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Review

Potential Contribution of the Grey Wolf Optimization Algorithm in Reducing Active Power Losses in Electrical Power Systems

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Abstract: Active power losses have the potential to affect the distribution of power flows along transmission lines as well as the mix of energy used throughout power networks. Grey wolf optimization algorithms (GWOs) are used in electrical power systems to reduce active power losses. GWOs are straightforward algorithms to implement because of their simple structure, low storage and computing needs, and quicker convergence from the constant decrease in search space. The electrical power system may be separated into three primary components: generation, transmission, and distribution. Each component of the power system is critical in the process of distributing electricity from where it is produced to where it is used by customers. By using the GWO, it is possible to regulate the active power delivered by a high-voltage direct current network based on a multi-terminal voltage-source converter. This review focuses on the role of GWO in reducing the amount of active power lost in power systems by considering the three major components of electrical power systems. Additionally, this work discusses the significance of GWO in minimizing active power losses in all components of the electrical power system. Results show that GWO plays a key role in reducing active power losses and consequently reducing the impact of power losses on the performance of electrical components by different percentages. Depending on how the power system is set up, the amount of reduction can be anywhere from 12% to 65.5%.

Keywords: GWO; optimization process; power systems; active power losses; power generation; radial transmission; smart distribution

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1. Introduction

Electric power has become a critical measure of the structure of contemporary society, with most of today's everyday activities predicated on the assumption that this power is always available. Regulations require the appropriate allocation and sizing of two types of distributed generation (DG) units to be optimized with a maximum size restriction of one megawatt (MW). The grey wolf optimization algorithm (GWO) is an optimization method used to reduce active power losses. Simulations have been used to evaluate the performance of the approaches, with numerical results compared in terms of optimum values and convergence characteristics [1]. Active power losses in electrical power systems are problematic because they can impact the distribution of power flows along transmission lines as well as the energy mix throughout power networks. As a result, because large-scale renewable energy sources are often located far from load centers, losses can have a particularly severe influence on the utilization of potential energy generated by them. Active power losses in electrical power systems can cause problems such as overloaded transmission and distribution lines, loss of stable voltage, and too much power loss [2].

Electrical distribution systems (EDSs) are composed of several components, each of which is critical to the process of distributing electricity from the power production location to where it is used by customers. The distribution system is essential in delivering electrical energy from the point of production to the site of consumption, which is accomplished via the use of the transmission system. The R/X ratio in the distribution network is high, where R signifies resistance and X denotes impedance, so the losses in the distribution system are larger. The DG systems used are a combination of photovoltaic (PV) panels for active power adjustment and capacitors for reactive power compensation. The degree of compensation offered by capacitors in a system is controlled by the position, range, and type of capacitor employed in the system, among other factors. A load flow is utilized to determine the position and size of the DGs, and losses in the radial network are considered. On the IEEE 69-bus standard network, the backward–forward sweep load flow method is utilized to move the load from one point to another. With the increasing use of plug-in hybrid electric vehicles (PHEVs) as tiny mobile power plants, greater study into the energy management of these power plants is required to keep pace with the expanding trend [3]. The charging and discharging capabilities of PHEVs may be used in active distribution networks (ADNs). To keep the operational expenses of the system as low as possible, an optimum strategy has been proposed for the charging and discharging schedule of plug-in electric vehicles (PEVs) in ADNs. The effect of PEVs has been examined regarding operational costs and other technical aspects of the system, such as power losses and the voltage profile [4]. To provide a fast-charging solution for lithium-ion batteries, a universal algorithmic framework that combines a model-based state observer and a deep reinforcement learning (DRL)-based optimizer has been suggested for the very first time. This framework combines a model-based state observer (LIB) within the DRL framework, and a multi-objective optimization problem is made by linking costs to bad things that could happen, such as overheating and degradation [5–7].

It has been shown that the performance of a chaotic swarm optimization (CSSO) method for addressing optimum power flow (OPF) issues is superior to other algorithms. The CSSO-based method is applied to five different types of objective functions (OFs), which include cost minimization in power generation, reduction of environmental pollution and emissions in power transmission; minimization of active power losses during transmission, enhancement of the voltage profile, and the improvement of system stability [8,9]. CSSO is a cost-effective approach for allocating renewable energy sources (RESs), particularly wind, solar PV, and energy storage systems (ESSs), in electrical distribution networks to reduce costs and active power losses. The method is needed to figure out how many possible and ideal sites there are for the hybrid RES–ESS [10]. A method for solving the optimal reactive power management (ORPM) problem involves using a multi-objective function and a modified differential evolution algorithm (MDEA). Through the solution of the ORPM issue, MDEA is being examined for its ability to improve the voltage profile as well as minimize active power losses [11]. To reduce transmission power losses and voltage deviation while considering system restrictions, the ORPM objective function is proposed as a power sharing control approach based on adaptive drooping. The major goal is to govern the distribution of active power transmitted via a high-voltage direct current network based on a multi-terminal voltage-source converter among numerous onshore alternating current grids or offshore loads depending on the required percentage share [12]. The shared electricity is produced by distant generating units or is offered as a surplus by alternating current (AC) power systems. The system operator optimizes the desired percentage shares of active power to meet the active power needs of the linked grids and reach goals such as supporting energy sufficiency, increasing the use of renewable energy, and preventing losses.

Figure 1 shows a detailed diagram of the inner current loop controller used to implement this concept. This controller is the main part of the system that contains the programming executable steps of the proposed GWO. Contrasting with disconnected designs, a unique framework for buildings-to-distribution network (B2DN) integration has been developed that decreases distribution network active power losses and increases voltage management while also decreasing building energy expenditures and ensuring occupant comfort [13,14]. A probabilistic multi-objective optimization approach has been used to determine the optimal sizes and locations of static variable compensators and thyristor-controlled series capacitors (TCSCs) in a power transmission network with a high penetration level of wind generation. This approach has been proven to be successful [15]. As a component of the Egyptian distribution network, the West Delta Network (WDN) has been thoroughly examined, factoring in a 30% increase in system loading. It was found that an oscillatory particle swarm optimization (OPSO) technique could be used to find the best places and sizes for a single or multiple distribution grids to achieve the goals of minimizing total active power losses and system voltage regulation as a single and multi-objective optimization problem in a distribution network [16].

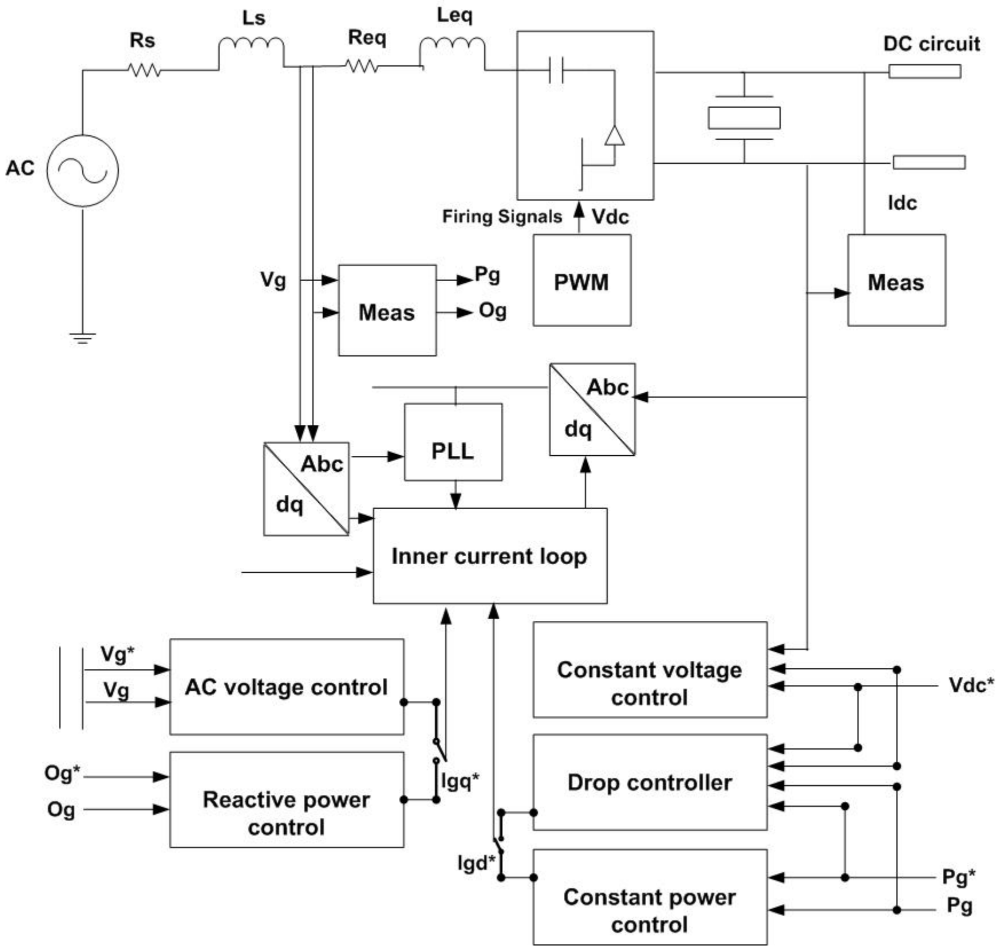

Figure 1. Detailed diagram of the inner current loop controller.

The most efficient way to connect unbalanced hybrid AC/DC micro-grids to the grid is to use a hierarchical power routing method. A three-phase, four-leg inter-linking converter is used to distribute electric vehicles (EVs) between charging stations (CSs) in the micro-grid while they are en route. The ICs dynamically route power between the three phases of the alternating current system to reduce active power losses and the power imbalance factor (PIF) at the point of common coupling (PCC), which is where the EVs are charged [17]. Electric vehicle chargers can be coordinated with other voltage/voltage control devices using a three-stage method described in [18]. This method can be used on both medium-term and long-term power lines. As shown by the numbers, this optimization method is better than others at finding the best way to allocate SCBs to cut network power losses, improve voltage profiles, and save money [19]. Electric power providers have been paying a lot of attention recently to the best places and sizes for various types of renewable energy production systems in their distribution networks. This is so that they can actively cut down on power loss. The IEEE 33-bus test system can be used to test a wide range of renewable energy generators (REGs) of different sizes and types. The size of REGs is based on how much power is lost in the distribution system. The best-distributed generator has been found and the right generator size has been chosen so that there are no power distribution losses [20].

Several studies have been carried out to find the best place for a REG based on factors such as active and reactive power loss and the overall efficiency of power systems, among other things. VSI performance improvement has also been investigated, using an online adaptive switching frequency technique to meet its performance goals (OASF). A new level of freedom has been added to the OASF algorithm to obtain the highest possible weighting factor and the best overall system optimization. Compensated math considers both the controller's reaction time and the inductance of the coupler [21]. A power-consumption limit is needed because there is not enough active power in the power system. This causes the supply network's frequency to drop because there is not enough active power in the system. Customer service and the technology used to make oil and its byproducts are damaged, as is the way that oil is made. Random disconnections of oilfield users should be avoided to keep the oil industry from going broke [22]. Active power losses must be kept to a minimum while the radial network works, and each node of the grid maintains a balance of power. To do this, the grid must be treated as an integer/mixed-integer linear programming problem. The authors generated a new metaheuristic optimization method that solves one of the most common problems in today's power systems. It was based on a lot of different things people do in a lot of different industries [23,24]. It has a high rate of convergence because the roulette wheel selection mechanism is used. The IEEE 30-bus system is used to obtain the most power. This has become the norm in the business world. There is an algorithm called Human Behavior-Based Optimization (HBBO) that helps find a way to solve the problem at hand. All these things are part of the problem with the OPF. People who know how to do things such as particle swarm optimization (PSO) and other things can try them out when HBBO is used [25]. A new method of dividing transmission losses has been discovered in a deregulated energy market. It is difficult to calculate the amount of loss in a shared transmission corridor because it is not a simple number [26]. Lossy lines are given transmission losses based on the amount of power that passes through them [27]. As this strategy uses real power flow in transmission lines for each load to allocate losses, the allocations made by the strategy make sense and are appropriate for each load connected.

GWO as an Effective Metaheuristic Algorithm in Problem Optimization

GWO is preferred when the communication range and number of objectives are increased. It is easy to implement due to its simple structure, fewer storage and computational requirements, faster convergence due to continuous reduction in search space and fewer decision variables; its ability to avoid local minima; and having only two control parameters to tune the algorithm's performance, which results in better stability and robustness. Increasing the number of objectives and communication ranges can significantly improve the system performance in GWO and thus improve the algorithm performance [28]. The pseudocode of the GWO has been presented in [29] as follows (Algorithm 1):

Algorithm 1 grey wolf optimization (GWO)

Set the algorithm parameters, including population size N, maximum number of iterations (max_iter), and control parameters α, β, and δ.
Set t to 0.
By using an opposition-based learning strategy, start the grey population Xi where i = 1, 2, . . . , N.
Determine each individual's fitness level.
Xα = the best individual
Xβ = the second best individual
Xδ = the third best individual
Do (t < max_iter) While
for Every individual
Update control parameter a first, then A and C.
Update Xα, Xβ, and Xδ
End while
Return Xα

GWO is a well-known algorithm that has been designed to solve single-objective optimization problems. It can be used in different ways to solve the problem of active power loss. In this article, we show how GWO works and how it can be applied to power systems. The main objective of this review is to shed light on the role of GWO as an optimization algorithm in reducing the active power losses in all components of the electrical power system, starting from the generation stage. To achieve this main objective, this review presents the single- and multi-objective frameworks that are used to achieve different operational, economic, environmental, and technological advantages. These objectives are utilized to construct the optimization problem, and at a later step, multiple goals are optimized simultaneously under the constraints of equality and inequality. The optimization problem could then be solved using one of the optimization algorithms.

2. GWO's Contribution in Reducing Active Power Losses in the Generation Stage

GWO is utilized in the process of lowering power losses and supply costs, as well as in the technique of reconfiguring distribution networks to incorporate distributed generation. An hourly reconfiguration strategy has been developed because of the time-varying energy costs and the fluctuating consumption of commercial, industrial, and residential loads. This approach was taken because of these factors [30]. Two metaheuristic-based methods have been devised to address the challenge of network reconfiguration in the presence of multiple renewable distributed generators [31]. There are a lot of ways to cut down on how much power is used when the IEEE 33-bus is used. A coordinated voltage control method is used for the best design of the DC generator's active and reactive power. The interruption profile of a distribution system may be predicted based on the system's design and the reliability data obtained from the components. Due to the growing use of distributed generators in transmission and distribution networks, one of the primary goals of distributed generation is to improve system dependability. If reliability is a priority, an optimization method should be utilized to identify the best placement for the distribution grid. Distributed producing units must be assigned in the most efficient way possible so that power loss is kept to a minimum and the distribution network's actual and reactive power needs are met.

An upgraded GWO and a particle swarm optimization technique have been proposed for explicitly determining the best location and size of DCs and CBs. Grey wolves served as inspiration for the GWO metaheuristic optimization technique [32], which was later developed by computer scientists. The optimization of the installation of renewable distributed generator (RDG) units may address several concerns with the current radial distribution system (RDS). The demand for RDSs has skyrocketed, but the voltage on the buses has dropped because of massive losses in the transmission lines that run across the entire system.

GWO and Reduction in Active Energy Loss by Determining the Best Allocation of DGs

The optimal allocation of DG units in power systems contributes significantly to reducing active power. GWO was used to obtain the best place for DGs in the power system. To reduce power losses in the distribution system, DGs' size and location may be optimized while network reconfiguration is considered [33]. Based on HPSOGWO and LSF, an optimization approach (COT) is suggested to determine the optimum allocation of distributed generators in radial distribution networks, which combines PSO with GWO and the LSF to identify the best location. Specifically, the COT consists of two phases that must be performed for it to work properly. The loss sensitivity factor (LSF) is used to choose high-potential buses in the first stage, which reduces both the search area and processing time required. This decision was followed by a decision to have HPSOGWO supervise site and size selection for DGs in stage 2. The COT's ability to handle rising loads on a standard IEEE 33-bus has been investigated [34].

The DG is effectively integrated with the DS to prevent power loss to the greatest extent possible. When dealing with DNR, it is vital to optimize a non-linear and multi-modal function while keeping in mind the limitations of the existing reality. When reconfiguring the DS, it is possible to find the best switching site using the mGWO technique, resulting in the largest possible decrease in power loss [35]. By updating its position from a high value to zero, the grey wolf's location is determined to be in the search area, resulting in the optimal balance between intensification and diversity for picking the fittest function while also demonstrating quick and steady convergence. DG systems incorporated into distribution networks have grown increasingly widespread in recent years. A well-implemented system can reduce energy production's negative environmental implications. It is possible that poor distribution network design and management might undermine the network's dependability despite the many benefits that DG provides. Improperly connecting a distributed generating system to the power grid may result in power losses, unstable voltages, and the failure of critical control equipment. By figuring out the best place and size for adding new DG units to the network, an approach has been made to reduce these negative effects by lowering power losses and raising voltage profiles at the same time [36].

A wide range of load scenarios need the simultaneous and separate allocation of the right position and size of PV-based distributed generators and distribution static synchronous compensators (DSTATCOMs) in the radial distribution grid. GWO is a high-performance optimization approach that is used to solve the issue of PV-based DG and DSTATCOM allocation in IEEE 85-bus distribution systems. To minimize power loss, six different load levels are examined: 25%, 50%, 75%, 100%, 125%, and 150%. DSTATCOMs and PV-based DGs work well together, and the best-case scenario is to use PV units with DSTATCOMs to reduce power loss while still achieving decent results. For the PV and DTSTACOM allocation issues, the simulation results show the relevance and effectiveness of GWO [37]. Battery energy storage systems (BESSs) may be optimally scheduled with the use of the MIGWO model, which considers the extensive use of renewable energy sources, such as solar and wind, in active distribution networks. Consequently, four modifications to the traditional GWO technique are made to alter the balance between exploration and exploitation and, consequently, speed up the algorithm's convergence. In this study, model validity and performance are evaluated on 23 classical benchmark functions in this study, comparing findings with those obtained by using the original technique [38]. In line with [39], a study was carried out to see how well the given goal functions worked with traditional distribution methods (69 bus radial distribution systems). With less time and better accuracy, a distribution network's active power loss may be reduced via the best allocation of distributed generating units (DGs). The novel approach has the advantages of being quicker to implement and more precise. This is a non-linear constrained optimization problem whose goal is to reduce power consumption while considering a variety of limitations. The one-by-one search method (OBOSA) is suggested in this work to find the DG sites that would result in the least power loss achievable. To examine and validate the efficacy of the suggested technology, an IEEE 33 and 69 radial distribution test bus system was employed. OBOSA's performance is assessed when compared to GWO and ALO-based techniques [40,41]. An alternative strategy to solve this non-convex, discrete issue is to use the hybrid grey wolf optimizer, a unique metaheuristic tool. There is a considerable decrease in power loss when this technique is used with IEEE 33-, IEEE 69-, and Indian 85-bus radial distribution systems. Based on this information, power loss and the voltage profile of the buses are shown to have decreased dramatically throughout the network. Distribution systems with DG and capacitor banks (CBs) might benefit from using a multi-objective optimization approach to better allocate their capacity (RDS).

Due to this, the advantages of CB and DG injections in the RDS are highly reliant on both the appropriate amount and volume of these drugs, along with the selection of an appropriate injection site. As a realistic alternative, renewable energy has received a lot of attention in recent years because of its numerous benefits. It has been a few years since the GWO and the cuckoo search, two new hybrid metaheuristic techniques, were created. Searching for the best possible solution is the goal of the HGWOCS algorithm used to solve DGs. The loss sensitivity factor may be used to restrict the search area (LSF). The active power losses will serve as the study's goal function, as specified. The IEEE 69-bus is used to demonstrate this concept when the demand is minimal [42]. Figure 2 shows the basic topology of the simple power distribution network with a distributed generation (DG) source. Specifically, a relay (R) is used to protect the main feeder, whereas fuses are used to protect the laterals that provide electricity to the loads. Most of the time, relays have mechanisms that can tell if they are receiving too much inverse time overcurrent in most cases.

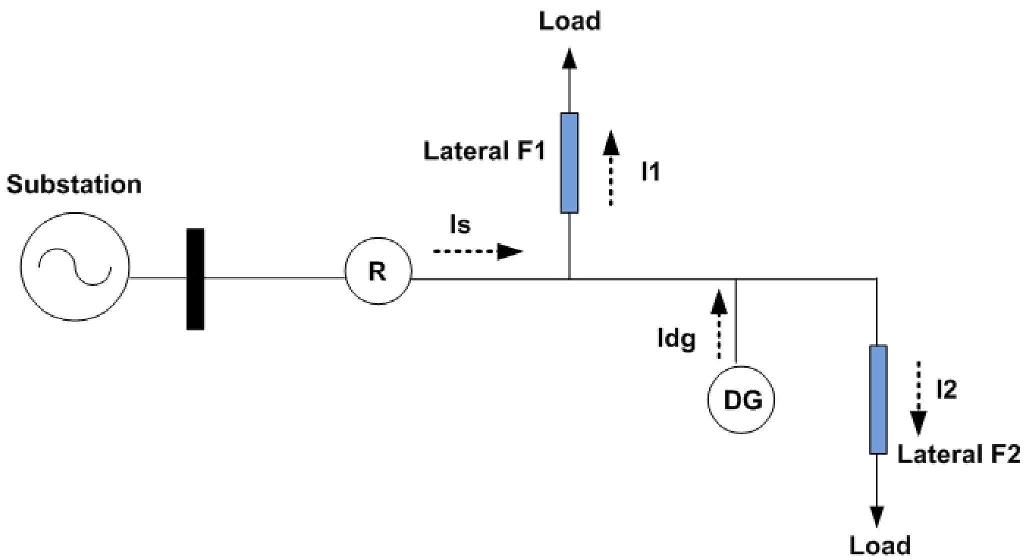

Figure 2. Topology of the simple power distribution network with a distributed generation (DG) source.

3. Minimizing Active Power Losses in Power Transmission Systems Using GWO

In response to rising energy demand, power system interruptions (generators, transmission lines, transformers), and unexpected breakdowns of network equipment, the power system becomes progressively crowded and overloaded, eventually resulting in the system entering an emergency condition of operation. Thus, it is necessary to develop suitable management or control procedures. Another essential emergency control activity is congestion management, which seeks to reduce or eliminate overloading and violations in the transmission power system. Congestion control based on appropriate load has been used to reduce load shed and active power losses, as well as to improve the voltage profile and voltage stability [43]. Due to the rapid increase in demand for power, the integrity of the electrical system, particularly regarding voltage stability, is in jeopardy. The use of a static voltage compensator (SVC) on the 500 kV Java-Bali electric power system with PSAT has been identified as one of the FACTS equipment to combat the instability of the most critical buses when operating on the 500 kV Java-Bali electric power system with PSAT. The power flow approach results in a total active power production of 12.144 p.u. and a total reactive power generation of 5.268 p.u. due to the power flow technique. The total active power load is 12.058 p.u., and the total reactive power load is 4.65 p.u. as a result of the power flow technique. The total active and reactive power loads are equal. The entire active and reactive power demands are equal in magnitude and value. The result is obtained when the total load on each bus and the total losses on the line are added up [44] and divided by two. The goal of improving the active filtering theory of multi-phase power supply systems, which tries to keep as much power as possible from being lost in transmission lines, has been set.

New relationships are established for the instantaneous active current and apparent power, and a new physical content is defined that considers the transmission line resistance ratio dependence and corresponds to similar integrated values of a multi-phase power supply system's periodic mode, respectively. The instantaneous and integral values of the least feasible losses are both related to the load power squared and, in the event of a short circuit, are inversely proportional to the power of the short circuit. As a result of the above-mentioned information, these numbers may be utilized to calculate the power factors and gain coefficients for power losses for a certain load. In the case of an active filter with control methods that arise in the transmission line vectors of the active current while using a shunt active filter, the private sector has put a lot of money into infrastructure improvements that allow it to work within the existing power system framework [45].

As a result, transmission lines must exert more effort to meet their temperature restrictions. The congestion caused by overloaded transmission lines resulted in an increase in power loss throughout the system because of the overload. One of the most successful methods to reduce congestion on the electrical system is to increase the available transfer capacity (ATC) of the system. The use of FACTS devices may help to increase the efficiency of air traffic control systems and procedures. The inclusion of the TCSC in the IEEE 30-bus system has allowed for the development of a novel way of dealing with crowded regions. When the TCSC is allocated, it is carried out with the help of ACPTDF sensitivity factors, and the parameters are determined with the help of the GWO method. When a multi-objective function is used, it has been found that when GWO is used, it helps to reduce active power loss, increase ATC value while lowering reactive power loss, and make the TCSC size as small as possible [46,47].

Transmission losses, emission limits, and the valve point impact on the cost functions of the generating units are all factors that have an impact on the characteristics of the problem. It is therefore critical to develop a dispatch solution strategy for this optimization problem that is both effective and economically sound. When applied to larger restricted problems, the convergence characteristics of most optimization algorithm techniques are sub-optimal. The GWO method has been used to solve the non-linear and non-convex economic dispatch problem [48]. This method considers the effects of valve points and transmission losses.

GWO in FACTS Devices

FACTS, which stands for flexible alternating current transmission system, is an electronic device that can be used to solve problems with the strength of electric power that can be sent. It has been explained in detail how the grey wolf optimization method can be used to reduce overall system losses and voltage variation through the optimal placement of FACTS devices [49]. The GWO method, which is based on wolf social hierarchy and hunting behavior, is used to find the best solution for the whole world. It has been proven to be a good way to find the best global solution while keeping a good balance between exploration and exploitation. According to experts in the field, there is an alternative to traditional devices for flexible control and growth in transmission line power transfer capabilities. This alternative is called the series-shunt FACTS device, which is also called the unified power flow controller (UPFC). As the number of UPFCs in a network grows, it becomes important to carry out calculations to figure out the right number of FACTS devices that would cause the least amount of loss in both normal and emergency situations. A Nigerian National Grid transmission line with 31 buses and 330 kV of power was used to test the method [50]. The MATLAB programming environment was used to do this.

The GWO method is used with AGC and multiple FACTS devices to choose gain settings for the PDF plus (1 + PI) controller, which is based on the PDF plus (1 + PI) controller. In this work, PI and PID controllers, as well as a PDF plus 1 + PI controller and GWO, are used to look at how the system moves. Three-area FACTS devices were compared, and the IPFC's dynamic response was found to be superior to other FACTS devices, such as the SSSC, TCSC, TCPS, and inter-line power flow controller (IPFC). This is because of the PDF plus (1 + PI) controller and GWO technique [51]. The FACTS controls the flow of both active and reactive power through the transmission lines that connect to the GWO. These lines are in series with the GWO [52]. It might be easier to reduce harmonic distortion in a system if an active power filter (APF) is used. A non-linear optimization problem with constraints must be solved to find and size the APF in a radial distribution system (RDS). In this paper, GWO and cost effectiveness are discussed in detail regarding the OPSAPF method. Scientists came up with the GWO, which is based on things that happen in the world. As a result, both exploration and exploitation methods have the same optimization properties. For harmonic voltage distortion (THDV), individual harmonic voltage distortion (IHDV), and the size of the APF to be safe, they must all meet three inequality rules. To obtain a harmonious load flow and simple integration, a 33-bus system should be used [53].

FACTS devices such as the UPQC have shown that the electric power system has become more stable in the last few years. The unified power quality conditioner (UPQC) was able to work well with power systems because of a lot of other changes. Despite this, the system's reliability did not get better, and there was no signal that the system could react to. A hybrid strategy is now being used to improve the quality of electrical power. This is a search engine optimization tool called "Cuckoo GWO." It is made up of the cuckoo search algorithm (CSA) and GWO [54]. This method, as previously stated, considers the cost of UPQC devices as well as the voltage stability index (VSI) and power losses to figure out where UPQC devices should be placed. Grey wolf optimization (GWO) has been used to make a new FACTS allocation method, called the improved grey wolf optimization method (IGWO). For real power losses, voltage changes, and system costs, the improved grey wolf optimization method (IGWO) is used to find the best location and size for the various FACTS controllers. After its first appearance, the UPFC quickly became known as a useful FACTS device. It has since been used a lot. A hybrid GWO and backtracking search optimization algorithm was used to find the best way to move power (BSA). This strategy was both time-saving and successful. It was shown that the proposed method worked on an IEEE 30-bus test system [55,56].

4. GWO's Functions in the Distribution Network

A new grey wolf optimizer, AGWO, was developed for radial distribution network reorganization. The optimal switch combination utilizing the approach employed to modify the topological structure of the system and lower overall real power losses while still fulfilling the system's operational requirements has been discovered. Alpha and beta grey wolves in the wild are the inspiration for this concept [57]. According to this study, the best strategy to integrate hybrid systems is to reduce the number of distinct functions that are being considered. For this integration, a novel metaheuristic method based on a collection of chaotic grey wolf optimization algorithms is used, which is discussed in depth below. Minimizing the proposed multi-objective functions is suggested as the optimum method for integrating hybrid systems. To reach this goal, a new metaheuristic method has been made that uses many different types of chaotic grey wolf optimization algorithms.

Increasing numbers of power system apps are using methods that optimize their applications. These methods are becoming more popular because of their simplicity, no requirement for gradient information, flexibility to bypass local optima, and the large variety of algorithms that may be applied [58]. This study's researchers claim they utilized a GWO approach that alters the value and speed at which a distribution network reaches a target to solve an operational model that incorporates a micro-energy network. GWO was selected largely due to its problem-solving abilities, speed, and search range. Using the suggested non-linear convergent factor formula and proportional weight made it simpler for the algorithm to discover items globally. The proportionate weight technique saved time, which is unprecedented in corporate history. Figure 3 depicts an agricultural park's micro-energy grid linked to node 11, with a maximum exchange power of 500 kW between the distribution network and the micro-energy grid. Six test routines were utilized to provide math tests. The findings were then compared to prove that the proposed strategy worked best. Based on the simulation, the researchers concluded that micro-grid distribution networks are secure, dependable, and cost-effective. The method improved voltage stability while lowering active power loss [59]. The DNR framework and the mGWO algorithm were utilized to reduce power loss in distribution networks. mGWO refers to the mGWO algorithm (DS). It increases the demand for power to charge electric vehicles on the road. This might be expensive and cause voltage drops. A grid of electric automobiles may transport energy. Electric vehicle owners may utilize their generated power to charge grid batteries or feed it back into the grid. This would be useful for future distribution. When parking an electric vehicle, how much electricity it consumes today and in the past could be considered. DFIGs are easy to use since they have PEC or PID interfaces. This interface connects the motor and stator. To generate energy, conventional inverters use the stator for electricity.

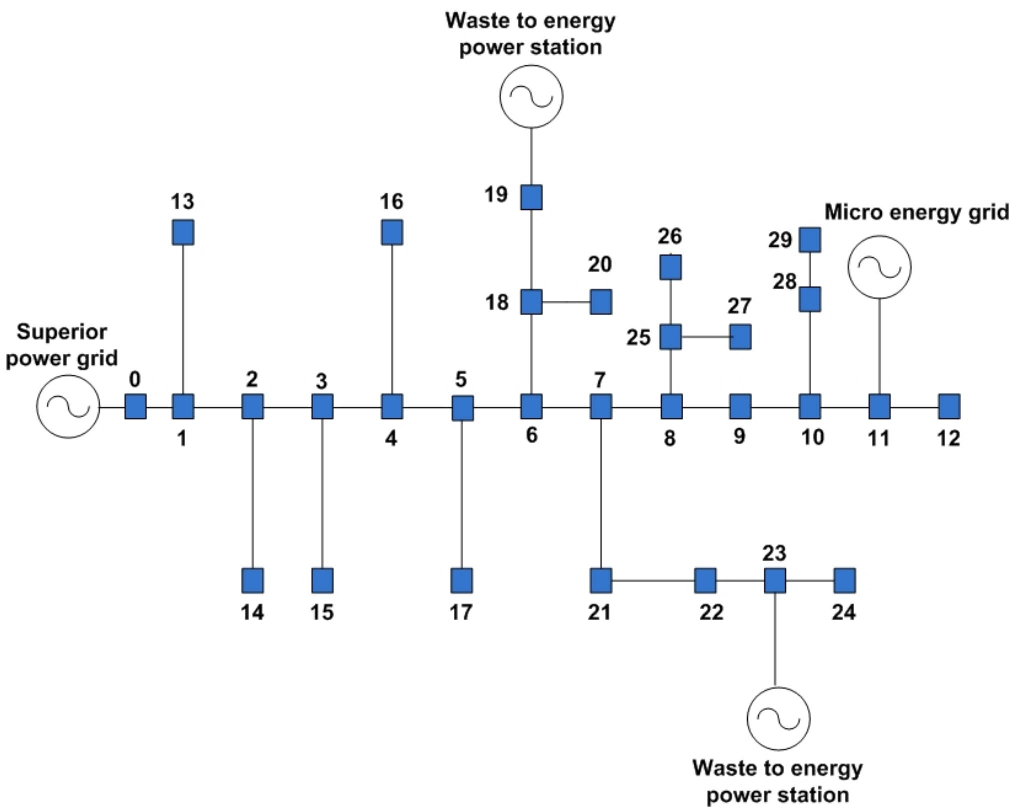

Figure 3. A micro-energy grid of an agricultural park.

When a new battery is acquired, the GSC and the RSC per unit can be managed. This generator can produce a list. The dual-purpose generator can be used sub- or super-synchronously. The battery may also be programmed to operate at various speeds, saving money, which represents a "slip" in business. A generator's stator winding sends energy to the grid while the rotor circuit receives it. In super-synchronous mode, both elements of the system provide electricity to the grid simultaneously. Aside from that, distribution system reconfiguration (DFR) is employed to effectively manage the V2G provision made available by electric cars using smart grid technology (EVs). GWO approaches are used to address the optimization issue that has been proposed. It has been shown that different case studies can be used to investigate the positive effects of DFR on a radial distribution system with 69 buses [60].

Figure 4 depicts a typical configuration of a doubly fed induction generator (DFIG). This figure contains two types of controllers, GSC and RSC. The two types contain executable code related to the GWO algorithm. The usage of unified power quality conditioners is utilized to demonstrate multi-objective planning for reactive power correction in radial distribution networks that are powered by wind energy (UPQC). It is decided to use the UPQC model, which is based on phase angle control (PAC). Achieving optimal performance of the UPQC-PAC requires concurrently decreasing numerous objective functions, such as grid power loss, the fraction of nodes suffering voltage drops, and the capacity of UPQC. The model that has been proposed is a non-linear optimization problem that is very difficult to solve. A probabilistic load flow technique based on a multi-objective grey wolf optimizer (MOGWO) is used to present a group of non-dominated solutions, and then a fuzzy set theory is used to determine the optimal response [61]. A simulation of a 33-bus distribution network was used to investigate the reliability of the method that was previously mentioned.

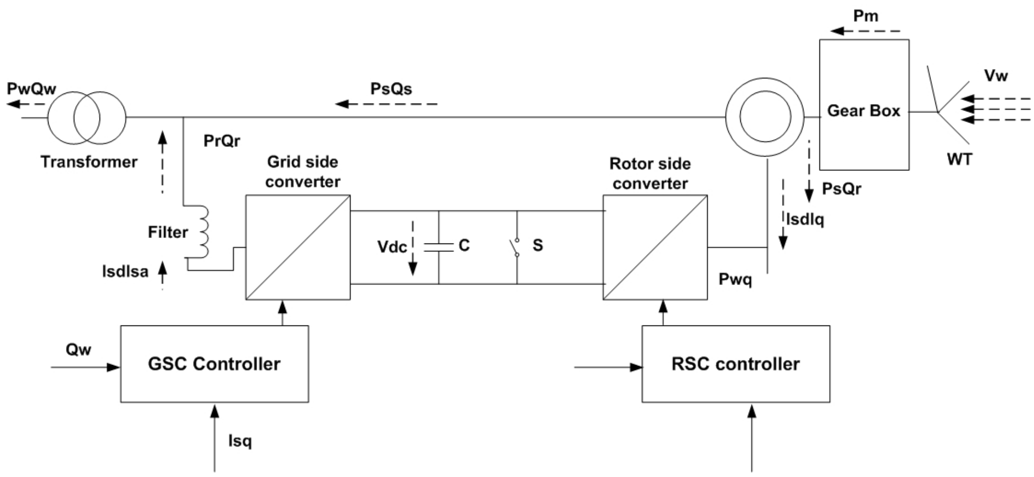

Figure 4. A typical configuration of a DFIG.

A smart distribution system's aim of active power loss reduction and voltage stability improvement is realized by suitable reconfiguration of the system, which is accomplished during the design phase. Renewable distributed generation (RDG) systems are distributed generation (DG) systems equipped with wind turbines and solar panels, among other items. Due to the availability of smart metering devices, it is possible to assess the present health of the network with pinpoint precision at any moment in time. Network conditions are taken into consideration to develop the optimal architecture. With the help of a newly proposed technique known as GWO, which is a version of the grey wolf algorithm, we were able to solve the problem of optimization. The validation condition in GWO is a retrieval validation, which entails comparing real retrieval products to values based on independent direct measurements of the same geophysical parameter. In situ measurements have been precise for validation purposes. To account for "smoothing error" and a priori information influence in retrieval products, the true profile is transformed as: $x_{sim} = x_a + A\,(x_{true} - x_a)$.

x_{sim} is the simulated retrieved profile, $\boldsymbol{x_{true}}$ is the true profile, $\boldsymbol{x_a}$ is the a priori profile, and $\boldsymbol{A}$ is the retrieval averaging kernel matrix. The elements of $\boldsymbol{x}$ linked with surface temperature and emissivity have been ignored since they are not dependable and independent [62].

To simultaneously minimize active power losses and utility operating costs while taking into consideration the uncertainties associated with vehicle load, it has been recommended to implement a demand response program and reconfiguration strategy that are integrated into one another. A demand response program based on a load management contract is created to control load consumption, and the GWO is employed for reconfiguration to optimize the configuration. The use of a conventional 69-bus system is being considered for authenticating the scheduled work. Losses were reduced by 57.2 percent with the implementation of reconfiguration and demand response, resulting in economic gains for both customers and utility companies [63].

Figure 5 explains how to reconfigure a distribution network (DN) using distribution network (DN) reconfiguration. For the charging station to maintain a healthy voltage profile and reduce power loss to the bare minimum, it must be placed at the most appropriate node possible. The assignment of electric vehicle charging stations in an IEEE 33-node radial distribution network has been accomplished. It has been determined that the distribution network would be divided into three zones to provide charging facilities in different portions of a particular geographic area. In each of the three sites, a charging station has been placed to facilitate the use of electric vehicles. To evaluate whether the issue is an optimization problem, researchers used the GWO and the whale optimization algorithm (WOA) to investigate the situation. Additionally, the GWO method was made to deal with the problem of changing the way feeders are set up in power distribution systems [64].

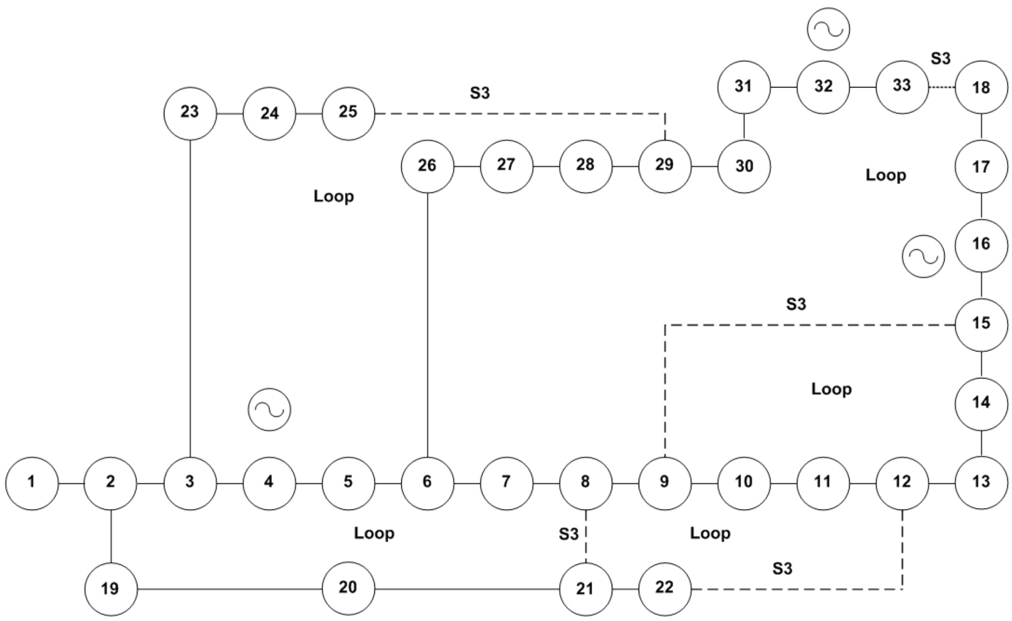

Figure 5. The distribution network (DN) reconfiguration.

The method makes use of a fitness function that corresponds to the optimal combination of switches in power distribution systems to address the issue of feeder reconfiguration in power distribution systems. For the reconfiguration problem to be solved successfully, it is important to simulate an objective function, which requires reducing the amount of real power lost. An algorithm for grey wolf optimization that is inspired by nature was used to restructure the power distribution system and discover the optimal switches that would result in the least amount of power loss throughout the distribution network [65]. The algorithm was designed to find the best switches for the least amount of power loss in the distribution network. Regarding smart grids, the reconfiguration of distribution networks (DNs) is being intensively researched to offer fault tolerance as well as the ability to quickly revert to an adaptable, dependable distribution network. Radiality is one of the most important parts of DN topology, so finding a good way to set up DN is an NP-hard optimization task. A DN is a distributed network with many nodes. This has resulted in the evaluation of the current manta ray foraging optimization (MRFO) approach in this context for the solution of comparable DN optimization challenges. Particle swarm optimization (PSO) and GWO are two common optimization methods that are used to compare the performance of MRFO and GWO. It is possible to study multiple operating scenarios for both the IEEE 33-bus and the IEEE 85-bus systems with the use of these optimization approaches, which are described below. A realistic reconfiguration of a DN that has the least amount of power loss while maintaining the optimum improved voltage profile is what we are trying to discover here. Based on the results of the simulations, the proposed MRFO approach provides efficient and remarkable performance in a wide range of operating conditions. This method has been proven to be efficient and long-lasting. Depending on the situation, the power loss reduction ratio is between 21% and 41%, and the voltage profile has been raised enough [66].

Multi-criteria optimization may be used to modify the distribution network to find the best design. Low-cost and technological methods for improving network attributes are discussed here. Unbalanced distribution networks can be redesigned to minimize power loss, voltage unbalance, voltage sag, and energy not supplied by customers while also improving voltage sag and using a new, improved coronavirus herd immunity optimizer algorithm. These methods are currently emerging. In systems to build up and scale distribution network systems, they beat GWO and HBBC, two other algorithms now under investigation, in terms of output quality. This is a reliable strategy [67,68]. People use grey wolf optimization and particle swarm optimization methods to cut their active power loss and make more money. IEEE 33- and IEEE 34-bus distribution systems are combined with these methods. Furthermore, the predicted strategy yields the same conclusion as the conventional GWO. This method, called the stochastic GWO approach, has been used to charge electric cars at the lowest possible cost [69].

It is possible to simplify complex multi-objective optimization problems by using this technique. Demand for electric cars is carefully regulated so that they may be charged at their desired level of charge while keeping the grid utility from being overwhelmed. A per-unit basis has been developed to guarantee that the charging fee is evenly spread among all electric cars [70]. Researchers have created a stochastic algorithm that draws inspiration from the workings of nature. A good mix between exploration and exploitation may be found in this game. An APF's current is characterized as the minimization of its current as a function with three inequality restrictions on its inputs and outputs. Twenty tests have been carried out on a 33-bus RDS to see how well the two algorithms work together [71].

GWO's Contribution to Smart Distribution System Active Power Loss Reduction

A new approach has emerged recently when it comes to maintaining a healthy balance between energy use and production. It offers several benefits over other solutions. Through the enhancement of voltage profiles and the reduction in power losses, it allows customers to create clean energy from their facilities. This metaheuristic optimization approach considers RDGs as well as other parameters to determine the ideal position of PV and WT units in an EDS design. As the creation of RDGs and the consumption of human energy vary over time, MOFs have been developed to reduce power loss, power modification, and the time necessary for an overcurrent relay to function properly (OCR activation duration). During a test, overcurrent relays are engaged and deactivated more often than normal (the IEEE 33-bus). The whale optimization algorithm (WOA) or the grey wolf optimization algorithm (GWO) can be used to cut down on active power losses in the bus test systems 33 and 69 [72,73].

As a result of the growth of distributed energy resources (DERs) and renewable energy sources (RESs) (EPRI), network operators will need to create new methods of controlling local supply and demand. In the next few years, distributed resources and renewable energy sources (DERs and REs) will play an increasingly important role in electricity distribution networks (RES). Demand response and energy storage technologies have transformed the retail energy industry in the United States, resulting in new arrangements for consumers [74]. The smart grid is becoming more popular as a method of power distribution. Furthermore, it is one of the most technologically advanced and cost-effective alternatives available on the market today. If the electric power system is to be both secure and effective, it is necessary to make changes to the way reactive power is distributed. To show how grey wolf optimization could be used to deal with issues with reactive power dispatch, the Lampung electric system could be used as an example to show how it could work [75].

Due to this design decision, a small decrease in active power is achieved. An optimization technique known as grey wolf optimization may be used to discover the most optimal reactive power dispatch. Active power losses are reduced because of this strategy, which maintains an extraordinarily high level of efficiency. With distributed generation (DG), three different voltage stability indices (IVM, VDI, and VSI) can be used to both decrease and improve power losses and voltage profiles. As part of the investigation, DC generators with a single power factor as well as those with a lower power factor (DGs) were examined to find the optimal size of autonomous production units in a power distribution network [76].

This information is needed to determine where and how many DG systems should be deployed. It may also be used to assess the proper size of any DG system. The project's primary goal is to reduce the amount of energy it consumes. Grey wolf swarm intelligence is often composed of a hierarchy of four distinct grey wolf species, of which each has its own intelligence. This has always been the case in the historical record. One of our company's first public statements was inspired by grey wolf behavior. Due to this growth in popularity, the use of swarm intelligence approaches has also expanded in the last several years. They have between 15 and 33 buses in their radial distribution networks, depending on the size of the network. The application of artificial intelligence (AI) in smart distribution networks may improve voltage regulation. Some people choose to work in a range of jobs because they have a strong desire to participate in a variety of activities. Active power losses, penalties for not meeting voltage level standards, and switching costs are some of the things we need to think about when we build something [77].

The approach is demonstrated with the use of an IEEE 34-node test feeder and a genuine feeder. The smart grid should be considered when designing distribution networks for solar energy production to improve the efficiency and reliability of solar energy generation [78]. An improved multi-period mixed-integer second-order cone formulation was created to improve the efficiency and effectiveness of distribution feeders. It is necessary to consider the following aspects when designing a power grid: photovoltaic inverters; discrete control equipment with a daily switching limit (such as tap changers and capacitor banks); solar energy; and unpredictability in load demand (such as wind turbines). A two-stage robust optimization framework may be employed to demonstrate how control actions may be implemented in both the first and second phases of the model. An out-of-sample technique was used to assess the results of the research. To make an informed decision, one must first consider how swiftly events have unfolded. Using data-driven techniques, it has been shown that it is possible to cut power losses by about 15% while also cutting hourly voltage violations by up to 98% [79].

5. Discussion

GWO has been used to minimize the amount of power loss in power systems. Most previous work has relied on the reconfiguration of the IEEE 33- and IEEE 69-bus radial distribution systems. However, due to their widespread use in power systems, some work has focused on using PV DGs during the reconfiguration process using the IEEE 33- and IEEE 69-bus systems. Optimal allocations and sizes of PVs and wind turbines (WTs) are presented in Table 1. In this section, we present the optimal data of the IEEE 33-bus systems in Tables 2–5 [1]. Furthermore, we present the optimal data regarding IEEE 69-bus systems in Tables 6–9 [1]. The device is being used to test and compare the many kinds of DG units. This is accomplished via the use of the IEEE 33-bus radial distribution scheme (RDS). Configuring the electric power distribution system is a critical activity for improving the efficiency of electric power distribution networks and should not be disregarded. As the reconfiguration problem has discrete choice variables in it, it is sometimes thought of as a hard combinatorial optimization problem.

Table 1. Optimal photovoltaic (PV) DG locations for the IEEE 33-bus test system using GWO.

Case	No of DGs	PV1 Site	PV2 Site	PV3 Site	PV4 Site
1	1	13	-----	-----	-----
2	1	31	-----	-----	-----
3	2	31	14	-----	-----
4	2	31	25	-----	-----
5	2	6	19	-----	-----
6	3	25	7	17	-----
7	3	32	7	11	-----
8	4	4	3	30	11

Table 2. Optimal photovoltaic (PV) DG sizes for the IEEE 33-bus test system using GWO.

Case	No of DGs	PV1 Size (kW)	PV2 Size (kW)	PV3 Size (kW)	PV4 Size (kW)
1	1	1000	-----	-----	-----
2	1	1000	-----	-----	-----
3	2	946	760	-----	-----
4	2	933	960	-----	-----
5	2	1000	439	-----	-----
6	3	959	1000	248	-----
7	3	360	810	343	-----
8	4	0	886	537	485

Table 3. Optimal wind turbine (WT) DG locations for the IEEE 33-bus test system using GWO.

Case	No of DGs	WT1 Site	WT2 Site	WT3 Site	WT4 Site
1	1	29	-----	-----	-----
2	2	6	14	-----	-----
3	1	6	-----	-----	-----
4	2	14	6	-----	-----
5	3	14	30	24	-----
6	2	30	13	-----	-----
7	3	24	14	30	-----
8	4	25	7	31	15

Table 4. Optimal wind turbine (WT) DG sizes for the IEEE 33-bus test system using GWO.

Case	No of DGs	WT1 Size (kW)	WT2 Size (kW)	WT3 Size (kW)	WT4 Size (kW)
1	1	1000	-----	-----	-----
2	2	1000	456	-----	-----
3	1	1000	-----	-----	-----
4	2	441	1000	-----	-----
5	3	418	659	708	-----
6	2	717	460	-----	-----
7	3	718	434	589	-----
8	4	513	517	411	338

Table 5. Optimal photovoltaic (PV) DG locations for the IEEE 69-bus test system using GWO.

Case	No of DGs	PV1 Site	PV2 Site	PV3 Site	PV4 Site
1	1	62	-----	-----	-----
2	1	11	-----	-----	-----
3	2	17	62	-----	-----
4	2	62	11	-----	-----
5	2	16	62	-----	-----
6	3	2	62	12	-----
7	3	16	62	24	-----
8	4	50	62	11	21

Table 6. Optimal photovoltaic (PV) DG sizes for the IEEE 69-bus test system using GWO.

Case	No of DGs	PV1 Size (kW)	PV2 Size (kW)	PV3 Size (kW)	PV4 Size (kW)
1	1	1000	-----	-----	-----
2	1	1000	-----	-----	-----
3	2	636	955	-----	-----
4	2	887	659	-----	-----
5	2	297	931	-----	-----
6	3	1000	904	569	-----
7	3	297	931	0	-----
8	4	868	895	325	188

Table 7. Optimal wind turbine (WT) DG locations for the IEEE 69-bus test system using GWO.

Case	No of DGs	WT1 Site	WT2 Site	WT3 Site	WT4 Site
1	1	61	-----	-----	-----
2	2	61	18	-----	-----
3	1	61	-----	-----	-----
4	2	61	18	-----	-----
5	3	61	21	11	-----
6	2	61	18	-----	-----
7	3	11	21	61	-----
8	4	61	12	13	18

Table 8. Optimal wind turbine (WT) DG sizes for the IEEE 69-bus test system using GWO.

Case	No of DGs	WT1 Size (kW)	WT2 Size (kW)	WT3 Size (kW)	WT4 Size (kW)
1	1	1000	-----	-----	-----
2	2	1000	329	-----	-----
3	1	1000	-----	-----	-----
4	2	1000	321	-----	-----
5	3	978	189	342	-----
6	2	1000	311	-----	-----
7	3	342	189	978	-----
8	4	993	240	0	199

Regarding the issue of feeder reconfiguration in power distribution networks, the GWO technique has been applied in several different research initiatives. Specifically, the technique uses a fitness function that corresponds to the optimal combination of switches in the system, which may be found in the literature. To achieve success while attempting to handle the reconfiguration issue, it is necessary to establish an objective function that minimizes the actual power loss. It is feasible to reconstruct the power distribution system and locate the ideal switches that result in the least amount of power loss in the distribution network by using the GWO algorithm, which was inspired by natural events. The GWO algorithm has been tested on a variety of typical IEEE 33-bus and IEEE 69-bus systems. The outcomes of the experiments demonstrated the importance of the GWO algorithm in decreasing active power losses in a network, which was previously unknown. Table 9 shows how the GWO algorithm assisted in reducing the amount of power used by the base structure, which was based on the structure of IEEE 33-bus systems at the time of creation. Figure 6 displays a statistical graph comparing the power losses in each related study. Statistical comparisons between various studies' findings in research on reducing power loss by applying a logarithm are seen in Figure 6. It can be seen in the figure that GWO can cut the power loss for the three DG units from 210.98 kW to 72.784 kW, which is significantly less than the original base case of 210.98 kW.

Table 9. The GWO algorithm contributes to reducing the amount of active power related to the base station.

GWO Contribution	Ratio of Reduction in Power Losses Using GWO %	Convergence Rate %	Ref
Maximum losses are 3.1 MW/h and lower losses are 2.25 MW/h.	27.42	19.64	[1]
Resolving network. Reconfiguration problems by optimizing the installation of various DG types.	30	44.4	[28]
Reduction in active power after three years with growth in load and optimal DG locations.	33.9	----	[34]
Power loss variation for one-year period.	12	----	[38]
As the number of DG units increases, the power loss reduces. For the GWO, the power loss reduces to 72.784 kW with an initial base case 210.98 kW for the 3 DG units.	65.5	21	[41]
There is a total harmonic distortion in voltage reduction using GWO.	17.67	54.54	[53]
GWO can reduce power loss from 130.07 (kW) in test system 1 to 90.6 (kW) in test system.	30.36	16.6	[61]
Power losses reduce to 141.82 kW with an initial base case 201.87 kW.	29.75	5.4	[69]
GWO can solve a constrained non-linear optimization problem of optimal placement and sizing of multiple active power filters.	47.83	80	[71]

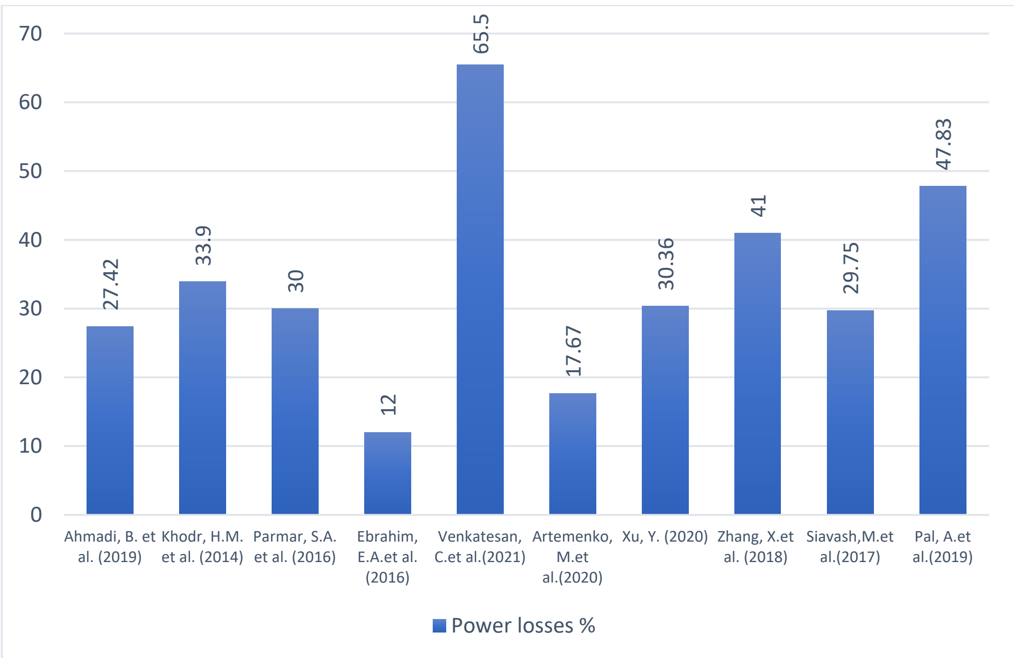

Figure 6. A statistical graph comparing the power losses in each related study [1,25,26,31,37,45,54,59,62,64].

Of all the approaches tried to date, optimization of distributed generator exports with a maximum DG output has the lowest percentage drop compared to the others. When the problem is constrained, it is shown that GWO can solve the non-linear optimization problem of optimal placement and size of multiple active power filters with a high reduction ratio. Depending on the circumstances, this ratio might be as high as 47.83% of the beginning point. Note that the optimal sizes and locations of the DGs depend on the structure of the bus systems and, accordingly, on the flow of power. Thus, the loss of active power depends on the scenario, most of which are presented in [27]. Figure 7 shows the power reduction in P-type (solar PV) DG installations depending on the reconfiguration process using GWO. This figure shows that the largest power reduction occurred during the installation process while the reconfiguration process was ongoing. Figure 8 shows a statistical calculation that compares the best fitness of GWO, particle swarm optimization (PSO), and the bat algorithm (BA).

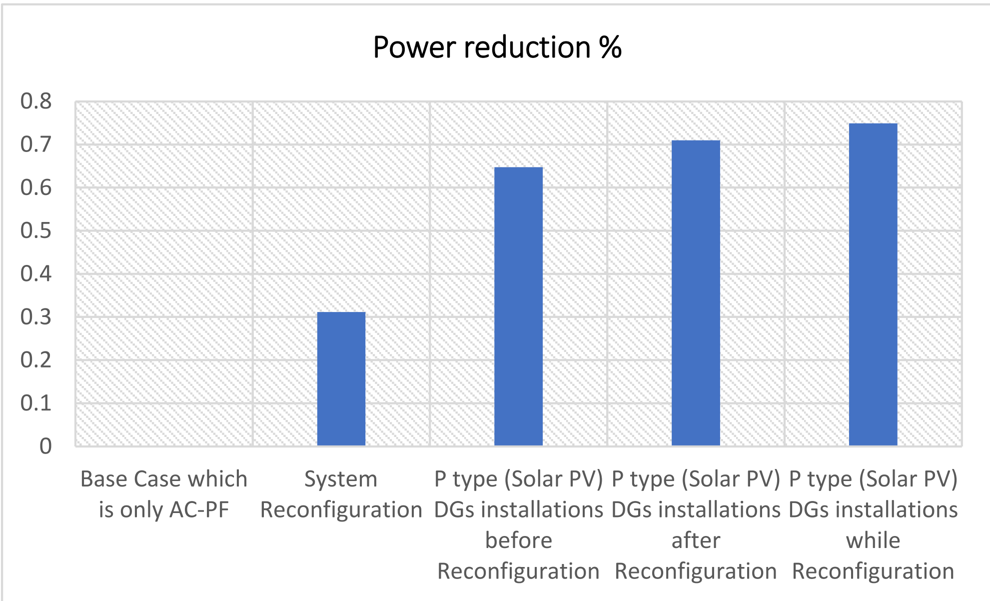

Figure 7. Power reduction in P-type (solar PV) DG installations depending on the reconfiguration process using GWO.

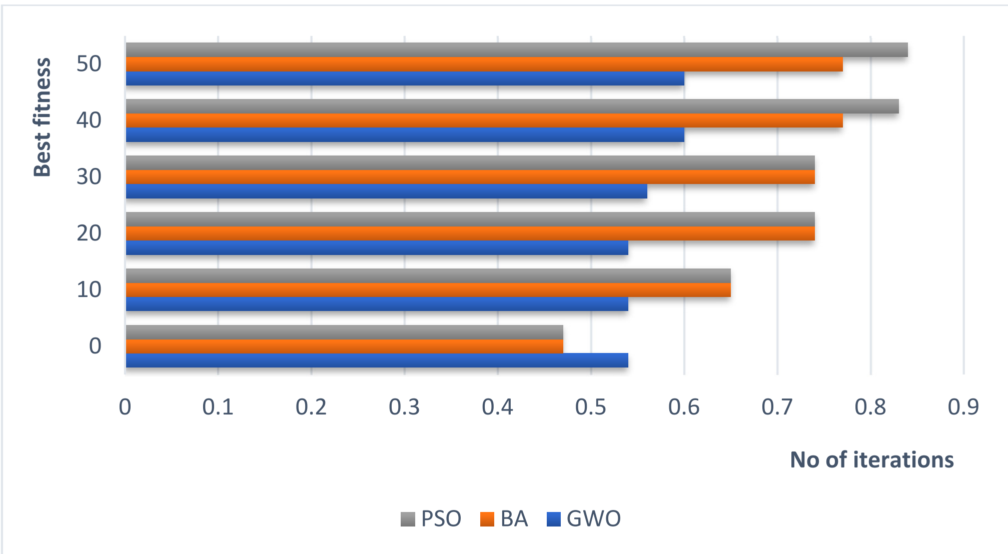

Figure 8. Comparison between the performance of GWO, BA, and PSO.

6. Conclusions

Active power losses have the potential to influence both the flow and distribution of power on transmission lines as well as the composition of power networks. Such active power losses may be caused by a variety of factors. It is possible to decrease power losses in the electrical system by utilizing an algorithm known as grey wolf optimization (GWO). The reduction in power losses depends on the arrangement of the components in the bus system. For quicker convergence and simpler implementation, GWO contains fewer decision variables and a smaller search area than other optimization algorithms. Transmission and distribution play a significant role in the electrical power system's overall efficiency and reliability. Each component of the power system is critical in the delivery of energy from the generation site to the final consumer or end-user. The GWO technique may be used to regulate the active power delivered by high-voltage direct-current network converters. Herein, the importance of GWO in minimizing active power losses in electrical power systems has been presented. This reduction in active power losses has been demonstrated in three primary components: generating, transmission, and distribution. The statistical results show that GWO can cut the power loss for the three DG units by 34.5%. The maximum ratio of reduction was 65.5% when the number of DG units increased to three. Furthermore, GWO can solve a constrained non-linear optimization problem of optimal placement and sizing of multiple active power filters. When the problem is constrained, it is shown that GWO can solve the non-linear optimization problem of optimal placement and size of multiple active power filters with a high reduction ratio. Depending on the circumstances, this ratio might be as high as 47.83% of the beginning point.

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