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REVIEW ARTICLE

A Comprehensive Review on Applications of Grey Wolf Optimizer in Energy Systems

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Abstract

In the field of optimization problems, the optimization of energy systems problems is of significant importance, mainly due to their dramatic role in achieving sustainability. The complexity of energy systems optimization problems, intense constraints, and various decision variables have led many researchers to utilize meta-heuristics optimization algorithms to optimize such issues and improve energy systems. Meta-heuristic algorithms that can find global solutions and prevent trapping in local optima can efficiently solve energy systems problems. Grey Wolf Optimizer (GWO), one of the well-known meta-heuristic optimizers inspired by the grouped hunting process of wolves, has been employed in different studies to deal with energy systems optimization problems. GWO has received much attention in the literature due to its proper exploratory and exploitative features, rapid and mature convergence rate, and simplicity in design and coding. This paper reviews various GWO applications for tackling optimization problems related to production, conversion, transmission and distribution, storage, and energy consumption. It is highly believed that this paper can be a practical and innovative reference for researchers, professionals, and engineers.

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Abbreviations

ABC	Artificial Bee Colony
ACOPF	AC Optimal Power Flow
ALO	Ant Lion Optimizer
AMO	Animal Migration Optimization
APF	Active Power Filter
BA	Bat Algorithm
BESS	Battery ESS
BFA	Bacterial Foraging Algorithm
BGWO	Binary Grey Wolf Optimizer
bHC	B-Hill Climbing
BMO	Bird Mating Optimizer
BWO	Black Widow Optimization
CBR	Case-Based Reasoning
CEED	Combined Economic and Emission Dispatch
CHP	Combined Heat and Power
CHPED	Combined Heat and Power Economic Dispatch
CPP	Critical Peak Pricing
CPPV	Curtailed Power of PV
CS	Cuckoo Search Algorithm
CSA	Crow Search Algorithm
DE	Differential Evolution
DEA	Dolphin Echolocation Algorithm
DELD	Dynamic Economic Load Dispatch

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DG	Distributed Generation
DNs	Distribution Networks
DO	Dragonfly Optimizer
DR	Demand Response
DSCOPF	Dynamic Security Constrained Optimal Power Flow
DSM	Demand Side Management
EC	Emission Cost
ED	Economic Dispatch
EMA	Exchange Market Algorithm
ESS	Energy Storage System
EV	Electric Vehicle
FA	Firefly Algorithm
FACTS	Flexible AC Transmission System
FC	Fuel cost
FCGWO	Fast Convergent GWO
FCs	Fuel Cells
FL	Fuzzy Logic
FOA	Fruit Fly Optimization Algorithm
FPA	Flower Pollination Algorithm
FSC	Fixed Series Compensation
GA	Genetic Algorithm
GBO	Gradient-Based Optimizer
GC	Generation Cost
GOA	Grasshopper Optimization Algorithm
GS	Generation Scheduling
GSA	Gravitational Search Algorithm
GTO	Gorilla Troops Optimizer
GAWDO	Genetic Algorithm Wind-Driven Optimization
GWO	Grey Wolf Optimizer
GWOCS	HGWO and CS
GWO-ES	GWO-Extended Searching
GWPS	Grey Wolf Pattern Search
HBA	Honey Badger Algorithm
HEMS	Home Energy Management Systems
HES	Home Energy Systems
HEV	Hybrid Electric Vehicle
HGWO	Hybrid Grey Wolf Optimizer
HHO	Harris Hawks Optimizer
HRES	Hybrid Renewable Energy System
HS	Harmony Search
HVDC	High Voltage Direct Current
ICA	Imperialist Competitive Algorithm
IEA	International Energy Agency
KH	Krill Herd
LOA	Lion Optimization Algorithm
LR	Lagrangian Relaxation
LRS	Local Random Search
LSF	Loss Sensitivity Factor
MGGWO	Multi-Group GWO
MGs	Microgrids
MGWO	Modified GWO

MO	Multi-Objective
MOGWO	Multi-Objective GWO
MPP	Maximum Power Point
MPPT	Maximum Power Point Tracking
MT	Micro-Turbine
Mtoe	Millions of tonnes of oil equivalent
NNA	Neural Network Algorithm
NSGWO	Non-Dominated Sorting GWO
OBL	Opposition Based Learning
OPF	Optimal Power Flow
PAR	Peak to Average Ratio
PBUC	Profit-Based UC
PHEV	Plug-In Hybrid Electric Vehicle
PID	Proportional Integral Derivative
PL	Power Loss
PMSG	Permanent Magnet Synchronous Generator
PPMGWO	Projection Pursuit and GWO
PSO	Particle Swarm Optimization
PSOGWO	Particle Swarm Optimization Grey Wolf Optimizer
PV	Photovoltaic
RES	Renewable Energy Sources
RRA	Runner-Root Algorithm
RTP	Real-Time Pricing
SA	Simulated Annealing
SCOPF	Security Constrained Optimal Power Flow
SFO	Sailfish Optimizer
SS	Social Spider Algorithm
SSA	Squirrel Search Algorithm
STNEP	Security constrained TNEP
SP	System Pollution
TAC	Total Annual Cost of the System
TC	Total Cost
TCO	Termite Colony Optimization
TCSC	Thyristor Controlled Series Compensator
TFC	Total Final Consumption
TFCs	Total Fuel Costs
TLBO	Teaching–Learning Based Optimization
TNEP	Transmission Network Expansion Planning
TOU	Time-Of-Use
TSCOPF	Transient Stability Constraint-based OPF
TSSCOPF	Transient Stability and Security Constrained OPF
UC	Unit Commitment
VD	Voltage Deviation
VP	Voltage Profile
VSC	Voltage Constrained Scheduling
WCA	Water Cycle Algorithm
WDN	Water Distribution Network
WECS	Wind Energy Conversion Systems
WOA	Whale Optimization Algorithm
WT	Wind Turbines
WWO	Water Wave Optimization

1 Introduction

In recent years in particular, with the comprehensive development of countries and the growing need of societies for energy demand, the world has witnessed a dramatic rise in energy consumption [1]. According to the provided data by IEA, the world TFC of energy between 1990 and 2019 has increased from 2.61E + 08 to 4.18E + 08 TJ (see Fig. 1) [2]. To meet such an essential need for energy stably and reliably, humanity had to conduct studies, research, and analysis for many years, achieving the design and development of "energy systems" to ensure the required energy [3–8].

“Energy systems” refers to the generation, conversion, transmission and distribution, and energy consumption processes [9–12]. More precisely, an energy system is designed to supply energy services to end users and consumers [13–17]. Taking a structural viewpoint, the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report has defined an energy system as "all components related to the production, conversion, delivery, and use of energy" [18].

In terms of energy economics, energy systems are the technical and economic systems that meet consumer energy demands in heat, fuels, and electricity forms [19–23]. Figure 2 displays the main components of an energy system. According to Fig. 2, the energy system involves energy sources, energy conversion, energy transmission & distribution, and energy consumption. All natural resources (Fossil fuels, nuclear fuel, and renewable energies) are considered primary energy resources. In contrast, refineries and types of power plants convert natural energy resources to consumable energies as energy conversion. Finally, the facilities’ fuel and electrical energy output can be delivered to end users using energy transfer equipment.

Oil is a primary energy resource for transportation, heating, and cooling. Other energy sources produce electrical energy, which is used for lighting, heating and cooling, electric vehicles, etc.

Global warming resulting from extensive fossil fuel consumption has become a challenging global phenomenon. Thus, electrification in the transport, residential, industrial, commercial, and other areas is indispensable for weaning the world off fossil fuels and realizing a low-carbon society. For this reason, energy is moving more toward electrical power due to its advantages, such as minimal environmental impact, relatively valuable energy production levels, minimal greenhouse emissions, high conversion efficiency, etc. According to the provided data by the IEA, world electricity final consumption between 1990 and 2019 has increased from 34,928,037 to 82,251,570 TJ [2].

According to the Fig. 3, total electricity consumption between 1990 and 2019 has increased from 14% to 20%. This represents a 6% increase in electrical energy consumption [2]. Therefore, technical and economic problems based on electrical energy systems are significant. Furthermore, sustainable energy focuses primarily on generating and operating electricity by means other than fossil fuel consumption, as fossil fuel emissions are very high.

A particular focus on energy efficiency and reduction of environmental pollution on the one hand, and the minimization of various costs associated with the production, transmission distribution, and consumption of energy, on the other hand, has led to exceptional attention to optimization of problems related to energy systems using optimization methods, especially in recent years. Therefore, solving the energy systems problems using optimization algorithms has been studied from the point of view of analyzing, designing, and optimizing both existing and future systems, as also their operation and control for production,

Fig. 1 World TFC from 1990 to 2019 by source (TJ) [2]

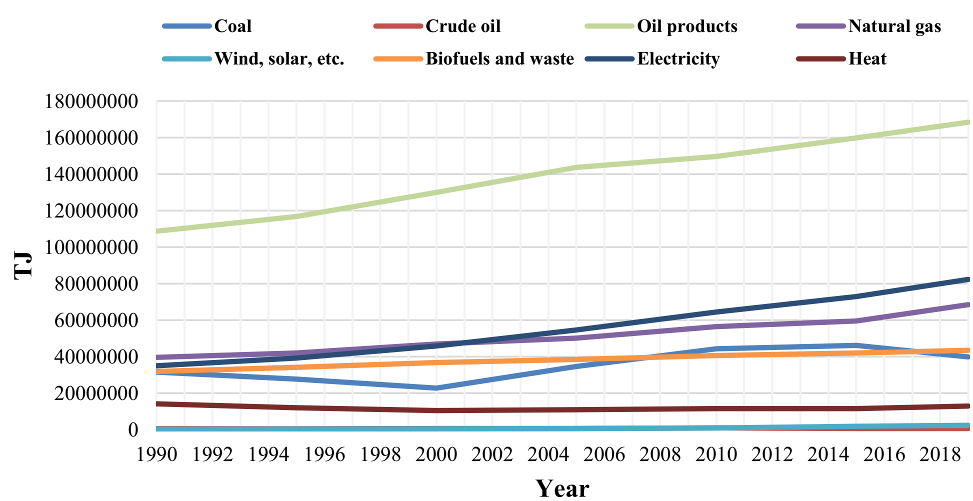


Fig. 2 Main components of an energy system

conversion, transmission and distribution, storage and consumption of electricity, heat and cooling and fuels in many articles [24–29].

In this regard, diverse classic methods have been employed for optimizing energy systems problems [30–34]. In recent years, some traditional methods, such as the Newton–Raphson method and Lagrange relaxation, have been used to solve different problems. However, these methods are inappropriate in large-scale systems with complex objective functions and practical constraints due to time-consuming processes, running limitations, and their non-differentiation nature [35].

Moreover, traditional methodologies can only be used to optimize some complex scientific problems requiring precise calculations and time. In this respect, artificial methods inspired by nature can be utilized to solve such complex problems [36–39]. Thus, utilizing meta-heuristic optimization algorithms has been recommended for finding optimal solutions.

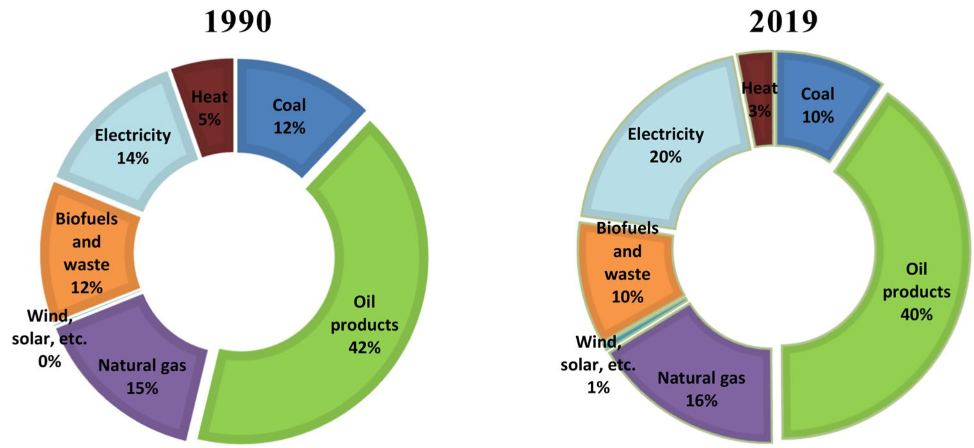


Fig. 3 1990 and 2019 source shares of TFC [2]

The solved problems using meta-heuristics in the published papers include a wide range of optimization problems in various energy systems sections, from energy sources to energy consumers. The range of coverage includes energy source optimization, the operation optimization of electrical energy systems, the generation, conversion, transmission, and distribution of energy, and optimization problems related to end consumers.

In the published papers in the literature, there are many and various optimization problems related to energy systems, such as sizing of PV power plant components (PV modules and inverters) [40–46], biomass power plant [47–49], PV/biomass hybrid energy systems [50–54], geothermal power plants [48, 55, 56], thermal power plant [57–59], nuclear power plant [60], optimization of refinery production planning [61–66], hydropower [67–72], forecasting of daily total horizontal solar radiation [73–75], sizing of the HRES [52, 76–82], optimal DG allocation problem [83–85], water source optimization [86–88], WECS [89–93], ED [94–99], CHPED [100–105], UC [106–111], OPF [112–119], SCOPF [120], GS and generation rescheduling [121–128], TNEP [129–133], optimal voltage control in DNs [134–136], ESS [137–141], tuning PID controller in MGs [142–144], MGs planning [145–148], HEMS [149–154] and EV [155–160].

On the one hand, the cost and waste reduction of generated energy and the effort to increase efficiency in achieving sustainable energy, and on the other, the complexity of energy systems optimization problems along with intense constraints and various decision variables have led many researchers, engineers, and professionals to use meta-heuristic optimization algorithms to improve energy systems.

From selecting the optimal size and placement of energy-related equipment and resources and energy management to trying to increase the efficiency of energy systems by employing optimization strategies for energy mitigation and developing smart grids of green energy-based resources, homes, cities, and vehicles as well, all provide redoubled efforts for shaping a secure and sustainable energy future, followed by a sustainable world [161–168]. By relying on their powerful capabilities, meta-heuristic optimization algorithms can pave the way for achieving such great success.

Meta-heuristics have considerable advantages, such as finding global solutions and preventing trapping in local optima to other methods. However, neither algorithm can solve all optimization problems alone and entirely. Novel algorithms that are highly capable of solving specific optimization problems are therefore being adopted.

Grey Wolf Optimizer (GWO) is one of the novel optimizers inspired by optimal searching of the grey wolves in nature for hunting prey [169]. Proper exploratory and exploitative features, rapid and mature convergence rate, and simplicity in design and coding make the GWO an efficient tool for dealing with large-scale and complex problems. Due to these advantages, the GWO has received more attention than other algorithms in the literature. In this regard, Fig. 4 depicts the citation number of papers based on meta-heuristics.

As seen in Fig. 4, the number of citations for articles containing GWO is considerably higher than that of other articles. The reported results show that the utilization of GWO among meta-heuristics in research is significantly increasing.

Figures 5 and 6 show the distribution of each year of published papers related to the GWO from 2014 to the present. The collected database was based on validated reports on Web of Science and Google Scholars using keywords such as "GWO," "grey wolf optimizer, " "grey wolf optimization," and "grey wolf optimization" to extract the desired results.

Based on the outcomes shown in Figs. 5 and 6, from 2014 to the present, the number of articles published has grown considerably each year. However, the number of publications written in 2020 and 2019 is significantly greater than in other years. Results indicate that the usage of GWO in different studies is increasing considerably year after year.

This review paper presents and discusses in detail the applications of the GWO for energy systems. It also explains

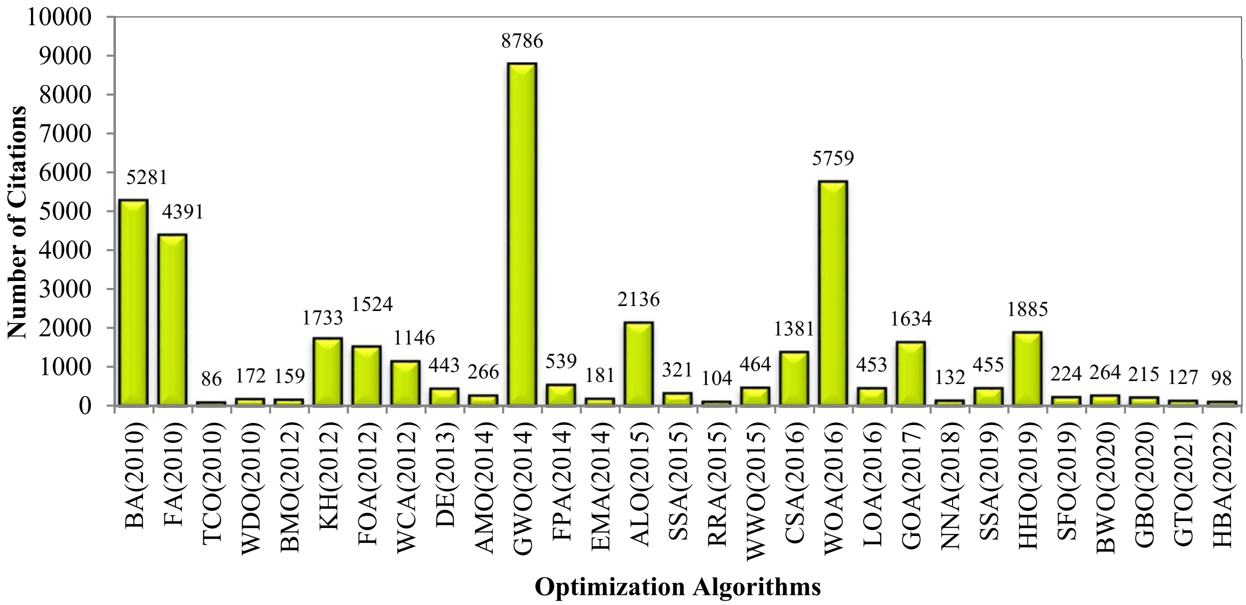


Fig. 4 Citations number of meta-heuristics based papers

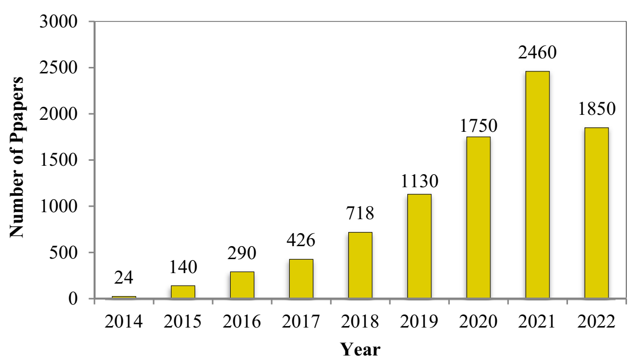


Fig. 5 Distribution per year of the published papers based on the GWO

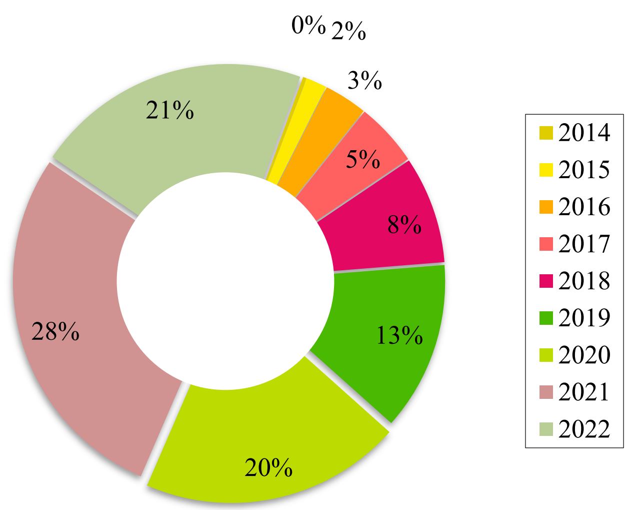


Fig. 6 Distribution per annum of presented papers based on the GWO

its variants and applications in evaluating studies conducted in the literature.

The remaining paper is arranged as follows. Section 2 explains GWO's concept, search operators, and step-by-step pseudo code. A wide range of GWO applications for energy systems has been provided in Sect. 3. Discussions and research trends about diverse applications and variants of GWO for energy systems, along with statistical results of GWO contributions in the literature, are provided in Sect. 4. Finally, Sect. 5 concludes all information provided in this review paper along with some future directions on the GWO, the findings, and the purpose of this review paper.

2 Grey Wolf Optimizer

The GWO algorithm was proposed in 2014, mimicking the social hierarchy and hunting mechanism of grey wolves in nature [169]. A pack of wolves has one of the fascinating social intelligence, in which wolves play different roles in coordinating activities in the pack. Wolves can be categorized into four groups (see Fig. 7) based on their position in the hierarchy power pyramid.

According to Fig. 7, the wolves are categorized into four types: alpha, beta, delta, and omega. In the pack, the

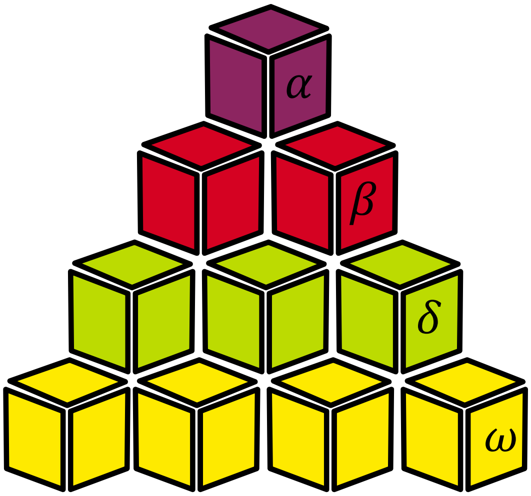


Fig. 7 Leadership hierarchy in a pack of grey wolves

alpha wolf is the dominant one. The alpha wolf has authority over the beta wolf. While it subjugates the omega wolves, the delta wolf obeys the dictates of the alpha and beta wolves. In addition, omega wolves are at the bottom of their social hierarchy. In other words, alphas are males and females who serve as the leaders. The alpha mostly makes decisions concerning hunting, sleeping arrangements, wake-up times, etc. The second rung of the grey wolf hierarchy is beta. The betas are subordinate wolves who assist the alpha with decision-making and other group duties. The beta wolf can be male or female, and he or she is most likely the best contender to be the alpha if one of the alpha wolves dies or grows old. The beta wolf should respect not only the alpha but also command the lower-level wolves. It serves as the alpha's counselor and pack discipliner. The beta reinforces the alpha's directives across the pack and provides feedback to him. Omega is the lowest-ranking grey wolf. The omega takes on the role of a scapegoat. Omega wolves are constantly forced to subordinate to all other dominant wolves. They are the final wolves allowed to eat. They are called delta if a wolf is not alpha, beta, or omega. Delta wolves are subject to alphas and betas, but they control the omega. Scouts, sentinels, elders, hunters, and caretakers fall within this category. Scouts are in charge of monitoring the territory's limits and alerting the pack if something dangerous occurs. Sentinels protect and ensure the safety of the pack. In the GWO algorithm, the three best solutions are considered to be alpha, beta, and delta during the optimization process. Indeed, each wolf represents a potential solution for the whole population, where the position of alpha represents

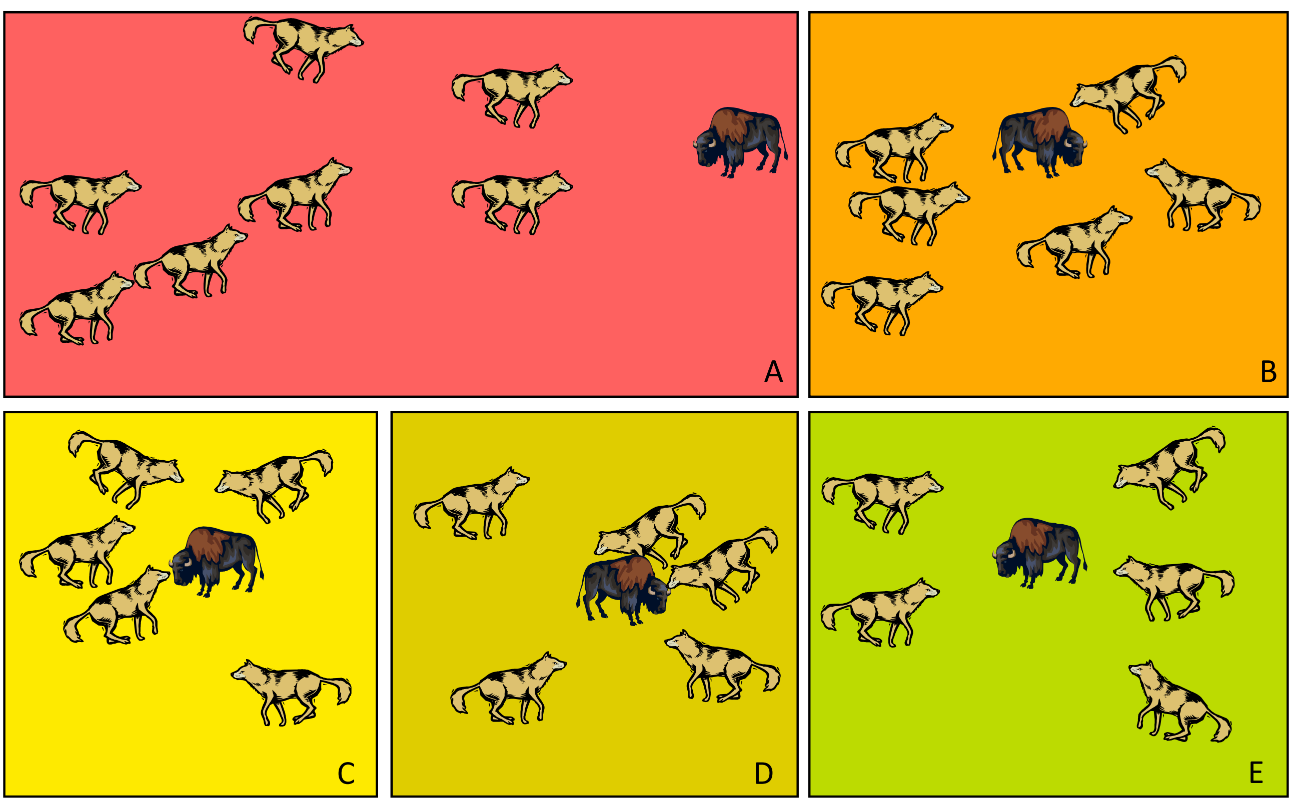


Fig. 8 Different steps of hunting in a pack of grey wolves

the best solution, and the position of beta represents a good solution. Finally, the delta position represents a sub-optimal solution. The rest of the wolves are omega wolves and update their positions based on the position of the three best solutions.

Figure 8 shows a conceptual model of gray wolf hunting behavior. As discussed above, the second mechanism implemented in the GWO algorithm is the hunt. Hunting is led by alpha, beta, and delta wolves, who mainly search, encircle, attack, and hunt prey. The original paper on GWO mentioned that grey wolves start the hunt by first chasing and harassing prey. Then, they constantly encircle the prey until the prey gets exhausted to start the final attack.

In this regard, mathematical models define grey wolves' searching, encircling, and attacking processes. Grey wolves search for possible solutions using a math model that copies how they hunt. When a good candidate for food is found in the encircling process, grey wolves work together to circle it. This helps them increase their chances of catching the prey. Finally, grey wolves pick the best target to attack after encircling their prey. This helps make the whole group stronger. To mathematical model the movement of grey wolves and their encircling mechanism, Mirjalili et al. proposed the following equations:

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

$$\vec{X}(t+1) = \vec{X_p}(t) - \vec{A}.\vec{D} \tag{2}$$

where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X_p}$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a grey wolf. The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2.\vec{r_2} \tag{4}$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 throughout iterations, and, r_1 and r_2 are random vectors in [0,1]. As mentioned earlier, the equations allow us to create a hypersphere between a wolf and prey with the radius of the Euclidean distance between a wolf and a prey. The position of the prey in hypersphere is defined as the average position of alpha, beta, and delta as follows:

$$\vec{D_\alpha} = \left|\vec{C}_1.\vec{X_\alpha} - \vec{X}\right|,\ \vec{D_\beta} = \left|\vec{C}_2.\vec{X_\beta} - \vec{X}\right|,\ \vec{D_\delta} = \left|\vec{C_3}.\vec{X_\delta} - \vec{X}\right|, \tag{5}$$

$$\vec{X_1} = \vec{X_\alpha} - \vec{a}_1.\left(\vec{D_\alpha}\right), \vec{X_2} = \vec{X_\beta} - \vec{a_2}.\left(\vec{D_\beta}\right), \vec{X_3} = \vec{X_\delta} - \vec{a_3}.\left(\vec{D_\delta}\right), \tag{6}$$

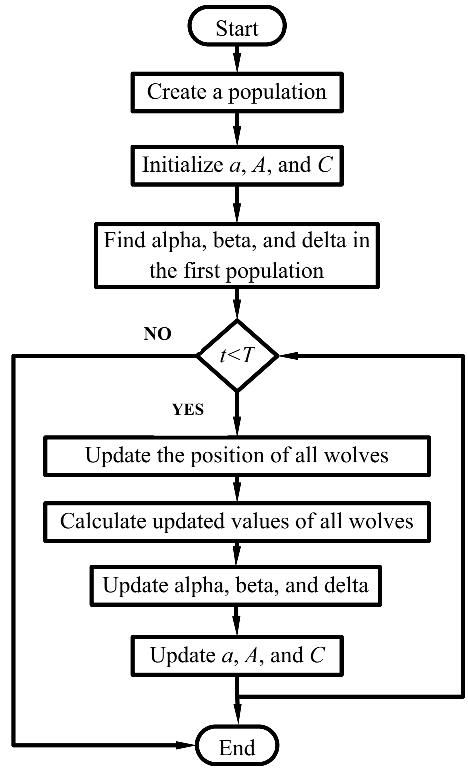


Fig. 9 The flowchart of GWO (t shows the current iteration, and T indicates the maximum number of iterations)

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \tag{7}$$

where X_α, X_β and X_δ are the position of α, β, and δ wolves position. Also, D_α, D_β and D_δ are average positions of alpha, beta, and delta wolves. Also, X_1, X_2 and X_3 are positions of α, β, and δ wolves.

The flowchart of GWO is shown in Fig. 9.

3 Applications of GWO for Energy Systems Optimization

In various studies, GWO has been implemented to optimize optimization problems related to energy systems. The reviewed papers in the current research include a wide range of problems and applications. Table 1 presents the investigated problems by GWO and their definitions in the reviewed papers.

3.1 Unit Commitment

The fundamental purpose of UC is to plan the production unit to meet load at minimum costs and constraints [170]. This turns UC into a large-scale, non-convex, nonlinear

Table 1 Investigated problems by GWO and their definitions in the reviewed papers

Problems	Definitions
ED	Planning production units while minimizing GC and meeting constraints
DELD	Economic Dispatch during 24 h
CEED	Planning generation units to minimize TFCs and emissions at the same time
CHPED	Planning generation units to produce heat and power to minimize the TFCs
UC	Determination of the generation units' operating schedule by minimal cost under various constraints at each interval
OPF	Minimization of TFCs for power generation by determining a set of control variables under constraints
Optimal DG allocation problem	Optimal sizing of DG units in the distribution network for minimization of PL
GS	Determining the commitment and generation of all schedulable power resources over a scheduling horizon to minimize production costs and meet demands and constraints
TNEP	Finding an optimal expansion plan with the aim of meeting demands Economically and efficiently
Optimal Voltage Control in Distribution Systems	Voltage maintenance and control at end consumers' buses
EV optimization	Reducing the CO2 and environmental emissions and saving energy in EV using different algorithms
Optimal sizing of ESS in DN	Optimal sizing of ESS to minimize TC in DNs
Sizing of PV plant components (PV modules and inverters)	Optimal sizing of parameters related to the PV power plants, such as PV cells and modules and inverter types, to improve energy cost
Forecasting of Daily Total Horizontal Solar Radiation	Estimation of solar radiation for PV and solar-thermal systems using solar-radiation data
WECS	Energy conversion of wind movement into mechanical power and subsequently electricity energy
Sizing of the HRES	Optimal sizing of the HRES to minimize the TC and meet the load
Tuning PID controller in MGs	The finding process of optimal values in the controller
MGs planning	Optimal sizing of components related to the MGs to improve cost
HEMS	A hardware and software system to monitor energy consumption and production users to minimize electricity costs and manually control and/or automate household energy use
Water sources optimization	Attaining optimal sizing for WDNs, minimizing water pollution, and optimal allocation
Heat exchanger optimization	Optimization of heat exchanger using tuning controllers

mixed integer programming [171]. Many mathematical and heuristic techniques have been used, mainly dynamical and LR techniques. The LR methodology uses a multiplier Lagrange to deal with system restrictions and modify the penalty-based objective function [172, 173].

Different single and hybrid meta-heuristics algorithms have been applied to tackle UC, such as GAs, [174, 175], ABC [176], PSO [177], WOA [178], Lagrangian Relaxation PSO [179], improved pre-prepared power demand table and Muller [180], NNA [181], Hybrid HS Random Search Approach [182] and HGWO and PSO method [183]. The binary nature of UC requires the utilization of real-valued GWO binary transformation. Thus, some studies have solved UC using BGWO.

A method based on dynamic penalty was presented to solve the problem of power resource scheduling with uncertain wind energy, thermal UC, and DRs using BGWO [184]. The UC consists of two sub-problems. In the first step, the ON/OFF status of the generator is determined, and the power and generation allocation to the committed units is followed. The thermal units' commitment or decommitment can be coded binary with 0 and 1 indicating the respective OFF and ON States. Thus, the wolves' position in the binary version of GWO is either 0 or 1 at any given time. Furthermore, Reddy et al. [185] presented an improved BGWO for solving the UC.

Srikanth et al. [186] suggested a quantum-inspired BGWO to solve UC. The method combines quantum computing concepts with BGWO to enhance the wolf pack hunting process. The inherent characteristics of the q-bit and q-gate concepts in quantum computing assist in achieving a better balance between exploration and exploitation. The update process of the wolf's position at different levels of the hierarchy is replaced by a dynamic and rotary angle by the individual probabilistic representation of q-bit. Consequently, solutions use GWO and quantum computing search capability, which uses quantum bits, gates, the principle of superposition, etc., to resolve the schedule of UCs.

Reddy et al. [187] presented different BGWO models for PBUC resolving in deregulated markets because of the binary nature of UC. Concerning the transformation function used to map a valued absolute position for the wolf, the models proposed by BGWO differ. Binary mapping of the commitment status was done by sigmoid and tangent hyperbolic transfer. Two binary transformation methods, crossover, and conventional sigmoidal transmission, were also presented in the sigmoidal transfer function, Reddy et al. [188] investigated the conversion from real-world to binary transformation in the solution of UC in two general ways: sigmoid transformation and hyperbolic transformation.

Panwar et al. [189] Two models of BGWO were represented to address UC. The first method involved the upstream binarization and crossover operations of wolf updates to the best global solution (s). The second approach estimated the wolves' continuous update on global best solutions, and sigmoid transformation was followed.

Lit and Liu [190] offered an enhanced dual GWO with binary and dogmatic elements. The BGWO optimizes the up and down state of units, and the exchange speed is modified by adding two dynamic factors to produce random numbers. During the decision-making process and after the solution, the GWO is used for load planning. Table 2 shows the main features of the papers on GWO applications in UC.

3.2 Economic Dispatch

ED aims to schedule generation units to meet the fixed load demand at a minimum TFCs and satisfy constraints [35, 191, 192]. Although the ED is only concerned with a one-hour time interval that must be met, DELD deals with the delivery of thermal generators within 24 h with numerous restrictions [193]. Nowadays, CHP production is utilized to increase the efficiency of the combined cycle plants, reduce environmental emissions, and save energy costs. The CHPED refers to electrical and heat energy produced from one source simultaneously to minimize TFCs [35, 194]. In general, problems based on ED require efficient methods to be resolved with strong operators. As a result, many studies have been carried out on ED-based problems.

In a study by Al-Betar et al. [195], a hybrid of GWO and bHC was proposed to improve the convergence properties of ED and balance the exploration and exploitation phases of GWO (Jayabarathi et al. [196] presented the GWO application to resolve the ED, while crossover and mutation were hybridized for better optimizer performance. Kamboj et al. [197] verified the better convergence of GWO to PSO, GA, etc., by testing the GWO on small-, medium- and large-scale systems in ED problems. Pradhan et al. [198] used OBL concept-based GWO to accelerate the convergence rate. The proposed algorithm first uses grey wolves' hunting behavior and social hierarchy to search for optimal solutions. Secondly, the oppositional concept is integrated with the GWO to accelerate its convergence rate. All these studies showed the proper performance of the GWO.

With the consideration of transmission losses and the valve-point effect, ED was solved using GWO, [199–201] and [202]. The results of the GWO demonstrated a good

Table 2 The main features of the papers on GWO applications in UC

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
[184]	UC	Operational cost	Operational cost reduction	Modified	BGWO
[186]	UC	TC (TFCs, start-up and shut-down costs)	Obtaining optimal value	Modified	Quantum computing concepts with BGWO
[185]	UC	TC (TFCs, start-up and shut-down costs)	High solution quality in terms of cost reduction and convergence	Modified	BGWO
[187]	PBUC	Profit maximize TC	High solution quality	Modified	BGWO
[188]	UC	TFCs of thermal generators Start-up cost	Fast convergence and better quality	Modified	BGWO
[189]	UC	TFCs Start-up cost	High solution quality	Modified	BGWO
[190]	UC	TFCs	Improvement of convergence rate and solution accuracy	Modified	GWO with binary and dogmatic parts

balance between exploration and exploitation. Maamri et al. [203] considered three scenarios for analyzing the impact of integrating this renewable energy (WT/PV) and gas turbine on the ED problems in Algeria using GWO. Results showed that incorporating PV and WT into the system illustrated an optimal cost. Singh and Dhillon [204] presented an ameliorated GWO that balances exploration and exploitation to solve ED. The method coordinates gray wolves' behavior, random exploration, LRS, and opposition heuristics learning behavior. To prevent premature convergence, LRS was embedded in the local search mechanism. The results validated the improvement of the GWO performance.

Paramguru and Barik [205] presented MGWO for the ED problem by including exponential operators in the GWO. There are two steps in the MGWO. In the first step, the individuals are dispersed across the search space, i.e., they cannot concentrate on the local minima. In the second step, individuals reach the minimum global level from the information collected. By correctly adjusting the two parameters, a and A, the proposed MGWO reaches the optimum point very quickly. In GWO,"a" is reduced from 2 to 0 linearly. However, the exponential function in the iteration process is used to explore better and exploit the "a" decaying process.

Xu et al. [206] proposed a modified GWO known as the NGWO for resolution of the ED. The GWO in the NGWO (GWOI) is supplemented with a local search strategy to explore the regional district of the global optimum location in depth and guarantee a better candidate. In addition, a local search method based on non-inferior solution neighborhood independence is integrated into the GWOI, GWO-II, to obtain a better solution in the non-inferior solutions neighborhood and to provide a higher probability of jumping from the optimal local solution.

Halbhavi et al. [207] introduced GWO-ES as the solution for the CEED. The hunting process in the GWO is performed by α, β, and δ. In contrast, the GWO-ES adopts another wolf called γ. It confirmed the robustness of the proposed algorithm in seven HRES test bus systems, combining the wind turbine and the thermal power plant in research performed by Jangir et al. [208], the MOGWO, known as NSGWO, was introduced to solve CEED. The NSGWO initially collects all the optimal Pareto solutions until the last iteration limit is evolved. From the Pareto optimal solutions collection, the best solutions are chosen using a crowding distance mechanism based on solutions and the Leadership hierarchy of gray wolves to guide the hunt for wolves in the dominated areas of MO search spaces.

Also, GWO was improved by six mutation operators for the CEED solution [209]. The study used mutation operators to better search for the best solution and improve exploration and exploitation in the search space. Li et al. [210] solved the short-term complementary scheduling problem of hydro-thermal-renewable power systems based on CEED using HGWO. To develop the MO version of GWO, the concepts of archive and leader selection were introduced into the optimizer mechanism. The results demonstrated that the proposed algorithm can achieve the best Pareto front for economic/emission bi-objectives.

Sattar et al. [211] addressed the DELD problem by considering four unique ramp rate handling approaches using the GWO. (1) Handling by starting DELD from hour one. (2) Handling by starting DELD from the last hour. (3) Handling by starting DELD for hour one and Power regulation for the rest of the hours by total load average production cost. (4) Handling by starting DELD from random hours. Comparisons indicated that Strategy 4 has achieved the best cost results, while Strategy 3 has achieved a minimum execution time. Furthermore, the results showed that the most precise and convergent rates in Strategy 2 can be seen.

Authors in [212] and [213] presented GWO to solve the CHPED in static and dynamic environments. Also, Jayakumar et al. [214] presented GWO for solving CHPED. The practical nature of the proposed method was validated on static ED, environmental-economic dispatching, and DELD. Table 3 displays the papers on GWO applications in ED.

3.3 Optimal Power Flow

OPF is a significant tool for effectively planning and increasing the operation of electricity systems. The OPF problem involves the determination of the best or safest operating point (control variables) for certain objective functions (transmission losses, cost of generation, and so on) while meeting system constraints. Several meta-heuristics optimizers to find the OPF solution have been proposed, including ABC [215, 216], PSO [217, 218], CS and krill herd technique [219], Sine Cosine Algorithm [220], HS [221–223], and so forth.

An attempt to solve OPF has been performed based on a developed GWO, using a random mutation to increase population diversity. At the same time, exploitation is improved by updating population location spiraling towards the best solution [224]. The method used an adaptive operator to maintain the local and global search parity. Rambabu et al. [225] presented the OPF of HRES using the GWO in the presence of TCSC. Singh et al. [226] employed GWO to solve OPF, mainly focusing on minimizing TFCs (with and without valve point effect) and minimizing transmission loss by incorporating FACTS devices TCSC and thyristor-controlled phase shifter. Dilip et al. [227] used the MOGWO solution to minimize TFCs at emission value and active loss in the OPF problem. Compared with NSGA-II (non-dominated sorting genetic algorithm), the MOGWO is best set for the Pareto-optimal front. El-Fergany and Hasanien [228] employed GWO and DE in optimizing single objective

Table 3 Main features of the papers on GWO applications in the ED

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
[195]	ELD	TFCs	Improvements in TFCs	Hybrid	bHC optimizer is utilized as a new operator in the improvement phase of GWO
[207]	CEED	TFCs EC	The efficiency of the GWO-ES in terms of TFCs and EC reduction	Modified	GWO-ES adopts an additional wolf termed γ
[208]	CEED	TFCs EC	The superiority of NSGWO is in terms of runtime and convergence rate	MO	MO version of the GWO
[196]	ED	TFCs	Convergence and cost improvement	Hybrid	GWO with mutation and crossover operators
[212]	CHPED	TFCs EC	Good computational efficiency	Standard	–
[213]	CHPED	TFCs	Obtaining a high-quality solution	Standard	–
[214]	CHPED	TFCs	GWO performs better in terms of solution quality and consistency	Standard	–
[197]	ELD	TFCs	Obtaining an optimal solution with high convergence	Standard	–
[201]	ELD	TFCs	Solution quality in terms of cost, convergence	Standard	–
[199]	ED	TFCs	The effectiveness the superiority of GWO	Standard	–
[202]	ELD	TFCs	Less runtime and premature convergence, and stable convergence	Standard	–
[200]	ED	TFCs	The efficiency of GWO	Standard	–
[209]	CEED	GC emission	Achieving optimal values	Hybrid	GWO with six mutation operators
[206]	ELD	GC	High convergence rate and solution quality	Modified	Using a local search strategy and a non-inferior solution neighborhood independent local search technique for the original GWO
[205]	ELD	TFCs	The effectiveness of GWO	Modified	Adjustment of the two parameters *a* and A
[198]	ELD	GC	Improving computational time and TFCs	Modified	Hunting behavior and social hierarchy of grey wolves are used to search for optimal solutions, and the oppositional concept is used to accelerate the convergence rate of GWO
[211]	DELD	TFCs	Improvement in cost and solution time	Standard	–
[204]	ELD	GC	Effectiveness of the method to search for the optimum generation	Hybrid	Combining GWO with a random exploratory heuristic method based on the LRS mechanism and OBL
[210]	CEED	TFCs emission	Improvement in cost and emission	MO	MO version of the GWO
[203]	ED	GC	Obtaining optimal values	Standard	–

functions and DE in optimizing MO functions using the Pareto front-line method to fix the OPF problem.

Siavash et al. [229] solved the OPF using the GWO in a system integrated into wind farms. Two additional cost components corresponding to the under- and over-estimated states are used to model the variable nature of the wind farm output. Hassan and Zellagui [230] considered the GWO for two terminal HVDC power systems. The OPF of AC-DC systems is extended to incorporate HVDC connections, taking into account the characteristics of power transmission control by GWO. Haddi et al. [231] performed OPF to assess the GWO impact on two IEEE30 and IEEE57 systems of variable wind power generation. The results demonstrated that GWO was superior to techniques like PSO, ABC, and so forth [232]. Ben Hmida et al. [233] used a hybrid approach for OPF of systems based on wind and solar generators by

GWO to strengthen the exploration ability of the ICA for exploration. The best ICA solution is calculated using this approach as an initial GWO condition. If it is less than the ICA solution, GWO is saved as the best value. The hybrid suggested is much more efficient and offers better solutions.

Mohamed et al. [234] presented the GWO and MOGWO for solving OPF and minimizing cost and emissions. In addition, a fuzzy decision is made to make the global Pareto-optimal solutions the most suitable. A modification has also been introduced to improve the balance between exploration and exploitation and GWO's convergence rate. As shown in the following formulation, two control parameters (μ and $\varnothing$) were proposed.

$$\alpha = \mu e^{-\varnothing \times t} \text{ (Numbering)}, \tag{8}$$

where control parameters govern the behavior of GWO's convergence characteristics over t-iterations. This accelerates the rate of convergence while maintaining the exploratory characteristics.

Salem et al. [235] solved SCOPF by GWO by considering transmission security and various contingency cases. Alam et al. [236] addressed TSCOPF by GWO. The calculated results showed that GWO is smart enough to find the best solutions for every aspect while complying with all operating restrictions. Teeparthi and Kumar [237] utilized the GWO to resolve DSCOPF while considering static and dynamic constraints. The results of the GWO demonstrated the ability to achieve a near-optimum global point for increasing diversity in search spaces.

Soni et al. [238] used Intelligent GWO to tackle the TSSCOPF problem, suggesting two GWO structural changes in

Table 4 Main features of the papers on GWO applications in OPF

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
[224]	Non-Smooth OPF	TFCs	Fast and stable convergence	Modified	Diversify population Updating the position of populations Parity exploration and exploitation
[236]	Transient stability constraint -OPF	TFCs	Better convergence	Standard	–
[233]	Simple- and MO OPF	TFCs PL Emission VD	Better solutions	Hybrid	ICA and GWO (Hybrid imperialist competitive -GWO)
[225]	OPF of Integrated Renewable Energy System	TFCs PL VD emission	Improvement of objective functions	Standard	–
[227]	OPF	TFCs PL emission	Fast convergence	MO	Pareto-based strategy
[234]	OPF	TFCs emission	Fast convergence	Single/MO	Pareto-based strategy
[228]	OPF	TFCs PL emission	Effectiveness of proposed algorithms	Standard	–
[235]	SCOPF	GC	Improvement of GC	Standard	–
[237]	DSCOPF	GC	Obtaining optimal solution	Standard	–
[238]	TSSCOPF	TFCs	Efficiency of proposed algorithms	Modified	Using sinusoidal truncated function and OBL mechanism
[226]	OPF with the incorporation of FACTS devices	TFCs Transmission loss	Fast convergence	Standard	–
[229]	OPF of Wind Integrated Power Systems	GC PL	Improvement of convergence rate and obtaining optimal solution	Standard	–
[230]	OPF of Two-Terminal HVDC Transmission System	GC	Less CPU time and minimized cost	Standard	–
[231]	OPF with the incorporation of Wind Power	TFCs VP	Operating cost reduction and VP improvement	Standard	–

the research. (1) the sinusoidal truncated function was proposed instead of the linear bridging mechanism for acceleration of the exploration and exploitation phase. (2) An OBL mechanism was incorporated to increase the exploration of GWO. The effectiveness of the method was determined by the observation of simulations and rotor angle trajectories under various contingencies. Papers features on GWO applications in OPF are shown in Table 4.

3.4 Distributed Generation Resources

DG units (e.g., the WT, PV) are defined as small-scale centralized generation units installed at DNs near energy consumers for improvement of the network characteristics [239, 240]. Due to the significance of the DGs type, size, and location in DNs in terms of technical, economic, and environmental objectives, the best types of DGs with the best size should be installed at the best places in DNs [241, 242]. The problem of finding the optimal type, location, and size of DGs in DNs is referred to as the "DG allocation problem" [239]. In some researches in literature, GWO variants have been used for optimal sitting and sizing of DGs resources in DNs.

Ahmadi et al. [243] and Mohsen et al. [244] presented DGs (PV and WT) optimal sitting and sizing using GWO to improve the VP and minimize active PL in DNs. Tyagi et al. [245] and Sultana et al. [246] demonstrated the application of GWO for sizing solar-based DGs in an unbalanced and balanced DN. Also, Sanjay et al. [247] presented HGWO and operators from evolutionary algorithms for sizing DG. The simulations showed that WT results are better than PV results because the reaction power component supplied by WT is available. In contrast, the system performance improvement was increased using two units.

Algabalawy et al. [248] presented a hybrid power generation system based on some DG units that consist of WT, PV, MT, and so forth using the GWO and dragonfly optimizer. The results of DO indicated better results than GWO for TAC, while GWO showed better results than DO for SP. Boktor et al. [249] suggested a hybrid PSO, GWO, and LSF for sizing DGs in DNs. The procedure is two stages. In the first stage, the LSF chooses the potential busses to reduce the search area and the calculating time. The hybrid will select the optimum DG locations and sizes in the second phase.

Lakum and Mahajan [250] discussed the DG impact on optimal sizing of APF in DNs using the GWO. The results of GWO showed superiority compared with the PSO and HS. Routray et al. [251] demonstrated the application of GWO for sizing solar-based DGs by considering the simultaneous effects of radiation from the obstruction astronomical model and implementing temperature and shadowing parameters in test systems. The solar panels were modeled on solar astronomy and obstructed the solar model as a global radiation source. The summary of the review papers on GWO applications in the DG is provided in Table 5.

Table 5 Main features of the papers on GWO applications in the DG

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
[243]	DG allocation	VPs	Improvements in VP	Standard	–
[248]	DG allocation	TAC SP	Improvements in results	Standard	–
[249]	DG allocation	PL VP	Small time with more stability and faster convergence	Hybrid	PSO with GWO
[250]	Impact of DG on sizing APF	Current of APF	Obtaining optimal solution	Standard	–
[244]	DG allocation	PL	The GWO is superior to GAs, CSA, etc	Standard	–
[247]	DG allocation	PL	Voltage and loss improvement	Hybrid	GWO with mutation and crossover operators
[246]	DG allocation	PL VP	Better performance of GWO to GSA and BA	Standard	–
[245]	DG allocation	PL VD	Voltage and loss improvement	Standard	–
[251]	DG allocation	PL	Voltage and loss improvement	Standard	–

3.5 Energy Generation, Transmission and Distribution Systems

3.5.1 Generation Systems

One of the most critical optimization problems related to electricity generation systems is the GS problem [252]. If the electricity generating units are correctly planned, the economic advantages of the power grid will undoubtedly increase. Therefore, to achieve a proper solution to the GS problem and reduce overall TFCs, an appropriate scheduling strategy should be used [253]. Mathematical and meta-heuristics methods such as dynamic programming [254], LR [255], simulated annealing [256], GAs [257], PSO [258], and ABC [259] are all prevalent optimization strategies used for two decades to solve GS issues.

Prajapati and Mahajan [260] used an energy management strategy to alleviate congestion on the transmission line by rescheduling generators to minimize the expense of rescheduling using GWO. The rescheduling of generators was carried out with and without RES on the updated IEEE 30 bus system. It was seen that the rescheduling costs, energy losses, and the use of fossil fuels with RES generators were minimized relative to the rescheduling of generators without RES generators.

Saravanan et al. [261] employed the GWO for the GS problem with the large-scale incorporation of RES, including PV, WT, thermal, and hydro plants. Using the penalty function process, the restrictions of the GS problem were treated. The GWO's analysis of findings with PSO, GSA, etc. revealed that the GWO can produce very competitive results relative to those well-known meta-heuristics.

3.5.2 Transmission Systems

The most necessary feature of the power system is the TNEP. The TNEP explains the cost-effective and optimal extension of new lines to meet the planning horizon load rise and is needed to provide enough capacity safely and economically to customer load demand [262, 263]. The purpose of the TNEP is to determine the optimal configuration of the circuit that should be applied to the device to meet load requirements and operational constraints [264].

Different mathematical models such as static model, hybrid model, and DC model are generated for the solution of the TNEP problem [265, 266]. The TNEP is a complex problem with various types of random and non-random uncertainties such as load, cost of generation, generator availability, line availability, transmission facility substitution, and market law [267, 268]. Due to their ability to solve unknown situations, these uncertainties can be treated independently using different expert systems such as artificial neural networks and FL [269–272].

In a study performed by Khandelwal et al. [273], an MGWO was used to tackle the TNEP for Graver's six-bus and Brazilian 46-bus systems. In the GWO, the solution can trap in the position of ω wolves. Therefore, the position of the ω should also be updated and participate in finding the best solution. In the MGWO, wolves and some wolves are also proposed to be involved in the hunt. Thus, with the help of δ and ω wolves existing, an updated family of δ wolves is created. Equation 9 is used for the creation of the new wolf family.

$$\overrightarrow{X3^{(new)}} = \frac{\overrightarrow{X3} + \overrightarrow{X4}}{2} \tag{9}$$

where $X4$ is ω wolves' position and $X3$ (new) is the new family position of δ wolves'. In the MGWO, the ω wolves' position is also updated similar to α, β, and δ wolves using Eq. (11):

$$\overrightarrow{\lambda_\omega} = \left|\overrightarrow{\varphi_4}.\overrightarrow{X_\omega} - \vec{X}\right| \tag{10}$$

$$\overrightarrow{X4} = \left|\overrightarrow{X_\omega} - \overrightarrow{\zeta_4}.\left(\overrightarrow{\lambda_\omega}\right)\right| \tag{11}$$

where X_ω is ω wolves' position, ζ_4 and φ_4 are coefficient vectors. The best-updated solution equation is displayed in Eq. (12):

$$\vec{X}(t+1) = \frac{\overrightarrow{X1} + \overrightarrow{X2} + \overrightarrow{X3(new)}}{3} \tag{12}$$

where X_1 and X_2 are positions of α, β wolves, and $X3(new)$ is δ wolf's new position.

The results showed that the algorithm proposed is both accurate and competent. Khandelwal et al. [274] solved ACOPF-based TNEP using the GWO. In the study, the ACOPF-based TNEP formulation is chosen, and the increased number of circuits to be reached is given during the planning timeframe so that the minor expansion costs are provided without any overloads. The GWO was checked via TNEP for six buses, Graver's solution, and 24 bus IEEE systems. The recorded findings demonstrated that GWO is a cost-effective and more detailed technique for solving this TNEP.

Khandelwal et al. [275] discussed the TNEP problem using L-index as a VSC problem and FCGWO. In the GWO, the position is updated using Eq. (7). A new position update equation was suggested, Eq. (13), to balance the solution convergence by changing the position update equation in the FCGWO.

$$\frac{1}{\vec{X}(t+1)} = \frac{1}{\overrightarrow{X1}} + \frac{1}{\overrightarrow{X2}} + \frac{1}{\overrightarrow{X3}} \tag{13}$$

where the reciprocal position is equivalent to the reciprocal sum of the α, β, and δ wolves' positions. In this equation,

$X1$, $X2$ and $X3$ are the position of α, β, and δ wolves. The GWO and FCGWO were utilized for the IEEE 24 bus system. The findings showed that FCGWO is an algorithm that converges more reliably and rapidly. In addition, the studies indicated that FCGWO is an efficient variant of GWO for the TNEP and VSC-TNEP solutions.

In research performed by Khandelwal et al. [276], the GWO was used to solve (N-1) STNEP problem based on contingency. The results accessed by GWO for Graver 6-bus and 46-bus Brazilian networks demonstrated the GWO's ability to determine the optimal system cost for STNEP.

Moradi et al. [277] suggested the GWO application for improvement of uncertainties management in the multi-year TNEP from the point of view of private investors with the consideration of FSC and uncertainty. The findings of this analysis on the IEEE 24-bus and 118-bus test systems suggested that in addition to lowering investment costs, adding FSC would provide private developers with an excellent vision to achieve viable transmission projects for investment.

3.5.3 Distribution Systems

Electricity distribution systems are carriers of electricity delivered by transmission system manufacturers to end users. The regulation of voltage in a distribution grid is essential for consumers and energy supplies. End customers require their buses to have their voltage under statutory limits. Voltage control can be done using a variety of techniques.

Mahmoud et al. [278] presented a MOGWO combined with a Lévy mutation operator (GWO-Lévy) to effectively solve the voltage regulation problem for DNs to consider the number of tap motions of transformers and the successful power reduction of PV devices. In the study, Lévy flight was used to achieve more effective outcomes and boost the efficiency of the GWO. Indeed, global and local search capabilities were improved by the Lévy mutation operator. The simulation's findings showed the feasibility of the suggested approach for solving the PV problem while simultaneously maximizing the tap activity rate and decreasing the PV's strength. The papers based on GWO applications in energy generation, transmission, and distribution systems are provided in Table 6.

3.6 Electric Vehicle

Despite advancements in transport technologies and power, the transport industry remains the fastest-growing energy user and source of greenhouse gasses, resulting in a marked decrease in emissions of such pollutants. Therefore, immediate attention must be paid to reducing the emissions of the present vehicle. Hybridizing a traditional vehicle could be one of the promising and necessary solutions for minimizing environmental effects, considering the available options.

Table 6 Main features of the papers on GWO applications in generation, transmission, and distribution systems

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
Generation systems					
[260]	Generator rescheduling	GC	The annual saving in GC and energy-saving	Standard	–
[261]	Generator scheduling	TC	Efficiency of the method	Standard	–
Transmission systems					
[273]	TNEP	Expansion cost	Efficiency of MGWO	Modified	Updating the position of α, β, and δ to find the best position
[274]	TNEP	Expansion cost	Efficiency of GWO	Standard	–
[275]	TNEP	TC of expansion	Better performance of the FCGWO than the GWO	Modified	Updating the position of α, β, and δ to find the best position
[276]	STNEP	Expansion cost	Obtaining optimum solution	Standard	–
[277]	TNEP	Investment cost for FSC	Achieving the best solution	Standard	–
Distribution systems					
[278]	Optimal voltage control	Voltage drop Voltage rise Tap movement rate of transformer CPPV	Good performance of GWO-Lévy	MO/Hybrid	Integrated with a Lévy mutation operator (GWO-Lévy)

The hybrid electric combination is a stronger alternative than available sources, integrating an internal combustion engine with an electric power-driven motor to deliver the advantages of traditional & electric technology. The fastest path for safe and effective transportation is electrification. The conversion of a traditional vehicle into a HEV or PHEV will, therefore, be one of the most effective, feasible, and improved transport system options that can follow requirements and keep emissions under control.

In research performed by Gujarathi et al. [279], to optimize primary FC and pollutants such as carbon monoxide, the GWO application was presented for multidimensional engine optimization of transformed parallel-operated diesel plug-in hybrid electric vehicles. It was obvious that with slight deviation, the GWO can offer the global minimum value, but less calculation time and simplicity make this algorithm a possible candidate for real-time implementation.

EVs and the ESS provide a new way of coping with the extreme energy and emissions problem. In addition to releasing the line overload and power quality loss caused by uncoordinated charging, improving the charge and discharge mechanism can also balance the load curve and modulate frequency, increasing the power system's reliability.

Liu et al. [280] suggested the real-time organized schedule model for large EVs and ESS to eliminate real-time scheduling difficulties considering the particular restrictions of each EV and the secure DNs operation. Two phases were used in the optimization process using the GWO. In the first step, the GWO was adapted to measure the EV cluster and ESS charging/discharging strategy. In the second step, the energy buffer factor consensus allocation algorithm was proposed to create a comprehensive plan for each EV in the cluster, considering precise constraints. The simulation findings proved that the proposed model has excellent success on huge EVs and ESS real-time scheduling optimization and practice capability compared to other algorithms. The critical characteristics of GWO applications in EV are presented in Table 7.

3.7 Energy Storage System

ESSs are electric energy storage devices that are used to compensate for the energy deficit in an abnormal electricity grid operating condition [162, 281, 282]. The ESSs are connected via an inverter to the network bus, converting the DC power supply from the storage system, battery, or FCs into an AC power supply [283]. Sizing ESSs is one of the major problems during the operation of DNs that improve the system's reliability. Many investigators recommend using meta-heuristics to size ESSs to enhance the reliability of the DN [284–290].

To determine the optimum ESS size and location on 30 and 69 bus power systems, the GWO was used [291]. Results achieved through the GWO indicated that the overall cost of the 30-bus system was saved by 14.12% for the basic case and 39.03% for the 69-bus system, respectively.

Sukumar et al. [292] presented optimum BESS sizing for the economic operation of microgrids with a mix-mode energy management system using the GWO, ABC, GA, and GSA. It was observed that GWO produces the best solution for others. The significant findings of GWO applications for papers based on ESS can be shown in Table 8.

Table 7 Summary of the papers on GWO applications in the EV

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)
[279]	Multidimensional engine optimization of converted PHEV	FC emissions	Obtaining the optimal solution	Standard
[280]	Schedule optimization of EVs and ESS	The average total load	Good performance of GWO	Standard

Table 8 Main features of GWO applications for the ESS

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)
[291]	Sizing of ESS in DN	TAC	Efficiency of the method to PSO and ABC	Standard
[292]	Sizing of BESS	TAC	GWO efficiency in obtaining a solution	Standard

3.8 Renewable Energy Resources

3.8.1 Solar Energy

PV systems are being used more frequently as RES. In this regard, the design of the PV model parameters, to determine the optimum values of those parameters resulting in the best performance and efficiency, should be defined and examined using mathematical models [293]. Furthermore, PV cells are usually designed as circuits. Thus, acquiring suitable PV cell circuit model parameters is critical to evaluating control, calculating efficiency, and MPPT of PV systems [294, 295].

Many meta-heuristic methods have recently been proposed to estimate solar PV cell model parameters, such as GAs [296], PSO [293], CS [297], ABC [298, 299], TLBO [300], WOA [301], WCA [302, 303] and so forth. These meta-heuristic algorithms could produce satisfactory results for the PV model parameter extraction compared to the analytical and numerical approaches.

AlShabi et al. [304] designed the MGGWO, which searches several wolves' clans/packages to find the prey and estimate the parameters of a single-diode PV cell model. The results showed that MGGWO performs better than the PSO, time-varying accelerated coefficient PSO, and so on.

Zidane et al. [305] proposed the optimum size of PV modules, including crystalline silicon and thin-film cadmium telluride and inverters based on the various candidates in GWO, WOA, and so forth for large-scale PVs. Flexibility, robustness, and simplicity of application are GWO advantages for the resolution of PV design problems.

Long et al. [40] developed GWOCS hybrid to estimate the parameters of the PV cell model under various operating conditions. The GWOCS proposes a strategy based on OBL to improve the diversity of the GWO for decision-makers individuals (i.e., α, β, and μ). The method has the advantage of being able to balance exploration and exploitation.

Stonier et al. [306] proposed the GWO and DE for improvement of inverter power quality by relying on reduction or control of the symmetrical multilevel inverter (MLI) harmonics effects. The result showed that GWO reduces harmonic distortions and improves power quality by setting the modulation index and switching angle.

Atici et al. [307] presented the single-ended primary-inductor converter along with GWO-based MPPT for PV systems. The GWO consists of two inputs and two outputs. The PV module's current and voltage is as input. The first output is the GWO-calculated alpha power value, and the second is the pulse-width modulation signal to the system's MPP. The results demonstrated that the method is faster and that the oscillation of the MPP is lower than conventional methods.

In a study investigated by Chauhan et al. [308], GWO-based MPPT was used in a uniform and varying radiation environment to obtain maximum power from the PV system. Results indicated that the designed controller performed better under variable environmental conditions.

Colak et al. [309] integrated multi-layer perceptron algorithm into GWO to predict the total horizontal solar radiation on a day-to-day basis. Multi-layer perceptron models are free from extrapolation and oscillatory interpolation drawbacks. The results indicated that the GWO model is suited to predict overall horizontal solar radiation every day efficiently.

Debnath et al. [310] used parallel GWO and OBL named Improved GWO to trace the MPPT of PV systems. In parallel GWO, the wolves are initially divided into two or several sub-groups. Afterward, each sub-group is implemented independently based on the main algorithm structure and each iteration time. It was found from the results that the improved GWO-based MPPT performance is enhanced than the Perturb and Observe (P&O) and PSO in terms of speed of tracking, steady-state oscillation under partial shading conditions, and accuracy.

Swief and Abdel-Salam [311] employed the GWO to size PV by considering the uncertainty of solar radiation and wind speed and using a probabilistic optimal load flow to formulate appropriate penetration levels to improve the VP. The results proved an improvement in GWO for GAs and HS.

3.8.2 Wind Energy

Wind power is one of the most significant alternative energy sources and one of the world's fastest-developing clean energy innovations. One of the most essential elements of wind energy systems is the WECS [262]. The WECS is powered by wind and creates mechanical energy that transfers electricity to an electricity generator for electricity production. A PMSG, double-fed induction generator, induction generator, synchronous generator, and so forth can be the generator of the WT. A pulse width modulation converter regulates the generator's rotational speed to achieve full power from the WECS. Onshore, offshore, seashore, or hilly areas may be spread like wind farms. The WECS is assessed using GWO in several works.

Kahla et al. [312] introduced MOGWO as a fuzzy sliding mode controller to optimize the power collected by wind turbines. In the research, the sliding mode control based on FL theory was generated by gathering the sliding surface data to reduce the chattering effect induced by the sliding mode control. Then, the GWO was added to solve WECS MO functions. The proposed process can ensure better dynamic behavior of the WECS.

Qais et al. [313] proposed an augmentation for the GWO (AGWO) for better hunting performance to increase the MPPT and low voltage ride through the output of grid-connected PMSG powered by variable speed WT. Updating the position of the search agents by the average position of alphas (first best position) and betas (second best position) was used to develop manipulation. Based on the reported optimization results, the proposed AGWO substantially improved the performance of the standard GWO. Table 11 shows the main features of the papers on GWO applications in wind energy.

3.8.3 Hybrid Renewable Energy System

Due to the different problems of depleting fossil fuels, greenhouse gas emissions, climate change, and so forth, there has been a dramatic increase in the use of RES [314]. Therefore, the proper sizing of the hybrid model based on the RES is critical, as the energy generated from RES fluctuates. Optimizing the renewable hybrid systems is essential with the high current cost of an HRES, which can significantly affect the long-standing economic performance of the hybrid system [315]. The complexity of optimal HRES design and drawbacks of classical methods also have led to the use of Meta-heuristics for sizing the HRES in many studies such as ABC [316], WCA [317], TLBO [318], and PSO [319]. In this regard, some works used the GWO to size HRES.

Anand et al. [320] utilized the GWO for the optimal sizing of the HRES based on PV, biomass, biogas and battery units providing electricity continuously to the various households of Haryana State Indian village clusters. Compared with HS and PSO, the results showed better model performance.

Geleta et al. [321] and Hadidian-Moghaddam et al. [322] measured the optimum PV, WT, and battery-based HRES sizing and the optimum number of solar panels, WTs, and batteries to minimize TAC by meeting the requested demand. The results showed that the reliability of the studied systems is improved by increasing the inverter power and decreasing the TAC.

Tabak et al. [323] used the GWO, GA, and SA to achieve the lowest costs and reliable system by optimal sizing HRES with PV/WT/biomass based sources. Also, Yahiaoui et al. [324] proposed the GWO for sizing of HRES based on PV, Battery, and diesel generator in an isolated rural village in South Algeria named “Djanet”. The results of the GWO for PSO, GAs, and SA confirmed the GWO’s improved problem-solving results. Table 9 represents the important attributes of the papers on GWO applications for renewable energies.

3.9 Smart Grid

Mahdad and Srairi et al. [325] introduced a hybrid called GWPS to resolve a security problem of smart grid management and prevent blackouts caused by faults occurring in generating units or significant transmission lines of the practical electricity system. The results demonstrated the efficiency of the proposed security strategy in critical situations.

In research performed by Singh and Mahajan [326], the advanced GWO was proposed to detect and propagate the cyberattack to avoid a failure in the smart grid substations. This method uses graph theory to model every wireless sensor node. This method takes nodes as wolves and classifies those considering trust values during cyber interference. The findings demonstrated the efficiency of the proposed method in reducing data losses for GA and FA [327]. Table 10 illustrates the main paper’s attributes related to the GWO applications for smart grids in detail.

3.10 Microgrids

MGs have emerged to remove the necessity of investment in long transmission lines and prevent the huge loss in transmission lines [328–331]. They commonly include small-scale renewable or non-renewable generation units, storage systems and responsive demands [171, 332–338]. MGs may be connected to an upstream grid or operate as an isolated network [338–344]. Due to their merits, large electric power systems are being replaced by MGs [345, 346]. The optimization problems in MGs can be classified into three main categories. The first category of problems, referred to as UC, minimizes the operation cost of MG with optimal commitment of generation units and optimal charge/discharge of electric storage systems. MG operation cost typically includes GC of DG units, start-up and shut-down cost of generation units, and degradation cost of storage systems [170, 347]. The second category of problems is planning problems, which aim to find the best planning decisions in terms of the size and/or location of facilities, and the third category includes problems that aim to find the optimal controller parameters for MG.

Sharma et al. [348] used GWO for optimal battery sizing in a grid-connected MG with MT, FCs, PV, and wind units. The achieved results indicated the superiority of GWO over GA, PSO, BA, and TLBO [349]. El-Bidairi et al. [350] utilized GWO for optimal sizing of battery in an isolated MG with diesel generators, WT, PV, and tidal power units, while emissions and cost of electricity were considered as objectives, and a minimum reserve constraint was considered at each time.

Zhang et al. [351] incorporated logistic chaotic map function into GWO, and the resulting chaotic GWO was

Table 9 The GWO applications for renewable energy resources

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
Solar energy					
[304]	Estimating PV	Root Mean Squared Error (RMSE), Maximum Absolute Error (MAE)	MGGWO efficiency to GWO in terms of convergence rate, RMSE, and MAE	Modified	Using clans/packs of wolves are finding prey
[305]	Estimating PV	Levelized cost of electricity (LCOE)	Efficiency of GWO in terms of convergence rate and avoidance of local optima	Standard	–
[40]	Estimating PV	RMSE	The better performance of GWOCS in terms of convergence rate	Hybrid	GWO with CS
[306]	Design of an MLI	Switching angle Modulation index	Achieving optimal values	Standard	–
[307]	Design of PV systems	PV module current PV module voltage	Good performance of GWO	Standard	–
[308]	Design of PV systems	PV module current PV module voltage	better performance of GWO than other method	Standard	–
[309]	Forecasting of Solar Radiation	Mean Absolute Percentage Error (MAPE) MAE Coefficient of determination (R2) measures	Efficiency of the proposed method	Hybrid	GWO with Multilayer perceptron models
[310]	Tracing MPPT in PV system	PV power	Good performance of the method	Hybrid	Parallel GWO with OBL
[311]	Estimating PV	PLes	The superiority of GWO over others	Standard	–
Wind energy					
[312]	MPPT of WECS	Extracting the maximum power	Effectiveness of the proposed method	Modified	MOGWO
[313]	Grid-connected PMSG-based WECS	Integral-squared error (ISE) Root mean square voltage	Efficiency of AGWO than GWO and PSO	Modified	An improvement based on an Augmentation
Hybrid renewable energy system					
[320]	Sizing of HRES	The net present cost (NPC)	The efficiency of the algorithm in achieving optimal value	Standard	–
[321]	Sizing of HRES	TAC	Fast convergence and lower cost	Standard	–
[322]	Sizing of HRES	TAC	Fast convergence and lower cost	Standard	–
[323]	Sizing of HRES	TAC PL	Efficiency of algorithm	Standard	–
[324]	Sizing of HRES	TAC	Fast convergence and lower cost	Standard	–

used to determine the parameters of the PID controller of the pumped storage unit in an isolated MG. In the study, controller parameters are found in a way to have an optimal frequency response in MG. The results implied the outperformance of the proposed chaotic GWO over others.

Gazijahani and Salehi [352] employed GWO for optimal planning of grid-connected MGs with reconfiguration. The

Table 10 The GWO applications for smart grid

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
[325]	Security smart grid management	Cost PL VD	GWPS efficiency to GWO and PS	Hybrid	GWO and PS
[326]	Cyber failure detection in smart grid	Data loss	Effectiveness of method	Modified	Using graph theory

network constraints were considered, and uncertainties of demands, renewable power, and electricity prices were dealt with through robust optimization. The reliability of the MG is included in the planning objectives. The results for an MG with PV, electric storage system, PV, and WT indicated the outperformance of GWO over others.

Kumar and Sinha [353] utilized GWO to tune a controller for voltage stability of a DC MG with a battery, permanent magnet DC generator, and solar thermal dish Stirling engine. The controller aims to keep the voltage of the common DC bus at the desired level. The effect of different controllers, such as fractional order PID and PID controllers, on MG was investigated. Mohseni et al. [354] used GWO to plan an isolated MG, which includes FCs and super-capacitors. However, the results achieved by the moth flame optimization algorithm are better than those of the GWO results. Table 11 provides the GWO applications for the MG.

3.11 Home Energy Systems

In DR programs, electric utilities set the prices or incentives in a way that the stress on utilities is reduced, so the consumers experience time-varying prices or are rewarded incentives for curtailment at specific time slots [355]. In TOU DR programs, typically, a day is categorized into off-peak times, mid-peak times, and peak times, and the consumers are charged based on the consumption time zone; in the RTP DR program, the price is different at different time periods and in incentive-based DR, the consumers are rewarded incentive for curtailment at specific periods [355].

Smart homes have HEMS that aim to minimize the house's electricity bill, while the comfort of residents, PAR, and emissions may also be considered [356]. Home appliances are commonly categorized into three categories: must-in appliances that cannot be controlled, shiftable but non-interruptible appliances such as rice cookers, and shiftable and interruptible appliances such as electric vehicles. In some cases, the home has its own renewable or non-renewable power generation units, commonly diesel generators or PV modules. Each appliance has a pre-specified allowed operating range and a certain energy that must be delivered to it during its operation.

On a day-ahead basis, HEMS determines the optimal schedule of appliances and dispatchable generation units in a way that the electricity bill is minimized and consumers' comfort, PAR as well as emissions are considered [357]. In cases where consumers' comfort is a concern, a base-line schedule is defined for appliances, and a discomfort index is determined based on the difference between a schedule and a base-line schedule [358]. The HEMS shifts the consumption of controllable appliances from high-priced time slots to low-priced time slots. For non-interruptible appliances, it is easier to take the starting time of appliances as decision variables, as the number of decision variables would be lower in the resulting integer optimization problem [358]; however, in the case of interruptible appliances, the status of appliances at different time slots form the decision vector, and a mixed-binary optimization problem is a more difficult result [359].

In some research in the literature, the GWO variants have been used to schedule home appliances in HEMS (Ayub et al. [360] provided an improved BGWO for optimal scheduling of home appliances under the TOU tariff. A baseline schedule has been pre-specified for appliances, the discomfort index has been defined based on the baseline schedule, and the discomfort is minimized for a maximum budget limit. In the proposed improved GWO, a random walk enhances alpha, beta, and gamma wolves. The results showed the outperformance of the proposed method over others. The effect of budget limits on the comfort of consumers has been investigated.

Molla et al. [361] used GWO for optimal scheduling of appliances in a home with a PV unit under TOU tariff. The electricity bills of the home and PAR have been minimized, while the discomfort index of consumers has been considered. The scheduling problem has been formulated as a mixed-binary nonlinear problem. The results indicated better performance of GWO to PSO. The PV effect on the scheduling appliances, bill, and PAR has been investigated.

Waseem et al. [362] used a hybrid of GWO and CSA for optimal scheduling of appliances in smart homes under

Table 11 The main GWO applications for the MG

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
[348]	MG planning (battery sizing)	Planning cost	The superiority of GWO over GAs, DE, etc	Standard	–
[350]	MG planning (battery sizing)	Planning cost	The effect of reserve constraint on planning decisions in MG has been investigated	Standard	–
[351]	Tuning PID controller in MG	Overshoot of frequency response	Outperformance of the proposed chaotic GWO over PSO and GWO	Modified	Using Chaotic mapping
[352]	MG planning	Planning costs, including reliability	Outperformance of GWO over GA, PSO, and ABC	Standard	–
[353]	Tuning PID controller for voltage stability	Frequency response	The outperformance of GWO over mine blast algorithm and PSO	Standard	–
[354]	MG planning	Planning cost	The moth flame optimization algorithm outperforms GWO	Standard	–

RTP tariffs, while electricity bills and consumers' discomfort have been minimized. As per the results, the proposed algorithm outperforms other methods in all terms of bill, PAR, and comfort.

Makhadmeh et al. [363] employed GWO to schedule home appliances optimally under the RTP tariff, while the scheduling problem was formulated with bill, comfort and PAR as objectives as the multiple objective optimization issue. Linear weighted sum has been used to convert the MO problem into a single-objective problem, and the scheduling was done with a 5-min time resolution. Seven different load profiles and RTP prices have validated the proposed scheduling method.

In a research performed by Jordehi et al. [364], GWO was used for optimal scheduling of shiftable, non-interruptible home appliances to minimize the home's electricity bill. As the appliances are non-interruptible, their starting time has been used as a decision variable, resulting in an optimization problem with integer decision variables. The planning was done using a combination of RTP tariff and incentive-based DR in the first scenario and a combination of TOU tariff and DR based on incentive in the second scenario.

ul Hassan et al. [365] assessed the HEMS performance using the BFA/GWO. To this end, home appliances are divided into two classes based on their power consumption pattern. The CPP pattern is used to calculate the electricity account. To reduce costs and PAR and manage electricity consumption, the load is balanced by scheduling appliances at peak hours and off-peak hours.

Javaid et al. [366] utilized the FPA, GWO, and hybrid FPA and GWO (FGWO) based HEMS along with the load shifting strategy of DSM in a smart grid, which has been used to reduce PAR at an affordable cost and improve user comfort. Simulations for a single home were conducted with 15 appliances, and the CPP Tariff was used to compute consumer electrical payment. The results demonstrated that the load was successfully transferred with FGWO to low-price times, ultimately leading to a 50.425 percent reduction in PAR, a waiting time of 24.148 h, and a reasonable 54.654 percent cost reduction. Many cases of the advantages of DSM in energy systems have been reported [367]. The primary highlights of the GWO applications for HES may be shown in Table 12.

3.12 Water Sources

The most critical resource challenge faced by humanity in the twenty-first century is the lack of water supplies [368]. Furthermore, in future decades, under the impact of climate change, the water crisis is ranked as the highest global concern [369]. Population growth, industrial and agricultural production operations, rapid urbanization expansion, and climate mutation have significantly affected limited water supplies and have steadily degraded the ecosystem, thereby threatening human well-being [370]. Therefore, optimizing water supply problems has received much attention, particularly in recent years. In this respect, the GWO algorithm has been used in some works to maximize water supplies.

Sweidan et al. [371] used CBR, GWO, and *K* case retrieval parameters to test water contamination. The datasets in their study used true sample microscopic photographs of fish gills exposed to copper and water pH at various

Table 12 Summary of the papers on the GWO applications in HES

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/Modified)	Modification (Type of Hybrid/Modified)
[360]	HEMS (optimal scheduling of home appliances)	Discomfort index	The outperformance of the improved GWO over binary GA, binary PSO, and BGWO	Modified	GWO enhanced with random walk operator
[361]	HEMS	Bill and PAR	Better performance of GWO to PSO for bill and PAR	Standard	–
[362]	HEMS	Bill and discomfort index	The proposed algorithm outperforms GA, GWO, FA, PSOGWO, and others in terms of bill, PAR, and comfort	Hybrid	The hybrid of GWO and CSA
[363]	HEMS	Bill, comfort, and PAR	The outperformance of GWO concerning PSO, GAs, and GAWDO	Standard	–
[364]	HEMS	Bill	Outperformance of GWO to PSO	Standard	–
[384]	HEMS	Bill, comfort, and PAR	The outperformance of GWO concerning GAs	Standard	–
[385]	HEMS	bill, comfort, and PAR	The scheduling has been done for RTP DR and critical peak pricing DR	Hybrid	The hybrid of GWO and DE
[365]	HEMS	TC	The superiority of GWO to BFA in terms of cost reduction and fast convergence	Standard	–
[366]	HEMS	PAR and TC	FGWO performed well compared to GWO and FPA in terms of PAR and waiting time. However, in terms of cost, FPA outperformed the other techniques	Hybrid	The hybrid of FPA and GWO called FGWO

histopathological stages. Considering the variety of water contaminants, findings showed that the average accuracy reached by the GWO-CBR classification model exceeded 97.2 percent.

Sankaranarayanan et al. [372] presented an HGWO along with Kalman Bucy's correction mechanism to adjust the solution obtained by the GWO. In addition, the shuttling back-and-forth mitigation algorithm was applied to a local search technique. For two separate WDN case studies, the HGWO has achieved cost-optimal results.

Rathore et al. [373] suggested a PID controller tuned using the GWO for water treatment plants in Doha. The proposed approach should minimize the error criteria so that intense flux and conductivity transient responses can be produced.

Yu and Lu [369] introduced an integrated water resource optimization distribution model in a transboundary river basin that was implemented into the PPMGWO. The results indicated that the PPMGWO model's average variance was the lowest, and its optimization allocation outcome was closest to reality, further showing the PPMGWO model's reasonability, viability, and precision.

Liu et al. [374] suggested a general optimization routine combined with the hydraulic simulation model to achieve the optimal dispatching and operation schedule of cascade pumping stations. The GWO was developed to limit the feasible area of the ideal problem of cascade pumping stations dispatching and running. The model's results, which comprised six pumping stations, showed that the GWO could achieve a better solution regarding both robustness and accuracy regarding the PSO. The GWO applications for water sources are shown in Table 13.

Table 13 The GWO applications for water sources

References	Appl	Obj. fun(s)	Main findings	Variants of GWO (Standard/Hybrid/ Modified)	Modification (Type of Hybrid/ Modified)
[371]	Assessing water quality	Indicating water pollution	High accuracy achieved by the GWO-CBR	Standard	–
[372]	WDN	Cost minimization of WDN	The superiority of method to PSO and GWO	Hybrid	GWO is equipped with a correction mechanism
[373]	Doha water treatment plant	Minimize the error and tuning PID parameters	The superiority of GWO to others	Standard	–
[369]	Water resources	Optimal allocation	Good performance of PPMGWO	Standard	–
[374]	Pumping stations	Optimal dispatching and economic operation of cascade	Efficiency of GWO	Standard	–

3.13 Heat Exchanger

Heat exchangers are an effective tool used to propose the conversion of thermal energy between different liquids at different temperatures, such as the transfer of heat from a hot liquid to a cold liquid [375]. Different forms of heat transfers operate in many industries, and one of the popular heat transfers is compact heat exchangers, which may be plate-fin or tube-fin style structures [376]. In certain heat transfers, the liquids are isolated by a heat transfer plane, and they do not interact or escape supremely. A direct transfer form protects them. Shell and tube exchangers, vehicle radiators, condensers, evaporators, air preheaters, and cooling towers are some of the central heat transfers [377].

Shell-and-tube heat transfer, which is primarily used with a wide variety of usable temperatures and pressures, is the most used worldwide. For refrigerators, power generators, heating and air conditioners, chemical processes, industrialized applications, and medical applications, it mainly provides the required control action on the control valve to maintain constant outlet temperature [378].

Anbumani et al. [379] presented the tuning of the PID controller using the GWO for the first-order transfer function model of the heat exchanger. The performance indices showed that the GWO gives PSO a better heat exchanger process. Furthermore, Lara-Montaño and Gómez-Castro [380] employed the GWO to solve the optimization problem for a heat exchanger shell-and-tube, simulated by the Bell-Delaware model, attempting to minimize the overall annual expense, while Roy et al. [381] designed shell-and-tube heat exchangers with the aid of GWO for obtaining optimal design parameters. Table 14 presents highlights of the papers on GWO applications for heat exchangers.

Table 14 The characteristics of the GWO applications for water sources

References	Appl	Obj. fun(s)	Results	Variants of GWO (Standard/Hybrid/ Modified)
[379]	Design of controller in exchanger	Finding optimum PID parameters	The performance improvement of the system	Standard
[380]	Optimal design of exchanger	Obtaining optimum total annual cost	Low computing time and reduced cost	Standard
[381]	Designing of shell-and-tube heat exchangers	Finding optimal weights to predict the exergetic plant efficiency, energetic cycle efficiency, and electrical power	Low time and maximum error accuracy	Standard

4 Discussions and Trends

The GWO is one of the well-known meta-heuristic optimizers used in many research and commercial projects to solve optimization problems related to energy systems. Some of the benefits of this algorithm are simple structure and implementation, fewer computational requirements, high search precision, the ability to avoid local minimums and to adjust algorithm performance with two control parameters (i.e., a and C) and, therefore, more excellent stability and robustness, faster convergence, as search space is reduced and decision variables (i.e., α, β, and δ) are reduced.

Over 100 research papers were reviewed in this survey to provide a comprehensive reference for researchers interested in using the GWO algorithm. The papers were filtered and collected using Google Scholar with keywords (i.e., grey wolf optimizer, grey wolf optimization, GWO, and energy systems-based applications). There are existing review papers on GWO. In this review, however, we reviewed documents in which GWO was applied to diverse applications and areas of study to identify the ones on energy systems, which is the focus of this study. Results indicate that the usage of GWO in different research and studies is growing considerably year after year.

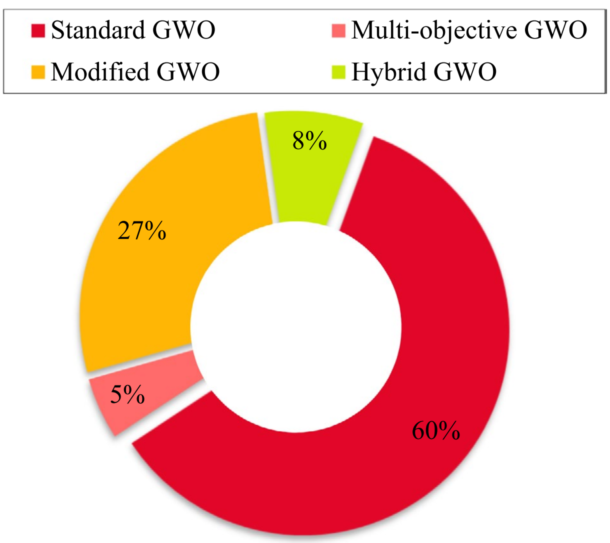


Fig. 10 Variants distribution of GWO algorithm in the reviewed papers

4.1 Variants of GWO

In the reviewed papers, different variants of the GWO algorithm are used to strengthen its performance, including improved versions of the GWO algorithm, hybridization of GWO with other algorithms, and variants of GWO for handling MO optimization, the so-called MOGWO algorithm. Figure 10 demonstrates the contribution percentage of GWO variants in the papers. Based on the statistical data in Fig. 10, the categories of "Standard GWO" and "Modified GWO" have more percentage of GWO variants.

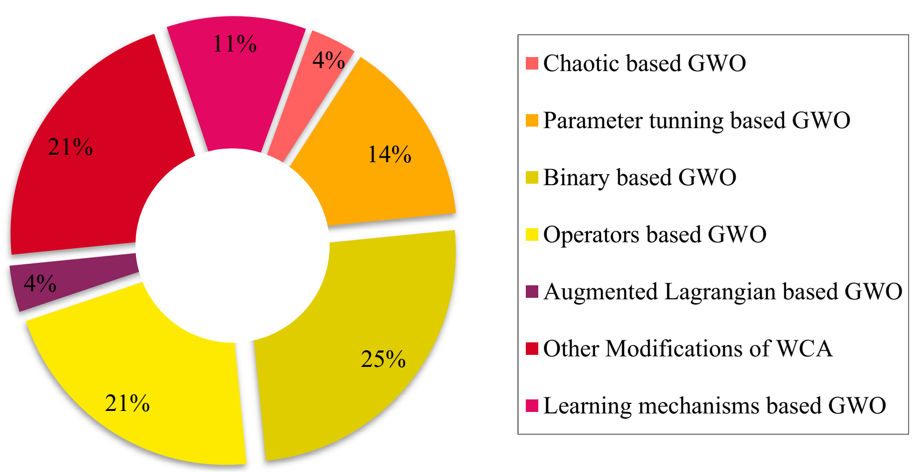
Studies on the GWO's performance and behavior indicate that it has proper capabilities in relation to the exploration and exploitation mechanisms. However, some researchers have modified the GWO to strengthen its efficiency in tackling optimization problems.

Numerous papers have used the GWO and its variants because of their strengths and capabilities to improve the performance of engineering systems and tackle various engineering issues. The following section represents the GWO modifications and hybridizations in the literature.

4.1.1 Modifications of GWO

In the majority of optimization algorithms, the primary concern is the maintenance of the exploratory and exploitative

Fig. 11 The GWO modifications percentage in the reviewed papers



balance in searching spaces and subsequently achieving the optimal solution [36]. The researchers have employed various techniques in various fields in recent years to improve GWO performance. The variants of the original GWO in this respect have been proposed in the literature about improvements, hybridizations, parameter set-up, the application of a set of evolutionary operators, and other methodologies. Moreover, Fig. 11 shows the percentage of GWO improvements in the literature. Based on the statistical results in Fig. 11, the "binary-based GWO" category has a higher percentage of GWO enhancement papers.

In the problems related to the energy systems, the binary nature of the UC and PBUC problems obligates the use of binary transformation of the real-valued GWO. Since the BGWO improves the quality of the traditional GWO solutions to solve the UC problem effectively, the binary version of the GWO has been utilized for solving the UC and PBUC problems in some research [185–190]. The binary number system, also known as the base-2 number system, represents numbers that count with a combination of only two numbers: 0 and 1.

The UC consists of two sub-problems where, in the first step, the ON–OFF status of the generator is established, and the power/generation allocation for the committed units is provided. Binary codes with 0 and 1 may denote OFF and ON states, respectively, which can be the commitment or disengagement of thermal plants. Therefore, the position of wolves at any given time in the BGWO is either 0 or 1. Two BGWO models are presented to solve problems based on UC. First, wolf update processes are immediately binarized towards the best global solution(s), followed by crossover operation. In the second method, wolves continuously update to the best global solution(s) and follow the sigmoid transformation.

To improve the performance of such an algorithm, it is evident that tuning the original parameters and updating the positions of individuals is crucial. To this end, in order to ensure accurate settings and update the position of wolves in the GWO to achieve efficient performance, numerous different methods were introduced.

In some works, researchers have balanced the exploration and exploitation processes by updating the parameters of GWO and providing different strategies for updating the individuals, resulting in efficiency improvement.

Paramguru and Barik [205] performed, tuning two parameters, a and A, using the exponential function to improve exploratory and exploitative search patterns of GWO. In the study, the parameters are reduced using the exponential function. In addition, Khandelwal [273] and [275] provided updating the position of the α, β, and δ parameters to find the best position and increase the frequency of updating the main solutions in GWO, which leads to higher search space awareness and is good for dynamic problems.

The OBL is one of the efficient tools of optimization to increase the convergence rate of different heuristic techniques [382]. The OBL performance includes the assessment of the current and opposite population of the same generation to acquire the optimal solution to a problem. In several meta-heuristics, the OBL concept has been successfully used to improve the conversion speed [297, 383].

In some research, the OBL concept has been used to increase the coverage of search space by exploring the opposite position of solutions in GWO and finally accelerating its convergence rate [198, 204, 238], and [310]. In several reviewed papers, researchers have incorporated new operators like mutation and crossover into the GWO or used a local search algorithm to improve the algorithm's ability.

The crossover operator aims to make it easier for packmates to share information. The aim of the mutation and local search method is to make small changes in the variables of each solution in GWO and to benefit from the high exploration and exploitation of evolutionary operators. Table 15 further describes the main attributes of the improved GWO versions in the reviewed papers.

4.1.2 Hybridizations of GWO

The hybridization of at least two or more optimization algorithms usually refers to the simultaneous use of algorithms to overcome the limitations in the algorithm as well as to obtain optimal solutions for complicated optimization problems [36].

Studies on the GWO searching operators show that, in combination with other optimizers, it will become a suitable, effective, beneficial, and powerful tool to address complex optimization problems. In addition, the hybridization of GWO with other optimizers compensates for its weaknesses and strengthens its advantages in achieving optimal solutions.

Therefore, various meta-heuristics were combined with GWO in recent years to tackle the complexity of the energy systems based problems and enhance its performance. Table 16 shows the hybridizations of GWO with other algorithms in energy systems-based papers.

4.2 Energy Systems Based Applications

Following the introduction of GWO, the literature has reported many different applications. GWO has demonstrated the appropriate performance for the optimal solution of optimization problems. In addition to its quick and mature convergence rate, good exploitation and exploration skills make GWO a suitable alternative for solving large-scale problems.

In addition, the other GWO strength that makes it famous for programmers and researchers is its simplicity of conceptualizing and coding, as shown in the literature. Because of its strengths and abilities, the GWO has been utilized to solve many problems related to energy systems such as UC,

Table 15 Modifications of GWO and their goals for solving energy systems-based problems in the reviewed papers

References	Modification	Goal
[184]	BGWO	Increment of the solution quality
[186]	Quantum computing concepts with BGWO	Increment of the solution quality
[185]	BGWO	Increment of the solution quality
[187]	BGWO	Increment of the solution quality
[188]	BGWO	Increment of the solution quality
[189]	BGWO	Increment of the solution quality
[190]	GWO with binary and dogmatic parts	Increment of the solution quality
[207]	GWO-ES adopts an additional wolf termed γ	To benefit from evolutionary operators of ES and increase the number of leaders in GWO, which leads to higher exploration
[206]	Using a local search strategy and a non-inferior solution neighborhood independent local search technique for the original GWO	To increase the local GWO search and the final solution's accuracy
[205]	Adjustment of the two parameters a and A	To change GWO's exploratory and exploitative search patterns
[198]	Oppositional concept	To accelerate the convergence rate of GWO
[224]	Applying a random mutation to increase the diversity of the population. Updating the position of populations in a spiral path around the best solution. Employing an adaptive operator to balance the exploration and exploitation phases during the iterative process	Increasing the population diversity in GWO leads to more exploratory behavior
[196]	GWO with mutation and crossover operators	To propose a memetic version of GWO that benefits from the high exploration of evolutionary operators
[209]	GWO with six mutation operators	Small changes in the variables of each solution in GWO should be made to increase the exploitation
[247]	GWO with mutation and crossover operators	To propose a memetic version of GWO that benefits from the high exploration of evolutionary operators
[278]	Integrated with a Lévy mutation operator (GWO-Lévy)	To increase the local search of GWO
[238]	Using sinusoidal truncated function instead of linear bridging mechanism and OBL mechanism	Increase search space coverage by exploring the opposite positions of solutions in GWO
[204]	Combining GWO with a random exploratory heuristic method based on the LRS mechanism and opposition learning heuristics	To increase search space coverage by exploring the opposite position of solutions in GWO while introducing more random changes to the algorithm
[273]	Updating the position of α, β, and δ to find the best position	Increasing the frequency of updating the main solutions in GWO leads to higher search space awareness and is suitable for dynamic problems
[275]	Updating the position of α, β, and δ to find the best position	Increasing the frequency of updating the main solutions in GWO leads to higher search space awareness and is suitable for dynamic problems
[304]	Multi-Group GWO (MG-GWO), where several clans/packs of wolves are searching for prey	To avoid premature convergence and prevent the population from rapid movements
[313]	An improvement based on an Augmentation	To increase the exploration of the GWO algorithm
[326]	Using graph theory	To adapt the GWO algorithm for solving combinatorial optimization problems
[351]	Using Chaotic mapping	To provide chaotic search patterns for GWO and increase its exploration
[360]	GWO enhanced with random walk operator	To improve the local search and convergence of GWO
[310]	Parallel GWO with OBL	To increase search space coverage in the opposite direction of search space

Table 15 (continued)

References	Modification	Goal
[309]	GWO with Multilayer perceptron models	GWO can be used as a trainer for neutral network learning enhancement in prediction problems
[372]	GWO is equipped with a correction mechanism	A probabilistic model should be used to increase the randomness of GWO

ED, OPF, DG resources, etc. Figure 12 illustrates the optimization problems related to the energy systems, which are evaluated using the GWO algorithm in the reviewed papers.

In addition, Fig. 13 demonstrates the percentage of the problems solved using GWO in the reviewed papers. Based on the statistical results displayed in Fig. 13, the categories of "ED," "Renewable energy resources," and "OPF" have higher percentages of problems solved using GWO in the reviewed papers.

Looking at Fig. 14, the distribution of GWO papers studied for each continent is demonstrated concerning the authors' affiliation. As shown in Fig. 14, with the maximum number of documents from India and China, Asia has the most significant proportion of GWO contributions to energy system-based issues, and America and Australia have the lowest contributions. As for Asia, GWO can thus be expected to effectively solve engineering applications in the continents above by witnessing more applications in America, Australia, and Europe.

5 Conclusions and Future Directions

In this review paper, an exhaustive investigation has been carried out into GWO applications and their recent advances in literature in a broad and diverse field of research based on energy systems. Significant efforts have been devoted to constructing this article to give readers and interested scholars a vital insight into this topic through the discussion and summary of the GWO findings in recent scientific papers while studying and analyzing many and various research papers relating to the GWO.

Because of the efficient attributes of the GWO between optimizers, the distinctive versions of the GWO were presented in a complete list of references in papers based on energy systems in terms of applications, improvements, hybridizations, and MO variants, the results obtained from studies and evaluations of these references support researchers' finding it useful and valuable to address problems based on the energy system. This review paper is believed to be practical and appropriate for students, academic researchers, experts, and engineers. It may also be a beneficial and effective reference in academic papers and GWO-related books, energy systems, optimization methodologies, and metaheuristics. Furthermore, the following results can also be summarized as follows from the different analyses:

- According to the statistical results, from 2014 to the present, the number of articles published using the GWO has grown considerably each year, which demonstrates its wide acceptance.

Table 16 Hybridizations of GWO and their goals for solving energy systems-based problems in the reviewed papers

References	Hybrid	Goal
[195]	Hybridization of GWO and bHC	Improvement of convergence speed, exploration phase, and exploitation phase
[233]	Hybridization of GWO and ICA	To increase the exploration of GWO
[249]	Hybridization of GWO and PSO	To increase the number of leaders in GWO and the extensiveness of the search in GWO
[40]	Hybridization of GWO and CS	To incorporate the operators of CS in GWO and influence its search patterns
[325]	Hybridization of GWO and PS	To increase the balance of exploration and exploitation
[362]	Hybridization of GWO and CSA	To increase exploration of GWO
[385]	Hybridization of GWO and DE	To benefit from the diverse mutations of DE, which increase population diversity in GWO
[366]	hybridization of GWO and FPA	To increase the exploitation of GWO

Fig. 12 The optimization problems solved using the GWO algorithm

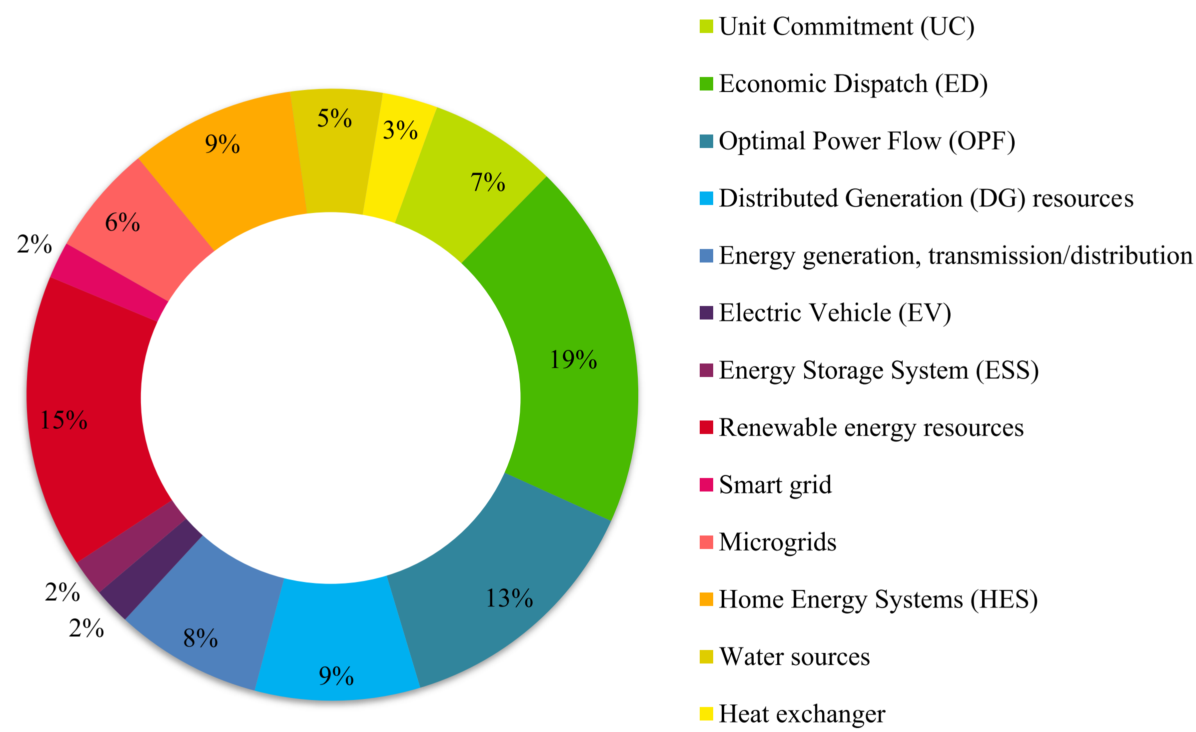


Fig. 13 Percentage of the problems solved using GWO in the reviewed papers

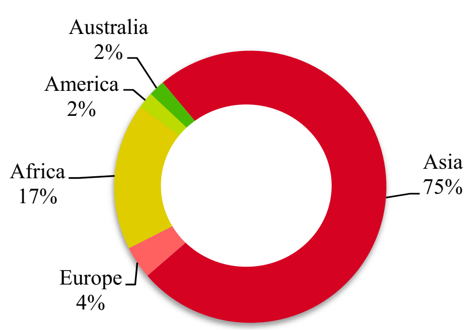


Fig. 14 Contributions by the GWO and its variants from different continents

- Till now, the problems of the "ED," "renewable energy resources," and "OPF" are the pioneers of solving by using GWO among the energy systems-based problems.
- Till now, the citations and number of published articles related to GWO are the highest since proposing the GWO.
- So far, the standard GWO is used mainly for tackling problems based on energy systems, which shows the efficiency and effectiveness of the algorithm.
- Asia has made the most outstanding GWO contribution, whereas the lowest countries are America, Australia, and Europe.

The GWO and its variants have been the subject of several research projects as the future guideline until now. In the future, however, this meta-heuristic optimizer is expected to be applied, improved, and hybridized in literature more and more. Nonetheless, numerous EAs and swarm intelligence algorithms were unconnected with the GWO, and several MO strategies in the GWO were not used. Indeed, the GWO is not well developed in the MO aspect, and serious attention should be taken into account in future research despite the MO nature of most real optimization problems. In addition, in future research, it would be necessary to consider more hybrid versions of GWO with efficient algorithms. The efficiency and ability of the algorithm to deal with various problems in the reviewed articles show that the algorithm can be used to solve other issues related to energy systems, such as optimal planning of energy hubs in energy systems, energy markets, etc.

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Declarations

Conflict of interest All authors declare that they have no conflict of interest.

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