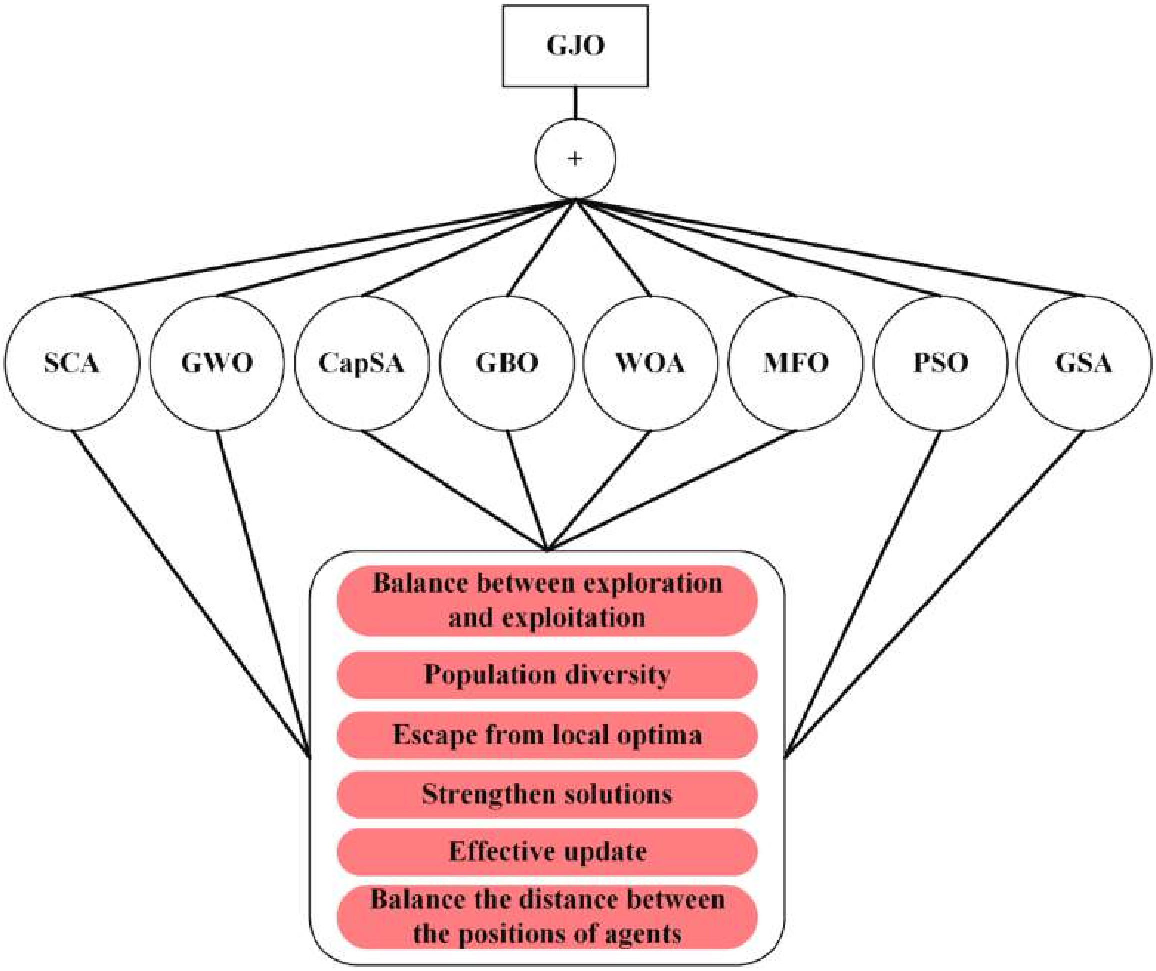

Fig. 15. The advantages of combining GJO with other algorithms.

stuck in local optima.

4.2. Improved

Challenges the GJO algorithm faces are characterized by its slow rate of convergence, a tendency to become ensnared in local optima, and an inability of the exploration and exploitation phases to address scenarios involving high-dimensional spaces adequately. Various enhancement strategies have been introduced in recent years in response to these limitations. Among these are adaptive strategies that adjust parameters dynamically, integrating deep learning and machine learning techniques to refine decision-making processes, Opposition-Based Learning (OBL) to explore alternative solutions, and employing parallel processing for efficiency improvements. Additionally, the sine and cosine algorithm has been proposed to enhance the GJO's ability to navigate complex search spaces, offering a more robust approach to global optimization.

4.2.1. Adaptive strategy

An enhanced version of the GJO algorithm termed Local-GJO (LGJO), which incorporates multiple strategic enhancements, is introduced [68]. Initially, the algorithm deploys a chaotic mapping technique for populating the initial solutions, diverging from the conventional approach of using random parameters. This method aims to produce initial solutions exhibiting broad diversity across the search space. Subsequently, the algorithm introduces a dynamic inertia weight, modulated by cosine variations, to enhance the realism of the search process. This modification is designed to balance the algorithm's ability to explore the search space broadly (global search) and exploit the areas around promising solutions in depth (local search). Lastly, the LGJO algorithm integrates a Gaussian mutation-based position update strategy, capitalizing on the optimal individual within the population to guide the search. This approach not only boosts the diversity within the population but also aids in effectively navigating uncharted territories of the search space, thereby mitigating the risk of the algorithm getting trapped in local optima.

Dimensional Gaussian mutation is applied to the position of the optimal individual within the population to enhance diversity and guide the evolutionary process towards the most promising regions of the search space. This technique is strategically employed to avoid the common pitfall of converging to local optima, ensuring a more comprehensive exploration of potential solutions. Additionally, using an inertia weight factor is crucial in accelerating the convergence rate while preventing the algorithm from getting stuck in suboptimal solutions. This inertia weight is mathematically articulated in Eq. (28) [68], where it likely adjusts the momentum of the search, balancing the exploration of new areas with the exploitation of known reasonable solutions to navigate the optimization landscape efficiently.

$$\omega = 1 - (t/\ \mathrm{MaxIter}\ )^2 \tag{28}$$

Several strategies have been implemented to enhance the algorithm's global search capability. An inertia weight factor is introduced at the optimal location to modulate the search momentum, promoting a broader search space exploration. Gaussian mutation is applied as a mutation technique, introducing variability and preventing premature convergence by diversifying the population. Moreover, a greedy strategy

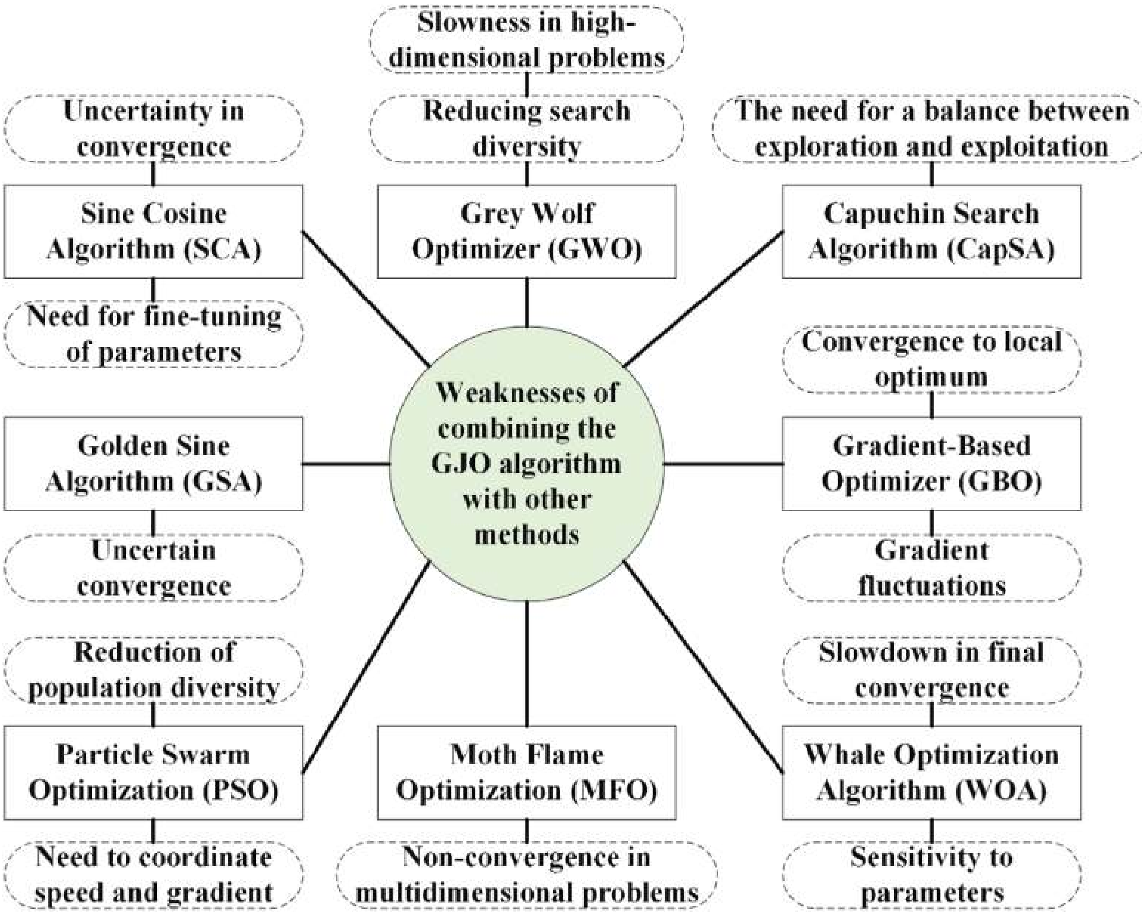

Fig. 16. The disadvantages of combining GJO with other algorithms.

is utilized to ensure that the best solution for each dimension is retained, optimizing the search process by selectively keeping the most promising solutions. This greedy approach is also used to update the fitness values of solutions, according to Eq. (29) [68], ensuring that the algorithm consistently progresses towards more optimal solutions by favoring those with better fitness. This methodical combination of strategies aims to strike a balance between exploring new areas and exploiting known reasonable solutions, thus improving the efficiency and effectiveness of the optimization process.

$$\text{Xbestbew}(j) = \omega * \text{ Xbest }(j) + \text{randn} * \text{ Xbest }(j) \tag{29}$$

$$\text{Xbest} = \begin{cases} \text{Xbestnew}, & \text{if } f\ (\text{Xbestnew}) < f\ (\text{Xbest}) \\ \text{Xbest}, & \text{else} \end{cases} \tag{30}$$

The LGJO effectiveness is rigorously assessed using a comprehensive set of 23 mathematical benchmark functions alongside the CEC-2019 and CEC-2021 test suites. The performance of this algorithm is benchmarked against several renowned and highly competent optimization techniques. This comparative analysis examines various aspects, such as solution quality, convergence trends, and the algorithm's robustness, to highlight its superior performance and high-quality outcomes. Furthermore, the practical applicability of the proposed algorithm is showcased through its deployment in solving four constrained industrial problems. The results from these real-world applications underscore the algorithm's capability to tackle complex, constrained challenges, establishing its competitive edge over other optimization methods. A flowchart illustrating the multi-strategy mixing approach, integral to the algorithm's design, is depicted in Fig. 17, visually representing the algorithm's workflow and strategic components. The Gaussian Mutation operator is a technique used in MH and optimization algorithms that makes minor changes to solutions using the Gaussian Distribution. In this method, a new value is generated for the current solution. This value is obtained by adding a random noise to the current solution. The Gaussian Mutation operator helps enhance the search capability in the exploration and exploitation phase.

An enhanced approach for optimizing rolling bearing dynamics models is introduced, utilizing an Improved IGJO algorithm combined with a technique for fusing sensitive features [69]. The initial step involves the development of the IGJO algorithm. This aims to tackle the complexities of multidimensional optimization and address the balance between the global and local search capabilities inherent in the GJO algorithm. Following this, the method introduces a strategy for combining sensitive features related to bearing faults, employing a binary version of the Improved GJO (B-IGJO) algorithm alongside Principal Component Analysis (PCA). The B-IGJO algorithm is derived using a discretization method based on the Sigmoid function. The parameters of the rolling bearing dynamics model are refined using the IGJO algorithm. It's noted that during the local search phase, the search scope narrows as the algorithm progresses through iterations, potentially increasing the likelihood of the algorithm converging to local extremes.

An adaptive weight, denoted as η is introduced, which is determined by the fitness value of the male golden jackal. Eq. (31) [69] allows each golden jackal in the algorithm to adjust its search range dynamically during the local search phase, avoiding convergence to local extremes. Upon entering the local search stage, each golden jackal is assigned a η value. A smaller η reduces the immediate search area around the prey, prompting the golden jackal to broaden its hunting territory. This strategy helps maintain a balance between intensively searching a promising area and exploring wider regions to discover potentially better solutions.

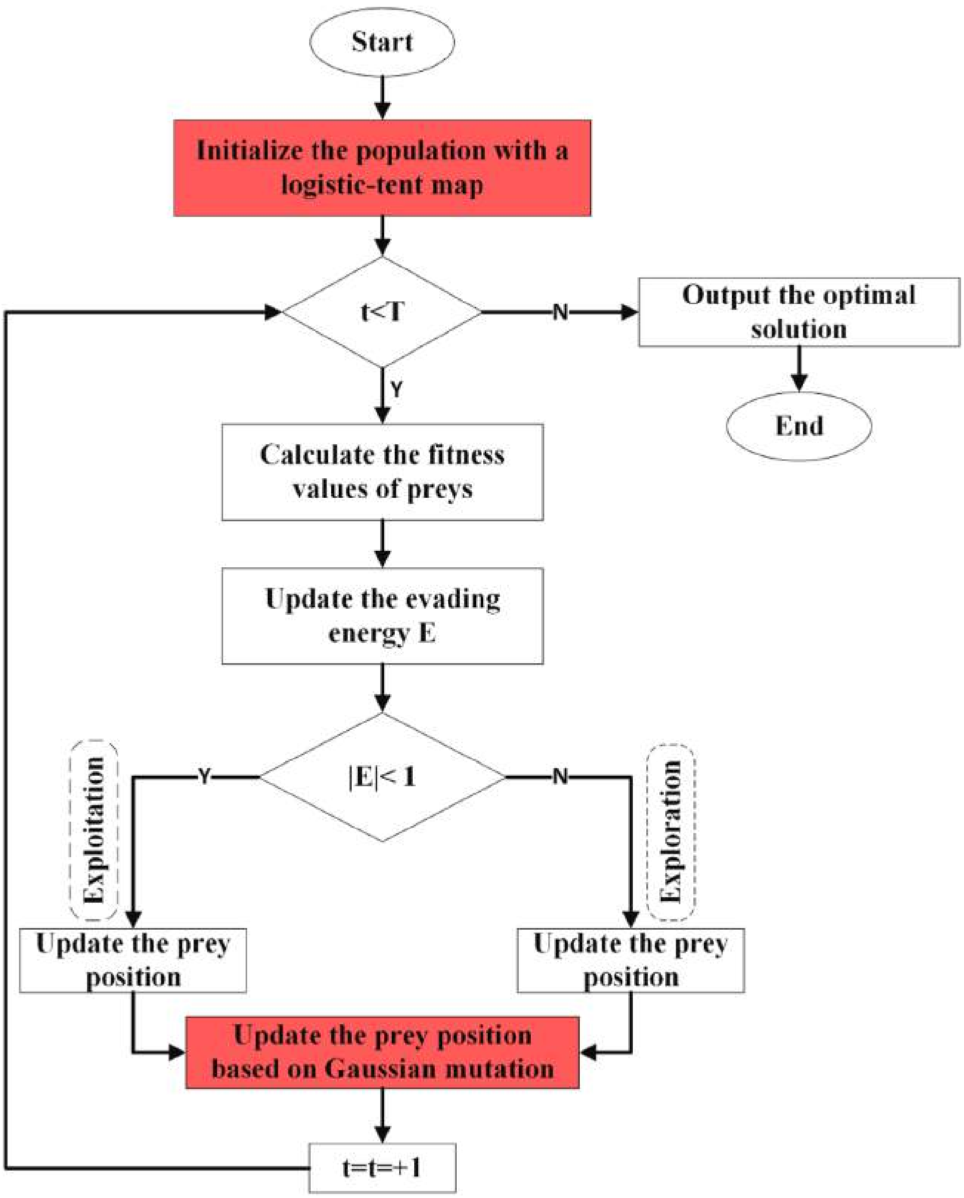

Fig. 17. The flowchart of multi-strategy mixing [68].

$$\eta = \begin{cases} \eta_{max} f_i \geqslant f_{avg} \\ \eta_{\min} + \dfrac{(\eta_{max} - \eta_{min}) \times (f_i - f_{\min})}{f_{\min}} f_i < f_{avg} \end{cases} \tag{31}$$

In the given context, fi represents the fitness value of the i^{th} golden jackal, f_{avg} represents the average fitness value of all golden jackals, $f_{\min}$ denotes the minimum fitness value among the golden jackals, and fmax denotes the maximum fitness value among the golden jackals. η_{min} stands for the minimum weight and η_{max} stands for the maximum weight. Consequently, during the capture stage, Eq. (4) undergoes an update to Eq. (9). The exploration stage of GJO is executed by Eq. (32) [69].

$$\begin{cases} X_{i\_M}(t+1) = X_M(t+1) - D \times \eta|\text{Levy}(\zeta) \times X_M(t+1) - X_i(t)| \\ X_{i\_FM}(t+1) = X_{FM}(t+1) - D \times \eta|\text{Levy}(\zeta) \times X_{FM}(t+1) - X_i(t)| \end{cases} \tag{32}$$

A new approach for detecting unusual behavior among users is introduced, which utilizes an adaptive form of the GJO [70]. This method establishes an array of weak learners in the initial stages, drawing upon data indicative of atypical user activities. This is achieved through a process of sampling with replacement, coupled with the application of filtering methodologies to pinpoint the foundational models for tri-training. To counteract the inherent issues of slow convergence rates and the propensity to fall into local optima that plague conventional optimization techniques, the adaptive GJO is applied to refine the parameter optimization process within the tri-training framework. When comparing the computational efficiency of the standard GJO algorithm against its adaptive counterpart, the latter exhibits a notable decrease in processing time by approximately 8.22 %. Furthermore, the adaptive GJO's nuanced mimicry of a golden jackal's hunting dynamics—specifically, the adjustments in velocity and the acceleration phase during the chase—is articulated through Eq. (33) [70].

$$\varphi = E_p \times \text{erf}\left(\left(\frac{\delta}{2(t-\gamma)}\right)^2\right) \tag{33}$$

Within this context, the symbol φ denotes the incremental function attributed to the golden jackal, whereas δ indicates the scaling parameter. The notation *Ep* is employed to represent the energy function of the body, with γ serving to mark the position parameter and t being used to signify the number of the current iteration in the generation sequence. The agent's endeavor to reach the target function is divided into two distinct segments: an adjustment and a pursuit phase. It is posited that the vigor of the agent is subject to variation in direct correlation with the distance of pursuit at any given instance. Reflecting the unique characteristics of the agents, this particular aspect is quantified with the aid of Eq. (34) [70].

$$E_p = 2\theta_0\left(\left(\sin\left(\frac{1}{t}\right)\right)^2 + 1\right) 0 \le t \le T \tag{34}$$

The initial physical capability is denoted by θ_0. Consequently, the hunting actions of the agents are revised according to Eqs. (35) and (36) [70].

$$\mathrm{Y}_1(\mathrm{t}) = \mathrm{Y}_\mathrm{M}(\mathrm{t}) - \mathrm{E}\varphi|r \times \mathrm{Y}_\mathrm{M}(\mathrm{t}) - \mathrm{prey}(\mathrm{t})| \tag{35}$$

$$\mathrm{Y}_2(\mathrm{t}) = \mathrm{Y}_\mathrm{FM}(\mathrm{t}) - \mathrm{E}\varphi|r \times \mathrm{Y}_\mathrm{FM}(\mathrm{t}) - \mathrm{prey}(\mathrm{t})| \tag{36}$$

Within the framework of an IEEE 33-bus radial distribution network, a thorough strategy for allocating and scheduling wind turbines and electric vehicle (EV) parking lots has been implemented [71]. The strategic placement and sizing of wind turbines and EV parking infrastructures are ascertained using an advanced version of the GJO, augmented with *Rosenbrock's* Direct Rotational (RDR) method. This enhanced algorithm, IGJO, is distinguished by its superior efficacy and ability to secure optimal solutions with greater precision and more favorable objective function values. The effectiveness of the IGJO method is particularly underscored by its substantial reduction in energy loss costs, grid energy expenditures, and fluctuations in network voltage, which are decreased by 29.76 %, 65.86 %, and 18.63 %, respectively, relative to the baseline network configuration. These improvements are further corroborated by statistical analyses that validate IGJO's superior performance against traditional optimization techniques. Moreover, the inclusion of considerations for EV battery degradation costs into the IGJO methodology yields further reductions in energy loss expenses, grid energy costs, and voltage irregularities by 3.28 %, 1.07 %, and 4.32 %, respectively, when contrasted with scenarios that overlook the implications of battery wear. The research additionally sheds light on the consequences of diminished EV availability, which is shown to escalate grid energy costs and compromise voltage stability within the network, thereby underscoring the significant influence of EV integration on the grid's overall performance.

A new version of GJO called the Ameliorated GJO (AGJO), is introduced to solve engineering problems [72]. Three strategies, including augmented movement, global search, and multi-way updating of prey position, are used to reduce the imbalance of GJO. Also, an environmental disturbance factor is added in the third strategy to enhance the ability of GJO to avoid local optima. The performance of AGJO is tested on 23 reference functions and engineering problems compared to GJO and seven other algorithms. The results show that AGJO achieves high convergence speed and optimization ability in >90 % of cases. A new algorithm, Q-learning-improved GJO (QIGJO), is introduced for optimization problems [73]. The method uses five update mechanisms and a two-population cooperation mechanism based on Q-learning. Also, a new convergence factor is added to the algorithm to enhance the convergence ability of GJO significantly. Evaluations are conducted on 23 standard benchmark functions, the CEC2022 function set, and three classical engineering design problems. The results demonstrate high convergence accuracy and improved algorithm global search capability.

4.2.2. Deep learning

Enhancing the precision of wind power generation forecasts is vital for power grids' secure and stable functioning. To address this, the paper introduces a novel wind power prediction model that leverages cutting-edge methodologies such as a GJO-optimized Bidirectional Long Short-Term Memory (*BiLSTM*) neural network, Kernel Principal Component Analysis (KPCA), and Empirical Mode Decomposition (EMD).

The paper introduces a tool life prediction model for dicing saws that employs an Adaptive GJO (AGJO) optimized Gated Recurrent Unit (GRU) to enhance prediction accuracy [74]. The conventional GJO algorithm faces challenges such as slow early convergence, reduced later-stage accuracy, and a tendency to get trapped in local optima. To overcome these issues, the study incorporates a nonlinear convergence factor and an adaptive weighting factor into the standard GJO, resulting in an improved AGJO. Experimental outcomes reveal that the proposed AGJO-GRU model significantly outperforms the original GJO-GRU model, showing a 1.96 % increase in accuracy and a 27.04 % reduction in root mean square error, demonstrating superior predictive capabilities. The overall methodology of the AGJO-GRU model is depicted in Fig. 18.

Challenges faced by the standard GJO include an imbalance in the exploration and exploitation phases and a lack of convergence precision. To address these issues, it is recommended that the standard GJO algorithm be augmented with a nonlinear convergence factor and an adaptive weighting factor. A key element of this enhancement is the dynamic modification of the prey energy value (E), which is crucial to the algorithm's effectiveness. In the traditional GJO approach, the linear decrement of the prey energy E_1 with the progression of iterations fails to achieve an optimal equilibrium between the algorithm's global search (exploration) and the local search (exploitation) components. The enhancement proposes a gradual decline in the prey's energy during the algorithm's early stages, permitting a broader search scope and enhancing global exploration capabilities. As the algorithm advances to the intermediate and final phases, a more pronounced reduction in the prey's energy is advocated. This adjustment aims to concentrate the algorithm's efforts on the most promising regions, thereby accelerating convergence and improving the overall efficiency of the optimization process. The revised methodology for calculating the prey's energy value is encapsulated in Eq. (37) [74], which incorporates these modifications to foster a more balanced and efficacious optimization strategy.

$$E_1 = \begin{cases} c_1 * \left(1 - \frac{1}{\mathrm{e}-1}\right) * \left(e^{\frac{t}{T}} - 1\right) & t \le \frac{T}{2} \\ c_1 * \left(1 - \frac{\mathrm{t}}{T}\right)^{\frac{1}{2}} & t > \frac{T}{2} \end{cases} \tag{37}$$

As per Eq. (37), E1′s value will gradually approach convergence during the initial half cycle of the iteration, broadening the algorithm's search range. In the latter half of the iteration, E1′s value will hasten convergence, enhancing the algorithm's efficiency. c_1 and c_2 are random parameters for the search equilibrium. t and T represent the current iteration and the maximum iteration.

In response to the challenge posed by the inherent unpredictability of traffic flow, which often leads to diminished prediction accuracy, the GJO-GRU data prediction model has been developed [75]. This innovative model employs the GJO to refine the GRU architecture, aiming to counteract the issues stemming from nonlinearity and temporal fluctuations. An initial decision made by the model involves opting for a more straightforward GRU framework over the more complex Long Short-Term Memory (LSTM) neural networks, a choice motivated by the desire to reduce complexity and accelerate training speeds. The next step involves the application of the GJO algorithm to adjust the GRU model's hyperparameters meticulously. This process is designed to diminish the influence of human biases and significantly improve the accuracy of predictions. Following these adjustments, the performance of the GJO-GRU model is rigorously evaluated against other models, including the GRU, LSTM, and GJO-LSTM, utilizing the data from the California Performance Measurement System (*PeMS*). The outcomes of these experiments reveal that the GJO-GRU neural network prediction model surpasses its counterparts, achieving the highest coefficient of determination alongside the lowest values in mean absolute error (MAE), root-mean-square error (RMSE), and mean absolute percentage error (MAPE). These findings highlight the model's exceptional ability to fit data and generalize, thereby markedly enhancing the precision of

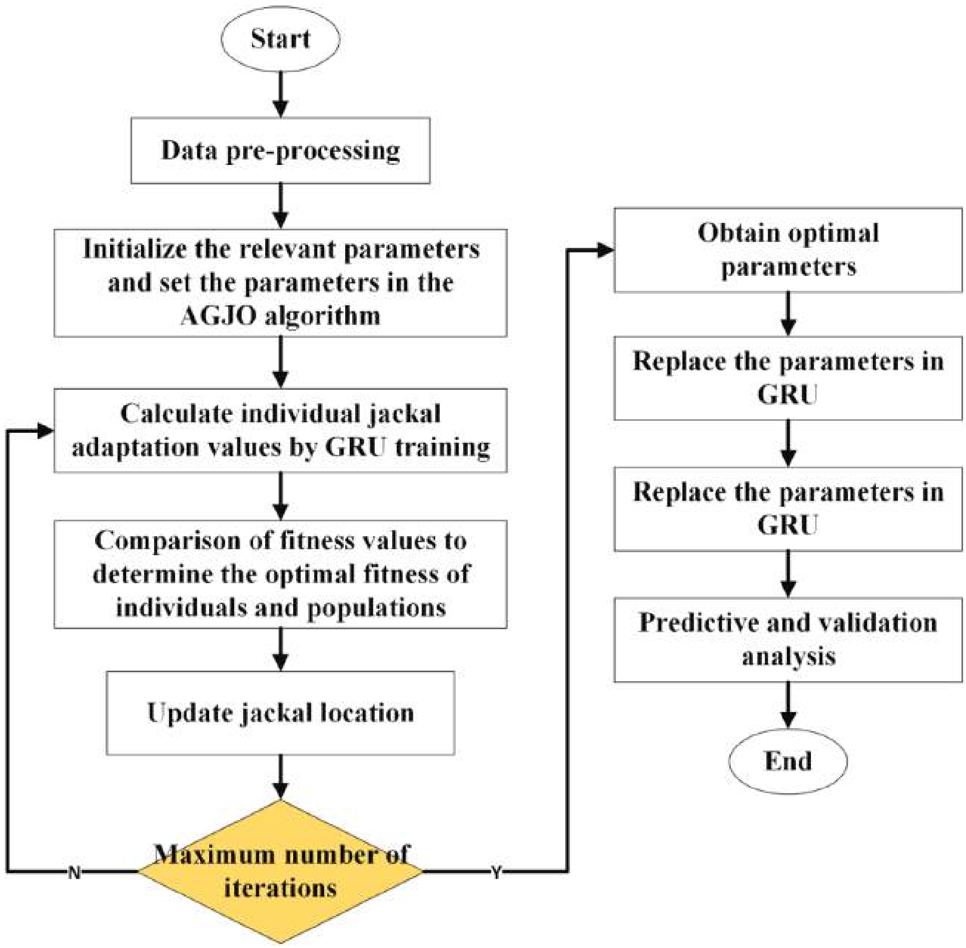

Fig. 18. AGJO-GRU overall flowchart [74].

traffic flow predictions.

A new Intrusion Detection System (IDS) model for IoT networks is developed using the Improved Binary GJO (IBGJO) algorithm and LSTM network [52]. Initially, the GJO algorithm is enhanced with OBL. The improved GJO operates in binary mode to select features from IDS data, optimizing subset selection. IBGJO further enhances GJO's performance by incorporating the OBL strategy and managing the initial population to avoid local optima. In the IBGJO-LSTM model, LSTM is employed for sample classification. While traditional machine learning techniques achieve high detection rates, their efficiency diminishes with larger datasets. Deep learning methods like LSTM are better for distinguishing samples from extensive data. This is attributed to the binary mode of the improved GJO algorithm effectively selecting relevant features from IDS data and LSTM accurately classifying samples.

A new methodology, termed GJODL-ADPW (GJO with Deep Learning-based Anomaly Detection in Pedestrian Walkways), has been introduced to enhance road traffic safety [76]. This innovative technique is engineered to effectively identify anomalies, such as vehicles or skaters, within pedestrian pathways. Employing the *Xception* model, the method excels in the efficient extraction of features, while the GJO algorithm is applied for the optimal tuning of hyperparameters. Anomaly detection within this framework is subsequently performed through the use of a bidirectional LSTM (*BiLSTM*) technique. A comprehensive series of experimental analyses is undertaken to ascertain the enhanced efficacy of the GJODL-ADPW system. Through detailed comparative evaluations, the GJODL-ADPW method is demonstrated to outperform other contemporary techniques, underscoring its superiority in anomaly detection on pedestrian walkways.

The GJO with Deep Learning-based Cyberattack Detection and Classification (GJODL-CADC) approach has been devised and subjected to evaluation on the Industrial Internet of Things (IIoT) platform [77]. This system's fundamental objective is identifying and categorizing cyber threats within the IoT framework. Optimization issues in IoT, such as offloading tasks and data security, are important [78,79]. To address these challenges, the GJODL-CADC algorithm integrates an innovative feature selection method based on GJO to enhance classification accuracy. In the next phase, the GJODL-CADC methodology combines an autoencoder with a deep belief network (AE-DBN) for cyberattack detection. The efficiency of the AE-DBN model is further augmented by integrating the pelican optimization algorithm (POA), which contributes to a notable enhancement in detection capabilities. A series of comprehensive simulations are performed to validate the efficacy of the GJODL-CADC approach. These extensive evaluations reveal that the GJODL-CADC method outshines existing techniques, showcasing its potential with promising results in detecting and classifying cyberattacks on IIoT platforms.

A cutting-edge hybrid methodology is introduced to predict closing prices of West Texas Intermediate (WTI) and Brent crude oil futures. The process begins with applying the variational modal decomposition (VMD) technique, which dissects the original dataset of prices into several sub-models. Each of these sub-models is then fed into an LSTM network. To optimize the performance of the LSTM, an improved version of the Golden Jackal Optimizer, known as IGJO, is deployed to adjust the network's hyperparameters [85] meticulously. In a subsequent step, an innovative form of the ensemble empirical mode decomposition method with adaptive noise (ICEEMDAN) is employed to break down further the error sequences generated. These decomposed sequences of errors are independently forecasted using the GRU network. The final forecasting results are compiled through a process of linear aggregation. Moreover, the research introduces kernel density estimation (KDE) for interval estimation, building on point predictions to forecast uncertainties. Empirical evaluations of the VILIG model demonstrate its superior performance compared to other leading models across various quantitative metrics. Given its demonstrated efficacy, this model is well-positioned to become a crucial tool for investors in crude oil futures and market regulators. It offers a solid basis for strategic decision-making and enhances the robustness of investment and regulatory strategies.

Predicting multivariate time series in wastewater treatment plants (WWTPs) poses a challenge due to their complex nonlinear nature. To address this challenge, a novel prediction framework is proposed in this study [48]. The findings underscore the efficacy of the proposed prediction system in accurately forecasting multivariate water quality time series data in WWTPs, highlighting its potential for practical applications in wastewater management and treatment.

The research introduces an innovative machine learning model named LSTM-GJO, which synergizes the LSTM neural network with the GJO algorithm to predict tribological properties [43]. It has been noted that there is a decrease in the coefficient of friction attributed to the diminished contact area between the composite materials and the corresponding disk. Considering the array of variables implicated in wear assessments, such as the composition of reinforcements, the velocity of sliding, and the applied load, a machine learning framework has been formulated to adeptly forecast wear rates. The construction of the LSTM-GJO model aims to augment the efficacy of the LSTM neural network by capitalizing on the optimization capabilities of the GJO. To assess the reliability of this model, empirical data from experiments on Cu–Al2O3 nanocomposites are used. Additionally, the performance of the LSTM-GJO is compared with alternative models, such as the SCA, GWO, and Salp Swarm Algorithm (SSA). The empirical results underscore the LSTM-GJO model's predominance over the models against which it was compared. An illustrative representation, found in Fig. 19, delineates the procedural steps involved in predicting tribological characteristics, emphasizing the LSTM-GJO model's dependency on the GJO algorithm to calibrate the parameters within the LSTM network. This methodological approach is intended to offer a more precise and effective prediction tool for tribological attributes, thereby contributing to materials science and engineering progress.

LSTM, GRU, and CNN algorithms are among the main algorithms in the field of deep learning that are used to predict, classify, and recognize objects [80]. Conventional machine learning approaches exhibit several flaws, including a constrained capacity to capture complex patterns and

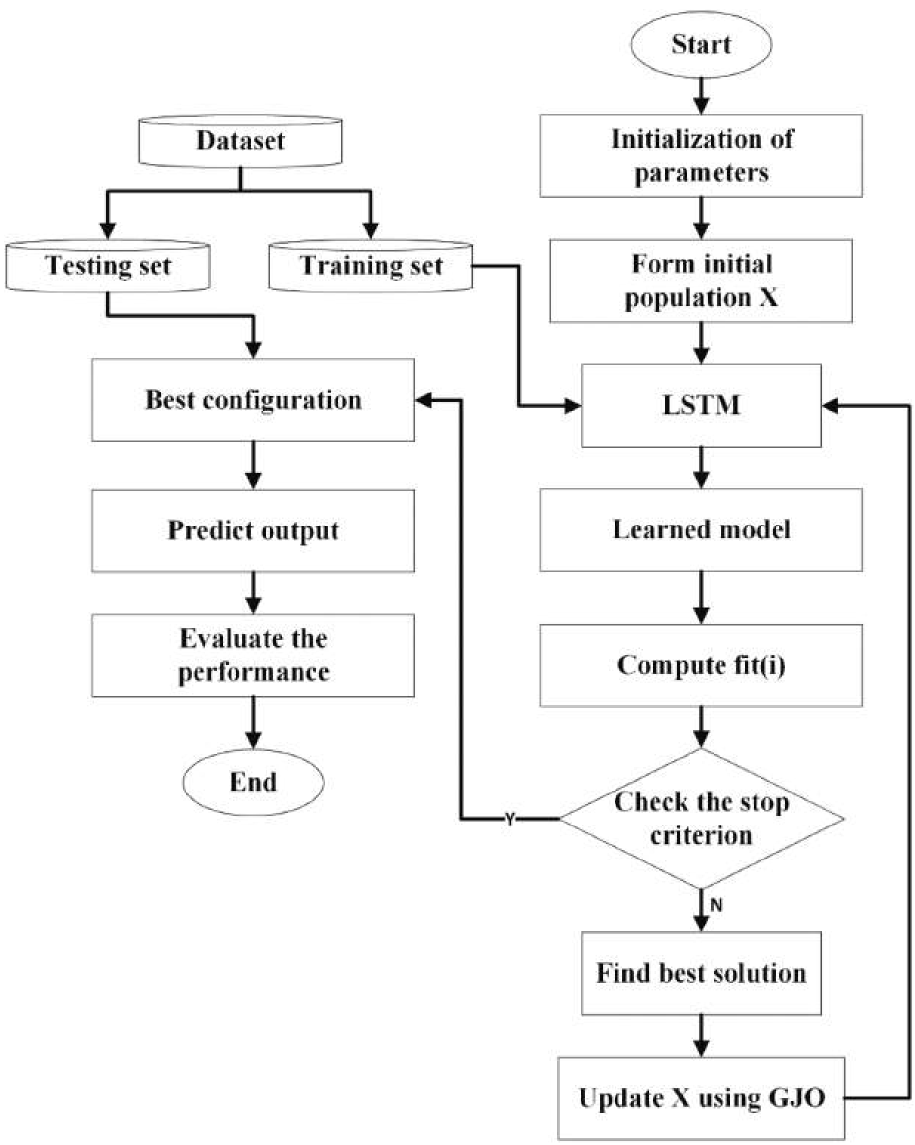

Fig. 19. Structure of LSTM- GJO model used to predict the tribological properties of the composites [43].

challenges in addressing nonlinear issues. These limitations affect the predictive performance of standard machine learning algorithms. However, the past few years have seen a surge in computing power, leading to the emergence of advanced deep-learning models that offer enhanced capabilities for modeling and generalization. These include technologies like Recurrent Neural Networks (RNN), LSTM networks, and GRU. GRU, a variant of RNN, is designed to overcome the vanishing gradient challenge often faced by traditional RNNs. Furthermore, GRUs excel in identifying relationships within nonlinear sequential data over time, making them particularly effective for predictive tasks.

The adaptive multi-level attention-based deeplabv3+ (AMLA-Deeplabv3+) model with the improved GJO algorithm is proposed for the semantic segmentation of small objects in aerial images [81]. This model uses multi-level attention units in the *Atrous* module and compression and excitation units in the decoder section. By carefully tuning parameters such as the number of neurons, learning rate, and batch size, the experimental results show an improvement in accuracy (99.65 %) and computation time (3.02 min) compared to conventional methods.

A new method for classifying cancer-related miRNA biomarkers, named Syntax-Guided Hierarchical Attention Network optimized with Golden Jackal Optimization Biomarker Categorization (SGHAN-GJOA-MiRNA-BC), is proposed [82]This model uses an SGHAN optimized with the GJO algorithm. SGHAN is used to classify miRNA biomarkers and is intended to aid in cancer diagnosis, treatment, and prognosis. The GJO algorithm improves the accuracy and performance of SGHAN. This method significantly improves accuracy, sensitivity, F-criterion, computational time, and error reduction compared to traditional techniques.

4.2.3. Machine learning

In [53], a deep learning-assisted intrusion detection system with a GJO algorithm for network security (GJOADL-IDSNS) is proposed, which marked a significant advancement in cybersecurity. The core aim of the GJOADL-IDSNS framework is to proficiently detect and categorize network intrusions, thereby bolstering the security of networks. The initial step in the GJOADL-IDSNS process involves normalizing data and transforming the input data into a format more conducive to analysis and processing. Within the GJOADL-IDSNS approach, a feature selection (FS) mechanism based on the GJO Algorithm (GJOA-FS) is employed to identify an optimal set of features for intrusion detection. Following this, the GJOADL-IDSNS system adopts an attention-based bidirectional LSTM (A-*BiLSTM*) model specifically tailored for the detection of intrusions. To refine the hyperparameters of the A-*BiLSTM* model and enhance its effectiveness, the GJOADL-IDSNS method integrates the SSA. The efficacy of the GJOADL-IDSNS technique is rigorously assessed using well-established benchmark datasets in a simulated environment. Comparative analysis establishes that the GJOADL-IDSNS technique surpasses competing models in intrusion detection and classification accuracy and efficiency. These findings indicate that the GJOADL-IDSNS method provides superior performance in safeguarding network security and effectively identifying and mitigating intrusions.

To overcome the challenges inherent in conventional photovoltaic (PV) power models, which frequently suffer from overfitting and the tendency to get ensnared in local optima, a new hybrid model named IXGBoost-KELM is introduced [83]. This innovative model synergizes the strengths of both XGBoost and Kernel Extreme Learning Machine (KELM) algorithms, capitalizing on their respective advantages to boost the dependability of predictive outcomes. The introduction of the IXGBoost-KELM model is particularly pertinent given the known issues with XGBoost, including its slow execution speeds, substantial memory demands, and the KELM's noted instability in performance. To address these concerns, the study optimizes the hyperparameters for both algorithms. This optimization is achieved by applying random search (RS) techniques alongside the GJO, which refine the model's stability and enhance its predictive precision while reducing the likelihood of overfitting. The effectiveness of the IXGBoost-KELM model is validated through experimental testing, demonstrating significant improvements in prediction accuracy under various environmental conditions. This development marks an important step forward in resolving the limitations of traditional PV power models, presenting a more effective and reliable method for forecasting PV power generation.

Predicting suspects in crime scenes involves categorizing potential perpetrators based on location, time, and the type of crime committed. However, electronic forensics poses significant challenges for investigators in scenarios involving large datasets. Law enforcement often relies on hand-drawn or computer-generated face sketches to identify perpetrators. Hence, developing an automated method for expanding face sketches becomes crucial in enhancing investigative processes. Deep learning models, such as the GJO-Artificial Neural Network (GJO-ANN), have emerged as valuable tools for generating face sketches that aid in crime detection [84]. These generated sketches are then compared with eyewitness descriptions and artist renditions to identify similarities, thereby facilitating perpetrator detection. Experimental results demonstrate the superior performance of GJO-ANN in synthesizing face sketches for crime detection purposes. This underscores the potential of advanced deep learning techniques in augmenting law enforcement efforts and improving investigative outcomes in criminal cases.

Introduced to address the shortcomings of conventional molybdenum ore grade identification methods, which typically grapple with inefficiencies and elevated costs, is a novel ore grade detection technique that capitalizes on ore spectral data. This method integrates a powerful combination of Multivariate Singular Value Decomposition (MTSVD), Tuned-GJO (TGJO), and Extreme Learning Machine (ELM), known as MTSVD-TGJO-ELM [85]. Instead of relying on traditional linear modeling techniques, the Extreme Learning Machine effectively models the ore grade, offering a more dynamic approach. The challenges posed by the inherently ill-posed nature of ore grade detection are tackled through the strategic application of TGJO and MTSVD for parameter optimization. This ensures that the model achieves robustness and maintains high accuracy levels. When subjected to a comparative analysis against other classical machine learning algorithms, the MTSVD-TGJO-ELM combination is distinguished by its superior accuracy, setting a new benchmark in the field. This innovative approach heralds a significant leap forward in rapidly detecting ore grades within the mining process, mainly benefiting the mining and beneficiation of molybdenum ores. It promises to elevate ore recovery rates by facilitating more precise beneficiation processes. By introducing a more efficient and cost-effective method, this advancement plays a crucial role in optimizing mining operations and enhancing resource utilization, particularly within the molybdenum mining sector.

A novel hybrid artificial intelligence model has been put forward to forecast the thermal dynamics of two distinct solar still (SS) designs, which are environmentally benign desalination apparatuses harnessing solar power to convert seawater into freshwater [45]. The first of these solar stills, designated as ALSS, features a basin and absorber plate made of aluminum, whereas the second, PCSS, is constructed from polycarbonate. Both designs incorporate a specialized absorber plate with an air cavity to enhance efficiency. This hybrid model is characterized by an Artificial Neural Network (ANN) that has been finely tuned through applying the GJO algorithm. The efficacy of this enhanced model is rigorously assessed through comparative analysis against standard ANN frameworks and two other models that have been optimized using either the Genetic Algorithm (GA) or the PSO. The findings from this comparison highlight the ANN-GJO model's exceptional precision in forecasting critical parameters such as the overall heat transfer coefficient, energy and exergy efficiencies, and the volume of distillate produced. Moreover, between the two SS designs, ALSS is shown to possess superior thermal performance, showcasing higher levels of water productivity, energy efficiency, and exergy efficiency, in contrast to PCSS. With its proven capability for accurately predicting the thermal behavior of solar still designs, this hybrid artificial intelligence model offers invaluable insights that can be leveraged to refine their performance in desalination processes, thereby contributing significantly to optimizing such sustainable technologies.

A novel approach called Dictionary-based Sparse Regression Learning with GJO (DSRL-GJO) is proposed for monitoring healthcare data within an Internet of Things (IoT)-based context-aware architecture (CAA) [86]. It holds promise for enhancing healthcare monitoring systems within IoT-based architectures, offering improved accuracy and efficiency in identifying patients' conditions.

An innovative reinforcement learning-enhanced GJO algorithm, dubbed QLGJO, has been developed for the segmentation of CT images to facilitate the diagnosis of COVID-19 [87]. This method is designed to overcome the limitations of the original algorithm's tendency to get trapped in local optima. To further augment the algorithm's efficacy, a hybrid model and three distinct mutation strategies have been integrated into the update mechanism to boost the population's diversity. Two different sets of experiments are undertaken to ascertain the effectiveness of the QLGJO algorithm. In the initial experiment, the performance of QLGJO is benchmarked against other sophisticated metaheuristic algorithms using the IEEE CEC2022 benchmark functions. In the subsequent experiment, the QLGJO algorithm undergoes experimental validation on CT images of COVID-19 cases, employing the Otsu method for this purpose. Its performance is then juxtaposed with that of several renowned metaheuristic algorithms. The outcomes from these experiments underscore the QLGJO algorithm's competitive edge in optimizing benchmark functions and the domain of image segmentation. Such results underscore the QLGJO algorithm's capability in effectively segmenting CT images to diagnose COVID-19, mainly when powered by reinforcement learning. This underscores the algorithm's utility and potential in the broader context of medical image analysis, pointing towards its applicability in enhancing diagnostic processes through advanced imaging techniques.

The continuous growth of electric vehicles (EVs) and conventional loads necessitates proper planning for electric vehicle charging stations and network development. A hybrid method for allocating fast-charging stations (FCSs) and battery energy storage (BES) systems by integrating photovoltaic (PV), along with scheduling, is proposed [88]. The results demonstrate that the proposed approach achieves lower energy loss than existing methods. Overall, the GJO–RFA technique presents an effective solution for optimizing the allocation and scheduling of FCSs, PV, and BES systems in EV charging infrastructure, contributing to the efficient and sustainable development of electric vehicle networks. Fig. 20 shows the advantages of the GJO algorithm in machine learning.

4.2.4. OBL

Opposition-Based Learning (OBL), as introduced by *Tizhoosh* [89], has proven to be a significant advancement in augmenting the performance of various metaheuristic optimization algorithms. This technique is predicated on generating the opposition of a given solution within the evaluation phase, thus presenting an alternative pathway to identifying a solution closer to the global optimum. By simultaneously assessing the feasibility of a solution and its anti-answer, OBL effectively broadens the algorithm's exploratory scope and enriches the diversity within the population. The methodology entails the selection of superior candidates from both the original and the inverse populations to constitute a new, enhanced population. This strategy is geared towards retaining high-caliber solutions while phasing out those of lesser quality, enabling a more expansive exploration of possible solutions. At its core, OBL is designed to refine the quality of initial solutions, avert the premature convergence of the algorithm to suboptimal local minima, and reduce the likelihood of engaging in ineffectual optimization during successive iterations. In summary, the introduction of OBL into MH algorithms serves to elevate their problem-solving efficacy substantially [90]. It achieves this by encouraging the investigation of a wider array of solution spaces and diminishing the propensity for early convergence, thus ensuring a more thorough and effective optimization process.

An innovative multi-threshold segmentation technique for breast cancer imagery is introduced, utilizing a refined variant of the Dandelion Optimization (DO) algorithm [91]. Integrating opposition-based learning principles enriches this technique and employs an enhanced DO algorithm to optimize the objective function, which maximizes between-class variance. Additionally, this method is fortified with fall-back strategies, introducing a memory matrix, and applying the GJO energy judgment mechanism to determine optimal threshold values. The optimization endeavor associated with the DO algorithm is fundamentally nonlinear, rendering simple linear correlations inadequate. Infusing a nonlinear function into the algorithm provides an extended exploration period, thereby contributing to a broadened diversity of solutions. Distinct from the conventional DO algorithm that functions autonomously within the decision space, opposition-based learning engenders opposite solutions and facilitates dual-directional exploration.

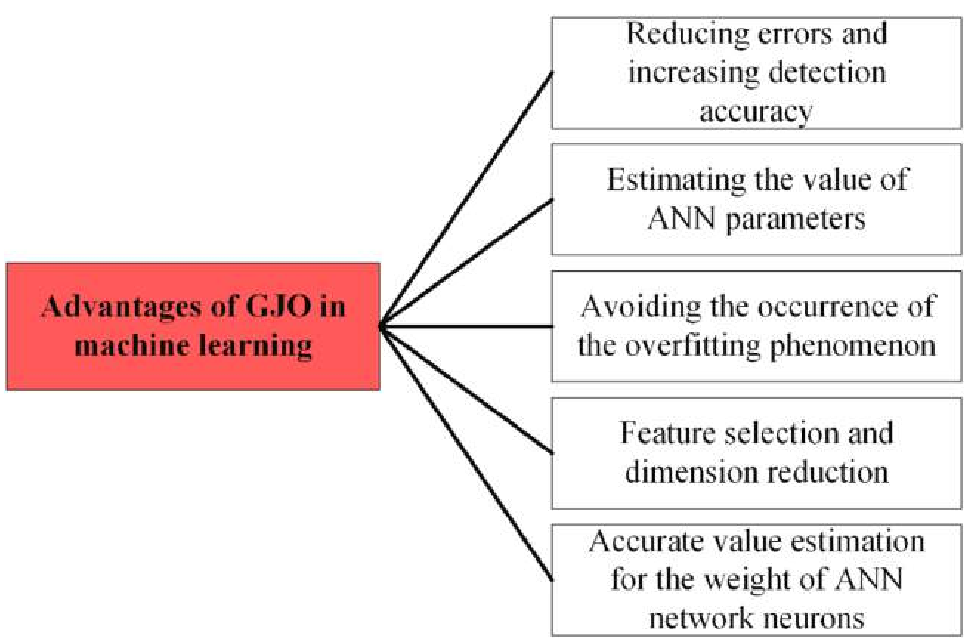

Fig. 20. The advantages of GJO algorithm in machine learning.

This dual-faceted approach bolsters solution diversity circumvents local optima's pitfalls and propels algorithmic convergence. In essence, this newly proposed method heralds a sophisticated strategy for the segmentation of breast cancer images, capitalizing on cutting-edge methodologies to elevate the efficacy and precision of optimization processes.

The issue of diminished accuracy in transformer fault diagnosis through Dissolved Gas Analysis (DGA) is adeptly tackled by the Stochastic Configuration Network (SCN) method, which is refined through the application of an Improved GJO (IGJO) [92]. This approach introduces a fault diagnosis technique for transformers that leverages an SCN optimized by IGJO. The initial phase involves using Kernel Principal Component Analysis (KPCA) to diminish the gas data's dimensionality and distill pertinent features. The SCN's capability is augmented by integrating an L2 parametric penalty term to bolster its generalization potential in real-world scenarios. To further elevate the efficiency of the GJO, elite backward learning, and golden sine algorithms are amalgamated into their structure, thereby amplifying its stability and the capacity to seek optimal solutions. The efficacy of the IGJO is corroborated through its application to 13 quintessential test functions, showcasing enhanced stability and an improved ability to identify optimal solutions. Additionally, the coefficient C of the penalty term within the SCN is optimized using the IGJO, resulting in the development of the IGJO-SCN model designed explicitly for diagnosing faults in transformers. The variables extracted through KPCA are then employed as inputs for this model, which undergoes simulation and validation across a spectrum of transformer fault diagnosis contexts. The findings reveal that the IGJO-SCN model surpasses other models in terms of diagnostic accuracy, underscoring the potency of this novel methodology in refining the precision of DGA-based transformer fault diagnostics. This advancement is instrumental in bolstering power systems' reliability and operational efficiency, marking a significant contribution to the field.

The Fast Random Opposition-Based Learning GJO (FROBL-GJO) algorithm has been developed to tackle optimization challenges, drawing inspiration from OBL and Random OBL (ROBL) strategies [46]. This new approach aims to enhance the accuracy and the GJO algorithm's convergence rate. Alongside FROBL-GJO, two additional variants, OBL-GJO and ROBL-GJO, are introduced for comparative evaluation. The efficacy of FROBL-GJO is rigorously tested against a suite of established metaheuristic algorithms by applying it to a range of benchmark test functions from CEC-2005 and CEC-2019, as well as to various real-world engineering problems. The outcomes of these experiments, supported by statistical analyses, highlight FROBL-GJO's enhanced performance in addressing a broad spectrum of global optimization and engineering design issues. Thus, the results derived from these benchmark tests and real-life engineering challenges affirm the effectiveness of the FROBL-GJO algorithm, positioning it as a viable and promising solution for addressing complex optimization tasks.

For the optimization of intricate Composite Shape-Adjustable Generalized Cubic Ball (CSGC-Ball) surfaces, an advanced rendition of the EGJO is employed [93]. Designing CSGC-Ball surfaces encapsulates a mathematical optimization challenge adeptly navigated through metaheuristic algorithms. The construction of CSGC-Ball surfaces leverages both global and local shape parameters rooted in a spectrum of cubic generalized Ball basis functions, with the derivation of conditions for G1 and G2 continuity on these surfaces. These shape parameters are pivotal in swiftly and effectively modifying and optimizing the surfaces' contours. Models for shape optimization based on minimum energy principles, catering to CSGC-Ball surfaces with both 1st-order and 2nd-order geometric continuity, are conceptualized. EGJO is then harnessed to navigate these optimization models, culminating in realizing CSGC-Ball surfaces characterized by minimal energy. Four exemplar cases are presented to underscore the preeminence and efficacy of EGJO in addressing the shape optimization quandaries associated with complex CSGC-Ball surfaces. The EGJO algorithm is portrayed as a potent tool in meticulously optimizing CSGC-Ball surfaces' shapes, signifying its broad applicability and promise in engineering endeavors.

To tailor the GJO for intrusion detection in Software-Defined Networking (SDN), a specialized adaptation known as the Modified GJO (MGJO) is introduced [94] to augment its efficacy through two principal enhancements. An Elite Dynamic Opposite Learning strategy is initially incorporated at each iteration step. This mechanism focuses on generating solutions that oppose the prevailing global optimal solutions, broadening the algorithm's population diversity and bolstering its exploratory capabilities. Subsequently, the exploitation phase integrates an update mechanism inspired by the Golden Sine II Algorithm. This addition is pivotal in refining the position updates of the golden jackal pairs, significantly hastening the identification process of the most optimal feature subset indexes. The MGJO algorithm undergoes rigorous testing across various datasets, including four from the UCI repository, the NSL-KDD dataset for conventional network intrusion detection, and the InSDN dataset, designed for intrusion detection in SDN frameworks. The empirical outcomes from these evaluations highlight the MGJO algorithm's enhanced performance in classification accuracy and feature subset selection for SDN intrusion detection tasks, outpacing traditional methodologies. The MGJO algorithm emerges as a robust and effective tool within the SDN intrusion detection domain, indicating its capacity to elevate security protocols within network infrastructures substantially.

An improved version of the GJO algorithm, named Helper Mechanism Based GJO (HGJO), is proposed to facilitate multilevel threshold segmentation of aerial images [95]. This enhanced approach incorporates several key modifications to the original GJO algorithm: 1) OBL is employed to enhance population diversity, aiding in exploring the solution space. 2) A novel approach to compute prey escape energy is introduced to accelerate convergence speed. 3) The Cauchy distribution is integrated to adjust the original update scheme, improving the algorithm's exploration capability. 4) A novel "helper mechanism" is devised to aid in escaping local optima, enhancing algorithm performance. In summary, HGJO exhibits promising performance in benchmark function optimization and aerial image segmentation tasks, underscoring its potential for various optimization and image processing applications.

An advanced iteration of the GJO termed the Opposition-Based Learning Golden Jackal Optimizer (OGJO) is introduced for optimization problems [96]. This incorporation is strategically designed to help the algorithm avoid local optima traps. Frequently, the prey's updated position largely depends on the male golden jackal's input, which may reduce diversity among the golden jackals. Such a scenario can lead to the algorithm's entrapment in local optima, especially when dealing with conventional and intricate issues. To counteract this tendency and foster a broader exploration within the search area, OBL is synergized with GJO, aiming to alleviate the stagnation issue of the solutions. The efficacy of OGJO undergoes scrutiny through a comparative analysis with leading search algorithms, utilizing 23 standard functions, 10 cutting-edge CEC2019 test functions, and a selection of six real-world engineering challenges. The empirical findings underscore OGJO's superior performance in terms of efficiency over both the original GJO and other algorithms under comparison. Fig. 21 illustrates the procedural flowchart of the OGJO algorithm, outlining its operational framework. In essence, OGJO emerges as a robust method for optimization endeavors, capitalizing on the OBL methodology to broaden its exploratory reach and reduce the likelihood of succumbing to local optima, affirming its utility and effectiveness across diverse problem settings.

The Enhanced GJO (EGJO), devised for adaptive infinite impulse response (IIR) system identification, integrates the sophisticated Elite OBL strategy with the simplex technique to elevate its search and optimization prowess [50]. The overarching goal of this method is to reduce error fitness values and pinpoint the most favorable control parameters for the system in question. Incorporating the elite OBL strategy not only broadens the diversity within the population but also amplifies the algorithm's capacity for exploration, broadens the search scope, and prevents the stagnation of the search process. On the other hand, the

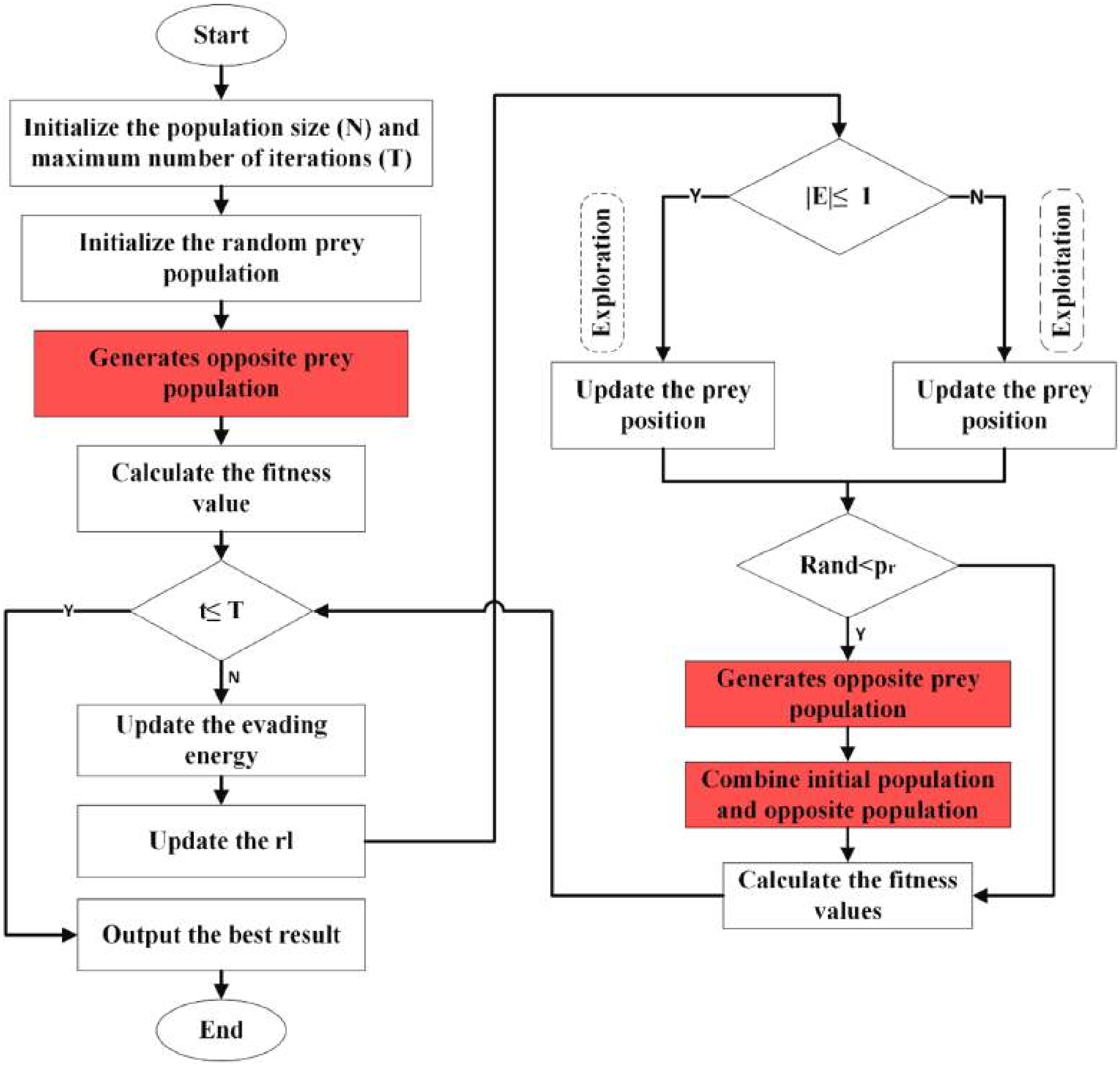

Fig. 21. The flowchart of OBL-GOJ algorithm.

simplex technique contributes to speeding up the search mechanism, boosting the ability to exploit the search space, refining computational accuracy, and deepening the optimization level. By harmoniously melding these two approaches, EGJO achieves a synergy that encompasses the strengths of both, effectively circumventing the pitfalls of search stagnation. This balanced approach ensures an equilibrium between exploration and exploitation, facilitating the attainment of optimal solutions. Through a series of three distinct experimental setups, EGJO has been shown to outpace traditional methods in terms of convergence speed, computational precision, the robustness of control parameters, and the quality of fitness values achieved. Additionally, it demonstrates remarkable stability and adaptability in addressing the challenges inherent in the IIR system identification problem. Ultimately, EGJO stands out as a viable and efficient solution for system identification tasks, exhibiting an enhanced performance profile surpassing traditional methodologies. This performance boost is mainly attributable to the strategic amalgamation of the OBL and simplex techniques, marking a significant advancement in system optimization.

The logical relationships of Aristotle's square of opposition concerning four fundamental categorical propositions—contrary, contradictory, subcontrary, and subaltern—are explored within the framework of Joint Opposite Selection (JOS)[97]. JOS integrates two opposition strategies, Dynamic Opposite (DO) and Selective Leading Opposition (SLO), in a mutually reinforcing manner. DO and SLO aim to enhance the balance of exploration and exploitation within a given search space. An improved version of the GJO algorithm, termed GJO-JOS, is proposed, incorporating Joint Opposite Selection. During the optimization process, JOS aids GJO by swiftly targeting prey using SLO, while DO assists in identifying optimal opportunities to locate the fittest prey. Through the integration of JOS, GJO achieves improved performance. The experimental findings validate the effectiveness of the GJO-JOS model in achieving equilibrium in the balance mechanism between exploration and exploitation, showcasing its potential as an enhanced optimization technique.

Skin cancer poses a serious health risk, necessitating the need for effective classification and prompt diagnosis to ensure the health and safety of individuals. A crucial step in this process is multilevel thresholding image segmentation, which plays a vital role in isolating regions of interest from images of skin cancer, thereby aiding in the classification task. To meet this requirement, a sophisticated version of the GJO algorithm, known as the opposition-based GJO (IGJO), has been introduced [41]. The IGJO algorithm incorporates OBL right at the GJO algorithm's initialization stage, aiming to boost the diversity of the population throughout the search phase. OBL, recognized for its prowess in local search, effectively counteracts the limitations associated with initializing populations at random, thereby promoting algorithmic convergence through enriching solution diversity. Through the integration of OBL, IGJO enhances the initial search phase, thereby augmenting the overall efficacy of the GJO algorithm during its inception phase. The application of IGJO is specifically directed towards addressing the multilevel thresholding challenge, employing Otsu's method as the guiding objective function. The efficacy of this algorithm is assessed based on four principal metrics: peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), mean square error (MSE), and feature similarity index (FSIM). The outcomes from these experiments highlight IGJO's superior performance over competing algorithms across all evaluated segmentation metrics, showcasing its ability to tackle the segmentation issue at hand. In essence, the IGJO algorithm emerges as a powerful tool for the segmentation of skin cancer images, outshining other methodologies in terms of performance. The systematic method adopted by the IGJO algorithm for image segmentation is graphically represented in Fig. 22, elucidating its structured approach towards overcoming segmentation hurdles.

Table 3 shows the advantages and disadvantages of improving the GJO algorithm by OBL.

4.2.5. Parallel

The Parallel Search-based GJO (PGJO) algorithm is introduced as a novel approach to optimization problems[98]. This algorithm incorporates parallel search strategies into its initialization, updating, and selection mechanisms to enhance convergence accuracy and reduce the required number of iterations. The PGJO algorithm introduces several key enhancements to address specific challenges encountered in optimization processes. Firstly, recognizing the significant impact of the initial population on optimization outcomes, a parallel chaotic pre-selection sequence is integrated into the initialization phase to ensure the generation of a superior initial population. The evaluations confirm the algorithm's ability to achieve enhanced convergence accuracy and effectiveness across various optimization scenarios.

Certain deficiencies in the original GJO were identified during the optimization process, particularly concerning the assignment of E0, a random number ranging from −1 to 1, for each individual in the program. This approach, where E_0 is uniquely assigned to everyone within the same population, lacks coherence and logic. E_0 plays a crucial role in determining E, which signifies how closely an individual approaches optimal or suboptimal conditions. However, assigning a random E_0 to each population member may lead to a chaotic optimization scenario. Individuals with unfavorable properties might undergo minimal mutation, while those with advantageous properties could experience significant changes, resulting in an imbalanced optimization process. To rectify this issue, a pre-optimization determination of E_0 is proposed. Furthermore, an adaptive E_2 operator is introduced according to Eq. (38) [98] to ensure that individuals with varying properties undergo different levels of mutation. By implementing these adjustments, the optimization process aims to achieve a more balanced and effective solution for space exploration, mitigating the original algorithm's chaotic behavior.

$$E_2 = \frac{f_i - f_{min}}{f_{max} - f_{min}} \tag{38}$$

In Eq. (38), f_{min} represents the fitness value of the male individual while f_{max} corresponds to the fitness value of the worst individuals within the population. It is crucial to acknowledge that in specific scenarios where the algorithm has successfully identified the optimal value, f_{max} and f_{min} may indeed become equal. In such cases, the value of E_2 will consequently be zero. This observation highlights a significant aspect of the optimization process. When f_{max} and f_{min} converge to the same value; it signifies that the population has reached a state of equilibrium where the fitness landscape no longer exhibits significant disparities between the best and worst individuals. As a result, the mutation operator, represented by E_2, becomes inactive, as there is no longer a need for extensive exploration or mutation within the population. Therefore, in instances where fmax and f_{min} coincide, indicating the optimal solution, the mutation factor E_2 effectively ceases to influence the population, facilitating a stable and balanced state within the optimization process.

4.2.6. Sine and cosine

Frequency control in small inertia microgrids (MGs), especially those incorporating renewable energies like wind and solar power, presents

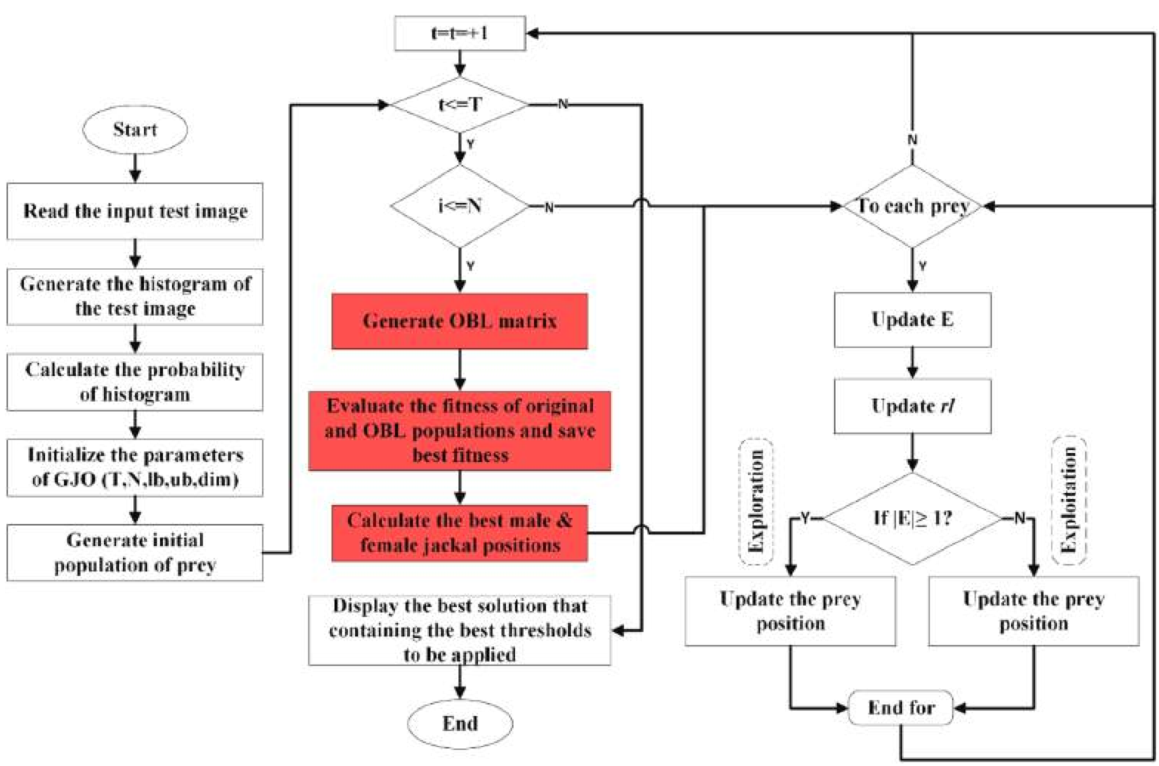

Fig. 22. Flowchart of the proposed IGJO algorithm for image segmentation.

Table 3
The advantages and disadvantages of improving the GJO algorithm by OBL.

Refs	Application	Advantages	Disadvantages
[91]	Multi-threshold segmentation	Rapid convergence and identifying the optimal global value	High execution time
[92]	Fault diagnosis method for power transformers	Find optimal solutions in a short time	The number of repetitions is high.
[46]	Engineering problems	Maintaining an effective equilibrium between exploration of and exploitation and ensuring problem-solving.	Getting stuck in local optima
[93]	Energy minimization	Rapid convergence and identifying the optimal global value	High execution time
[94]	intrusion detection	Achieving a harmonious balance between broad, global search strategies and focused, local search tactics to improve the overall efficiency of the search process.	Lack of diversity in the population of solutions
[95]	multilevel thresholding image segmentation	Find optimal solutions in a short time	High execution time
[96]	Engineering problems	Rapid convergence and identifying the optimal global value	The number of repetitions is high.
[50]	infinite impulse response (IIR) system identification problem	Maintaining an effective equilibrium between exploration of and exploitation and ensuring problem-solving.	Lack of diversity in the population of solutions
[97]	Optimization Problems	Find optimal solutions in a short time	The rates of problem parameters are not optimal
[41]	image segmentation	Achieving a harmonious balance between broad, global search strategies and focused, local search tactics to improve the overall efficiency of the search process.	Getting stuck in local optima

significant challenges. Virtual Inertia Control (VIC) aims to address these challenges by enhancing the inertia of MGs by utilizing storage elements. A novel approach called the Optimized Fuzzy Adaptive Virtual Inertia Control Strategy is proposed to optimize the allocation of virtual inertia constants within the VIC scheme. This strategy involves the development of an Improved GJO (I-GJO) method tailored for tuning the suggested controllers [99]. The sensitivity of controllers is evaluated under conditions of irregular load changes and varying rates of renewable energy source (RES) integration. Overall, the proposed I-GJO method offers enhanced performance in optimizing fuzzy adaptive virtual inertia control strategies within small inertia microgrids, demonstrating its efficacy in addressing the challenges of frequency control in renewable energy-integrated MGs.

An advanced approach combining the Improved GJO (IGJO) algorithm with Support Vector Machine (SVM) for power transformer fault diagnosis is introduced in this study [100]. The proposed method aims to enhance fault diagnosis accuracy through effective feature selection and optimization of SVM parameters. Initially, Kernel Principal Component Analysis (KPCA) is employed to screen data features and extract those with significant impacts. This step helps reduce the data's dimensionality and focus on the most relevant features for fault diagnosis. Two techniques are introduced to enhance the original GJO algorithm's optimization capability: Reverse Learning and Adaptive T-Distribution Perturbation. These improvements boost the algorithm's global optimization ability, enabling it to search for optimal solutions in complex search spaces effectively. The IGJO algorithm is then utilized to optimize the main parameters of the SVM model, such as the kernel and regularization parameters. Incorporating the optimized parameters establishes an IGJO-optimized SVM model for power transformer fault diagnosis. Experimental results demonstrate the effectiveness of the proposed IGJO-SVM model, achieving an accuracy of 91.43 %. Compared to traditional GJO-SVM and Particle Swarm Optimization (PSO)-SVM models, the IGJO-SVM model exhibits a significant improvement in accuracy, with an increase of 4.29 % and 1.43 %, respectively. These findings highlight the potential of the IGJO-SVM approach in enhancing the accuracy of power transformer fault diagnosis.

An enhanced version of the GJO algorithm, termed Improved GJO (IGJO), is proposed for solving the three-dimensional path planning problem of unmanned aerial vehicles (UAVs) in complex inspection environments, particularly within distribution networks [101]. The IGJO algorithm introduces several improvements to enhance its performance in solving complex path-planning tasks. Firstly, a refined observation strategy is implemented, which considers the boundary information of the search space. This enhancement ensures that the algorithm explores the solution space more effectively, leading to better-quality solutions. Furthermore, a balanced renewal mechanism is proposed to improve the population's ability to escape local extremums. This mechanism helps prevent the algorithm from getting stuck in suboptimal solutions by promoting diversity within the population. A fitness function model is developed to apply IGJO to the UAV path planning problem-based on the specific characteristics of distribution network inspection tasks. Furthermore, a three-dimensional simulation map model is constructed to accurately simulate the complex inspection environment. The effectiveness of IGJO is validated through extensive simulation experiments. The experimental results demonstrate that IGJO consistently produces solutions of superior quality, exhibits robustness across different scenarios, and shows fast convergence characteristics. These findings underscore the feasibility and superiority of IGJO in addressing complex three-dimensional path planning problems, particularly in the context of UAV inspection missions within distribution networks.

Frequent regulation poses considerable challenges in the context of low-inertia microgrids, which often incorporate asymmetrical renewable energy sources such as solar and wind power. To efficiently fine-tune the parameters of the Adaptive Fuzzy Proportional-Integral-Derivative with a Derivative Filter (AFPIDF) controller, the introduction of a Modified GJO (MGJO) algorithm is proposed [102]. The MGJO algorithm enhances the foundational GJO algorithm by integrating a Variable Sine Cosine Adopted Scaling Factor (SCASF), a modification to improve the algorithm's efficiency in exploration and exploitation during optimization. The efficacy of the MGJO algorithm is assessed through a comparative analysis against the original GJO algorithm and a variety of other established optimization algorithms across a selection of standard benchmark test functions. In further developments, the traditional Proportional-Integral-Derivative (PID) controller and the newly introduced AFPIDF controller parameters undergo optimization utilizing the MGJO technique. The MGJO algorithm's superiority is evident, particularly in its ability to ascertain optimal controller parameters for regulating microgrid frequencies, especially in systems integrating asymmetric renewable energy sources. The resilience of the optimized controller is then evaluated in scenarios characterized by intermittent load fluctuations and variable degrees of asymmetric renewable energy source integration. This extensive analysis confirms the efficiency and resilience of the MGJO-based optimization strategy in overcoming the frequency regulation hurdles encountered in low inertia microgrids with asymmetric renewable energy contributions.

4.3. Variants of aha

This part of the text explores binary and multi-objective frameworks. Real-world optimization tasks often involve multiple objectives that need to be optimized together. Multi-objective problems (MOPs) consist of several different goals. The primary challenge in addressing multi-objective issues is the conflicting nature of the objectives, where enhancing one goal may lead to the deterioration of others. In these cases, there isn't a single best solution but rather a set of optimal compromise solutions referred to as feasible solutions (Pareto).

4.3.1. Binary

Feature selection (FS) is an essential step aimed at eliminating superfluous features from datasets, which is crucial in data mining and machine learning to mitigate the issues arising from high-dimensional data. Tackling FS efficiently is challenging due to its inherent combinatorial complexity, with computation time escalating as the problem size increases. In response, a robust metaheuristic approach known as Binary Enhanced GJO (BEGJO) [49] is introduced, refining the original GJO algorithm. The GJO algorithm struggles with high-dimensional FS tasks due to its propensity for getting stuck in local optima. To overcome this, BEGJO incorporates several improvements, including using Copula Entropy (CE) for dimensionality reduction while ensuring high classification precision with the K-Nearest Neighbor (KNN) classifier. Furthermore, four enhancement strategies are integrated to boost the GJO's exploratory and exploitative functions. BEGJO is adapted to FS tasks through a binary version, employing the sigmoid transfer function. Its efficacy is validated on various high-dimensional benchmark datasets, showcasing superior classification accuracy and reduced feature dimensionality and maintaining competitive processing times. CE is highlighted explicitly for its contribution to the algorithm's performance compared to traditional FS methods. Statistical analyses further affirm BEGJO's effectiveness and superiority in addressing high-dimensional FS challenges.

In binary optimization, a Transfer Function (TF) is employed to modify the position of an agent within the search space, which can be visualized as a hypercube. This function dictates the probability that an agent's position will flip from 0 to 1, or conversely from 1 to 0, essentially enabling the agents, conceptualized as search entities in the Binary GJO (BGJO) algorithm, to traverse to the extreme points of the hypercube by toggling specific bits. The process begins by setting up a two-dimensional matrix to represent the initial positions of the agents, filled randomly with zeros and ones, symbolizing the binary nature of the search space. The positions of the male and female jackal leaders are updated similarly to the original GJO algorithm's methodology. Subsequently, the positions of the other agents, referred to as preys, are updated using a sigmoid function according to specific Eqs labeled 39 and 40 in the referenced material [49]. These equations consider a randomly generated number between 0 and 1, ensuring the stochastic nature of the position updates.

$$\overrightarrow{X}_k = \mathrm{Sigmoid}\left(\overrightarrow{X}_k\right) = \frac{1}{1 + e^{-10(X_k - 0.5)}} \tag{39}$$

$$X_k = \begin{cases} 1, & \text{if rand} < \mathrm{Sigmoid}\ (X_k) \\ 0, & \text{Otherwise} \end{cases} \tag{40}$$

The IBGJO algorithm, an advanced version of the standard GJO algorithm, is explicitly introduced for feature selection tasks [55]. It is designed as a search technique for wrapper-based feature selection and incorporates three main enhancements: an initial population generation using a chaotic tent map (CTM) to boost exploitation capabilities and ensure diversity among the population, an adaptive position update method that employs cosine similarity to avoid early convergence and a binary framework that is ideal for dealing with binary feature selection challenges. The performance of IBGJO was tested on 28 classic datasets from the UC Irvine Machine Learning Repository. The findings indicate that integrating the CTM mechanism and the adaptive position update strategy based on cosine similarity significantly enhances the convergence speed of the traditional GJO algorithm while also providing superior accuracy compared to other existing algorithms. This suggests that the novel CTM mechanism and the cosine similarity-based position update strategy effectively accelerate the convergence of the conventional GJO algorithm.

4.3.2. Multi-Objective optimization

In MOO challenges, the complexity escalates with the increase in objective function clashes [103]. Unlike the single-objective (SO) optimization, which has one solution, MOO results in a group of solutions due to the competing objectives, referred to as the Pareto optimal set (POS) within the decision space. Its equivalent in the objective space is called the Pareto optimal front (POF). A solution is considered part of the POF when improving any objective necessitates the compromise of at least one other objective.

An advanced placement strategy utilizing the Improved GJO (IGJO) algorithm is introduced for optimally positioning multiple capacitor banks and various types of Distributed Generators (DGs) within distribution networks [104]. This approach addresses both single and multiple objective scenarios. The model enhances the conventional GJO algorithm by incorporating memory-based equations and a random walk strategy to improve accuracy and hasten convergence. The simulation outcomes demonstrate that the IGJO approach outperforms its competitors in all tested scenarios, establishing its efficacy for the optimal integration of DGs within distribution networks amid uncertainties in generation and demand.

Wind power forecasting is pivotal in effectively integrating large-scale wind energy into the power grid, which is essential for achieving a carbon-neutral energy portfolio. A novel forecasting system is introduced, utilizing a two-way deep learning model designed to identify nonlinear characteristics of wind power generation and fine-tune its critical meta-parameters through an enhanced GJO algorithm variant [105]. This modified GJO approach facilitates the derivation of Pareto optimal solutions, incorporating a conventional statistical method to distill linear aspects from the error series and apply corrections effectively. It also integrates regression for more accurate interval forecasting. The findings from this new multi-objective model demonstrate its superiority in predicting wind power variations compared to existing models, indicating its significant applicability in real-world scenarios.

A sophisticated GJO algorithm is introduced for managing energy in systems with distributed generation, such as battery storage systems (BSSs) and hybrid energy sources (HESs) [44]. The primary goals of this method are to reduce operational expenses and address energy management challenges in microgrids (MGs). Various factors influence the microgrid energy management system, such as power balance, generation limits, consumer demand, and the charging-discharging dynamics of energy storage devices. This approach is implemented and tested within the MATLAB environment, where its performance is benchmarked against existing strategies. The outcomes of the simulations reveal that this method is more cost-effective than the current alternatives. Moreover, compared to other established methods like PSO, Artificial Bee Colony (ABC), and Tabu Search (TS), the introduced model demonstrates superior efficiency.

A new multi-objective GJO (MOGJO) algorithm is introduced, designed to enhance both the coverage of solutions and the convergence towards the actual Pareto optimal front (POF) in MOO problems [106]. The MOGJO algorithm incorporates four distinct reproduction phases within its search process: Initially, the golden jackal population is initialized within the defined search space, followed by an update phase. Then, an opposition-based learning approach is employed to broaden the range of Pareto optimal solutions. It outshines the top-performing algorithm from a group of thirteen by >41 % and vastly surpasses the least effective one, MOALO, by 84 % in ZDT and DTLZ1 test suites. Moreover, in the DEEPD challenge, MOGJO achieved a 1.89 % reduction in overall energy cost and a 1.48 % decrease in total emissions compared to the best existing outcomes, making it a highly recommended solution for novel applications.

A Multi-objective GJO (MOGJO) [107] algorithm is presented to tackle the complexities of designing fractional-order controllers for magnetic levitation systems, which often come with diverse design parameters and complex tuning processes. The algorithm determines the positions of both male and female Golden Jackals by considering factors such as diversity and rapid convergence. This is achieved by assessing the iteration stage, applying suitable evaluation methods, and enhancing the position update formula by incorporating the individual's past experiences. This adjustment in the update mechanism significantly refines the original algorithm's strategy for updating positions. When applied to the magnetic levitation control system employing fractional order, the MOGJO algorithm demonstrates a commendable control performance. This success showcases the algorithm's capability to manage the system effectively and provides a solid foundation for setting parameters within such control systems. This approach ensures that the fractional-order controllers for magnetic levitation systems can be fine-tuned more efficiently, addressing the challenges associated with their design and debugging.

4.4. Optimization problems

Engineering optimization has garnered significant attention in recent years due to its direct relevance to engineering design. Several optimization techniques, including gradient-based methods and MH algorithms, have addressed these problems. However, contemporary engineering optimization challenges are characterized by their involvement of mixed variables, multiple constraints, and the absence of a clear functional relationship between objectives and variables. Gradient-based methods encounter three main shortcomings in this context: firstly, they rely on gradient information to refine initial solutions, which may not always be readily available or definable; secondly, they necessitate a continuous design space, limiting their applicability to problems involving discrete variables; and thirdly, they are prone to becoming trapped in local optima, thereby failing to identify the global optimum in complex landscapes. Consequently, these limitations restrict the effectiveness of gradient-based methods in tackling modern engineering optimization challenges.

Optimization problems are common in engineering domains, and various optimization methods have been created to handle a wide range of engineering optimization. Table 4 shows the general review of GJO in the optimization field.

Constrained integer stochastic optimization problems (CISOP) represent a challenging subset of optimization tasks where the objective function's behavior is stochastic, yet the constraints imposed are deterministic [115]. These problems are classified as NP-hard, indicating that finding exhaustive solutions within a reasonable timeframe can be infeasible. The complexity of CISOPs stems from three primary factors: the vastness of the design space, the requirement for simultaneous satisfaction of constraints, and the time-intensive nature of accurately assessing the cost function. To tackle these challenges, the theory of ordinal optimization (OO) is introduced. OO is built around two fundamental concepts: sorting comparison and goal softening. Sorting comparison relies on relative comparisons between different solutions to establish an order, without needing precise values. Goal softening, on the other hand, focuses on identifying solutions that are 'good enough' rather than pursuing the absolute best solution, which may be impractical to ascertain.

The OO theory has proven effective in addressing complex optimization issues across various fields, including routing optimization in queuing networks, enhancing efficiency in sorting conveyor systems, job-shop scheduling, and optimizing staffing in emergency department healthcare, among others. By applying OO, the design space can be significantly narrowed, and the search process expedited. However, the

Table 4
The general review of GJO in the field of optimization.

Refs	Application	Advantages	Weaknesses	Publisher
[108]	Color compensation and correction	Underwater image enhancement	The number of repetitions is high.	Elsevier
[60]	Detection of wave modes	recognition and acoustic emission source localization	The population in the problem space is not coherent.	Elsevier
[109]	Energy management	improved convergence speed and robustness to diverse search space characteristics	High execution time	Elsevier
[110]	image segmentation	This model balances exploration and exploitation to obtain the best segmentation effect.	High execution time	Elsevier
[111]	Optimization problems	quicker convergence rate and greater computation precision	Slow convergence rate	Springer
[112]	Optimization problems	Optimizing the laser drilling process and reducing errors in the production process	The number of repetitions is high.	Springer
[113]	Load Dispatch and Power Flow	This technique ensures rapid convergence and boosts the effectiveness of the search, leading to faster and more reliable results.	Lack of diversity in the population	MDPI
[114]	Voltage fluctuations	The GJO algorithm is utilized to fine-tune the PI control parameters within the phase difference control loop, optimizing performance during the pre-synchronization phase across various phase differences.	Slow convergence rate	MDPI
[115]	Optimization problems	The GJO algorithm is crafted to efficiently identify an exceptional solution to the CISOP, achieving this within a practical timeframe.	Slow convergence rate	Elsevier
[116]	image segmentation	Optimal convergence and finding optimal solutions	The population in the problem space is not coherent.	Elsevier
[117]	Renewable energy	Maintaining equilibrium between exploring new possibilities and exploiting known strategies to discover the optimal value for complex mathematical functions.	Lack of diversity in the population	Elsevier
[118]	Unmanned Aerial Vehicle	Enhancing the algorithm's global search capability.	Slow convergence rate	Springer

(continued on next page)

Table 4 (*continued*)

Refs	Application	Advantages	Weaknesses	Publisher
[119]	Unmanned Aerial Vehicle	The findings suggest that the suggested model can boost global convergence and durability, decrease the time needed for convergence, enhance the operational coverage of UAVs, and cut down on energy usage.	Lack of diversity in the population	MDPI
[120]	optimization problems	Finding the best optimal value for multivariate problems	High execution time	IEEE
[121]	photovoltaic system placement	Discover optimal solutions	Lack of diversity in the population	Springer
[122]	Photovoltaic (PV)	Accurate parameter estimation and error reduction	High execution time	Others
[123]	renewable energies	Precise determination of parameters and the enhancement of electrical circuit efficiency for electric current flow	The population in the problem space is not coherent.	MDPI
[124]	robotic	Finding the shortest path and reducing the energy consumption of robots	Lack of diversity in the population	Elsevier
[125]	Photovoltaic system	Accurate parameter estimation and error reduction	High execution time	Elsevier
[126]	Internet of Things	Allocating tasks to resources and reducing energy consumption of smart devices	Lack of diversity in the population	IEEE
[127]	Optimization problems	Finding global optimal points and fast convergence	The number of repetitions is high.	IEEE
[128]	Distributed generation (DG)	The GJO algorithm is used to find the ideal location and sizing of DGs.	The population in the problem space is not coherent.	Others
[129]	Feature selection	Selecting the best feature in the least amount of time while also elevating the accuracy rate.	Lack of diversity in the population	MDPI
[130]	wireless sensor networks	Reducing energy consumption and optimal clustering	The population in the problem space is not coherent.	IEEE
[131]	flow shop scheduling	Efficient allocation of tasks to resources while minimizing energy usage.	High execution time	Tandfonline
[132]	flow shop scheduling	Optimal assignment of tasks to resources and reduction of energy consumption.	High execution time	IEEE
[133]	Optimization problems	Speeding up convergence and finding the best value for polynomial mathematical functions	Slow convergence rate	Springer

Table 4 (*continued*)

Refs	Application	Advantages	Weaknesses	Publisher
[134]	Optimization problems	Maintaining equilibrium between the exploration of new possibilities and the exploitation of known strategies to discover the optimal value for complex mathematical functions with multiple variables.	The number of repetitions is high.	Springer
[135]	Optimization problems	Balancing exploration and exploitation phases and finding the best value for multivariate mathematical functions	High execution time	Springer
[136]	Optimization problems	Accelerating the convergence process and identifying the optimal value for polynomial mathematical functions.	Lack of diversity in the population	Springer
[137]	Optimization problems	Striking a balance between the phases of exploration and exploitation to identify the optimal value for multivariate mathematical functions.	The population in the problem space is not coherent.	IEEE
[138]	radio environment map	Finding the optimal answer at the optimal time	High execution time	IEEE
[139]	Power distribution systems	Increasing the speed of convergence	The number of repetitions is high.	IEEE
[140]	Distributed generation (DG)	The GJO algorithm is used to find the ideal location and sizing of DGs.	Lack of diversity in the population	IEEE

stochastic nature of the cost function in CISOPs still poses a substantial impact on computational efficiency. To mitigate this, the GJO approach is suggested. Utilizing OO, a rough evaluation is conducted to identify a promising subset of solutions. This subset is then subjected to more detailed simulations, which are both necessary and justifiable, to pinpoint standout solutions. This approach significantly lessens the computational load, making it a viable strategy for tackling the complexities of CISOPs.

Robot manipulator control is a fascinating area due to its intricate dynamical characteristics. The analysis of a robotic model's dynamics delves into the relationship between the positions of the robotic arm and the joint torques produced by its actuators. The complexity of achieving accurate and reliable control is heightened by the system's coupled relationships and nonlinear dynamics. Consequently, developing a control strategy based on the system's dynamics using traditional control methodologies presents significant challenges. The Proportional-Integral-Derivative (PID) controller is renowned for its straightforward mathematical framework and ease of use, which has led to its widespread adoption in both industrial and academic settings. Its effectiveness across a wide array of control tasks is well-documented, highlighting its capability to manage systems efficiently. A critical aspect of enhancing a system's performance and efficiency lies in the fine-tuning of the PID controller, as optimal tuning ensures the feedback loop of the PID controller offers optimal disturbance rejection. However, traditional optimization methods for tuning PID gains, such as the Ziegler-Nichols method, often fall short of achieving satisfactory outcomes. To address this, the GJO algorithm was proposed as a method to optimize parameter selection for the three degrees of freedom (3DOF) robotic manipulator system [124]. Beyond robotic manipulators, the GJO algorithm has been successfully applied to optimize parameters in various engineering designs showcasing its versatility and effectiveness in a broad spectrum of engineering optimization problems.

Liver image segmentation encompasses a variety of challenges such as segmenting the liver itself, the bile ducts, estimating liver volume, segmenting vessels, and identifying lesions [116]. Due to the complexity of these tasks, enhancing the accuracy of liver segmentation requires considerable effort. While deep learning-based approaches are currently the most prevalent for image segmentation, their limitations are well-recognized. These include a reliance on large volumes of data, slow training speeds, and intricate architectures, all of which require careful consideration and balancing by researchers. On the other hand, threshold-based image segmentation methods are widely favored for their stability, simplicity, ease of implementation, and ability to produce accurate segmentation results. This method provides a quick and straightforward way to extract precise image data, fulfilling critical needs such as speed, accuracy, and minimal storage requirements. Accurate segmentation of liver conditions from CT scans is crucial for early diagnosis and determining the appropriate treatment, especially within computer-aided diagnosis (CAD) systems. To overcome the issues of inconsistent liver visibility and indistinct boundaries in imaging, the GJO algorithm has been proposed as a novel solution.

5. Convergence behavior analysis

This section performs a general analysis based on convergence on different algorithms. The GJO algorithm is compared with three other algorithms regarding convergence and complexity. The Elk Herd Optimizer (EHO) [141] algorithm features strong convergence and scalability in optimization problems. Convergence analysis is performed with various test functions from CEC-2017. The convergence behavior of EHO is compared with several other optimization methods. The results show that EHO converges quickly in the early stages of the search process and maintains stability. The complexity of the EHO algorithm depends on the number of iterations and the size of the problem search space. In particular, the complexity increases with the problem dimension, because higher dimensions require more iterations to explore a more extensive search space. The EHO algorithm maintains competitive performance due to its effective balance between exploration and exploitation. Therefore, EHO is a strong choice for solving complex engineering optimization tasks in the real world. In some situations, the EHO algorithm may encounter difficulties in local exploration, especially when the optimization must achieve high accuracy in certain regions of the search space. This problem may lead to getting stuck in local optima.

The White Shark Optimizer (WSO) [142] algorithm is based on white sharks' behavior designed to solve optimization problems. This algorithm generally has a high convergence ability and can move well towards optimal solutions in the search space. The WSO algorithm uses two stages of exploration and exploitation. This algorithm can search in different regions of the search space and can effectively avoid local optima. The convergence time of the algorithm depends on the number of iterations and the population size. The convergence analysis of the algorithm shows that it can reach optimal solutions with a reasonable speed, especially when its parameters are set correctly. The time complexity of the WSO algorithm depends on the number of sharks (n), the dimensions of the search space (d), the number of iterations (K), and the cost of evaluating the function. The time complexity of the entire WSO algorithm is expressed according to Eq. (41).

$$\mathscr{O}(WSO) = \mathscr{O}(1 + nd + Kcn + Knd) \tag{41}$$

This formula shows that the time complexity of WSO depends mainly on the number of iterations and the problem dimension. This algorithm generally has polynomial time complexity and is suitable for large-dimensional problems. As a result, this algorithm is efficient in terms of time complexity. Although WSO has good convergence and time complexity performance, it also has some challenges. One of the main problems of this algorithm is the need for fine-tuning of parameters, which requires a lot of time. Also, the algorithm may encounter problems such as reduced population diversity and getting stuck in local optima in very large-dimensional problems. These problems are especially observed in complex search spaces with a large number of variables.

The Walrus Optimizer (WO) [143] algorithm is designed based on the social behavior of walruses and is able to effectively guide the exploration and exploitation phases of optimization problems. The convergence analysis of this algorithm shows that the convergence speed is very fast in the early stages and it performs well especially in solving single-dimensional problems. Due to the combination of local and global search phases, the WO algorithm effectively avoids high-dimensional optimization problems and local optimums. The convergence curves show that WO has the fastest convergence speed compared to many other algorithms and has the ability to consistently reach the best solutions compared to other algorithms. The time complexity of the WO algorithm depends on three main processes: initialization, objective function evaluation and updating of new positions. The overall time complexity of the algorithm is $O(N \times (T + T \times D + 1))$, where N is the population size, T is the number of iterations and D is the problem dimensions. This complexity shows that the execution time of the algorithm is directly dependent on the problem size and the number of iterations. Although the WO algorithm generally avoids local optima, in some problems it may not be able to avoid this state in the exploitation phases.

The WO, WSO, and EHO optimization algorithms are powerful tools for solving complex optimization problems. All three algorithms are designed with a focus on the balance between exploration and exploitation phases and have a remarkable ability to avoid getting stuck in local optima and efficiently search the solution space. All three algorithms have remarkable performance, but they have challenges such as sensitivity to parameter tuning and increased computational complexity in very high-dimensional problems. However, these algorithms are flexible tools that can be adapted to appropriate settings for different problems. Along with these three algorithms, the GJO is an efficient algorithm for optimization problems, and there is a solution enhancement in this algorithm based on combinatorial or adaptive methods.

6. Discussion

In the PSO algorithm, achieving a balance between the solution quality and the computational time is a critical challenge. The fine-tuning of parameters and managing various constraints add to the complexity of using PSO effectively. Selecting the optimal values for parameters is a tricky process that significantly impacts the results' quality. A persistent issue with PSO is the difficulty in distinguishing whether the obtained solution represents a local or a global optimum. Moreover, PSO is known to struggle with local optima stagnation, leading to a slower convergence rate toward the optimal solution. In contrast, the GJO algorithm exhibits remarkable capabilities in both exploitation and exploration. This feature enables the algorithm to guide search agents more efficiently towards the global optimum, reducing the required computational time. The GJO algorithm has demonstrated promising results across various engineering problems. The effectiveness of GJO has been rigorously evaluated using multi-modal test functions and in the context of structural optimization challenges. Multi-modal functions, characterized by their numerous local optima, serve as a robust testbed for assessing an algorithm's ability to navigate the search space effectively and to circumvent local optima. GJO has consistently emerged as either the most efficient or the second-best algorithm in these tests, showcasing its superior performance in most multi-modal test scenarios. To overcome possible errors in the GJO algorithm, the following solutions and suggestions can be considered: Choosing fixed steps in GJO may create instability in some problems and cause large or small jumps in the convergence path. To overcome this problem, the correction steps should be adjusted dynamically. Adaptive step approaches can change the step size dynamically and according to the current state of the algorithm. The GJO algorithm may struggle in complex or nonlinear environments and cannot achieve the global optimum effectively. Using grouping techniques such as adaptive clustering algorithms can effectively improve the search in such environments.

MH algorithms often encounter performance limitations and critical challenges when tackling complex problems. They may become ensnared in local optima, which impedes global optimization, especially in scenarios characterized by high-dimensional spaces and complex inter-variable relationships. [144]. Furthermore, suboptimal parameter configurations can significantly impair the algorithms' convergence rates, especially as problem complexity escalates, leading to diminished scalability. Strategies focused on algorithm enhancement and hybridization have been developed to overcome these hurdles. Hybrid methodologies meld various techniques to strike a balance between exploration (searching through the entire solution space) and exploitation (refining solutions within promising regions) [145]. On the other hand, adaptive strategies aim to automate the parameter adjustment process, thereby improving the algorithms' adaptability to different problems. These innovations enhance the efficiency, effectiveness, and robustness of MH algorithms by leveraging the strengths of diverse approaches. The introduction of novel algorithms with unique exploration and exploitation mechanisms further expands the capabilities of MH methodologies. Integrating the inherent advantages of the GJO algorithm with other algorithms results in a more effective exploration of the search space and enhanced fine-tuning of potential solutions. This amalgamation extends the optimization capabilities and fosters the development of adaptable and robust algorithms capable of addressing complex optimization challenges with increased proficiency.

The Sine Cosine Algorithm-GJO (SCA-GJO) [63] hybrid demonstrates exceptional robustness and stability, efficiently toggling between exploration and exploitation phases to prevent search stagnation and secure the optimal solution. Experimental findings reveal that SCA-GJO maintains remarkable stability and resilience in attaining precise, feasible solutions and effectively marries the aspects of exploration and exploitation. This synergy enhances the convergence rate and computational accuracy, rendering SCA-GJO a viable and practical approach for optimization tasks.

Optimization is a widespread mathematical challenge to find the best possible solution from a large set of feasible options while adhering to certain restrictions. Traditional optimization methods often struggle with complex, large-scale, and combinatorial problems, leading to issues like inefficient computing, excessive time consumption, premature convergence, and combinatorial explosion [146]. In contrast, evolutionary algorithms, inspired by the behavioral traits of various biological entities in nature, exhibit significant stability and robustness, effectively mitigating these issues. They adeptly balance the processes of exploration (searching through the solution space) and exploitation (refining promising solutions) to pinpoint the optimal solution. The GJO algorithm stands out for its simple structure, minimal parameter requirements, robustness, high computational precision, quick convergence, and ease of application, making it a popular choice across various fields.

When addressing optimization challenges, the GJO algorithm offers multiple advantages over contemporary optimization techniques like PSO, Tabu Search (TS), and ABC. GJO stands out for its computational efficiency and rapid convergence rates, effectively facilitating the discovery of superior solutions to optimization issues. It is known for maintaining various solutions, enhancing the algorithm's ability to explore the solution space thoroughly. Unlike some methods that rely heavily on memory mechanisms, GJO's more flexible approach avoids local optima traps. Its robustness makes it suitable for many problems, including those with complex nonlinear constraints and objective functions, thus expediting the optimization process. Furthermore, GJO is adept at MOO, efficiently handling scenarios with multiple, often conflicting, objectives that need to be optimized concurrently.

The Sine Cosine GJO (SCGJO) [63] algorithm consists of three main steps: initialization of the population, evaluation of the objective value, and updating the positions of the golden jackal agents based on exploration and exploitation mechanisms. In the context of SCGJO, N represents the size of the population, T stands for the maximum number of iterations, and D indicates the problem's dimensionality. The computational effort required for initializing the population is represented as O (N), signifying that it scales linearly with the size of the population. The process of evaluating the objective value and updating the positions of the golden jackals involves a computational complexity of $O(T \times N)$ for each iteration, plus an additional $O(T \times N \times D)$ for updating each agent's position across all dimensions and iterations. SCGJO is distinguished by its adaptability and reliability, effectively leveraging the synergies between exploration and exploitation to enhance convergence precision. It also successfully addresses the issue of search stagnation, guiding the algorithm towards the optimal solution. Consequently, the total computational complexity of SCGJO can be summarized as $O(N \times (T + T \times D + 1))$, showcasing SCGJO as an efficient and dependable method for tackling optimization challenges.

The complexity of the GJO-GWO [64] algorithm is primarily determined by three principal activities: initialization, fitness evaluation, and individual updating. The initialization phase of GJO-GWO involves setting up both jackal and wolf populations, leading to an initialization complexity of *O(2N)*, considering both sub-processes. Male and female jackals and wolves are updated based on different constraint conditions during the updating phase. The updating complexity for both male and female jackals is $O(T \times \mathrm{N})$ for the iterations, plus $O(T \times N \times d)$ for adjusting each individual's position across all dimensions. Similarly, the update process for wolves also incurs a complexity of $O(T \times N \times d)$. Therefore, the cumulative complexity of updating individuals within the GJO-GWO algorithm is $O(T \times N) + O(T \times N \times d) + O(T \times N \times d)$. Consequently, the overall computational complexity of the GJO-GWO algorithm can be expressed as $O(N(T + 2Td + 2))$, where N is the population size, T is the maximum iteration count, and d represents the problem's dimensionality. This formulation captures the algorithm's combined complexities of initialization, fitness evaluation, and individual updating processes.

In multi-dimensional optimization challenges, updating a single dimension within a solution can be adversely affected by the interactions with other dimensions, leading to slower convergence rates and less precise optimization outcomes [69]. To address this issue of inter-dimensional interference, a strategy known as the dimension-by-dimension reverse learning approach is suggested. This technique involves applying reverse learning to each dimension of the candidate solution sequentially after every update. During this reverse learning process, the dimension currently under consideration is modified, forming a new potential solution along with the unchanged dimensions. The fitness value of this new solution is then calculated and compared with the fitness value before the reverse learning. If the new fitness value shows improvement, the updated candidate solution is kept; otherwise, it is discarded in favor of the original solution before the reverse learning. By adopting this elitist strategy of selectively retaining only those updates that result in a fitness improvement, the algorithm sequentially progresses through each dimension, updating them one at a time. This method effectively reduces the negative impact of inter-dimensional interference, leading to enhanced accuracy in the algorithm's output.

The standard GJO algorithm begins with a randomly initialized population lacking any prior information [92]. This approach can lead to a lack of diversity within the initial golden jackal population, potentially hindering the algorithm's ability to explore the search space effectively. The quality of the initial population is crucial for the algorithm's overall performance in navigating the optimization landscape, with a well-diversified initial population being advantageous for global search efforts. This method significantly improves the convergence accuracy and speed of the GJO algorithm, making it more efficient and effective in finding optimal solutions.

Fig. 23 shows the percentage of GJO methods based on four different areas.

Table 5 shows the general advantages and disadvantages of the GJO algorithm.

Table 6 summarizes different versions of the GJO algorithm based on various factors.

MH algorithms are characterized by two fundamental phases: exploration and exploitation. Exploration involves scanning the entire search space, highlighting the algorithm's ability to conduct a global search and discover diverse potential solutions. Conversely, exploitation focuses on refining the search around promising solutions to identify local optima [147]. A common observation in optimization algorithms is a trade-off between these two phases. An algorithm with strong exploration capabilities may struggle with efficient exploitation, while an algorithm proficient in exploitation may not explore the search space as thoroughly. Historically, techniques such as random walks were employed to enhance exploration, allowing the algorithm to traverse various regions of the search space. Gradient descent methods were utilized to improve exploitation by methodically navigating toward the optimum solution within a local area. To overcome the limitations of these methods and reduce the overall computational burden, researchers are now integrating chaotic maps into MH algorithms. Chaotic maps are known for their unpredictable yet deterministic nature, which can significantly enhance the diversification and depth of search within global and local contexts [148]. This integration aims to strike a better balance between exploration and exploitation, facilitating the discovery of optimal solutions without excessively increasing computational costs.

Table 5
Advantages and disadvantages of the GJO algorithm.

Factors	Criteria
Advantages	✓ The GJO algorithm is straightforward, adaptable, and easy to execute. ✓ Excellent performance for optimization problems ✓ The GJO algorithm addresses many optimization challenges in real-world scenarios. ✓ The GJO algorithm is suitable for enhancing solution quality and speeding up the convergence process. ✓ The GJO algorithm maintains an equilibrium between its exploratory and exploitative functions. ✓ Low computational time ✓ GJO with sustainable diversity in the population avoids getting stuck in local optima too early. Furthermore, monitoring convergence metrics and adjusting optimization parameters can help improve the algorithm's overall convergence behavior. ✓ Achieving high-quality outcomes efficiently within a shorter computational timeframe. ✓ Diversity of the population ✓ Maintaining equilibrium between local and global search efforts. ✓ The GJO algorithm is strong for solving other combinatorial optimization problems.
Disadvantages	✓ Incomplete exploitation in the solution of complex problems ✓ GJO does not guarantee to find the global optimal solution

The GJO algorithm typically starts with a randomly generated initial population, which may not ensure optimal diversity or a logical distribution within the search space. This lack of strategic initialization can affect the algorithm's efficiency and effectiveness in finding optimal solutions. To enhance the optimization process, chaotic sequences, known for their randomness, ergodicity, and sensitivity to initial conditions, are employed to improve the exploration of the search space [67]. Among the various chaotic maps available, the Tent map is particularly favored for its straightforward design and proficiency in producing uniformly distributed outcomes. Its excellent ergodicity ensures that initial solutions are spread uniformly across the solution space, allowing for a more exhaustive search space exploration.

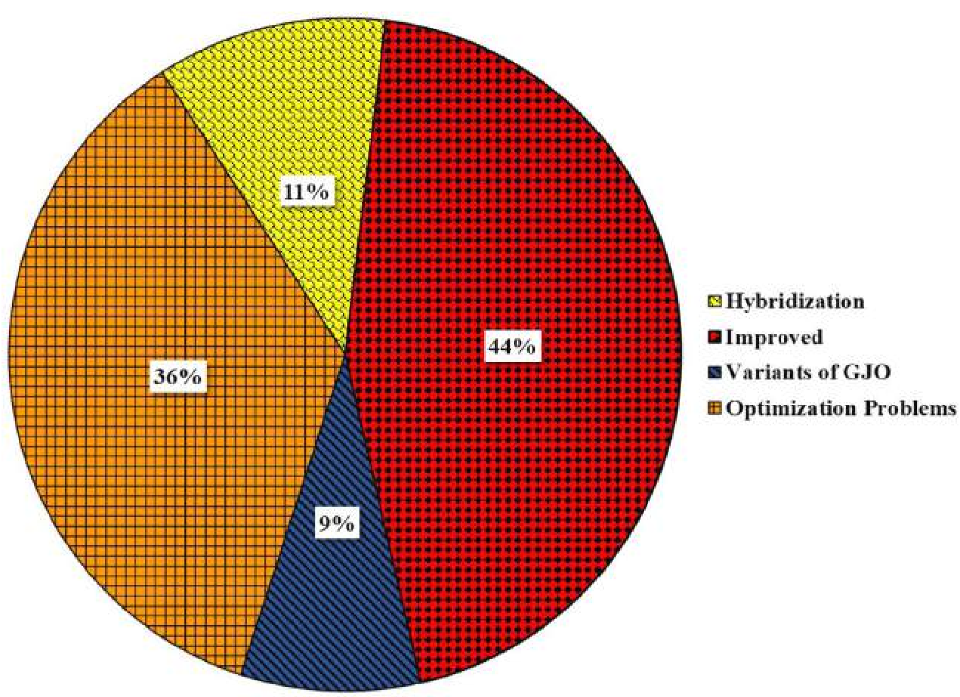

Fig. 23. Percentage of GJO methods based on four different areas.

Table 6
A summary of different versions of the GJO algorithm based on various factors.

GJO versions	Features	Applications
Hybrid	GJO hybrid models can optimize search in complex spaces by utilizing extensive exploration.	• Image segmentation • Robot path planning • Feature selection • Proportional integral derivative (PID) • Bone metastasis detection • Global optimization problems • Proton exchange membrane fuel cell
Improved	Improved GJO models focus on reducing the weaknesses of the original version, using features such as dynamic and adaptive step adjustment and methods resistant to getting stuck in local optima to increase the accuracy and speed of convergence.	• Solving engineering optimization problems • Fault diagnosis • Identification of abnormal user behavior • Optimal allocation and scheduling • Wind power generation • Traffic data prediction • Intrusion detection • Road Traffic Safety • Industrial Internet of Things Systems • Crude oil futures prices • Water quality prediction • Network security • Clustering • Crime detection • Image segmentation • Electric Vehicles • Dissolved Gas Analysis (DGA) • Global optimization and engineering problems • Optimization-based 3D path planning
Binary	These methods define the search space based on bits, and binary vectors are defined instead of continuous values.	• Feature selection
Multi-objective	Multi-objective methods seek solutions where none is superior to the other in all objectives.	• Voltage stability • Wind power prediction • Microgrid energy management • Multi-objective engineering problems • Magnetic levitation system
Optimization	Focus on optimizing a specific metric (such as minimizing cost or maximizing profit).	• Optimization problems • Load dispatch and power flow • Voltage fluctuations • Image segmentation • Renewable energy • Wireless sensor networks • Flow shop scheduling

Integrating the Tent map with the GJO algorithm enhances the initial population's quality, improving convergence accuracy and overall optimization performance by ensuring a more systematic and comprehensive search.

Like many optimization algorithms, GJO seeks to minimize (or maximize) a specific objective function. The objective function represents a model or system behavior used to reduce costs and maximize efficiency. One of the main strengths of the GJO algorithm is its ability to handle nonlinear systems and constraints. The GJO algorithm is designed for systems where the relationships between variables are not perfectly linear or cannot be easily handled by linear programming.

The OBL method increases the algorithm's convergence speed and accuracy by examining the search space's opposite points and bypassing local optima. However, it increases the computational overhead, especially in large search spaces. The main reason for using OBL is its ability to improve the performance of the GJO algorithm in complex problems. The Deep Learning method allows the GJO algorithm to process complex and nonlinear data. Its main advantage is increased accuracy and efficiency in time-consuming issues, but it requires high computational resources and complex settings. The Machine Learning method predicts the algorithm's behavior and optimally adjusts parameters. Its advantage is high flexibility and adaptability to diverse data. The reason for using this method is to increase the algorithm's accuracy when faced with different data. The Adaptive Strategy method improves the stability and speed of the GJO algorithm by dynamically and adaptively adjusting its parameters. This method is effective by adapting important parameters to changes in the search space.

This paper's potential limitations and biases are as follows: 1) In some optimization problems, the choice of initial conditions significantly affects the performance of the GJO algorithm. In this study, the initial settings may have been chosen to give the best performance to the GJO algorithm. Still, in the real world, these conditions may vary, and the performance of the GJO algorithm under different initial conditions should be investigated. 2) In the studies conducted by GJO, the effect of interactions between different parameters and problem characteristics has not been comprehensively investigated. In many optimization problems, complex interactions between input parameters and optimization objectives may affect the performance of the GJO algorithm. These interactions may reduce the accuracy of the GJO algorithm in some scenarios. 3) The GJO algorithm has been compared with several popular metaheuristic techniques. Still, the variety of benchmark functions and application scenarios may not fully reflect the wide range of challenges in real-world scenarios. 4) In some optimization problems, especially in situations where the data is noisy or uncertain, the GJO algorithm should have the ability to withstand changes and be more stable. In these studies, insufficient attention has been paid to issues such as the robustness of results to data changes or unstable environments.

7. Conclusion and future works

MH algorithms are potent and effective for solving optimization problems in a reasonable amount of time. Metaheuristic algorithms aim to generate optimal and practical solutions to challenging optimization problems in the real world. In this paper, a comprehensive review of the GJO algorithm and its applications in engineering sciences and complex issues was done. The search procedures were carried out systematically through search engines and reliable databases such as Google Scholar, IEEE, Elsevier, Springer, MDPI, Tandfonline, etc. The advantages, limitations, and challenges of the GJO algorithm were investigated in various practical problems. The GJO algorithm was analyzed in hybrid, improved, binary, multi-objective, and optimization domains. According to studies, GJO has been successfully used to solve a wide range of optimization problems in engineering science, including continuous functions, image processing, power and transmission networks, parameter tuning, feature selection, clustering, classification, scheduling, etc. The results showed that the improved domain for machine learning and deep learning algorithms used the GJO algorithm to solve optimization problems. The GJO algorithm has been used to solve complex problems by exploiting the balance between exploration and exploitation. Of course, in some cases, strategies such as opposition-based learning, weighted methods, and sine and cosine functions have been used to solve the problem of getting stuck in the local optimum and fast convergence.

The studies showed that this algorithm performs optimally in solving complex problems, especially in areas that require a balance between exploration and exploitation. For example, in machine learning problems, GJO tuned parameters and improved prediction accuracy. Also, in deep learning, using GJO to tune hyperparameters has led to increased efficiency of neural networks. However, some research gaps were also observed. Firstly, the algorithm's performance on high-dimensional problems or accurate data has not been thoroughly investigated. Secondly, investigating the impact of noise or unbalanced data on algorithm performance in machine learning and deep learning applications can have a negative effect. Future research directions to overcome the limitations and improve the GJO algorithm are as follows: Developing algorithms and approaches that can make optimization problems more optimal and reduce time and processing costs. Tuning parameters to increase the stability of results and reduce errors in real applications that are more complex. Applying the GJO algorithm to optimization problems such as interference detection in mobile networks, drought prediction, automated aircraft management, and stock forecasting.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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