Golden Jackal Algorithm for Optimal Size and Location of Distributed Generation in Unbalanced Distribution Networks

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ABSTRACT

The Golden Jackal Optimization algorithm (GJO) is used in this study to address the problem of optimal placement and sizing of single and multiple distributed generators (DGs) on the IEEE123 test system. The proposed approach attempts to minimize the total power loss of the system while respecting the voltage and power limits. The GJO algorithm is a new meta-heuristic algorithm inspired by the behavior of the golden jackal in the wild. The GJO algorithm is used to find the ideal location and sizing of DGs, and the results are compared with those obtained by other meta-heuristic techniques. According to the simulation results, the GJO method outperforms other metaheuristic algorithms in terms of problem-solving, while satisfying all constraints of the system. The proposed approach also demonstrates the effectiveness of the GJO algorithm in the solution of complex optimization problems in power systems.

I. Introduction

The persistent rise in power demand is saturating the capacity of distribution networks in many regions; however, this situation can be alleviated by connecting distributed generators (DGs) in the form of firm generation or intermittent renewable energy sources such as wind and solar farms [1]. It is well known that DGs in a distribution network can compensate for transmission network energy demand, improve voltage profile in feeders, increase reliability, and reduce losses. the integration of distributed generators (DG) units causes changes that create several technical challenges [2]. A true description of grid behavior also requires advanced studies and trustworthy algorithms due to the complexity of these new systems' modeling, Due to complex methods with graphical interfaces that have developed from basic voltage drop calculators of balanced loads, grid characteristics can be determined and quantified [3].

Distributed Generation (DG) placement and sizing is a critical issue in power system planning due to the increasing demand for electricity and the integration of renewable energy sources. The placement and sizing of DG units can significantly affect the overall performance of the system in terms of reliability, efficiency, and cost. Metaheuristics are optimization techniques that can be used to solve complex problems such as DG placement and sizing in power systems [4]. Metaheuristic algorithms are capable of finding near-optimal solutions quickly, making them a popular choice in power system planning. This approach involves searching for the best combination of DG placement and sizing by iteratively evaluating a large set of candidate solutions. In this way, metaheuristic algorithms can help power system operators make informed decisions about where to place and how to size DG units to optimize system performance.

In recent years, metaheuristic optimization algorithms have emerged as promising tools for solving this problem, as they can efficiently search the solution space and find high-quality solutions that are difficult to obtain using traditional optimization techniques.

Metaheuristic optimization algorithms are a class of heuristic search algorithms that can explore the solution space by iteratively generating and evaluating candidate solutions. These algorithms are inspired by natural phenomena, such as evolution, swarm behavior, or animal foraging, and can efficiently handle non-linear, non-convex, and multi-objective optimization problems. By leveraging the strengths of metaheuristic optimization algorithms, researchers and practitioners have been able to determine the optimal placement and sizing of DG units in various power systems, ranging from small microgrids to large-scale power grids [5].

The use of metaheuristic optimization algorithms for determining the optimal placement and sizing of DG units has several advantages over traditional optimization techniques. First, metaheuristic algorithms can handle complex and non-linear objective functions that are difficult to optimize using traditional techniques. Second, metaheuristic algorithms can efficiently search the solution space and find high-quality solutions in a reasonable amount of time. Third, metaheuristic algorithms are flexible and can be adapted to different types of DG units and power grid configurations [5-16].

In this context, this paper aims to test the performance of one of the metaheuristic optimization algorithms (GJO) for determining the optimal placement and sizing of DG units in a power system. The paper will also discuss the advantages and limitations of this algorithm and provide insights into future research directions in this field.

II. OpenDSS simulation platform

II.1. OpenDSS software

The American Electric Power Research Institute created OpenDSS (The Open Distribution System Simulator), a modeling and simulating tool for distribution systems. The OpenDSS is a simulator created particularly to simulate electrical power distribution systems. The majority of power distribution planning analyses related to the connecting of distributed generation (DG) to utility networks are supported by OpenDSS. Additionally, it enables a wide variety of additional frequency-domain circuit simulations that are frequently carried out on utility electric power distribution systems. Compared to many other tools, including commercial solutions, it depicts imbalanced circumstances, stochastic processes, and other features of electrical power distribution networks and equipment in far more detail. Other programs can use OpenDSS to drive highly customized simulations, Monte Carlo analysis, etc. through COM (The Component Object Model) and scripting interfaces. Through automated processes, scripting, or dynamic linking, users can define their own models [6].

II.2. PV System Element Model for OpenDSS

A schematic of the photovoltaic system model used by the OpenDSS program is shown in Figure 2. The present version of the model combines the generator photovoltaic and the inverter to perform simulations with a time interval greater than or equal to 1 second. Thus, it is assumed that the inverter can quickly determine the maximum power point (MP) of the panel, simplifying the individual, solar panel, and inverter component modeling. The majority of research involving connections with the distribution network ought to be compatible with this strategy [6].

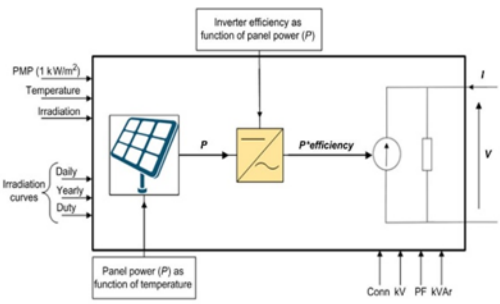

Figure 1. The PVSystem Component Model Block Diagram [6].

The photovoltaic system is an energy conversion element. Basically, the model has an active power injected at the interconnection point P, which is a function of irradiation, temperature, converter efficiency, network voltage, and the Panel's nominal power at the point of maximum power (Pmp). A Pmp applied at the required temperature (25°C), and an irradiation of 1, $0kW/m2$, the power value at the panel output in an instant $t0$, is calculated as follow [7]:

$$P(t0) = Pmp(1kW / m^2).irrad(pu)(t0).irrad(base).Pmp(pu,T(t0)) \quad (1)$$

P: Panel output power

Pmp(1kW/m2): Maximum power at the rated power level

Irrad(pu)(t0): Irradiance value in pu at the moment $t0$

Irrad(base): Maximum irradiance value on the selected day

Pmp(pu, T(t0)): Pmp correction factor as a function of temperature at the time $t0$

The active power supplied by the photovoltaic system is presented in Equation 2:

$$P_{active}(t) = P(t).eff(P_{active}(t)) \quad (2)$$

eff (Pactive (t)): Inverter efficiency for a given output power.

Separately from the active power, reactive power is specified. It can be specified as fixed kVAR values or fixed power factor values. The model maintains a constant output power factor if the PF parameter is specified until the PF property is updated (default mode). Regardless of the current value of the panel power, if the Kvar attribute is given, it is assumed that the inverter will maintain that value. If the inverter's rated kVA is exceeded, the actual kVAR output is reduced [6].

II.3. MATLAB OpenDSS co-simulation

Co-simulation is a technique used to integrate different simulation tools by exchanging data between them in real. In the context of power systems, co-simulation between MATLAB and OpenDSS (Open Distribution System Simulator) can be used to study the behavior of distribution systems under different operating conditions [8].

MATLAB is a programming language and numerical computation environment commonly used for power system modeling and simulation. OpenDSS is a free and open-source distribution system simulator that is widely used for distribution system analysis and design.

A simulation between MATLAB and OpenDSS involves running MATLAB and OpenDSS in parallel and exchanging data between them. MATLAB can be used to generate input data for OpenDSS, such as load profiles and fault data. OpenDSS can then simulate the distribution system and provide output data, such as voltage and current profiles, to MATLAB.

To perform a co-simulation between MATLAB and OpenDSS, different approaches can be used. One approach is to use MATLAB's External Mode function to communicate with OpenDSS. Another approach is to use the OpenDSS Direct DLL to call OpenDSS functions directly from MATLAB.

Overall, co-simulation between MATLAB and OpenDSS can be a powerful tool for the simulation and analysis of distribution systems and for developing control algorithms for distribution system components.

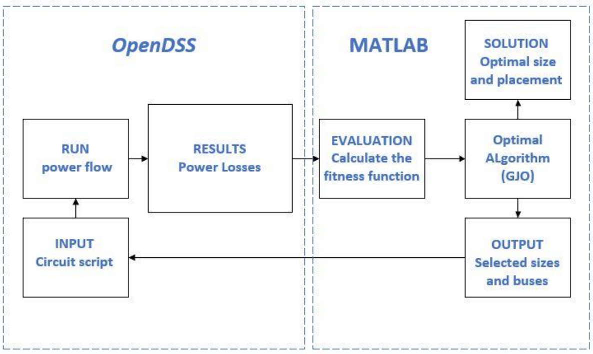

Figure 2. Co-simulation between MATLAB and OpenDSS.

III. PROBLEM FORMULATION

III.1. Objective function

The aim of this work is to study the impact of integrating Distributed Generators (DG) in radial distribution networks on active and reactive power losses and the voltage profile. The objective function is to minimize the total power losses and improve the voltage profile of the system by optimal placement and sizing of the DGs. The optimization problem can be formulated as follows:

$$min\ f\left(x,u\right) \tag{3}$$

Subject to:

$$g\left(x,u\right)=0 \tag{4}$$

$$h\left(x,u\right)\leq 0 \tag{5}$$

where F is the objective function that needs to be minimized, and x is the vector of dependent variables like node voltages and bus loads. u is the vector of independent variables mainly the DGs size and location. g is the equality constraints that represent the load flow equations. h is the system operating constraints like allowable sizes of DGs and voltage stability.

$$x=[\mathrm{V}_{1,\ldots..,}\mathrm{V}_{n},P_{L},\mathrm{Q}_{L}] \tag{6}$$

$$u=[\mathrm{P}_{DG1},\ldots.,\mathrm{P}_{DGn},\mathrm{Q}_{DG1},\ldots.,\mathrm{Q}_{DGn},\mathrm{DG}_{loc_{1}},\ldots.,\mathrm{DG}_{loc_{n}}] \tag{7}$$

Here, x is the vector of dependent variables, such as node voltages and bus loads, and F is the objective function that needs to be minimized.

The primary independent variables in vector u are the size and position of the DGs. The equality constraints, or g, are what the load flow equations are represented by. H stands for the system operational constraints, which include voltage stability and permissible DG sizes.

Our aim function shows the overall power loss of the given distribution network because the major goal of this study is to reinforce the imbalanced multiphase distribution network while lowering operational costs. The objective function is therefore given as

$$f_{1}=\sum_{i=1}^{N}P_{L_{i}} \tag{8}$$

Where P_{L_i} is the power loss in each distribution node (or lines) and N is the number of nodes (or lines).

In the scope of this work, strengthening distribution networks means improving the voltage profile of the system. This can be achieved by enforcing the voltage at every node in the distribution system to be within the acceptable range of 0.95 pu and 1.05 pu. Hence the following inequality constraint is applied to ensure the acceptable voltage profile of the distribution network.

$$V^{\min}\leq V_{i}\leq V^{\max},i=1,\ldots..\mathrm{N} \tag{9}$$

$$P_{DG}^{\min}\leq P_{DG_{i}}\leq P_{DG}^{\max},\ldots.\mathrm{DG}_{units}. \tag{10}$$

$$Q_{DG}^{\min}\leq Q_{DG_{i}}\leq Q_{DG}^{\max},\ldots.\mathrm{DG}_{units}. \tag{11}$$

where $P_{DG}^{\min}$ and $P_{DG}^{\max}$ are the available minimum and maximum real powers and $Q_{DG}^{\min}$ and $Q_{DG}^{\max}$ are the available minimum and maximum reactive powers.

III.2. Golden Jackal Optimization Algorithm

Chopra et al. provide the GJO approach [9]. The pair-bonding hunting behavior of golden jackals in nature served as the model for GJO. The chorus howling of a couple of golden jackals reveals their symbiotic relationship. The golden jackal's howling is seen as some sort of engagement. Golden jackals alert others to their location and communicate with those individuals to find their prey by their choral sighing. In the GJA, a population of golden jackals is randomly distributed in the search space, and their positions are updated iteratively using a set of rules that mimic the hunting and foraging behavior of jackals. The scaling factors c(i) and d(i) control the search direction and distance of each golden jackal, while the best and worst golden jackals about each individual are used to update their position. The global best golden jackal is updated based on the fitness values of all golden jackals in the population.

During the initialization phase, a randomly distributed set of prey position matrices is generated by Equation (1):

$$\begin{bmatrix} Y_{1,1} \cdots Y_{1,j} \cdots Y_{1,n} \\ Y_{2,1} \cdots Y_{2,j} \cdots Y_{2,n} \\ \cdots \; \cdots \; \cdots \; \cdots \; \cdots \\ \vdots \; \vdots \; \vdots \; \vdots \; \vdots \\ Y_{N,1} \cdots Y_{N,j} \cdots Y_{N,n} \end{bmatrix} \tag{12}$$

where N denotes the number of prey populations and n denotes dimensions.

The mathematical model of the golden jackal's hunt is as follows (|E| > 1):

$$Y_1(t) = Y_M(t) - E.\left|Y_M(t) - rl.\mathrm{Prey}(t)\right| \tag{13}$$

$$Y_2(t) = Y_{FM}(t) - E.\left|Y_{FM}(t) - rl.\mathrm{Prey}(t)\right| \tag{14}$$

where t is the current iteration, YM(t) indicates the position of the male golden jackal, YFM (t) indicates the position of the female, and Prey(t) is the position vector of the prey. Y1(t) and Y2(t) are the updated positions of the male and female golden jackals. E is the evading energy of prey and is calculated as follows:

$$E = E_1.E_0 \tag{15}$$

$$E_1 = c_1.(1-(t/\ T)) \tag{16}$$

where E is a random number in the range [–1, 1], indicating the prey's initial energy; T represents the maximum number of iterations; c1 is the default constant set to 1.5; and E1 denotes the prey's decreasing energy.

Equations (13) and (14), denote the distance between the golden jackal and the prey, and 'rl' is the vector of random numbers calculated by the Levy flight function.

$$rl = 0.05.\mathrm{LF}(y) \tag{17}$$

$$LF(y) = 0.01 \times (\mu \times \sigma) / \left(\left|\nu^{(1/\beta)}\right|\right)$$
$$\sigma = \left\{ \frac{\Gamma(1+\beta) \times \sin(\pi\beta / 2)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times \left(2^{\beta-1}\right)} \right\}^{1/\beta} \tag{18}$$

where u and v are random values in (0, 1) and β is the default constant set to 1.5.

$$Y(t+1) = \frac{Y_1(t) + Y_2(t)}{2} \tag{19}$$

where Y (t + 1) is the updated position of the prey based on the male and the female golden jackals.

When the prey is harassed by the golden jackals, the evading energy is decreased. The mathematical model of the golden jackals surrounding prey and devouring it is as follows (|E| ≤ 1):

$$Y_1(t) = Y_M(t) - E.\left|rl.Y_M(t) - \mathrm{Prey}(t)\right| \tag{20}$$

$$Y_1(t) = Y_{FM}(t) - E.\left|rl.Y_{FM}(t) - \mathrm{Prey}(t)\right| \tag{21}$$

Here is the pseudo-code implementation of the GJO algorithm:

Pseudo-Code of GJO algorithm
Inputs: population size N of golden jackals and the maximum number of iterations T.
Outputs: The location of prey and its fitness value
Initialize the random prey population Y_i (i = 1, 2, . . ., N)
While (t < T)
Calculate the fitness values of prey.
Y_1 = best prey individual (Male Jackal Position)
Y_2 = second best prey individual (Female Jackal Position)
for (each prey individual)
Update the evading energy 'E' using Equations (15) and (17)
Update 'rl' using Equations (17) and (18)
If (|E| < 1)
Update the prey position using Equations (13), (14), and (19)
If (|E| > 1)
Update the prey position using Equations (19), (20), and (21)
end for
t = t + 1
end while
return Y_1

Overall, the GJO algorithm aims to find the optimal solution to a given optimization problem by mimicking the foraging behavior of golden jackals in the wild, where the jackals search for food while balancing their exploration of new areas with the exploitation of known food sources.

Figure 3 is a flowchart that illustrates the steps of the proposed algorithm.

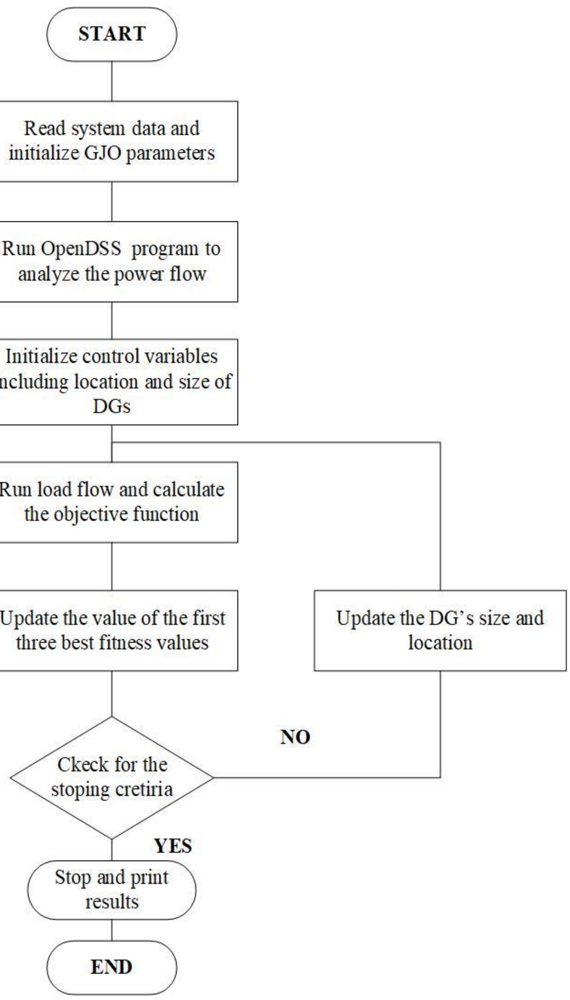

Figure.3. Algorithm Flowchart.

IV. CASE STUDY

The IEEE123 test system is a widely used benchmark for evaluating the performance of DG placement and sizing algorithms. The system consists of 123 buses and is characterized by high levels of nonlinearity and complexity, The IEEE 123-node distribution system is a well-known benchmark system used for testing various power system algorithms. It is a radial distribution system with 123 buses, 174 branches, and 97 loads. The system has a mix of residential, commercial, and industrial loads, making it a challenging problem for optimization algorithms.

For this work, which will be simulated through OpenDSS derived through MATLAB, the powers, and voltage behaviors through the insertion of DG at unity power factor will be discussed, for this, the system has been analyzed before the insertion of distributed generations for comparison purposes.

Figure 5 depicts the IEEE123 system diagram, which is built by the EPRI team [14], with a voltage level of 4.16 kV.

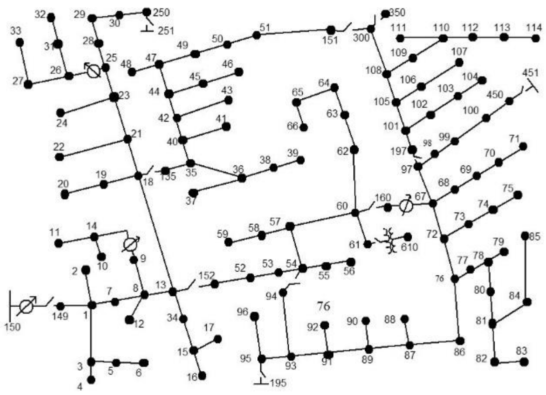

Figure.4. IEEE-123 Node Test Feeder Diagram.

V. SIMULATION STUDIES

V.1. IEEE123 node test feeder simulation with no DGs units

In the base case the system fed only from the grid through bus 1 (without DG units) and the voltage profile curve per bus, displayed in Figure 6, showed that the voltage magnitude at many busses is less than the minimum acceptable voltage, the simulation results indicate that the total active power losses 95.61kW and total reactive power losses 193.72kVAR.

Figure 5 depicts the voltage profile of a power system without any Distributed Generators (DG) integrated. The voltage profile is a plot of voltage magnitude versus distance along the transmission lines in the power system.

The plot shows that the voltage magnitude decreases as the distance from the substation increases. This is a typical characteristic of power systems, as voltage drop occurs due to the resistance and reactance of the transmission lines.

Figure 5 also shows that there are some points in the power system where the voltage magnitude drops below the acceptable range.

Overall, the figure highlights the importance of maintaining a stable and reliable voltage profile in power systems. The voltage profile can be improved by integrating Distributed Generators (DG) at strategic locations in the power system. DG can inject power into the system at the point of consumption, reducing the distance between the generation and consumption points and mitigating the voltage drop.

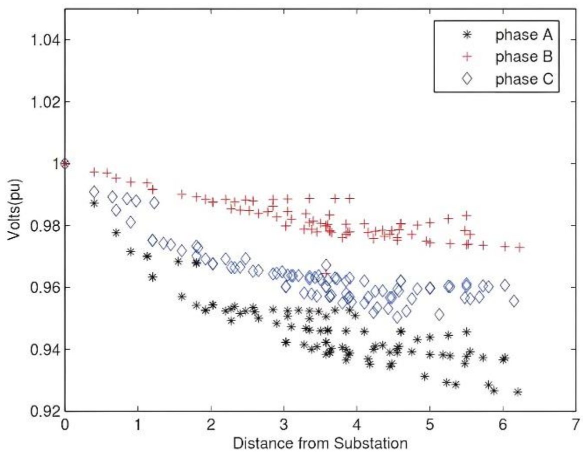

Figure.5. voltage profile without DGs integration.

The simulation of the IEEE123 system using the Golden Jackal Optimization (GJO) algorithm to optimize the size and location of distributed generation (DG) units have provided valuable insights into the potential benefits and challenges of integrating DG into the power system. In this discussion, we will examine the results of the simulation and their implications for the optimal deployment of DG in the IEEE123 system.

The objective of the simulation was to minimize the total system power losses while maintaining the voltage quality and reliability of the system. The GJO algorithm was used to optimize the size and location of DG units.

The simulation was run after integrating a single DG unit for 200 iterations, and the results were compared to a base case scenario without DG. The results obtained by the GJO algorithm are compared with those obtained by mixed-integer nonlinear programming (MINLP), genetic algorithm (GA), particle swarm optimization (PSO), biogeography-based optimization (BBO), grey wolf optimizer (GWO), Coyote Optimization Algorithm (COA).

Table.1. Optimal allocation and size of single DG unit for the IEEE123-bus system.

method	*Connection Bus*	*Losses (kW)*	*Loss Redaction (%)*
Base case [14]	-	95.61	-
MINLP [15]	83	85.19	10.89
GA[15]	83	83.28	12.89
PSO [15]	83	81.75	14.49
BBO [15]	83	79.29	17.07
GWO [15]	83	71.03	25.71
COA [15]	83	69.28	27.54
GJO	83	48.76	48.99

The optimized system had a single DG unit with a capacity of 1.59MW, which was located in the node indicated in Table.1. The DG unit was able to supply a significant portion of the total load demand. Moreover, The GJO algorithm has shown high effectiveness when compared to other optimization algorithms, GJO outperforms them in terms of solution quality, and the active power losses were reduced to 48.76kW, which signified 48.99%.

The simulation was run after integrating 4 DG units, and the results were compared to a base case scenario without DG. The results obtained by the GJO algorithm are compared to the base case losses.

Table.2. Optimal allocation and size of 4 DGs for the IEEE123-bus system.

method	*Connection Bus*	*DG SIZE (MW)*	*Active Losses (kW)*	*Reactive Losses (Kvar)*	*Loss Redaction (%)*
Base case[14]	-	-	95.61	193.72	-
GJO	72, 90,74, 83	2.04, 0.53, 0. 01, 1.82	36.37	69.08	61.96%

The simulation results in Table 2, show that the GJO algorithm was able to find an optimal solution that significantly reduced the total system power losses compared to the base case scenario with no DGs connected. Specifically, the optimized system had a total loss of 36.37KW, which was 61.96% lower than the base case losses of 95.61KW. This reduction was primarily driven by the deployment of DG units in strategic locations that reduced the system losses and peak demand.

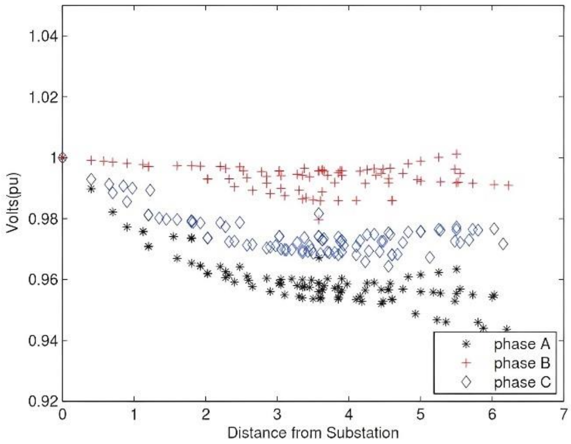

Figure.6. voltage profile with 4 DGs integration.

Figure 6 depicts the voltage profile of a power system with four Distributed Generators (DGs) integrated. The voltage profile is a plot of voltage magnitude versus distance along the transmission lines in the power system.

The plot shows that the integration of DGs has significantly improved the voltage profile of the power system. The voltage magnitude is more uniform throughout the system, and there are no points where the voltage drops below the acceptable range.

The integration of DGs has also reduced the overall voltage drop in the system. This is particularly evident at the points where the DGs are located. At these points, the voltage magnitude is significantly higher than the surrounding areas, indicating that the DGs are injecting power into the system and compensating for the voltage drop.

The plot also shows that the placement of the DGs is critical for optimizing the voltage profile. The DGs are strategically located in the system to minimize the voltage drop and improve the voltage profile. The placement of the DGs considers various factors such as load demand, distance from the substation, and available capacity.

Overall, the figure highlights the significant impact of DG integration on the voltage profile of power systems. The integration of DGs can improve the overall performance of the system, reduce power losses, and enhance system reliability. It also demonstrates the importance of careful planning and placement of DGs to optimize the voltage profile and achieve the best results.

convergence plot in Figure 7 typically shows the value of the objective function, in this case, power losses as a function of the iteration. The plot can show how quickly the algorithm converges to the near-optimal solution. indicating that the algorithm is making progress and approaching an optimal solution.

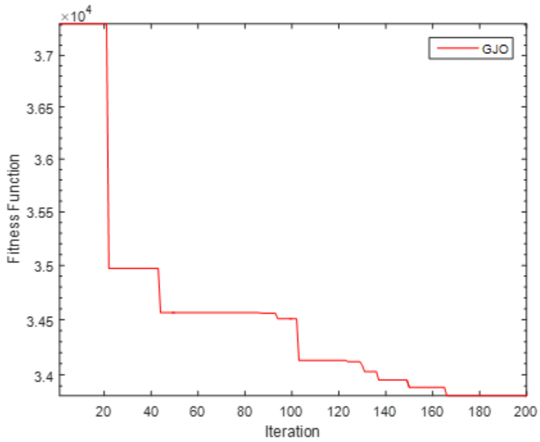

Figure.7. Convergence characteristic of power loss using the GJO algorithm.

III. Conclusion

In conclusion, the study demonstrated that the Golden Jackal Algorithm (GJO) is a promising method for optimizing the placement and sizing of multiple Distributed Generators (DGs) in power systems. The GJO algorithm was found to be an efficient and effective approach to solving this complex problem. The GJO-based solution can help power system operators to improve the overall performance of the system by reducing voltage drop and enhancing system reliability. Furthermore, the proposed approach can be applied to other power systems and optimization problems, making it a useful tool for power system planning and operation. Overall, the study highlights the potential benefits of using advanced optimization techniques like the GJO algorithm in power systems engineering applications. In addition to the benefits mentioned, the use of the GJO algorithm for optimal placement and sizing of multiple DGs in power systems has several other advantages. One of the significant advantages is that the GJO algorithm is a meta-heuristic optimization algorithm that can handle complex and non-linear problems with multiple objective functions. This makes it suitable for solving optimization problems in power systems that involve multiple objectives such as minimizing power losses and improving voltage stability.

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