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Original Article

Allocation and Optimal Dimensioning of Distributed Generation Using Grey Wolf Optimized Cuckoo Search Algorithm

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Abstract *- Distributed Generation (DG) has become a complementary energy source for centralized generation, and it has gained a lot of space in distribution systems. In addition, the large plants involve high costs, large greenhouse gas emissions, and difficulty in obtaining environmental permits; these factors have also boosted the use of DG with renewable resources (wind, solar, and water). The core objective of this paper is to find an optimal solution for the dimensioning of Distributed Generation (DG) in distribution networks using a metaheuristic optimization technique. A novel algorithm, the grey wolf optimized cuckoo search algorithm, is used to obtain the low voltage connection between distribution transformers and end users. The DG units are coupled in the low-voltage distribution nodes, improving the voltage profiles and reducing the electrical losses generated by the existing distance of the conductors.*

Keywords *- Active power losses, Cuckoo Search algorithm, Distributed Generation, Grey Wolf Optimization.*

1. Introduction

With the rapid growth of the population and the accelerated adoption of new household technologies, energy demand has been rising continuously. The constant rise in demand has caused a continuous lack of supply, making it urgent to find more and more reliable ways to make energy [1]. Traditional large-scale plants that use nonrenewable resources like water, oil, gas, and coal are often located far from where the energy is used. This means that there are high transportation losses and expensive infrastructure growth [2]. So, carefully placing Distributed Generation (DG) from green energy sources near load centres has become a realistic and environmentally friendly option that makes electricity distribution systems work better and be more reliable. In order to protect their budgets, some countries have even limited the use of electricity systems that are spread out. Integrating green energy and DG systems is still very important for saving the earth and making life better, even with these limits. For example, hydropower plants have a big effect on river environments and the people who live nearby, even though they are considered "clean energy." In parallel, electricity markets worldwide are undergoing a paradigm shift. Large companies historically dependent on fossil fuels are divesting from conventional energy assets and investing heavily in clean energy technologies. Several countries have even restricted the use of autonomous (isolated) electrical systems to protect national economies. Despite these restrictions, the integration of renewable energy and DG systems remains essential for preserving the environment and improving the quality of life for the population. For example, in [3], hydropower plants have been shown to have big effects on the environment by changing river ecosystems and affecting the people who live nearby, even though they are considered clean energy. The damage to the earth is even worse when the problems caused by nonrenewable energy plants are added. This case shows how important it is to use DG as a main way to lower the damage that power production does to the environment. However, the rapid expansion of distributed generation presents its own challenges. Transmission and distribution networks were originally built so that power could move only in one direction from centralized plants. To handle two-way flows and irregular renewable sources, these networks need to be repowered, expanded, and structurally improved. The move towards smart grids, which actively coordinate DG units, requires accurate sizing, planning, and optimal distribution of distributed generation to ensure minimal losses, better voltage profiles, and higher reliability.

2. Literature Review

In recent years, several studies have been carried out on planning electrical distribution networks. According to the authors of [4], they point out that this problem began to grow in the mid-20th century, and they give a very concrete summary of the mathematical models and optimization algorithms of existing distribution networks, which they simplify into two basic methods: the method of exhaustion and the method of binding and branching [4].

On the other hand, the authors of [5] make studies of various types of algorithms for the reconfiguration of electrical distribution systems and their applications, with adaptation to the theory of graphs. These authors point out algorithms such as population-based algorithms, meta-heuristic techniques, the immune algorithm, evolutionary algorithm, taboo search, particle swarm optimization, and ant colony optimization, among others [5].

It is proposed to plan an electrical distribution network of both medium and low voltage, jointly integrated with DG units, with the objective of minimizing the total losses of the system, raising the voltage profiles and analyzing the possibility of increasing the resilience levels of the electrical system, in the event that a natural disaster occurs which results in a failure in the system, or if it is the case, this failure may occur for other reasons inherent to the electrical system, partially or fully feeding the distribution grid only with the use of DG units [6]. A mathematical model is developed so that its objective function is the minimization of the distance between each connecting branch [7, 8].

This paper aims to obtain the best possible configuration of DG units in distribution systems, so that technical losses are minimal. As will be shown in the results, losses significantly decrease due to energy injection by the DG unit. The reduction of losses accounted for in the results only covers the analyzed system and the distribution. However, there are cascade reductions, as the volume of energy injected directly into the distribution system is no longer transported by the transmission lines, as in the case of centralized generation. Other benefits provided to the system by the DG allocation are the postponement of investments to expand the network's capacity, increase reliability, the possibility of serving isolated communities, and improvement in voltage levels.

3. Novelty of Proposed Work

To fill the research gap, the present study proposes a Grey Wolf Optimized Cuckoo Search algorithm (GWOCS) for the optimal allocation and sizing of DG units. GWOCS gets a better balance between discovery and exploitation and faster completion than either algorithm alone. It does this by combining the leadership order and hunting mechanism of the Grey Wolf Optimizer with the brood parasitism behavior of the Cuckoo Search. The suggested method is different from other optimization methods because it is especially made to deal with the fact that DG planning in current distribution systems has more than one goal. This means that the results will be more accurate and stable. In Comparative Context and Literature Background, Different metaheuristic methods for DG planning have been studied in recent years. As an example, [4, 5] used GA and PSO to assign DG, which led to better loss minimization but longer processing times and local optima traps. Some ideas to speed up convergence are hybrid algorithms like ACO–PSO or CS–GA [6].

Still, not many studies have combined the Grey Wolf Optimizer and Cuckoo Search to use their unique strengths for DG placement and size. Also, previous research has mostly only looked at technical measures like lowering power loss and not at all at voltage stability scores or economic cost factors. These gaps can be fulfilled by using GWOCS to find the best way to assign and size DG units while keeping several goals in mind. The results show that the new method is better at reducing losses, improving voltage profiles, and using less computing power than previous ones. This makes it a useful and original tool for planning modern distribution networks.

4. Proposed Methodology

In keeping with this line of study from literature, this work suggests using the grey wolf optimized cuckoo search algorithm to address the DG allocation and dimensioning problem. The goal is to determine the optimal location for the DGs while accounting for the system's voltage stability.

4.1. Mathematical Modelling of the Problem

The actual losses of the system are calculated according to Equation (1):

$$P_r = \sum_{i=1}^{n} \sum_{j=1}^{n} A_{ij}\left(P_i P_j + Q_i Q_j\right) + B_{ij}\left(Q_i P_j - P_i Q_j\right) \tag{1}$$

Where,

$$A_{ij} = \frac{R_{ij}\cos(\delta_i - \delta_j)}{V_i V_j} \tag{2}$$

$$B_{ij} = \frac{R_{ij}\sin(\delta_i - \delta_j)}{V_i V_j} \tag{3}$$

Where p_r represents the real losses, p_i and Q_i are active and reactive power injections in bus i , respectively, R_{ij} is the line resistance between buses i and j, V_i and δ_i are voltage and angle in the bus , respectively, and n is the total number of buses in the system. The GWO-CS looks for the best values of the variables p_i, Q_i, V_i, and δ_i so that the real losses are minimal. The formulation of the optimization problem is as follows.

$$Min\ P_r \tag{4}$$

Subject to:

$$CH_i \cdot P_{DGi} + P_{Gi} - P_{Di} + \sum_{i=1}^{n} \sum_{j=1}^{n} f_{Pij} = 0 \quad (5)$$

$$CH_i \cdot Q_{DGi} + Q_{Gi} - Q_{Di} + \sum_{i=1}^{n} \sum_{j=1}^{n} f_{Qij} = 0 \quad (6)$$

$$P_{DGi}^{min} \leq P_{DGi} \leq P_{DGi}^{max} \quad (7)$$

$$Q_{DGi}^{min} \leq Q_{DGi} \leq Q_{DGi}^{max} \quad (8)$$

$$Z^{min} \leq Z \leq Z^{max} \quad (9)$$

In Equation (4), the objective function of the problem is defined, by which any proposed solution is evaluated. Constraints (5) and (6) are power balance equations in buses. With i meaning the bar, the variable CH_i represents a switch that turns DG on or off (7), p_{DGi}, is the active power injected into the network by DG, p_{Gi} is the active power generated, p_{Di} the demand for active power, f_{pij} is the active power flow between buses i and j, Q_{DGi} is the reactive power injected or consumed by DG, Q_{Gi} is the reactive power generated, Q_{Di} the reactive power demand, and f_{Qij} represents the reactive power flow between the bars i and j, The ranges in which the problem variables can assume feasible values (7), (9), and (9) are shown by the lower and upper bounds P_{DGi}^{min}, P_{DGi}^{max}, Q_{DGi}^{min}, Q_{DGi}^{max}, Z^{min} and Z^{max}, where Z is a generic vector with other variables contained in the GWO-CS.

4.2. Grey Wolf Optimized Cuckoo Search Algorithm

4.2.1. Cuckoo Search Algorithm

The parasitic behavior of young cuckoos is combined in CS with Lévy's flight to efficiently search for new nests. The Lévy flight, named after the French mathematician Paul Lévy, is a random walk model characterized by step length and obeying the power law, Equation (10) [9].

$$N(s) = s^{-1} \quad (10)$$

The probability distribution is called the stable distribution of the Lévy distribution. The length l of running or jumping steps is distributed according to the power law $P(l) = l^{-\mu}$ at $1 < \mu \leq 3$ [10].

CS is a metaheuristic recently established by the authors of [11], originally developed to solve multimodal functions. The following ideas are taken as a basis:

- Each cuckoo lays one egg after another and chooses a nest at random.
- Good quality nests can be passed on to new generations.
- The number of host nests is fixed, and the host bird can detect eggs laid by cuckoos with a probability $p_\alpha \in [0,1]$.

Cuckoo i generates a new solution $x_i^{(t+1)}$according to Equation (11) via Lévy's flight:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus Lévy(s, \lambda) \quad (11)$$

Where α is the length of the step taken after the Lévy flight distribution in Equation (12):

$$Lévy(s, \lambda) \sim s^{-\lambda}, \quad (1 < \lambda \leq 3) \quad (12)$$

Which has variance and infinite mean value [11]. Where s is the step size of the Lévy distribution.

The search for a new random solution $x^{(t+1)}$ using the Lévy flight, is carried out according to the following formula:

$$X^{(t+1)} = X^{(t)} + \alpha \oplus Lévy(\lambda) \quad (13)$$

4.2.2. Grey Wolf Optimization Cuckoo Search Algorithm

This section describes the proposed GWO-CS algorithm designed to select the optimal solution for optimizing the model. The GWO-CS algorithm was developed by modifying the GWO using a population-based Cuckoo Search (CS) algorithm. GWO is a metaheuristic algorithm developed based on the hunting behavior of gray wolves, such as when they hunt, circle, and attack their prey. In the GWO-CS. In the algorithm, the GWO location update is modified to account for the CS update equation so that the proposed algorithm provides faster convergence. The set of ideal polarization limits is calculated by the GWO-CS by following these steps:

To formulate the position update in the GWO-CS algorithm, the Equation is modified to include a fourth term in the numerator, as shown in the following Equation (14):

$$\vec{G}(t+1) = \frac{\vec{G}_1 + \vec{G}_2 + \vec{G}_3 + \vec{G}_4}{4} \quad (14)$$

Where $\vec{G}_1$, $\vec{G}_2$, and $\vec{G}_3$ are hunting agents after the best hunting agents G_α, the second and third best hunting agents are G_β and G_δ. Where $\vec{G}_4$ the position vector is projected using the CS update rule. CS is a metaheuristic algorithm based on reproductive behaviour, that is, the parasitism of chickens, cuckoos, according to the flight characteristics of Lévy birds. Each egg in the nest is a solution that is replaced with a better one. This behaviour is used to update positions in the proposed GWO-CS algorithm using the term, defined as follows:

$$\vec{G}_4 = \vec{G}_t + \gamma \oplus Lévy\ (\lambda) \quad (15)$$

Where $\vec{G}_t$ the agent's position in the current iteration is, is the step size, which ranges from 0 to 1, and is multiplied by the input. $Lévy\ (\lambda)$ is the Lévy flight equation that provides a random walk and is defined as $Lévy \sim v = (t - \lambda)$, where λ is a parameter whose values are in the interval [1, 3]. With the advent of $\vec{G}_4$, the proposed algorithm becomes more efficient as it explores the search space using Lévy flights.

Pseudo Code for GWO-CS

Initialize Grey Wolf Population $G_i = (i = 1,2, \ldots, n)$
Assign parameters a, A *and* C
Calculate the fitness value of each agent.
Find the values of G_α, G_β and G_δ
G_α *= Agent with the best position in the population*
G_β*= Agent with the second-best position in the population*
G_δ*= Agent with the third-best position in the population*
while (t< Maximum number of iterations)
for each agent
Find the positions of the available search agents by Equation (15).
update.
end for
Update parameters a, A *and* C

Calculate the fitness value of each agent

Calculate $\boldsymbol{G_\alpha}$, $\boldsymbol{G_\beta}$ and $\boldsymbol{G_\delta}$ *parameters*
t = t+1
end while
return $\boldsymbol{G_\alpha}$,

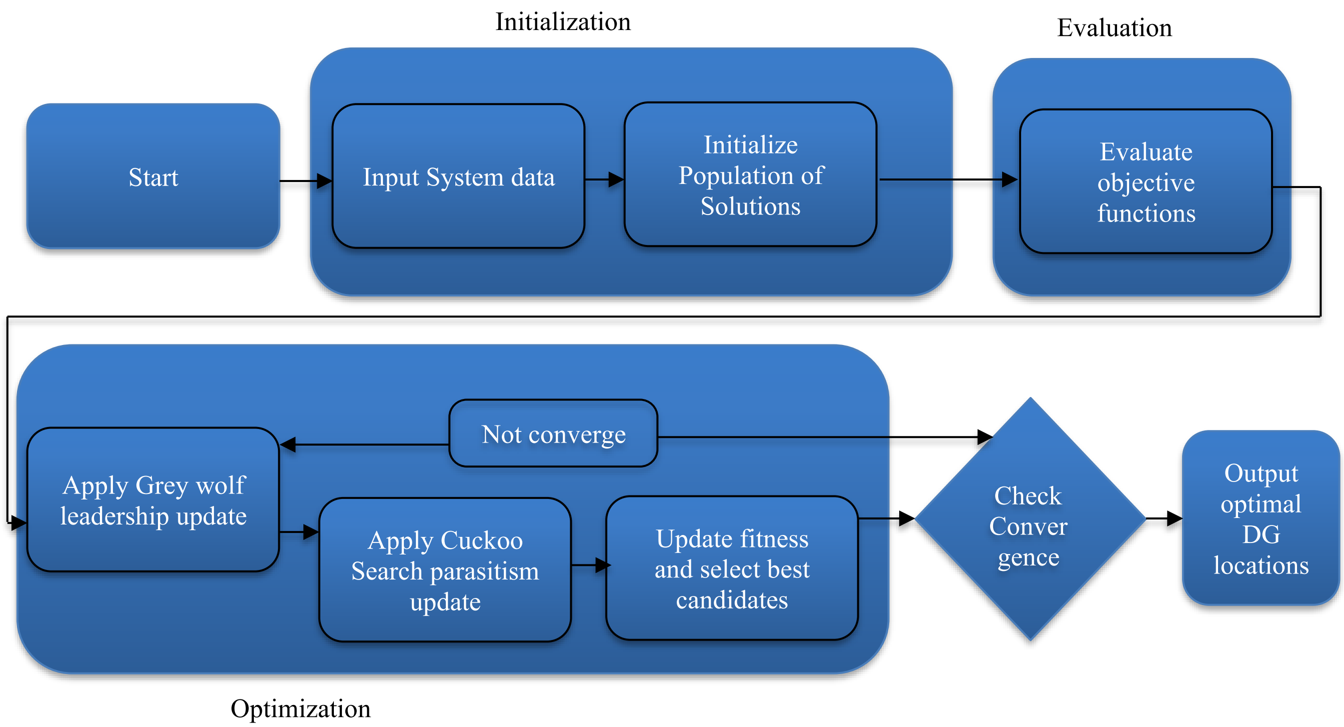

Fig. 1 Flowchart of the proposed method

5. Simulation Results

As mentioned in the previous section, the flow chart steps shown in Figure 1 have been followed, and the results have been extracted accordingly.

The graphs below represent the results obtained: The impact of DG on active and reactive losses both before and after DG deployment is shown in Figures 2 and 3.

Losses have been shown to be decreasing with Types 1, 2, and 4 DG. Of all these varieties, Type 4 DG is exhibiting encouraging outcomes.

The precise comparison and effects of applying different DG locations on the voltage profiles of various Buses are depicted in Figure 4. In this instance, Type 4 DG appears to be more promising than any other Type of DG. Figure 5 illustrates how both algorithms-with and without DG-have been utilized to lower active reactive losses in the distribution system, as was previously indicated in the objective of the article.

Additionally, it enables the keeping of DGs at several locations to ascertain the ideal placement. Table 1 makes it very evident that the GWO-CS algorithm was employed to compute and compare the power loss when Dg was placed at bus number six, as well as active and reactive power.

The outcome clearly indicates that this is the greatest option with the fewest losses.

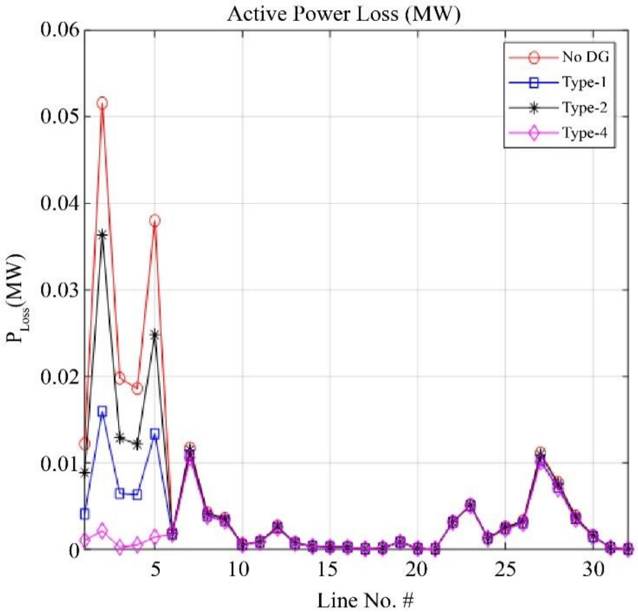

Fig. 2 Comparison of active power losses for no DG and DG placement

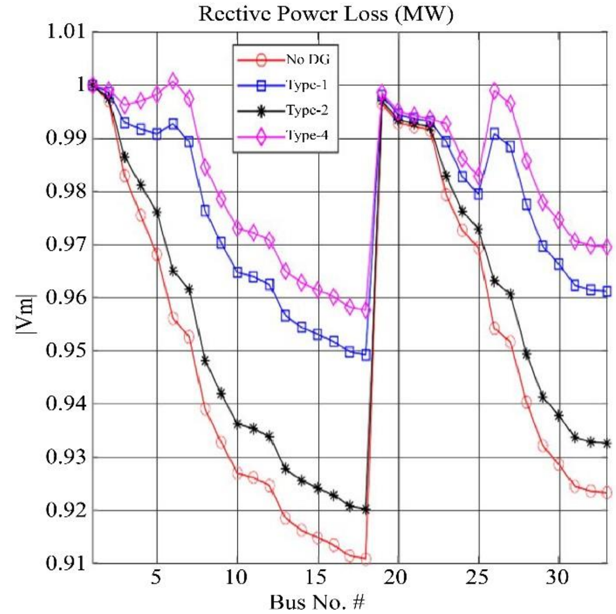

Fig. 4 Comparison of the voltage profile for no DG and DG placement

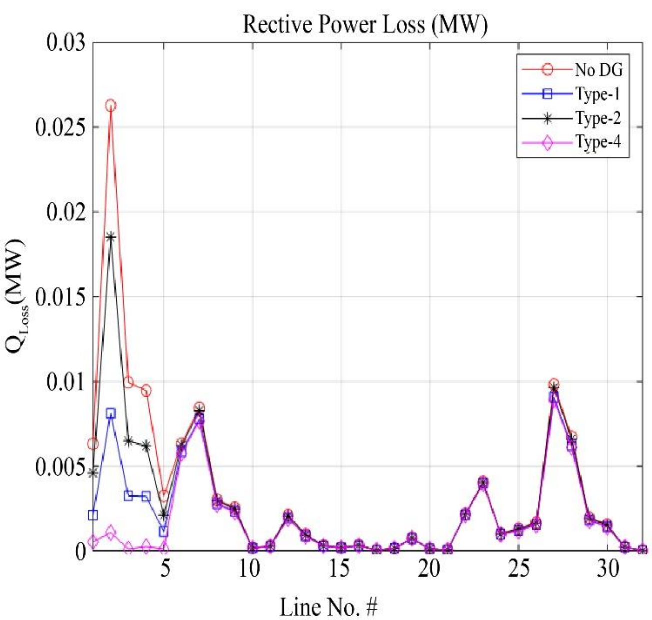

Fig. 3 Comparison of reactive power losses for no DG and DG placement

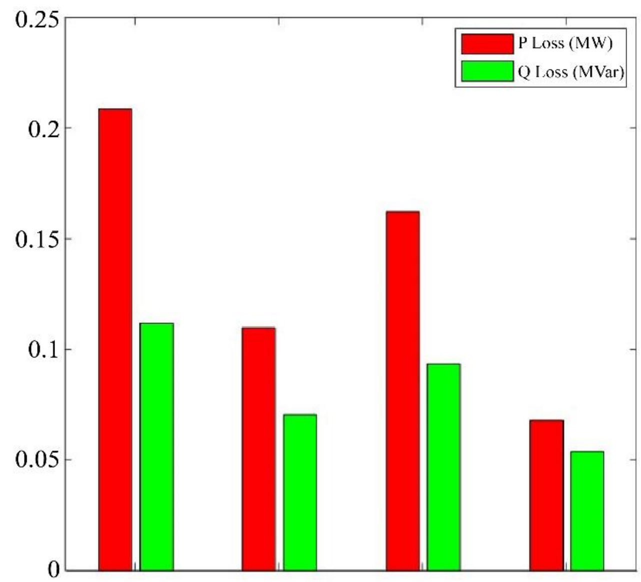

Fig. 5 Comparison of active and reactive power loss minimization with no DG and DG placement

Table 1. Comparative analysis of results

Distribution of bus types	Bus number	Power loss with no DG placement		Power loss with optimal DG placement using GWO-CS algorithm	
		Active power loss (MW)	Reactive power loss (MVAr)	Active power loss (MW)	Reactive power loss (MVAr)
Type-I	6	2.6110	-	0.1100	0.0700
Type-II	6	-	1.7705	0.1620	0.0930
Type-IV	6	2.580	1.7550	0.0680	0.0540

6. Conclusion

Two radial electrical energy distribution systems disseminated in the specialized literature were considered for evaluation of the proposed methodology. In the simulations carried out here, the objective is to minimize technical losses in the energy distribution system through the allocation and optimal sizing of distributed generation units, with these generations being active and/or reactive. Therefore, the proposed methodology makes use of bio-inspired optimization to determine the optimal allocation of distributed generators and an optimal power flow in the sizing of active and/or reactive power dispatch. Beyond technical improvements, the study highlights several practical implications, including reduced operational costs, improved grid reliability, and enhanced integration of renewable resources into existing networks. However, certain limitations must be acknowledged, such as the dependence on accurate load forecasting, scalability challenges for large networks, and the need for high-quality data for precise modeling.

References

[1] Noman Bashir et al., "Lifetime Maximization of Lead-Acid Batteries in Small Scale UPS and Distributed Generation Systems," *2017 IEEE Manchester PowerTech*, Manchester, UK, pp. 1-6, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[2] Priyanka Chaudhary, and M. Rizwan, "Voltage Regulation Mitigation Techniques in Distribution System with High PV Penetration: A Review," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 3279-3287, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[3] Xibao Xu et al., "Unravelling the Effects of Large-Scale Ecological Programs on Ecological Rehabilitation of China's Three Gorges Dam," *Journal of Cleaner Production*, vol. 256, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Muntather Almusawi et al., "Chaotic Grey Wolf Optimization for Energy-Efficient Clustering and Routing in Wireless Sensor Networks," *2024 International Conference on Integrated Circuits and Communication Systems (ICICACS)*, Raichur, India, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] M. Naga Raju et al., "A New Optimization Approach Based on Firefly and Cuckoo Search Algorithm for Dynamic Multi-Objective Optimization Problem in Workflow Scheduling," *2023 International Conference on Evolutionary Algorithms and Soft Computing Techniques (EASCT)*, Bengaluru, India, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] S. Lakshmikanth et al., "A Novel DC-DC Converter Design for Electric Vehicles Based on PID Control Optimized by a Hybrid Grey Wolf-Cuckoo Search Algorithm," *2025 6th International Conference for Emerging Technology (INCET)*, Belgaum, India, pp. 1-8, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[7] Wenxiao Wang et al., "Multi-UAV Path Planning Based on Grey Wolf-Cuckoo Composite Optimization Algorithm in Mountainous Environments," *2025 40th Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, Zhengzhou, China, pp. 689-693, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] Hengyi Huang, "Research on Multi-UAV Track Planning by Improving Grey Wolf Fusion Cuckoo Algorithm," *2024 9th International Conference on Robotics and Automation Engineering (ICRAE)*, Singapore, pp. 12-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Hua Fu, Zhaoliang Zhang, and Hui Zhang, "Research on Transformer Fault Diagnosis Based on GWO-CS Optimized SVM," *2023 5th International Conference on Intelligent Control, Measurement and Signal Processing (ICMSP)*, Chengdu, China, pp. 278-281, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Ritika Tilwalia, Anisha Jain, and Deepak Gupta, "Optimization of Electricity Consumption using Grey Wolf Algorithm," *2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA)*, Greater Noida, India, pp. 401-407, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] G. Sreeramulu Mahesh et al., "An Optimized Filter Design with Cuckoo Search Algorithm for Industrial Microgrids," *2023 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication (IConSCEPT)*, Karaikal, India, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]