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A Systematic Review of Applying Grey Wolf Optimizer, its Variants, and its Developments in Different Internet of Things Applications

Mohammad H. Nadimi-Shahraki[1,2*], Hoda Zamani[1,2], Zahra Asghari Varzaneh[3], Ali Safaa Sadiq[4], and Seyedali Mirjalili[5]

[1]Faculty of Computer Engineering, Najafabad Branch, Islamic Azad University, 8514143131, Iran
[2]Big Data Research Center, Najafabad Branch, Islamic Azad University, 8514143131, Iran
[3]Department of Computer Science, Shahid Bahonar University of Kerman, Kerman, Iran
[4]Department of Computer Science, Nottingham Trent University, Nottingham, United Kingdom
[5]Centre for Artificial Intelligence Research and Optimisation, Torrens University Australia, Brisbane 4006, Australia
∗ E-mail: nadimi@iaun.ac.ir & nadimi@ieee.org

Abstract- The Internet of Things (IoT) shapes an organization of objects that can interface and share information with different devices using sensors, computer programs, and other innovations without human intervention. IoT problems deal with massive amounts of data with critical challenges such as complex and dynamic search spaces, multiple objectives and constraints, uncertainty, and noise that require an efficient optimizer to extract valuable insights. Grey wolf optimizer (GWO) is an efficient optimizer stimulated by the hunting mechanism of wolves. The increasing trend of applying GWO shows that although it is a simple algorithm with few control parameters, it effectively solves optimization problems, particularly in various IoT applications. Therefore, this study reviews applying GWO, its variants, and its developments in IoT applications. This systematic review uses the PRISMA methodology, including three fundamental phases: identification, evaluation, and reporting. In the identification phase, the target search problems are defined based on suitable keywords and alternative synonyms, and then 693 documents from 2014 to the end of 2023 are retrieved. The evaluation phase applies three screening steps to assess papers and choose 50 eligible papers for full-text reading. Finally, the reporting phase thoroughly examines and synthesizes the 50 eligible articles to identify key themes related to GWOs in IoT applications. The eligible GWOs are reviewed in the development, commercial, consumer, and industrial categories. The paper visualized the spreading of eligible GWOs according to their publisher, application, journal, and country and then suggested future directions for research.

Keywords: Metaheuristics, Swarm-based Optimization Algorithms, Grey Wolf Optimizer, Internet of Things (IoT), IoT applications

1. Introduction

The Internet of Things (IoT) enables physical items to connect and exchange data with other devices and systems using sensors, software, and other technologies over the Internet [1, 2]. IoT allows items to sense, think, interact, and learn from each other, creating new possibilities for services in various domains, such as smart homes [3], smart healthcare systems [4-7], industrial automation [8], intelligent transportation [9], resource management [10], energy management [11], smart cities [12], and cybersecurity [13]. Moreover, IoT offers numerous services such as storing, computation, and communication that leverage emerging technologies [14]. These developments expand the variety and volume of data derived from these IoT applications and form a large and complex problem space that poses many challenges to handling these data and finding accurate solutions in recent years. According to Google Trends, scientists and researchers frequently investigate and propose various methods to address IoT challenges and deliver effective solutions for different objectives and applications. Fig. 1 illustrates the popularity of IoT from 2004 to the end of December 2023. Fig. 2 (a) shows the worldwide search interests in IoT ranging from grey to blue, in which the grey color indicates no data available or interest in IoT. The blue color ranges from high to low search interests, with darker shades representing higher search interests and lighter shades indicating lower search interests in IoT. In addition, Fig. 2 (b) shows countries with the most search interests in IoT.

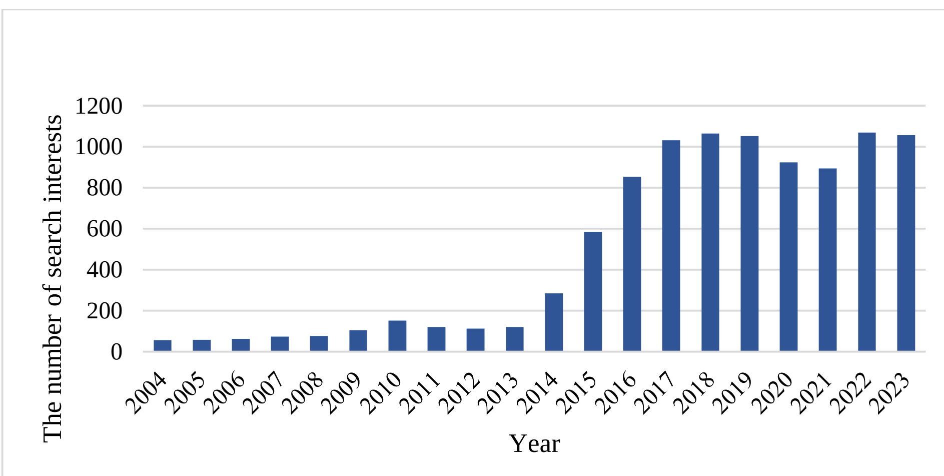
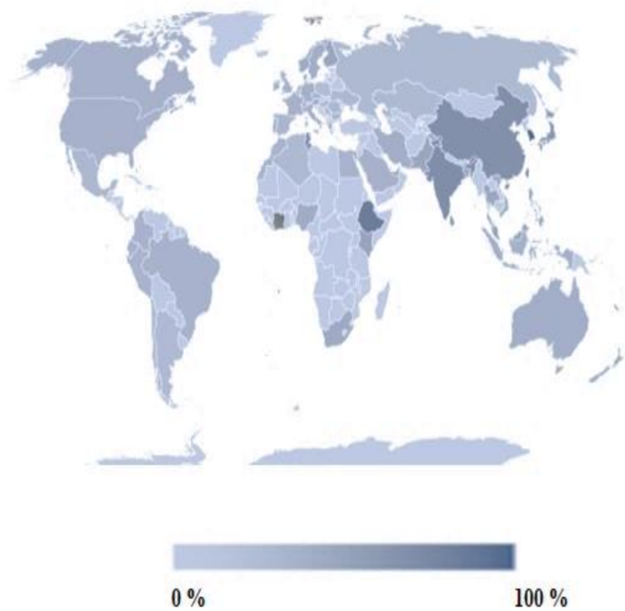
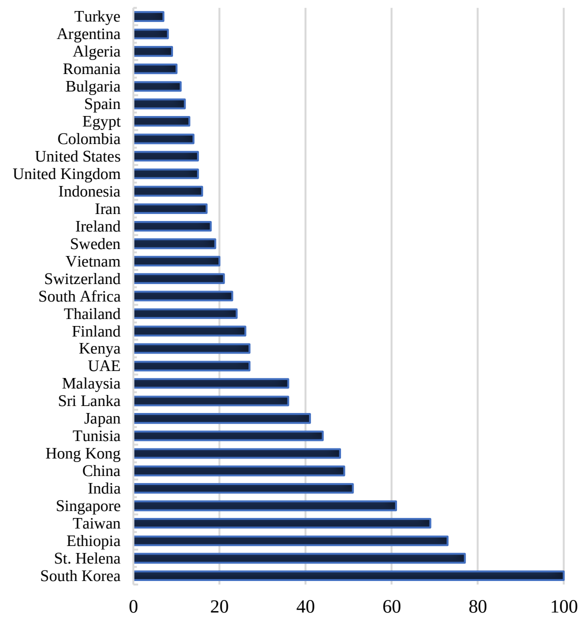


Fig. 1. The popularity of IoT from 2004 to the end of 2023 according to the number of search interests

Although IoT networks have become ubiquitous to different extents, such as smart cities, healthcare, farming, and manufacturing applications [15-17], they still face significant security challenges that need to protect the network of connected devices, such as sensors, cameras, and vehicles, from cyberattacks [18, 19]. Therefore, security solutions such as implementing strong authentication and authorization, encrypting data and communications, and securing communications protocols and channels are needed to ensure IoT networks [20-23]. The prevailing research indicates that IoT requires a powerful paradigm to explore the complex search space efficiently and extract valuable insights for enhancing efficiency, competitiveness, productivity, decision-making, and quality of life in IoT-based applications [24, 25]. IoT problems pose challenges such as large and dynamic search spaces [26], multiple objectives and constraints [27], uncertainty and noise [28], high computational complexity [29], and high dimensionality [30-32]. The adaptability and robustness of metaheuristic algorithms make them a successful paradigm for coping with such challenges of IoT problems and searching for near-optimal solutions in a sensible time [33]. There are five main groups of metaheuristic algorithms [34]: evolutionary-based, which simulates the biological evolution and genetic variation processes [35-37]; mathematical and physic-based, which performs mathematical concepts and physical laws [38, 39]; human-based, which imitates human intelligence, creativity, and social activities [40, 41]; and swarm-based, which mimics the collective behavior of insects [41-44], terrestrial animals [45-47], aquatic animals [48, 49], and birds [50-53]. Although these algorithms effectively solve optimization problems [41, 54-56], they have weaknesses, such as low population diversity and imbalance issues [57-60]. Hence, they are often enhanced by hybridizing with other algorithms [61-65], improving their search strategies [66, 67], adapting their parameters and operators [66, 68, 69], and using archive mechanisms [70]. Uniyal et al. [71] reviewed and mathematically evaluated the nature-inspired optimization methods that developed over time and were inspired by natural phenomena. Moreover, Kumar et al. [72] presented a comprehensive overview of the widely used and studied metaheuristic optimization methods and nature-inspired algorithms.



(a) The worldwide search interests in IoT



(b) Countries with the most search interests in IoT

Fig. 2. Distribution of search interests in IoT

Among them, swarm-based optimization categories are adopted or improved to solve the challenging issues in IoT-based applications [24, 73, 74]. Grey wolf optimizer (GWO) [45] is a prominent technique based on swarm intelligence that formulated the social construction of grey wolves to search the solution space. The GWO has a simple form and few control parameters, making it a candidate for solving various optimization problems and has attracted much attention from researchers [75]. GWO is widely applied to system reliability optimization [76], especially for nuclear power plant safety systems [77] and life support systems in space capsules [78]. Fig. 3 shows the distribution of GWO citations per year over time, revealing a remarkable growth curve from 144 in 2015 to 3268 in 2022, and even it will grow more in 2023. This exponential increase in citations indicates the increasing popularity of the algorithm and its great importance in solving various optimization problems. Accordingly, as Fig. 3 shows, in the same fashion, applying GWO in different IoT applications [79-82] has increased since its introduction.

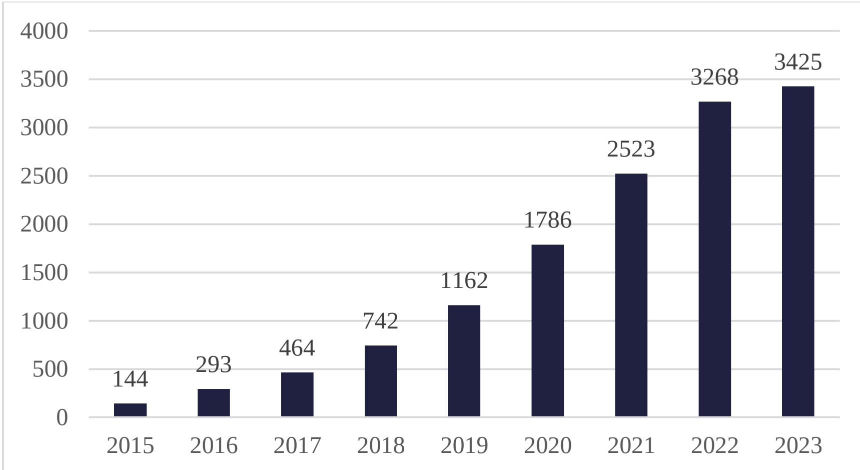


Fig. 3. The annual citation count of GWO

GWO is implemented in the smart home application to optimize the energy consumption for thermostats, lighting, and security systems [83]. GWO is successfully used for path planning in the smart city application to determine the optimal path for unmanned delivery robots by considering the distance, traffic, and obstacles [84, 85]. Moreover, GWO in IoT healthcare applications used as IoT-enabled healthcare monitoring devices to diagnose disease at an early stage [86-88], IoT-based healthcare devices to optimize the design and performance of wearable sensors [86, 89], and healthcare transformation to improve the efficiency, quality, accessibility, and affordability of healthcare service [90]. Sharma et al. [91] investigated how artificial intelligence, blockchain, and IoT can improve smart healthcare and telemedicine systems. They also address security and privacy issues, electronic health record storage, service quality and safety, and intelligent healthcare and telemedicine cloud computing platforms. GWO in agriculture IoT applications are used for autonomous robot path planning to find optimal paths by considering the distance, obstacles, and crop yield [85], smart irrigation to optimize the water distribution and fertilizer [92], and crop disease detection to analyze the images from drones and IoT-enabled sensors to diagnose crop diseases [93]. GWO in manufacturing IoT applications applied for task scheduling to schedule the tasks by considering the processing time, date, and resource availability [94], resource allocation to assign the resources by evaluating the demand, cost, and quality [95], and machine control to control the machines by considering the energy consumption [96], performance [97], and maintenance [98].

These applications reveal that GWO can offer a reasonable convergence rate, accuracy, and robustness for IoT problems with large-scale data, high-dimensional features, and complex objectives. However, GWO still suffers drawbacks such as poor search strategies, low population diversity, early convergence, and a trade-off problem in these applications [99-101]. These deficiencies motivate researchers to enhance GWO by improving it with novel methods or search strategies, hybridizing it with other optimizers, and adapting its control parameters [83, 102-104]. Some possible ways to improve GWO using the most well-known methods such as quantum computing [105-107], chaotic maps [108-110], Lévy flight [111-113], fuzzy hierarchical operator [114], and opposition-based learning [115-118]. GWO can also be integrated with other optimizers such as particle swarm optimization motivated by the collective motion of particles [119-121], ant colony optimization inspired by ants [122, 123], genetic algorithm [124, 125], sine cosine algorithm [126-128], harmony search algorithm [129, 130], or invasive weed optimization [131] that can balance its strengths and weaknesses and improve its convergence speed and solution diversity [132-134]. Moreover, GWO can be affected by its control parameters, such as A, a, r_1, r_2, and C, or the population size that can influence its performance and robustness and need proper tuning or adaptation [135-137]. As shown above, GWOs, including the canonical GWO, its variants, and its improvements and hybrids, impact growing IoT development which is the main reason to devote this study to systematically reviewing applying GWOs in different IoT applications.

This systematic paper follows the modified PRISMA guidelines [138] for conducting and reporting systematic reviews and meta-analyses. It consists of three primary stages: identification, evaluation, and reporting. The first phase defines the target search problems based on suitable keywords and alternative synonyms, and then 693 papers from January 2014 to the end of 2023 are extracted from diverse databases. The evaluation phase employs the Rayyan tool [139] and consists of three screening stages to select relevant papers. The first stage filters out 421 high-quality papers by eliminating duplicates and papers from non-scholarly or low-quality journals. The screening phase checks the scope of the reputable papers and extracts 101 related papers by reading their titles and abstracts. Then, the third screening step extracts 50 eligible papers by full-text reading and inclusion criteria defined in this study. Finally, in the reporting phase, we carefully study the 50 eligible papers to review and explain critical themes related to applying GWOs in different IoT applications. In addition, we suggest some future research directions in the conclusion section.

2. The Canonical Grey Wolf Optimizer (GWO)

Wolves typically form groups of 5–12 individuals. They are top predators with a rigid social order of alpha, beta, omega, and gamma ranks. The alpha makes most of the decisions for the pack, such as hunting, sleeping, waking, etc. The beta is the deputy leader and helps the grey wolf alpha make decisions and lead the pack activities while overseeing the subordinate wolves. The omega is the bottom-ranked wolf and must obey all the other higher-ranking wolves. The delta is the lowest level in the order and follows the alphas and betas but dominates the omega. This behavior motivated Mirjalili et al. [45] to propose a grey wolf optimization algorithm (GWO) to find the best answer for continuous and engineering optimization problems. Fig. 4 shows how the wolves' population changes its location.

2.1 Social Hierarchy Mechanism

The best solution is the alpha, which is indicated with α; the following two best solutions are beta, which is specified with β and delta δ, and the rest are omega, which is marked with ω. The social hierarchy mechanism is based on these ranks.

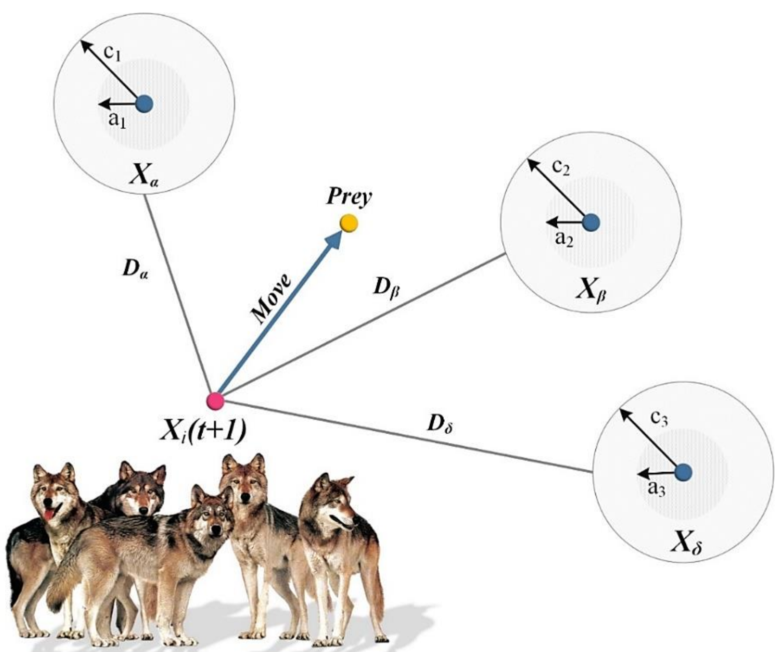


Fig. 4. The position updating schema

2.2 Encircling Prey Mechanism

The encircling prey mechanism of grey wolves during their hunting behavior is mathematically modeled in Eq. (1), where $\vec{X}_i(t)$ is the current position and $\vec{X}_i(t+1)$ is the next position of the i^{th} grey wolf, the prey position shown with $\vec{X}_P(t)$, and $\vec{A}(t)$ is the coefficient is computed using Eq. (2) and vector distance $\vec{D}(t)$ is calculated using Eq. (3).

$$\vec{X}_i(t+1) = \vec{X}_P(t) - \vec{A}(t) \times \vec{D}(t) \tag{1}$$

$$\vec{A}(t) = 2 \times \vec{a} \times \vec{r_1} - \vec{a} \tag{2}$$

$$\vec{D}(t) = \left|\vec{C}(t) \times \vec{X}_P(t) - \vec{X}_i(t)\right| \tag{3}$$

$$\vec{C}(t) = 2 \times \vec{r_2} \tag{4}$$

Vector $\vec{a}$ in Eq. (2) linearly reduces in the range 2 to 0, and the vector $\vec{r_1}$ is a random value from zero to one. $\vec{C}(t)$ in Eq. (3) is obtained using Eq. (4) and $\vec{r_2}$ is random values between intervals 0 to 1.

2.3 Hunting Mechanism

The hunting mechanism modeled grey wolves' locating and surrounding behavior when chasing their target. The alpha often guides the hunt, and the beta and delta wolves sometimes participate in the hunt. Thus, the omega wolves are forced to change their locations according to the location of the best search agents, which are the first three best solutions kept so far. Eq. (5) illustrates the hunting mechanism where position vectors $\vec{X}_1(t)$, $\vec{X}_2(t)$ and $\vec{X}_3(t)$ are computed using Eqs. (6-8) respectively.

$$\vec{X}_i(t+1) = \frac{\vec{X}_1(t) + \vec{X}_2(t) + \vec{X}_3(t)}{3} \tag{5}$$

$$\vec{X}_1(t) = \vec{X}_\alpha(t) - \vec{A}_1(t) \times \vec{D}_\alpha(t) \tag{6}$$

$$\vec{X}_2(t) = \vec{X}_\beta(t) - \vec{A}_2(t) \times \vec{D}_\beta(t) \tag{7}$$

$$\vec{X}_3(t) = \vec{X}_\delta(t) - \vec{A}_3(t) \times \vec{D}_\delta(t) \tag{8}$$

$$\vec{D}_\alpha(t) = \left|\vec{C}_1(t) \times \vec{X}_\alpha(t) - \vec{X}_i(t)\right| \tag{9}$$

$$\vec{D}_\beta(t) = \left|\vec{C}_2(t) \times \vec{X}_\beta(t) - \vec{X}_i(t)\right| \tag{10}$$

$$\vec{D}_\delta(t) = \left|\vec{C}_3(t) \times \vec{X}_\delta(t) - \vec{X}_i(t)\right| \tag{11}$$

In Eqs. (6-8), $\vec{X}_\alpha(t)$, $\vec{X}_\beta(t)$, and $\vec{X}_\delta(t)$ denoted the three best positions obtained in t-th iteration t. Parameters $\vec{A}_1(t)$, $\vec{A}_2(t)$, and $\vec{A}_3(t)$ are calculated through Eq. (2), and distance vectors $\vec{D}_\alpha(t)$,

$\vec{D}_\beta(t)$, and $\vec{D}_\delta(t)$ are computed using Eqs. (9-11). $\vec{C}_1(t)$, $\vec{C}_2(t)$, and $\vec{C}_3(t)$ denoted in Eqs. (9-11) are obtained by Eq. (4).

2.4 Attacking Prey Mechanism (Exploitation Strategy)

The attacking prey mechanism intensifies the exploitation ability by attacking the prey by setting the values of vectors $\vec{A}_1(t)$, $\vec{A}_2(t)$, and $\vec{A}_3(t)$. When $|A|$ is less than one, the wolves are compelled to chase the prey, and the wolves' next location can be anywhere between their present location and the prey's location.

2.5 Searching for Prey Mechanism (Exploration Strategy)

The wolves separate to rummage around for prey and merge to assault prey, utilizing the looking-for-prey component. The values of parameters $\vec{A}_1(t)$, $\vec{A}_2(t)$, and $\vec{A}_3(t)$ with greater than one or smaller than -1, the wolves scatter away from the prey. When $|A| > 1$ powers the wolves to wander from the prey to ideally discover a fitter prey. Furthermore, coefficient C generates random numbers for exploration not only in the initial emphasis but also in the final cycles.

The flowchart of the GWO algorithm is shown in Fig. 5, where the grey wolves' position is reorganized by two main steps: initialization and optimization process. The GWO algorithm starts by randomly placing N wolves in the look space and calculating their fitness values in the initialization step. Then, the optimization process is begun through predefined iterations. In each iteration, first, the control parameters' initial values are calculated by Eqs. (2) and (4). Next, the locations of the top three wolves (X_α, X_β, and X_δ) are identified. Then, Eqs. (6-8) are used to compute the new values for vectors $X_1(t)$, $X_2(t)$, and $X_3(t)$, and Eqs. (9-11) are used to compute $D_\alpha(t)$, $D_\beta(t)$, and $D_\delta(t)$. Next, Eq. (5) is used to update the location of each wolf $X(t)$, the new wolf positions' fitness value is calculated, and a new place is chosen between the current and the new ones by a greedy selection. The iterations continue until the iteration limit is reached. These iterations are repeated until the maximum number of iterations is satisfied. Ultimately, the wolf with the highest fitness value is the optimal or near-optimal solution the algorithm can find.

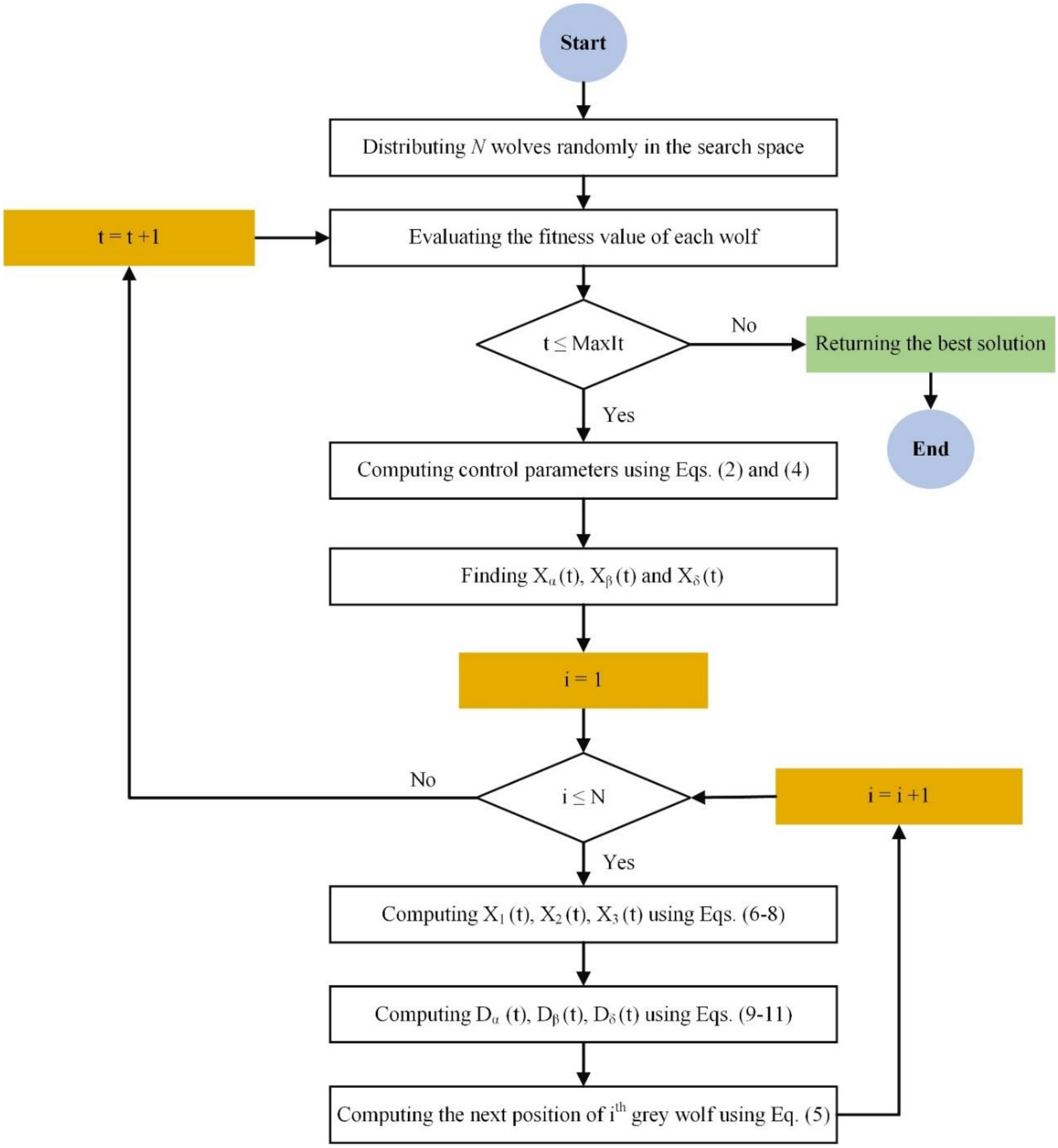


Fig. 5. The diagram of the GWO

3. Prior studies on applying metaheuristic algorithms in IoT applications

The IoT has grown tremendously with the increasing integration of interconnected smart devices and sensors across numerous applications. Extensive research has been conducted to explore the capabilities and address the challenges associated with IoT technology. Given the immense scale and ongoing enhancements in IoT advancements, it is critical to systematically review the different techniques proposed for solving the various challenges in this domain. Therefore, several review studies have been published to assess the state of the art. These review studies are vital in identifying trends, applications, research gaps, and guidance for future work. Shan and Yaqoob [140] provided a comprehensive IoT overview covering protocols, technologies, applications, and related issues. It emphasizes the integration of various technologies to enable autonomous applications and discusses the development of IoT in terms of Internet, smartphone, and machine-to-machine technologies. The paper explores IoT architecture, technical aspects, and its relationship with emerging technologies.

Laghari et al. [141] explored the utilization of IoT technologies in cloud and fog computing, along with their applications and security aspects. They focused on the design and development of IoT architecture, incorporating sensors in the context of 6G. Additionally, they delve into the existing research, propose solutions, and highlight open issues for future investigation in IoT. The emergence of diverse applications across various domains has brought forth numerous security concerns, including protecting devices and networks, addressing security threats in IoT networks, and efficiently managing resource-limited IoT networks. Several security solutions, such as web app Protectors and intrusion detection systems (IDS), have been proposed to address the IoT scalability and security challenges. Thakkar and Lohiya [142] surveyed IDS in the IoT context, focusing on 2015-2019. They examined different strategies for placing IDS within the IoT architecture and analyzed various intrusion detection techniques, including deep learning algorithms and machine learning. Additionally, their paper addresses security concerns and challenges specific to IoT networks.

Furthermore, the integration of meta-heuristic algorithms in IoT has gained significant attention. Meta-heuristic algorithms offer powerful optimization techniques for solving complex problems in IoT applications. These algorithms have shown remarkable capabilities in addressing challenges such as network optimization, resource allocation, energy efficiency, and routing in IoT systems. As a result, numerous review papers have explored the integration of meta-heuristic algorithms in the IoT domain. These papers focus on applying meta-heuristic algorithms to tackle the unique challenges posed by IoT, providing comprehensive analyses of their effectiveness and limitations. By highlighting the advancements and methodologies employed in these studies, these review papers offer invaluable insights into the prospective advantages and upcoming trajectories of leveraging meta-heuristic algorithms in the IoT landscape. Zedadra et al. [143] investigated the technical components of swarm intelligence algorithms (SI) and their potential application in IoT-based systems. It begins by examining existing SI algorithms and their primary applications.

Subsequently, it investigates IoT-based systems that utilize SI algorithms. Finally, the study discusses emerging trends that bridge the gap between SI and IoT-based systems.

Sun et al. [144] presented a comprehensive review of SI algorithms and their applications in the IoT. It explored SI-enabled applications in wireless sensor networks (WSN) and discussed research challenges in that domain. Additionally, the paper explored SI applications in other areas of the IoT, such as UAV-aided wireless networks. It compared various SI-based algorithms for selecting cluster head routing protocols in WSN applications, summarizing their validation platforms, parameter selection, advantages, and limitations. They also surveyed other state-of-the-art SI algorithms in IoT applications and provided insights into potential future development directions. Sharma et al. [24] systematically reviewed metaheuristic algorithms employed in IoT applications. It classified existing metaheuristic algorithms and highlighted their applications in IoT systems. Their paper also presented current research questions to inspire further exploration and discussed emerging trends in IoT, offering potential future directions. Abualigah et al. [145] conducted a thorough review of SI algorithms and their use in solving the main problems of the IoT. SI algorithms, which emulate the hunting behavior of agent communities, demonstrate desirable qualities such as flexibility, resilience, dissemination, and scalability, making them well-suited for IoT requirements. Their paper provided an overview of SI-based algorithms employed in the IoT domain to tackle its key challenges. The methods are classified based on the specific SI algorithm used, namely bee colony optimization (ABC), ant colony optimization (ACO), and particle swarm optimization (PSO). These algorithms were examined about three primary concerns within the IoT landscape: routing protocols and selection of cluster heads, power management, and data management.

4. Methodology of Systematic Review

We explain in this section the methodology of our systematic review to select the eligible papers in which GWOs, including the canonical GWO, its variants, and its improvements and hybrids, were applied in different IoT applications. We follow the adopted PRISMA methodology [138] for systematic reviews and meta-analyses to choose an eligible set of papers for full-text reading within three main phases: identification, evaluation, and reporting. The systematic review's methodology and details are presented in Table 1.

Table 1. The adapted methodology and its details used in the systematic review

Identification Phase							
First step	Defining relevant queries to find related documents						
Second step	Extracting related documents (N = **693**)						
Evaluation Phase							
First screening step **(Finding reputable papers)**	Removing duplicate papers (N = **683**) Removing papers published by non-academic journals (N =**421**)						
Second screening step **(Finding related papers)**	Scanning title and abstract to select only GWOs (consisting of the canonical GWO, its existing variants, and its new improving and hybridizing) applied in different IoT applications (**N = 101)**						
Third screening step **(Finding eligible papers)**	Full-text reading based on inclusion criteria to select eligible papers to explain (N = **46**) Studying and evaluating the references of eligible papers to select more papers that meet the inclusion criteria (N = **50**) **Inclusion criteria:** **C1.** Papers from 2014 to the end of 2023 **C2.** Papers in English languages **C3.** Papers from credible journals **C4.** Papers attentive to applying GWOs in IoT applications as the study scope						
Reporting Phase	The final set of papers that met the eligibility criteria (N = **50**)						
Classifying publishers	Elsevier	Springer	WILEY	Taylor & Francis	IEEE	MDPI	Hindawi
	15	**13**	**5**	**2**	**11**	**3**	**1**
Reviewing	Reviewing **50** eligible papers						

4.1 Identification Phase

This phase has two steps. First, we define the final search problems based on suitable queries, and next, we extract the related documents from different databases. The target search problems are determined based on keywords and alternative synonyms, including " GWO and IoT, GWO and Internet of things, Grey Wolf and IoT, Grey Wolf and Internet of things." From 2014, the introduction of GWO, to the end of 2023, these keywords were used to search the Google Scholar database, resulting in 693 documents. Fig. 6 shows the variety and distribution of documents identified in this phase based on different publications, such as journals, books, and dissertations. Most of the publications are journal articles (421 papers, 60%), followed by conference and symposium papers (101 papers, 15%) and disreputable documents (151 papers, 22%). Only a few publications are books and book chapters (11 papers, 2%) and dissertations (four papers, about 1%).

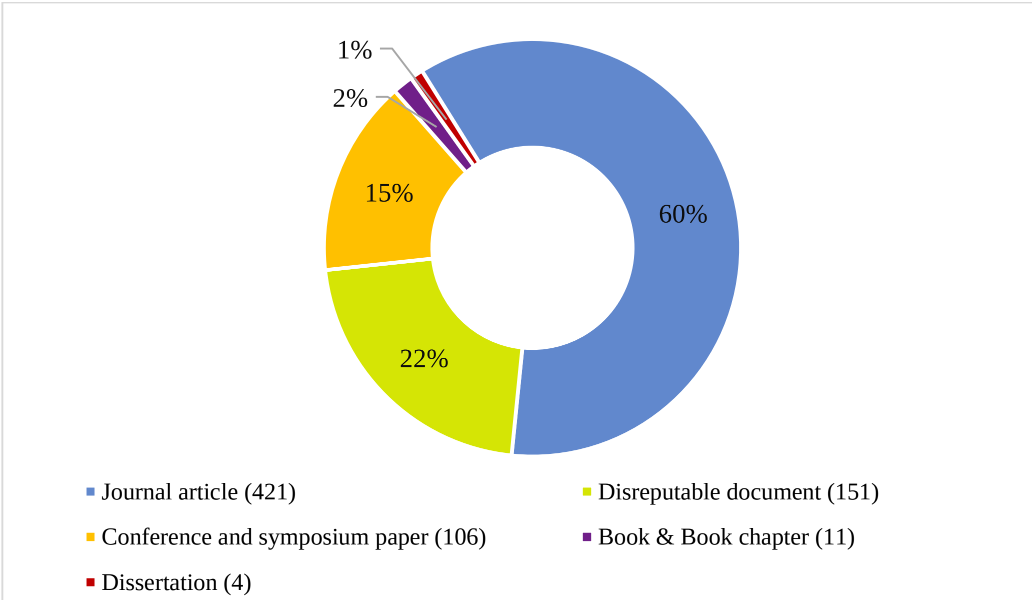


Fig. 6. The variety of identified documents

4.2 Evaluation Phase

This phase consists of three screening steps. First, nine duplicates and non-academic publications such as conferences, non-Scopus indexed journals, books, and dissertations are removed from the 693 papers, leaving 421 reputable papers. Second, the title and abstract of each paper are scanned to select only those that have applied GWOs in different IoT applications, resulting in 101 related papers. The third step is to examine and study the full text of these 101 related papers, and those that meet the following inclusion criteria are selected for analysis, resulting in 46 papers.

C_1. Papers published from 2014 to the end of 2023.
C_2. Papers written in English languages
C_3. Papers from credible journals.
C_4. Papers are attentive to applying GWOs in IoT applications as the study scope.

Finally, the references of 46 papers are investigated based on inclusion criteria to find more eligible articles, resulting in a final set of 50 GWOs in IoT applications.

4.3 Reporting Phase

In this phase, we use Rayyan to select 50 papers that meet the criteria [139] and are first classified by seven publishers: Elsevier (15), Springer (13), WILEY (5), Taylor & Francis (2), IEEE (11), MDPI (3), and Hindawi (1). Then, the eligible papers are qualitatively analyzed and reviewed into four main categories: IoT development, commercial IoT, consumer IoT, and industrial IoT.

5. Different Types of the Internet of Things

The IoT describes a vast network of physical devices equipped with sensors, software, and internet connectivity [146]. The IoT development class includes contributions such as reducing power consumption, optimal positioning, finding the optimal path, enhancing load balancing, and resource allocation. Considering the generic IoT architecture shown in Fig. 7 [147], IoT development extends and makes IoT more applicable, mostly in sensing, network, and data processing layers. Commercial IoT, consumer IoT, and industrial IoT classes are applied in the application layer. The commercial IoT class includes usages in the healthcare and transport industries, such as smart pacemakers and monitoring systems. The consumer IoT class uses every day such as home appliances, voice assistance, and light fixtures. The commercial IoT class has primarily been used with industrial applications, including the manufacturing and energy sectors, such as digital control systems, smart agriculture, and industrial big data [146, 148]. Fig. 8 shows different types of IoT applications.

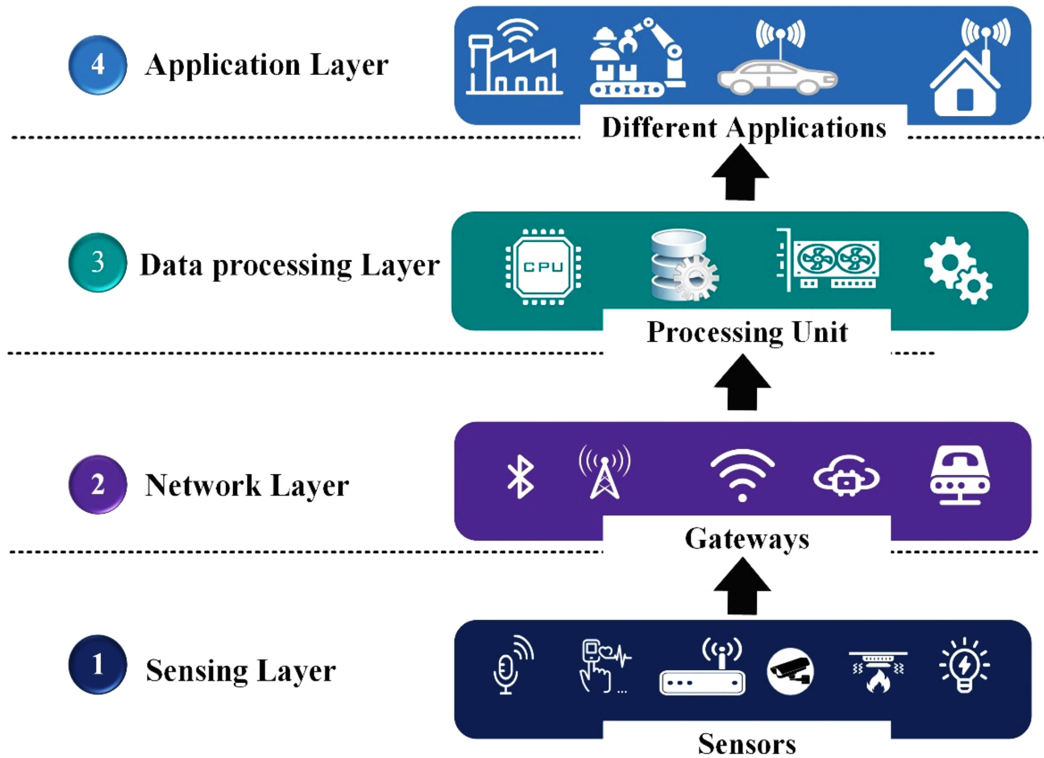


Fig. 7. A generic IoT architecture [147]

Although IoT has brought many benefits, it also poses challenges that must be tackled to achieve optimal performance. Evaluating IoT platforms with multiple considerations can be formulated as a multi-criteria decision-making problem [149]; since it has various preferences and criteria, different techniques exist to evaluate IoT platforms [150]. The commercial IoT class has challenges such as improving data transmission, diagnosing IoT wearable medical devices, and monitoring patients. Key challenges in the consumer IoT class include energy consumption reduction, smart device scheduling, and service quality enhancement. Industrial IoT networks face issues like optimal sensor placement, efficient data analytics, and minimizing network latency [148]. Furthermore, several problems arise in developing IoT networks, such as finding optimal routing paths, clustering devices, placing sensors, and allocating resources [151, 152]. Traditional optimization techniques are often insufficient to handle the complexity and scale of large IoT networks, and metaheuristic algorithms have proven that they are powerful in searching for global optima in complex systems [153]. These algorithms can provide significant advantages over traditional optimization algorithms, particularly in cases where the search space is high-dimensional or non-linear. By applying metaheuristic algorithms, IoT networks can be optimized to function more efficiently and effectively. This adaptation can result in significant cost savings, improved performance, and increased network reliability. As such, the use of metaheuristic algorithms in IoT networks is rapidly gaining popularity, and these techniques will likely continue to play a critical role in developing next-generation IoT systems [33].

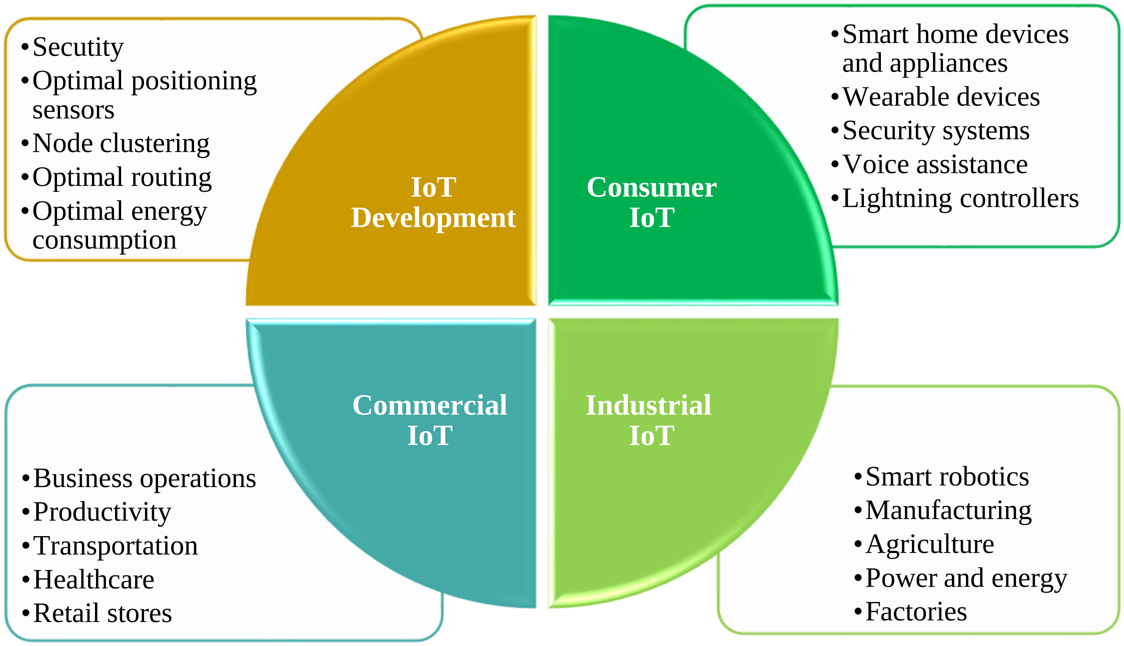


Fig. 8. Different types of IoT applications

Metaheuristic algorithms with effective mechanisms can enable them to find near-optimal solutions for complex and large-scale problems in a reasonable time [154-157]. They can effortlessly adapt to problems with low computational complexity [158-161]. They are valuable for IoT applications such as routing, clustering, and data analysis. They optimize the data transmission paths among IoT devices, considering factors like energy consumption, latency, reliability, and security. They improve the network's scalability, efficiency, and performance by clustering IoT devices based on proximity, similarity, or functionality. Metaheuristic algorithms can process and analyze the massive amount of data generated by IoT devices, such as sensor readings, images, or videos, using techniques like feature extraction, dimensionality reduction, or classification. The grey wolf optimizer (GWO) is a prominent metaheuristic algorithm with high performance and robustness in solving various optimization problems.

GWO is a simple and powerful metaheuristic algorithm for solving IoT optimization problems, such as resource allocation, energy efficiency, network routing, sensor placement, security, and fault detection [96, 99]. For example, the GWO offers a powerful tool to improve the security of IoT, contributing to the reliability and resilience of smart cities and other IoT-enabled applications

[97, 162]. The GWO can detect and mitigate potential vulnerabilities, identify anomalous behavior, and proactively respond to emerging threats within IoT networks. Fig. 9 visualizes the key challenges faced in the realm of IoT. The GWO is a viable solution for addressing these challenges. By leveraging GWO, IoT applications can optimize resource allocation, enhance energy efficiency, improve network routing and traffic flow, optimize sensor placement, strengthen security measures, and facilitate fault detection and diagnosis. The following sections review and summarize the application of GWOs as a prominent metaheuristic to solve various problems in different IoT applications.

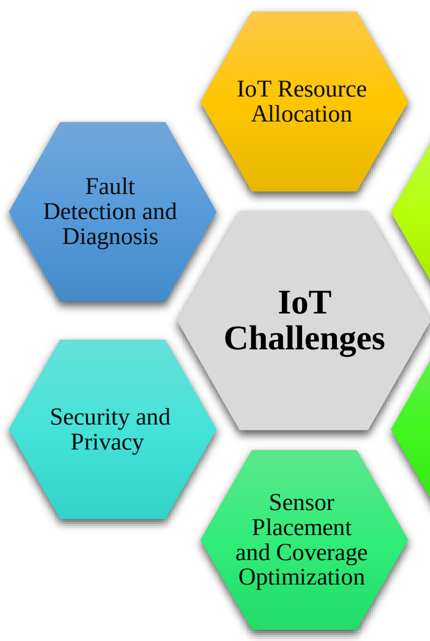


Fig. 9. Key challenges in different types of IoT applications

6. Applying GWOs in IoT Development

This section reviews 28 out of 50 papers that either apply the canonical GWO and its variants or develop GWO by improving and hybridizing it to solve different problems to develop IoT. Table 2 summarizes the fundamental properties of GWOs when solving IoT development problems.

Dhumane et al. [163] suggested FGGWO, a fractional gravitational GWO, sending data through multiple paths in IoT applications. The fractional gravitational search algorithm selects the cluster heads, and the FGGWO algorithm creates many directions from the origin to the end. The experimental results indicate that the fractional gravitational search algorithm and FGGWO perform better than some contender algorithms. Aziz et al. [164] put forward a highly effective multi-hop cluster-based aggregation scheme, which employs hybrid compressive sensing (EMCA-CS) to carry out data gathering in IoT-based heterogeneous wireless sensor networks (WSNs). The introduction of EMCA-CS significantly prolongs the network's lifespan and diminishes the reconstruction error by integrating compressive sensing and routing protocols. EMCA-CS leverages the GWO algorithm to approximate the most optimal route for the cluster head and base station. Furthermore, the paper proposes utilizing the GWO algorithm for compressive sensing matrix optimization to find the matrix with the minimum error.

Haddadpajouh et al. [100] announced a multi-kernel support vector machine employing the GWO to detect malware in IoT cloud-edge gateways. The GWO algorithm identifies the most suitable characteristics distinguishing malicious and benign applications, subsequently assessing these extracted features through a multi-kernel SVM classifier. The performance of the multi-kernel SVM classifier surpassed that of the compared classifiers in terms of accuracy and computational expense. Davahli et al. [165] employed a fusion of genetic algorithm and grey wolf optimizer (GA–GWO) to fabricate a sophisticated and efficient intrusion detection system tailored explicitly for wireless networks in the Internet of Things (IoT) domain. The GA–GWO algorithm selects informative traffic features to reduce the dimensionality of the extensive wireless network traffic by choosing traffic features that provide valuable information. Shorman et al. [97] presented an unsupervised evolutionary technique for detecting IoT botnet attacks from compromised IoT devices. This approach implements a GWO to fine-tune the hyperparameters of the one-class support vector machine and identify the most compelling features for characterizing the IoT botnet issue. Chouhan et al. [166] suggested TSGWO, a tunicate swarm GWO, for multi-path routing in WSNs with IoT support. TSGWO performs the multi-path routing process, where the shortest path is chosen as the best one.

Jeniffer et al. [167] suggested OHGHE, an optimal homomorphic scheme with hybrid heat transfer search and GWO. OHGHE chooses an optimal key with the largest key-breaking size to encrypt sensitive data and fix the existing flaws. The OHGHE scheme uses an adaptive convolutional kernel-based artificial neural network with Aquila algorithm optimization to sort IoT data into sensitive and non-sensitive. The results indicate that OHGHE can achieve longer key-breaking time, faster encryption/decryption time, and less memory for encryption and decryption. Ojha et al. [168] suggested an intelligent data routing method for WSNs with multi-objective GWO to avoid early network failure and improve lifetime performance. This mechanism divides the entire network into clusters of the most suitable sizes and subsequently determines the most optimal rendezvous points. The mobile sink effectively acquires data from sensor nodes through the ideal route to each rendezvous point. This mechanism could improve the network performance and prevent premature death than the compared algorithms. Dev et al. [169] introduced an overtaker-assisted wolf update (OA-WU) as a clustering technique by hybridizing a rider optimization algorithm and GWO to enhance lifetime in IoT by selecting the optimal radius for the cluster head. The findings of their study reveal that the implementation of OA-WU resulted in notable improvements in energy preservation and convergence rate within a short period.

Pingale et al. [170] introduced a routing protocol for IoT networks based on a hybrid optimization algorithm called SFG, which combines sunflower and grey wolf optimization techniques. The protocol starts by simulating the IoT network and creating multiple paths for routing. Then, it uses the SFG algorithm to choose the optimal way, considering various criteria such as delay, energy, throughput, and network lifetime. The experimental results demonstrated that the SFG algorithm performed better than some existing methods on these metrics. Jena et al. [171] formulated a synchronized cyber-physical assault within an IoT-enabled intelligent power network, accounting for the constraints on intruder reachability. This predicament was subsequently addressed by employing a binary GWO algorithm. The findings presented in this study, pertain to the IEEE 14, 30, and 57 bus benchmark power systems demonstrate the efficacy of disrupting the state estimation process by optimizing attack cost. Keserwani et al. [83] introduced a well-balanced model for intrusion detection, namely the GWO-PSO-RF IDS model, which serves as an intelligent algorithm for identifying different attacks in IoT networks through the utilization of GWO, particle swarm optimization, and a random forest model. The balanced GWO-PSO-RF IDS model incorporates a hybrid approach involving GWO and PSO to extract pertinent features from IoT networks. Then, the RF model classifies the extracted features to detect attacks. According to the experimental results, this model outperformed the other algorithms in solving the biasing problem and enhancing the detection of less frequent types of attacks.

Xu et al. [172] developed a new method for estimating the outage probability of IoT networks on mobile devices using a hybrid technique called IGWO-Elman. This technique combines an enhanced version of the grey wolf optimizer with an Elman neural network. The IGWO employs a modified strategy to generate and diversify the initial population of wolves. Then, IGWO optimizes the hyperparameters of the Elman neural network. Jaiswal et al. [173] applied the GWO algorithm to the node deployment problem to achieve high-quality service metrics, such as coverage, connectivity, and network cost. The GWO algorithm finds the best locations for sensor nodes in different scenarios, satisfying the required coverage and connectivity. Salimian et al. [174] introduced an autonomous Internet of Things (IoT) service placement methodology utilizing the Grey Wolf Optimization (GWO) algorithm for deploying IoT applications on fog nodes. The findings indicate that this algorithm surpasses competing algorithms in achieving a near-optimal deployment of applications on fog nodes. Sarma [175] proposed the FAE-GWO-DBN algorithm to identify and detect attacks within the Internet of Things context. The FAE-GWO-DBN algorithm optimized the deep belief network's (DBN) hyperparameters by combining Firefly and GWO to attain satisfactory performance when determining the presence of attacks.

Agrawal et al. [176] developed a new security-enhancing technique for IoT sensor nodes using a hybrid optimization algorithm called PSO-GWO, which combines binary particle swarm optimization and GWO. The algorithm uses random forest to initialize the population of particles and wolves intelligently. Besides, they introduced a new fitness function and performance metric. Liu et al. [177] developed a novel clustering method for industrial WSNs based on a hybrid optimization technique called QEGWO, which combines quantum and grey wolf optimization. The process enhances the clustering quality of IWSNs by finding the optimal cluster configuration, as shown in Fig. 10 [177]. It also uses a new evaluation function considering the node energy, cluster distance, and base station distance. The method employs a new quantum elite operator to increase the global search ability. This operator keeps a quantum probability matrix for each individual and updates it with quantum gates during the evolutionary process of the algorithm.

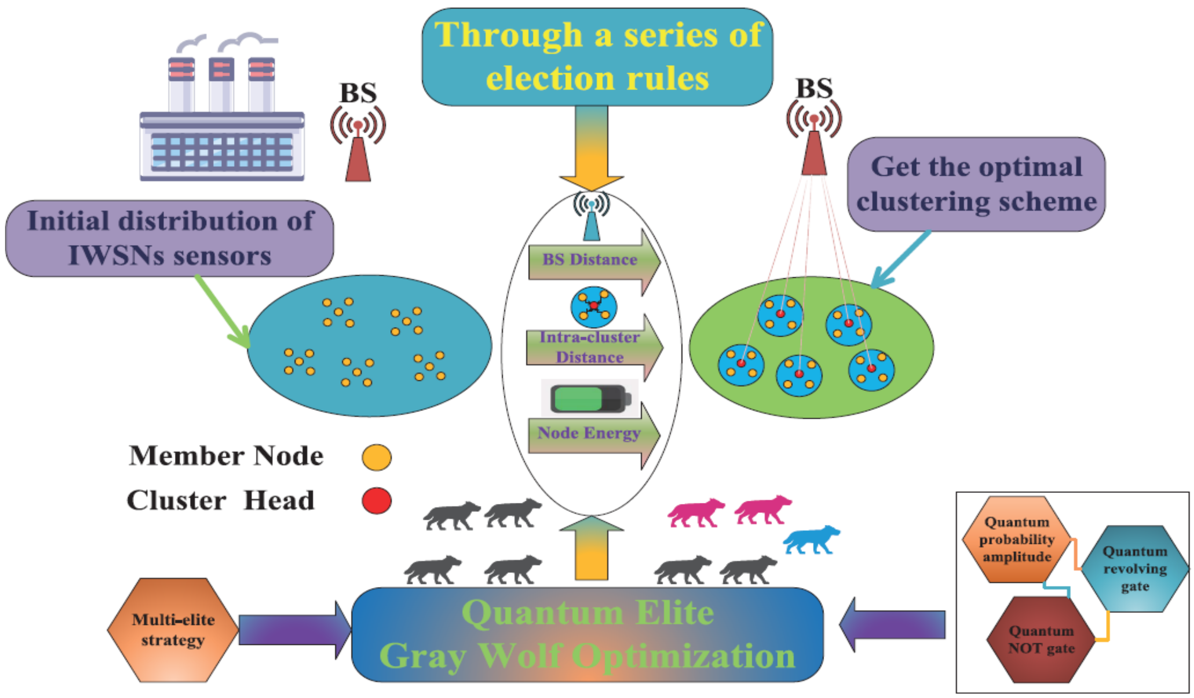


Fig. 10. Schematic diagram of the QEGWO [177]

Alazab [178] developed a method for detecting IoT botnet attacks using a discrete time-varying grey wolf hybrid technique. This technique uses a time-dependent function to transform continuous spaces into discrete ones. Gupta et al. [179] proposed an enhanced deep reinforcement learning model, GMFA-DRL, to improve fog-IoT load-balancing. GMFA-DRL applies the GWO and modified moth flame optimization to boost the effectiveness of deep reinforcement learning. According to the experimental results, the GMFA-DRL model improved the load-balancing performance of the fog-IoT system, achieving better Throughput, energy consumption, Latency, and Makespan than other methods.

Xu et al. [180] proposed a method for reducing energy consumption in IoT networks on mobile devices using a hybrid technique called transmit antenna selection and amplify-and-forward relaying. In this schema, the exact expressions are first derived, and the performance of physical layer security is analyzed. The improved grey wolf optimizer (IGWO) algorithm extracts the allocation parameter. Reported results indicate that the IGWO obtains better optimization performance than compared algorithms regarding precision and convergence speed. Bedi et al. [181] developed a method for cluster head selection in wireless body area networks using a hybrid technique called MGWOQL, which combines a modified version of the GWO and Q learning. The method aims to reduce the energy consumption of clusters by finding the best cluster head node. The results show that the MGWOQL can successfully deploy the wireless body area networks, resulting in better residual energy, network longevity, and path damage. Tong et al. [182] developed a network architecture that combines mobile edge computing and satellite-terrestrial integration to support IoT devices in performing computation tasks. The paper also presented a novel scheme for inter-satellite cooperation, which optimizes task offloading and resource allocation decisions. This scheme involves a resource allocation algorithm that uses the Lagrange multiplier technique and a task-offloading decision method that uses the GWO.

Verma et al. [183] developed a clustering method for IoT applications based on a hybrid technique called GWO and fuzzy logic, improving wireless sensor networks' energy efficiency. The algorithm uses the GWO to form clusters and a fuzzy inference system to choose the cluster heads. The experimental results demonstrated that the protocol significantly improved energy efficiency and network lifetime. Seyyedabbasi et al. [184] proposed energy-efficient routing methods based on expanded and incremental GWO to find optimal paths and data transmission with a minimum cost between the nodes. The methods find the best paths and data transfer between nodes, reducing costs. They also improve the network quality and lifetime by calculating the best coefficients for different factors, such as energy, traffic, distance, buffer, and hop. Dey et al. [185] developed a new method for identifying and preventing cyberattacks in IoT networks using an intelligent framework for threat detection. This framework uses grey wolf optimizer and binary gravitational search algorithms to find the best features and apply the decision tree, AdaBoost, and random forests to classify threats.

Manokaran et al. [186] presented an improved anomaly detection model for IoT edge scenarios using the optimized stacked ensemble learning algorithm. The paper uses the improved version of GWO to tune the parameters of the ensemble learning algorithms. The paper evaluated the model on different datasets and showed that it achieved high detection accuracy and generalizability. The paper also performed a chi-square statistical test to assess the suitability. To achieve efficient resource utilization in IoT networks, the key factors affecting the quality of service (QoS) must be determined [187]. By extracting QoS parameters from different directions, including cost, response time, energy consumption, and resource utilization, Rostami and Bidgholi [187] developed a load-balancing method using a multi-objective GWO, optimizing resource allocation to workflows. The method uses a framework for task allocation, as shown in Fig. 11 [187]. The method assigns tasks to resources based on the multi-objective GWO algorithm, which has low complexity, high accuracy, and fast convergence. The method also uses a controller to direct traffic to the best resource for user demand while maximizing the satisfaction of service providers and infrastructure.

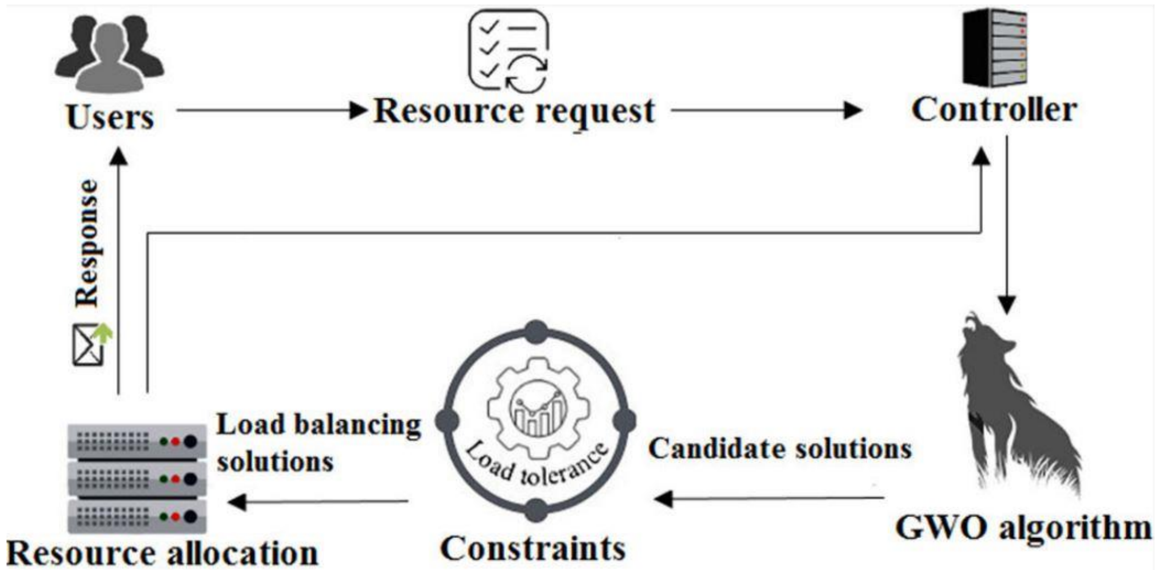


Fig. 11. Structure of the task allocation problem for achieving load balance [187]

Table 2. GWOs applied in IoT development

Authors name	Year	The objective of applying GWOs	Application
Dhumane et al. [163]	2018	Providing optimal paths in WSN-based IoT networks to overcome the energy constraint problems	WSN-based IoT networks
Aziz et al. [164]	2020	Prolonging WSN's lifetime and reducing power consumption	Heterogeneous WSNs
Haddadpajouh et al. [100]	2020	Extracting optimal features between malicious and benign applications with high accuracy and low computational cost	IoT cloud-edge gateway
Davahli et al. [165]	2020	Reducing data traffic dimensionality in WSNs	WSN-based IoT networks
Shorman et al. [97]	2020	Identifying the key factors that define the IoT botnet challenge	Online IoT devices
Chouhan et al. [166]	2020	Finding an optimal path with the minimum distance	IoT-assisted WSNs
Jeniffer et al. [167]	2021	Choosing the best key with the longest breaking time to improve the speed and memory of encryption/ decryption	Cloud-based IoT environment
Ojha et al. [168]	2021	Improving network lifetime using an intelligent data routing mechanism	IoT-based smart systems
Dev et al. [169]	2021	Enhancing lifetime and energy conservation and selecting the optimal radius for cluster head	IoT devices

Pingale et al. [170]	2021	Selecting the optimal routing path with minimal delay and maximal network life	Multi-path routing in IoT networks
Jena et al. [171]	2021	Finding the best network structure for increasing the damage of physical attack	IoT-based smart grid
Keserwani et al. [83]	2021	Extracting relevant IoT network features to identify various attacks	Network intrusion detection system
Xu et al. [172]	2021	Improving Elman network parameters to predict the outage probability	Mobile IoT networks
Jaiswal et al. [173]	2021	Determining the best number and locations of sensor nodes	WSN-based IoT networks
Salimian et al. [174]	2021	Proposing an autonomic approach for cost-efficient IoT service placement	IoT applications on fog computing
Sarma [175]	2021	Extracting optimum features from IoT network to identify attacks	IoT network of physical devices
Agrawal et al. [176]	2022	Reducing the dimensions of the dataset for network intrusion detection	IoT and sensor nodes
Liu et al. [177]	2022	Reducing energy consumption and energy uniformity in industrial WSNs	WSN-based IoT networks
Alazab [178]	2022	Discovering the optimal set of features with a fast execution time for detecting intrusions	Intrusion detection systems
Gupta et al. [179]	2022	Improving the load distribution, which leads to high Throughput, low energy usage, minimum Latency, and minimum Makespan	Fog-IoT environment
Xu et al. [180]	2022	Improving the energy efficiency of mobile IoT networks using a power allocation algorithm	Mobile IoT
Bedi et al. [181]	2022	Finding the best cluster head for reducing energy usage in WSNs	Wireless body area networks-based IoT
Tong et al. [182]	2023	Proposing a resource allocation optimization scheme	Mobile edge computing
Verma et al. [183]	2023	Enhancing energy-efficient clustering protocol and extending network lifetime	WSN-based IoT
Seyyedabbasi et al. [184]	2023	Increasing network resilience, lifetime, and energy consumption	WSNs and decentralized IoT systems
Dey et al. [185]	2023	Picking the ideal features to solve the high dimensionality issue for effective learning	IoT-compatible cybersecurity
Manokaran et al. [186]	2023	Tuning the parameters of the ensemble learning algorithms	IoT edge computing
Rostami et al. [187]	2023	Enhancing the speed and affordability of the service for users, the power efficiency for the provider, and the CPU usage for the infrastructure	IoT devices

7. Applying GWOs in Commercial IoT Applications

This section reviews 12 papers from the final set of eligible papers that apply GWOs in commercial IoT applications, including the healthcare and transportation industries, such as smart pacemakers and monitoring systems. Table 3 summarizes GWOs applied in Commercial IoT Applications. The Internet of Medical Things (IoMT) is revolutionizing the healthcare industry, providing numerous commercial opportunities that enable medical devices to share sensitive data, improving patient care. As shown in Fig. 12 [188], in IoMT, metaheuristic algorithms can be applied to tune the machine learning parameters usually run in the cloud layer, and they also can be used in the preprocessing step typically run in the fog layer.

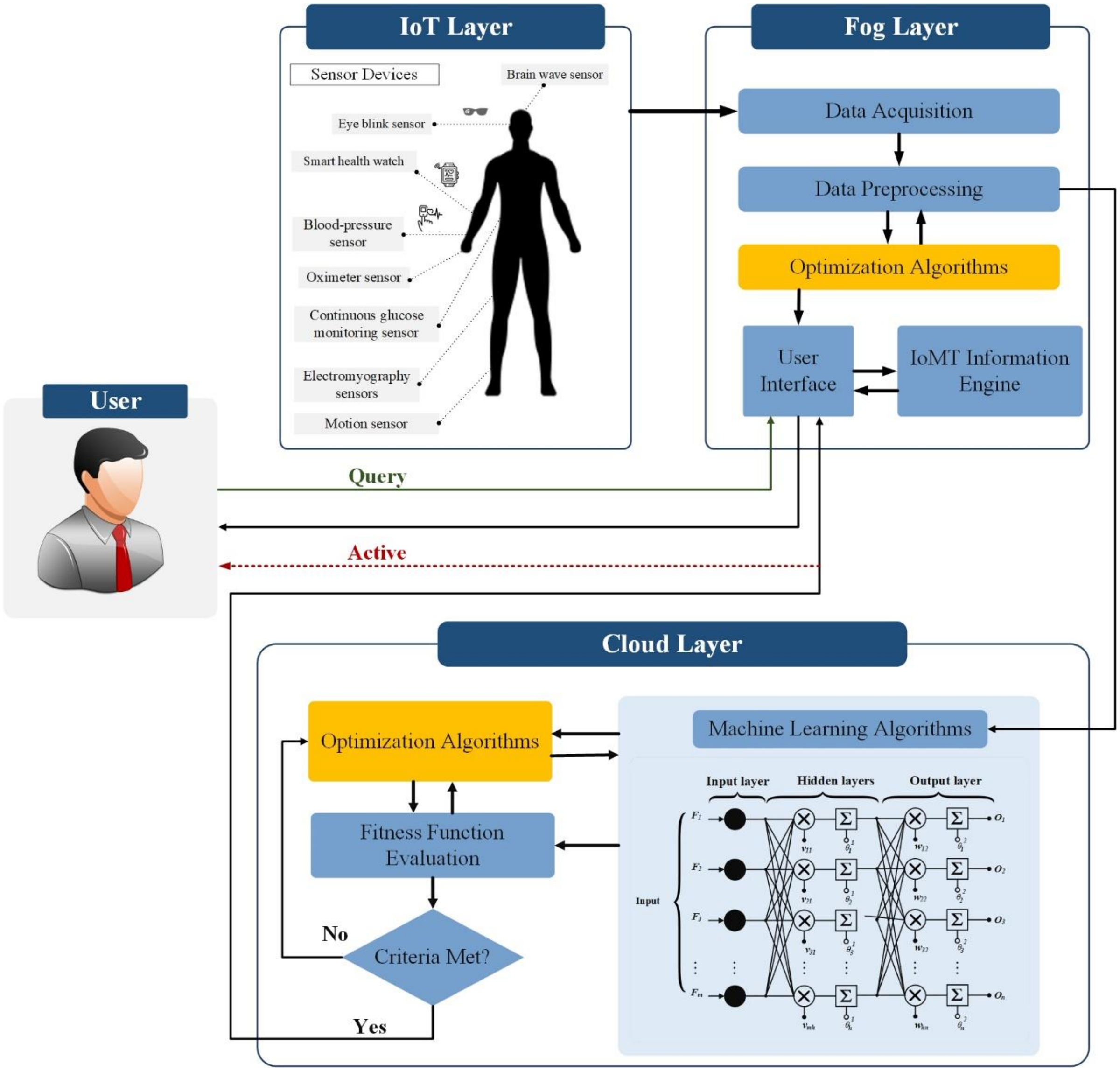


Fig. 12. Generic architecture for applying metaheuristic algorithms in IoMT

Bharathi et al. [189] proposed a model (EEPSOC) utilizing particle swarm optimization to select cluster heads among IoT devices in e-healthcare applications to improve energy efficiency. EEPSOC selects optimal cluster heads that forward sensed healthcare data to fog devices and the cloud, reducing energy consumption in data transmission. Moreover, the EEPSOC model applies an ANN in the cloud to classify healthcare data and identify disease severity levels. The EEPSOC-ANN model assesses using a student healthcare dataset, outperforming the compared methods regarding the various performance metrics. Hasnony et al. [188] introduced a fog-based model that combined an adaptive neuro-fuzzy inference system (ANFIS) with the hybrid PSO and grey wolf optimizer (PSOGWO) algorithm for predicting Parkinson's disease. The PSOGWO algorithm tunes the ANFIS parameters that the leveraged model uses. Moreover, this model uses a chaotic tent map to initialize the optimizations and fog computing to collect and analyze data at the edge of gateways. The results showed that this model outperforms optimization algorithms and other recent research. Fig. 12 [188] shows the proposed three-layer architecture for IoT-based processing and prediction of Parkinson's disease. The IoT layer collects and analyzes data from wearable sensors in real-time. The fog layer stores data locally and provides an expert system for user queries and emergency alerts.

In IoMT, there are various apprehensions regarding security and privacy, including but not limited to replay attacks, man-in-the-middle attacks, impersonation attacks, privileged-insider attacks, remote hijacking, password guessing, denial of service (DoS) attacks, and malware attacks pose significant risks. Utilizing machine learning algorithms, the IDS detects and classifies attacks; however, the unpredictable and ever-changing nature of malevolent assaults poses difficulties when formulating scalable remedies. RM et al. [190] presented a deep neural network (DNN) based IDS for the IoMT environment, optimizing and tuning network parameters through hyperparameter selection methods. This approach enhanced the promptness of alert responses and mitigated the subsequent consequences of unauthorized access to confidential cloud-based data storage. The outcomes underscored the model's efficacy in identifying and predicting unforeseen cyberattacks, contributing to the ongoing development of IoMT security. Ghorpade et al. [99] introduced a multi-objective GWO to strategically locate wireless sensor nodes enabled with IoT technology within a parking area. This optimization method incorporates two distinct objective functions, one for measuring distance and the other for assessing geometric topology constraints. The results show that a multi-objective grey optimizer could minimize a localization error compared to the compared algorithms.

Ghorpade et al. [191] proposed an IoT-based localization method for smart city applications named HOFTELM algorithm was developed by combining an extreme learning machine, fuzzy system, and modified swarm intelligence. Particle swarm grey wolf optimizer was used to identify the moving sensor node direction. A fuzzy-weighted centroid optimized the irregular movement of nodes. The proposed method outperformed existing algorithms regarding localization accuracy, number of localized nodes, and runtime. Human activity recognition (HAR) is essential in various applications, including elderly care, assisted living, smart homes, and healthcare monitoring. However, the high dimensionality of collected data impacts the quality of HAR models. Therefore, Helmi et al. [192] proposed a lightweight feature selection method to improve classification. The GBOGWO method leveraged gradient-based optimization and GWO to select features. Then, support vector machines classified the activities. Experiments using UCI-HAR and WISDM datasets showed that GBOGWO achieved the most optimal outcomes compared to various optimization algorithms.

Kumar et al. [102] proposed a system that automatically detects and classifies arrhythmia using IoT-based electrocardiogram (ECG) signals and a deep-learning classifier. The system processed the ECG signals to generate features for classification. A deep convolutional neural network (deep CNN) classifier, based on the coyote GWO (Coy-GWO) algorithm, was developed to detect anomalies in the ECG signals. The Coy-GWO algorithm combined canines' social hierarchy and hunting experience to update classifier parameters effectively. This Coy-GWO-based deep CNN achieved 95% accuracy, outperforming the compared techniques. Munagala et al. [193] proposed a fuzzy-LSTM model for a heart disease monitoring system. The fuzzy-LSTM model employs a Harris Hawks optimization (PF-HHO) that is population and fitness-based to identify the most optimal characteristics, which maximize intra-class and minimize inter-class correlation. The simulation results showed this model possesses the potential to enhance the efficiency of healthcare on heart disease and diminish mortality rates. Hashimi et al. [90] used GWO and the genetic algorithm (GA) to build an electronic health system that enables remote monitoring, diagnosis, and data storage by optimizing and analyzing the sensor data for electronic healthcare monitoring. The GWO's spiral search path ensures diversity, while the GA encourages convergence. Support vector machine (SVM) and Naive Bayes classifiers were used to extract and analyze critical information from the heart sensor data. The findings demonstrate that the hybrid algorithm produces more accurate mining models than canonical GWO and GA for data mining.

The IoT wearable devices collect heart disease-related data from publicly available benchmark sites. Vellameeran and Brindha [86] hybridized a PSO with the GWO (PS-GWO) algorithm that obtains features collected from heart disease diagnosis using the IoT wearable medical devices. Moreover, the PS-GWO algorithm optimizes the hyperparameters of the deep belief network (DBN). The DBN analyzes the selected features to categorize and monitor the patients accurately. Mojjada et al. [194] proposed the hybrid whale GWO approach to select cluster heads for IoT healthcare devices. This approach uses the deep classification model, which identifies patient conditions using the data transmitted to the cluster heads. The results reveal that this approach could achieve significant accuracy and specificity compared to the techniques. Irshad et al. [195] present a healthcare monitoring platform that utilizes the IoT and a deep convolution neural network (DCNN) model based on an enhanced GWO (IGWO). The selection of pertinent features for lung nodule diagnosis was accomplished using the Tasmanian Devil Optimization (TDO) algorithm, while the convergence rate of the standard GWO algorithm was modified, leading to an enhanced GWO algorithm. Subsequently, a DCNN model based on IGWO was trained on the optimal features obtained from the IoT platform, and the outcomes were stored in the cloud for medical professionals to evaluate. The accuracy and efficiency of their model were assessed against state-of-the-art lung cancer detection models.

Table 3. GWOs applied in commercial IoT applications

Authors name	Year	The objective of applying GWOs	Application
Bharathi et al. [189]	2020	Selecting optimal cluster heads among IoT devices	Healthcare systems
Hasnony et al. [188]	2020	Optimizing ANFIS model using hybrid metaheuristic algorithms	Parkinson's disease prediction
RM et al. [190]	2020	Identifying and predicting unforeseen cyberattacks, contributing to the ongoing development of IoMT security	Healthcare industry
Ghorpade et al. [99]	2020	Optimal placement of IoT-based sensor nodes in the smart parking systems	Smart parking systems
Ghorpade et al. [191]	2021	Developing a localization technique for the Internet of Things to determine the direction of motion of sensor nodes	Smart city applications
Helmi et al. [192]	2021	Proposing an efficient human activity recognition system using a lightweight feature selection	Human activity recognition in healthcare monitoring
Aliyar et al. [86]	2021	Extracting relevant attributes from IoT-based wearable devices for diagnosing heart diseases	Heart disease diagnosis
Kumar et al. [102]	2022	Using IoT-based ECG signals and a deep learning classifier to generate features for classification	Arrhythmia detection
Munagala et al. [193]	2022	Choosing the optimal attributes to increase the similarity within classes and reduce the difference between classes	Heart disease monitoring system
Hashimi et al. [90]	2022	Lowering expenses, enhancing productivity, precise data evaluation, and improving patient care	E- healthcare monitoring
Mojjada et al. [194]	2023	Selecting the best cluster head and using deep learning techniques to monitor patients more accurately	Smart healthcare
Irshad et al. [195]	2023	Identifying the key attributes for detecting lung growths	Healthcare systems

8. Applying GWOs in Consumer IoT Applications

In this section, four papers from the final set are reviewed. These papers study the use of GWOs in IoT applications for everyday use, such as home appliances, voice assistance, lightning devices, etc. Table 4 summarizes GWOs applied in Consumer IoT Applications. Fig. 13 [196] shows different applications of consumer IoT.

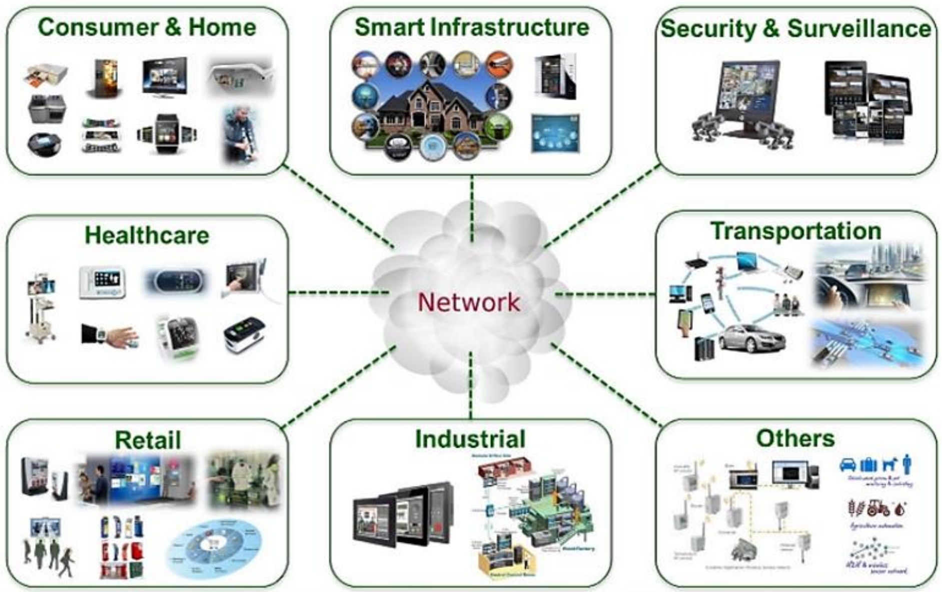


Fig. 13. Different applications of consumer IoT [196]

The power scheduling problem in smart homes (PSPSH) is a challenging scheduling problem that falls under the category of NP-hard problems. It possesses a search space that is both deep and rugged, mainly due to the presence of numerous constraints and objectives. The primary aim of PSPSH is to optimize electricity bills, power consumption during peak periods, as well as the comfort levels of users. Various optimization techniques have been employed to tackle PSPSH, with metaheuristics emerging as the most widely used approach. However, it has been observed that metaheuristics exhibit limited effectiveness when dealing with large-scale search spaces, so hybridization approaches are used to improve their performance. Makhadmeh et al. [25] hybridized a multi-verse optimizer (MVO) and GWO to tackle PSPSH efficiently. The proposed method showed high performance compared with other methods. Forestiero [197] proposed a heuristic approach to constructing a recommender engine within the IoT setting by employing swarm intelligence techniques. Vectors, derived from the Doc2Vec model, are utilized to represent smart objects, and mobile agents associated with these vectors move in a 2D space using a bioinspired flocking model. A rule of similarity, which is founded upon vectors, empowers agents to discern akin entities and assemble them collectively. This intelligent positioning allows for fast and effective selection operations.

Rajesh et al. [198] proposed a hybrid method, self-feedback optimization adaptive neuro-fuzzy inference system (SFOANFIS), for managing the energy system in smart homes using the IoT. The SFOANFIS approach led to the efficient management of power and resources in the distribution system by connecting household appliances with cloud IoT and collecting demand response data. The results were compared with other existing algorithms, provided optimal use of resources, and satisfied the overall supply and energy demand. Yin et al. [199] introduced an optimization algorithm for power allocation in consumer IoT with decode-and-forward (DF) relaying. The algorithm uses a grey wolf optimizer to reduce the outage probability. The paper derives mathematical expressions for the outage probability and compares the algorithm with others. The paper proves the algorithm can achieve a lower outage probability and a faster running time than the different algorithms.

Table 4. GWOs applied in consumer IoT applications

Authors name	Year	The objective of applying GWOs	Application
Makhadmeh et al. [25]	2021	Improving the cost, peak load, and comfort of electricity consumption	Power scheduling problem
Forestiero et al. [197]	2022	Constructing a recommendation system for the Internet of Things using collective intelligence methods	Recommender system
Rajesh et al. [198]	2022	Managing the power and resources of the distribution system by connecting household appliances with cloud IoT	Smart home
Yin et al. [199]	2023	Optimizing power allocation in consumer IoT and minimizing the outage probability	Power allocation

9. Applying GWOs in Industrial IoT Applications

This section reviews six eligible industrial IoT papers that apply GWOs in different industrial applications, such as energy sectors, digital control systems, and intelligent agriculture. Table 5 summarizes GWOs applied in industrial IoT Applications.

Rathinam et al. [93] presented a Taylor-WWO-based GAN (generative adversarial network) approach to detect diseases in the agricultural industry. In this method, IoT nodes sense plant leaves and send the data collected using fractional gravitational GWO to find the optimal path for data transmission. The Taylor-WWO-based GAN approach exhibited enhanced performance in terms of maximum accuracy, sensitivity, and specificity compared to previous methodologies. Safaei et al. [200] focused on creating optimal value through smart awareness in enterprise business service composition for IIoT manufacturing. An integer linear optimization model for enterprise service composition (ESC) was proposed using a hybrid multi-objective GWO (HGO). The model was evaluated based on four factors and compared with other multi-objective optimizations. The proposed model's Pareto front converged better than the others. The results showed that HGO had better convergence and enhanced the optimality rate in IIoT manufacturing. Bhookya et al. [201] proposed a system for monitoring and controlling the liquid level in a single tank in real time using an IoT framework that utilizes a Proportional – Integral – Derivative (PID) controller with parameters set by an enhanced GWO (mGWO) algorithm. The mGWO algorithm optimized the PID controller parameters, and the microcontroller programming and interface for the Android application were created using the Arduino integrated development environment (IDE). The results showed that the mGWO-based control system outperformed Ziegler-Nichols and simple internal model control (SIMC) tuning approaches, and the IoT application-based user interface improved the plant's ability to control and monitor its operations with added flexibility. The system contributes to the ongoing development of industrial automation.

Fog computing is becoming a popular model for IoT applications, working alongside cloud computing. Nethaji et al. [202] utilized a differential evolution-based GWO algorithm for optimal resource management. It incorporated a model for optimal resource allocation that combined a stochastic gradient and deep reinforcement learning-based approach. This method achieves quality of service (QoS) for end-users by effectively reducing energy consumption and managing cache resources. Jagadeesh et al. [203] proposed a group key management system based on deep augmented adversarial wolf learning named MDROWL-GKM. The goal of this system is to effectively monitor data acquired in the IoT, which ensures that network traffic and computational overhead are not maximized when a group member joins or leaves. By incorporating an opposition-based learning GWO algorithm, the modified deep boosting method overcomes the overload problem and improves performance. The efficiency of MDROWL-GKM system was evaluated using various criteria, including computation overhead, storage overhead, space complexity, access response time, policy setting accuracy, re-evaluation time, and communication overhead. The results proved that the MDROWL-GKM model is better than other state-of-the-art algorithms.

Rajagopal et al. [204] introduced a data collection algorithm for WSN in precision agriculture. The algorithm assigned rendezvous points and a mobile sink to acquire data from sensor nodes. The algorithm also applied a hybrid method based on a meta-heuristic algorithm to discover the shortest path for the mobile sink. The paper evaluated the algorithm on network lifetime, energy consumption, and latency. The paper confirms that the algorithm is effective and reliable.

Table 5. GWOs applied in industrial IoT applications

Authors name	Year	The objective of applying GWOs	Application
Rathinam et al. [93]	2021	Finding the optimal path for data transmission	Agricultural industry
Safaei et al. [200]	2022	Creating optimal value through smart awareness in enterprise business service composition for IIoT manufacturing	Enterprise business service
Bhookya et al. [201]	2022	Creating a plant management and control app for the Internet of Things using Blynk and Android	Industrial process control
Nethaji et al. [202]	2022	Improving cache resource management and energy efficiency to provide quality of service for end-users	Resource allocation in fog environment
Jagadeesh et al. [203]	2023	Reducing network traffic and computing overhead	IoT devices
Rajagopal et al. [204]	2023	Discovering the shortest path for the mobile sink	WSN-based IoT

10. Discussion, Statistical Analyses, and Limitations

This systematic review investigated the research using metaheuristic algorithms in IoT, especially the GWO algorithm. This study has provided a comprehensive overview of applying GWOs in different IoT applications, including IoT development, commercial IoT, consumer IoT, and industrial IoT. We used an adapted PRISMA methodology [138] for reviewing, screening, and evaluating the papers published from the introduction of GWO in 2014 to the end of 2023, in which GWO has been employed in various IoT applications to select the most eligible papers the adapted methodology encompassed three main phases: identification, evaluation, and reporting. In the identification phase, a thorough search utilizing specified keywords in the Google Scholar database yielded 693 papers. Fig. 14 illustrates the dispersion of scholarly papers published from 2014 to the end of 2023. Among the 693 papers published during the specified period, a notable majority of research efforts, totaling 254 papers published in 2023, have been done in applying GWOs in different IoT applications.

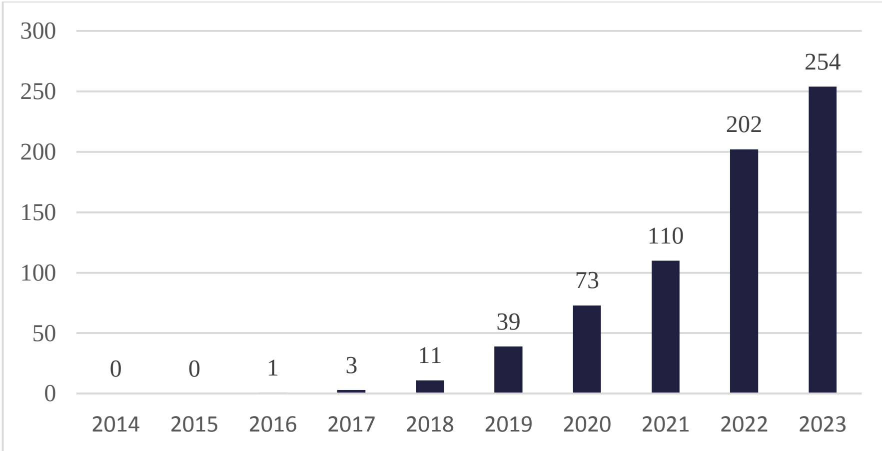


Fig. 14. The distribution of papers using GWOs in different IoT applications

Next, we used three screening steps and implemented rigorous inclusion criteria during the evaluation phase to select the most eligible papers from reputable journals published between 2014 and the end of 2023. Out of the initial pool of 693 documents, the evaluation phase identified 50 papers as the final set. The first screening step removed ten duplicate papers and 262 publications from non-academic sources, leaving 421 reputable papers for further analysis. Fig. 15 illustrates the dispersion of the reputable papers chosen in the first screening across respectable publishers, including Springer, IEEE, Elsevier, MDPI, Hindawi, WILEY, and Taylor & Francis. Among these 421 papers, Springer and Elsevier publishers emerge, contributing to 26% and 20% of the related papers, respectively.

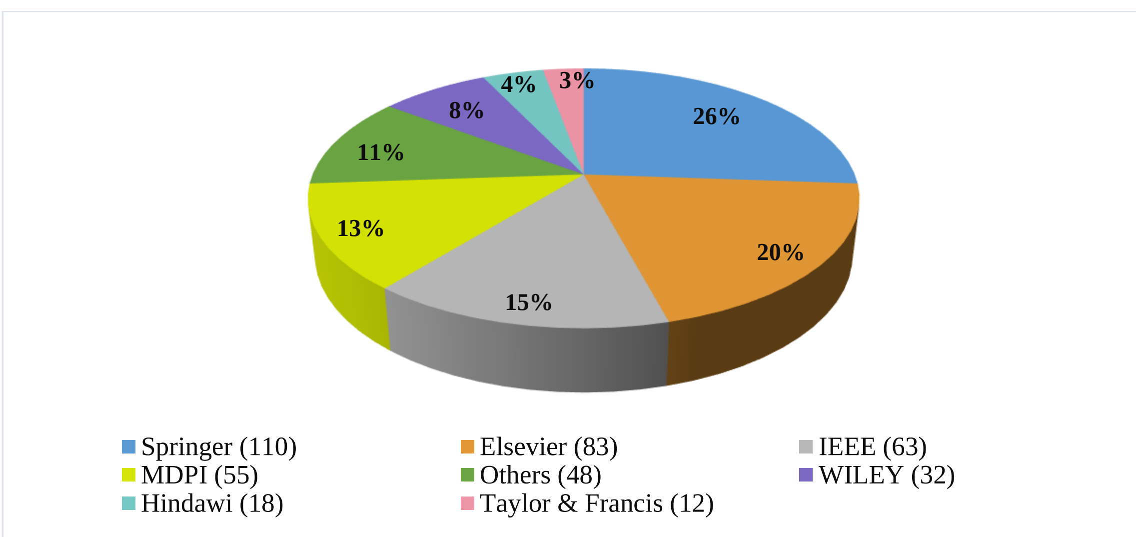


Fig. 15. Percentage of reputable papers published by different publishers

IEEE Access journal, with 30 papers, has published the most among the 421 papers chosen through the first screening. Fig. 16 shows the journals in which more than four papers have been published.

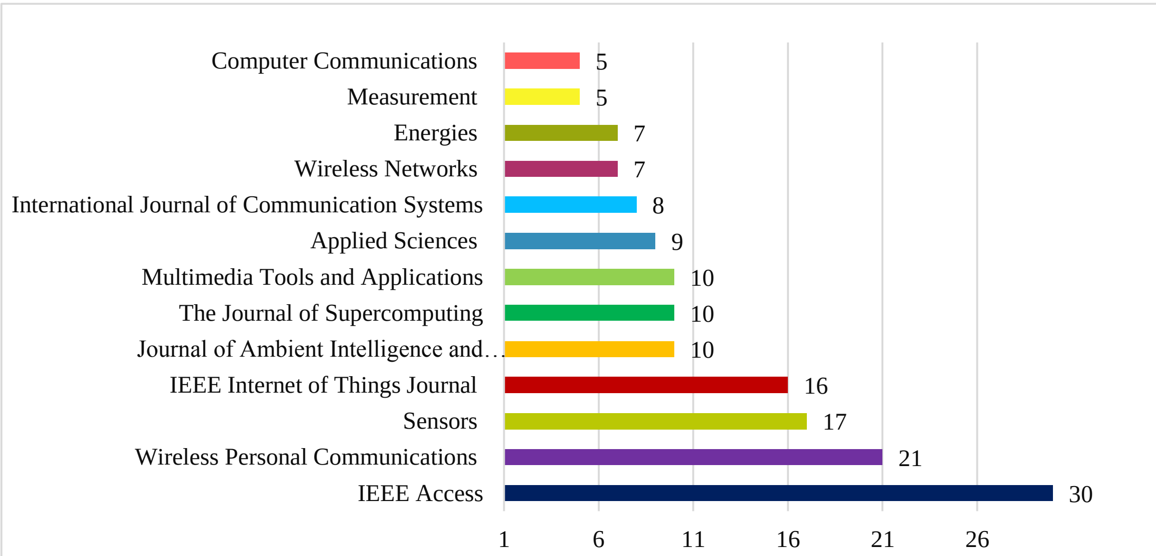


Fig. 16. The number of papers published in journals

The second step in the evaluation phase is to find related papers among reputable papers by screening their titles and abstracts. It removed 320 reputable papers outside the study scope and did not apply GWOs, including the original GWO, existing variants, and new improvements and hybrids for different IoT applications. The second screening left 101 related papers for full-text reviewing. Fig. 17 shows the distribution of selected associated articles in various IoT applications, including IoT development, commercial IoT, consumer IoT, and industrial IoT. Among these 101 related papers, IoT development had the highest percentage, with 57%.

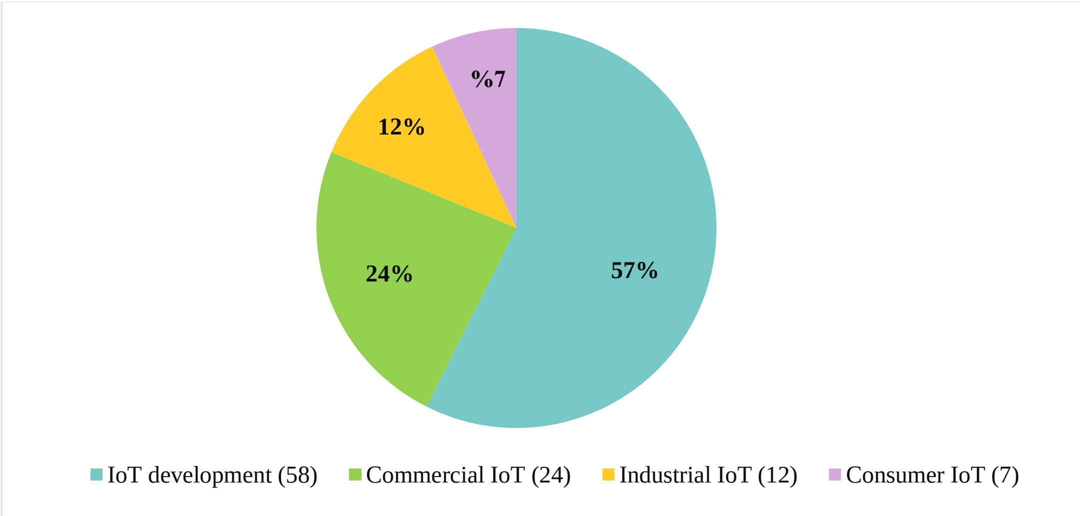


Fig. 17. Percentage of the related papers applied in different IoT applications

The final screening step checked the 101 related papers against the inclusion criteria for eligible papers described in the methodology. We confirmed that 46 papers met the eligibility requirements and added them to the final set. We also searched the reference lists of these 46 eligible papers and found four more papers that met the inclusion criteria, making the total final set of 50 papers. The 50 eligible papers were then classified by publisher and year of publication. Fig. 18 indicates the continuous publication of GWOs' eligible papers in IoT applications in recent years.

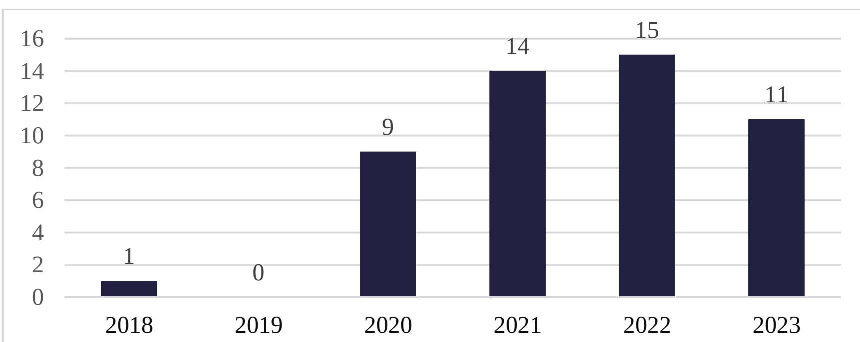


Fig. 18. The number of eligible papers published per year

In the reporting phase, the eligible papers selected as the output of the evaluation phase are reviewed for further review and analysis. Fig. 19 shows the distribution of eligible papers published by reputable publishers. As shown in the figure, among these 50 papers, most papers were published by Elsevier and Springer, with 15 and 13 numbers.

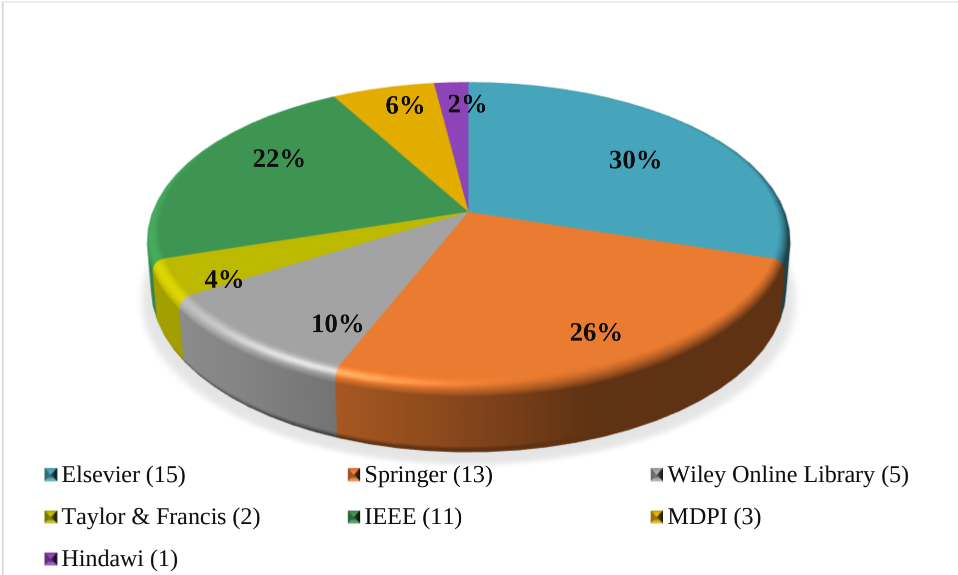


Fig. 19. Percentage of eligible papers published by different publishers

In addition, the number of eligible papers published in different reputable journals is shown in Fig. 20. Among the 50 eligible papers selected by the evaluation phases, the International Journal of Intelligent Systems has published the most significant number of papers, with four. After that, five journals, IEEE Access, IEEE Internet of Things Journal, The Journal of Supercomputing, Journal of Ambient Intelligence and Humanized Computing, and Expert Systems with Applications, occupied the second rank with three publications.

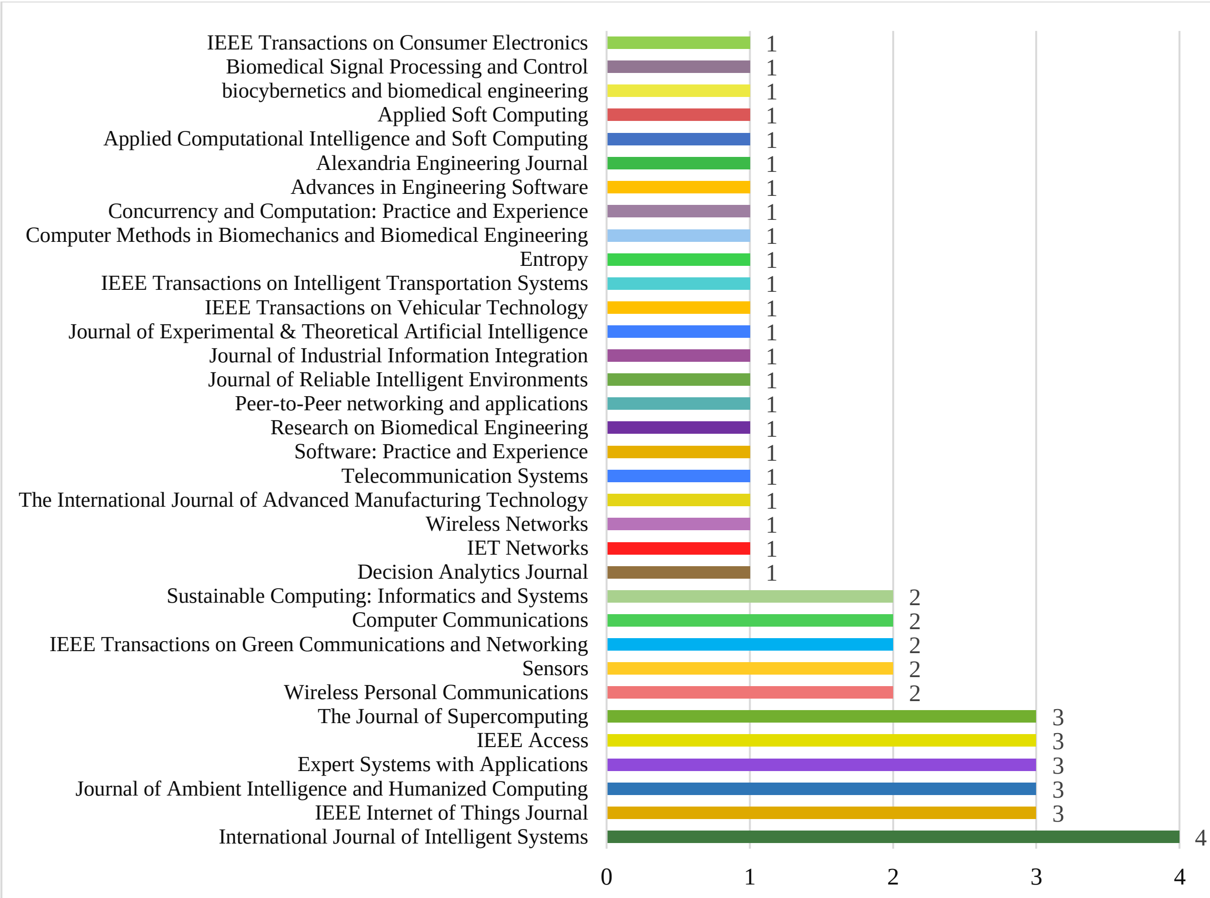


Fig. 20. The number of eligible papers published in reputable journals

Fig. 21 shows the distribution of eligible papers in IoT applications, including IoT development, commercial IoT, customer IoT, and industrial IoT. It can be seen that GWOs have been applied mainly for IoT development, with 56%. Commercial IoT applications account for 24% of the applications among the papers in the final set, and the contribution of customer IoT and industrial IoT applications is 12% and 8%, respectively.

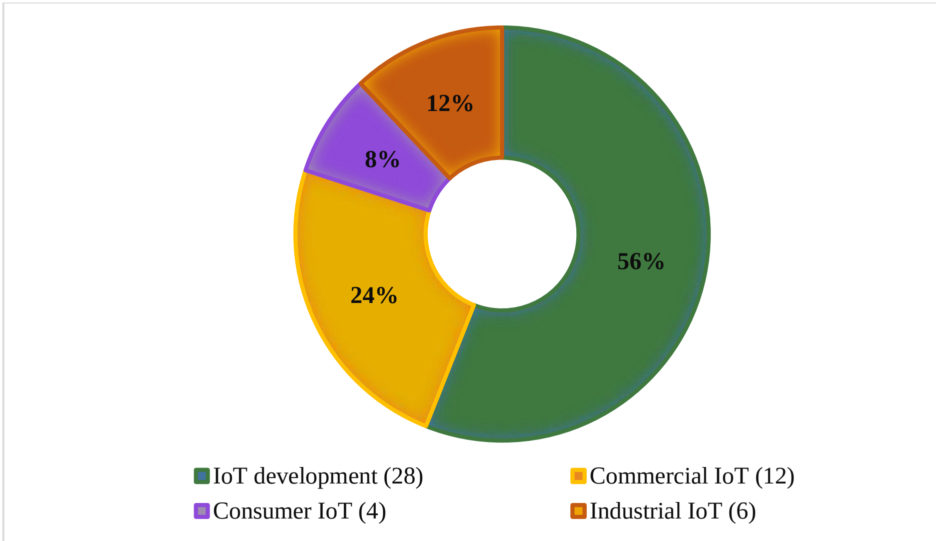


Fig. 21. Percentage of eligible papers published in different IoT applications

Fig. 22 illustrates the distribution of eligible papers based on country. This figure indicates the number of eligible papers that apply GWOs for different IoT applications. India has more papers than any other country, with 30 papers, followed by China (5) and Iran (4). The global map illustrates these results.

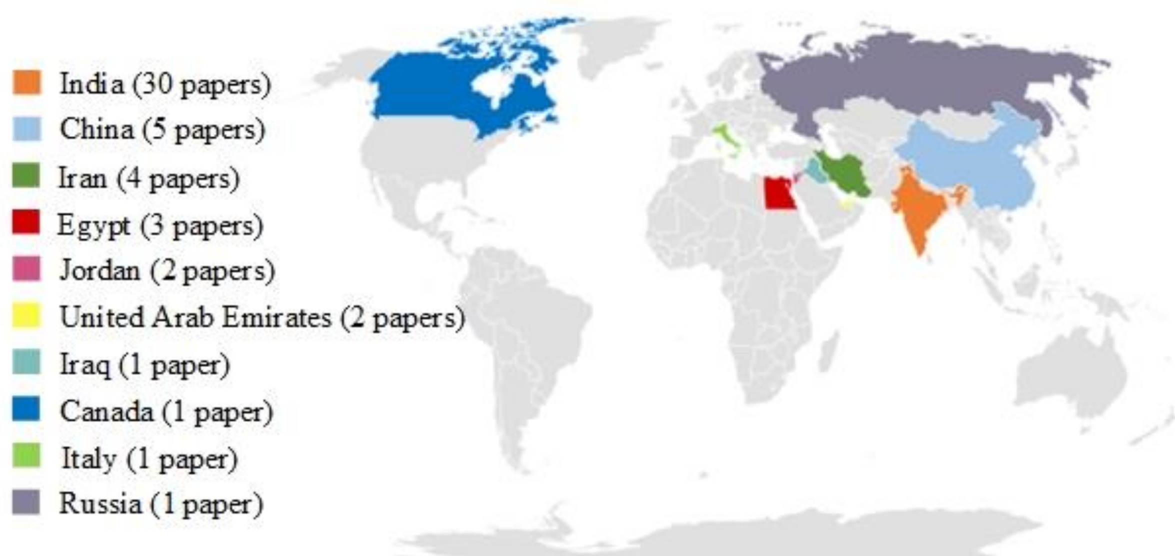


Fig. 22. The number of eligible papers published by different countries

The PRISMA methodology used in this study offers several advantages. First, it allows for a comprehensive and rigorous review of the available evidence by systematically searching multiple databases. This broad search strategy minimizes the risk of publication bias and ensures a comprehensive literature representation. Second, by applying predefined inclusion and exclusion criteria, we aimed to ensure that the selected eligible papers were relevant to the main objective of this study. In addition, the approach used in the systematic review enabled us to perform a meta-analysis and provide a quantitative summary of the available data, increasing the statistical power of our study.

Despite its strengths, this systematic review has the following limitations. First, this study relies solely on literature published in peer-reviewed journals and does not consider unpublished studies, such as preprinted papers, that may include potential sources. Second, language restrictions were applied, and studies published in languages other than English were not included, which could lead to language bias. In addition, the quality and limitations of the included studies varied, which may affect the strength of the overall conclusions. Because what was considered as study inclusion/exclusion criteria, data extraction, and quality evaluations were the result of the subjective decisions of the authors.

11. Conclusion and Future Works

This systematic review explored the eligible papers published by reputable journals in which the author(s) have applied GWOs, including the canonical GWO, its existing developed variants, and improvements and hybridizations of GWO for tackling optimization problems in different IoT applications. The study followed an adapted PRISMA methodology [138] with three main phases: identification, evaluation, and reporting. In the identification phase, an initial search was performed using appropriate keywords and queries to retrieve potentially 693 documents from various databases and sources. In the evaluation phase, a three-step screening process was applied to the initial search results to identify the eligible final set of papers for analysis and review. Strict inclusion criteria were utilized to ensure that only related papers published in reputable journals were considered in which GWOs have been applied in different IoT applications. The evaluation process reduced the initial pool of over 693 papers to 50 eligible papers. In the reporting phase, the eligible papers were carefully subjected and synthesized to identify key themes related to applying GWOs in IoT applications such as IoT development, commercial IoT, consumer IoT, and industrial IoT.

The review results revealed that GWOs hold significant promise in addressing optimization challenges in the IoT domain. Among the 693 papers identified on this topic from 2014 to the end of December 2023, a remarkable majority of the research efforts, 254 papers, were conducted in 2023. However, 2022 has published 15 eligible papers, more than 2023. Springer and Elsevier were prominent publishers that have published the most eligible papers. The results showed that GWO is a simple yet effective algorithm for addressing optimization problems in various IoT domains, including smart cities, healthcare, smart homes, manufacturing, agriculture, etc. Researchers have developed numerous GWO variants for IoT applications. Key techniques for developing GWO to apply in IoT applications include hybridizing with other algorithms, adapting parameter control, and improving search strategy. In addition, the review results showed that applying GWOs in IoT has expanded mainly IoT development with 28 eligible papers compared to other IoT applications. Indian researchers, with 30 eligible papers, have applied GWOs more than other researchers worldwide in IoT.

We present a thorough and current analysis of how different GWO variants and parameters affect IoT problems, such as task scheduling, routing, clustering, security, privacy, energy management, load balancing, and fault tolerance. We also review hybrid and adaptive GWO methods that can adapt to IoT networks' dynamic and uncertain features, such as network topology, task distribution, resource availability, and user demand. We reveal that the GWO algorithm can achieve better accuracy, stability, convergence, and diversity outcomes. These results suggest that GWO is a promising technique for solving optimization problems in IoT networks and can be further enhanced and expanded. This study suggests the following direction for future research.

- Applying GWO to other problems in IoT networks, such as data aggregation, data fusion, data compression, data mining, and data analytics.
- Developing effective GWO variants by optimizing its parameters to adapt to different optimization problems' characteristics in IoT.
- Assessing GWO's scalability and interoperability for various IoT architectures, protocols, and applications.
- Critical analysis of optimization problems in IoT applications to comprehend their features and requirements.
- Enhancing the GWO's search capability to efficiently address the search space challenges in IoT applications' problems.

- Hybridizing GWO and other advanced algorithms to solve challenging optimization issues in IoT applications and developments.
- Developing GWO and its variants for tackling multi-objective optimization challenges in IoT applications to trade-off between optimization metrics, such as energy consumption, latency, reliability, and cost.
- Analyzing and reviewing other advanced algorithms that can solve optimization issues in IoT applications and developments.

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