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Distribution network reconfiguration considering DGs using a hybrid CS-GWO algorithm for power loss minimization and voltage profile enhancement

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ABSTRACT

This paper presents an implementation of the hybrid Cuckoo search and Grey wolf (CS-GWO) optimization algorithm for solving the problem of distribution network reconfiguration (DNR) and optimal location and sizing of distributed generations (DGs) simultaneously in radial distribution systems (RDSs). This algorithm is being used significantly to minimize the system power loss, voltage deviation at load buses and improve the voltage profile. When solving the high-dimensional datasets optimization problem using the GWO algorithm, it simply falls into an optimum local region. To enhance and strengthen the GWO algorithm searchability, CS algorithm is integrated to update the best three candidate solutions. This hybrid CS-GWO algorithm has a more substantial search capability to simultaneously find optimal candidate solutions for problems. The obtained test results for the 33-bus system show that minimization of active power loss was enhanced by 74.73%,73.35%, and 80.37% for light, nominal, and heavy load conditions, respectively, and similarly for 69- bus system is 81.50%, 84.74%, and 88.86%. The minimum voltage value for 33- bus system under nominal load condition was enhanced from 0.9130 p.u to 0.9865 p.u and similarly for the 69-bus system is 0.9094 p.u to 0.9842 p.u. Respectively. Furthermore, to validate the effectiveness and performances of the proposed hybrid CS-GWO algorithm with existing methods is presented. This method is tested and evaluated for standard IEEE 33-bus and 69-bus RDSs by considering different scenarios. Finally, the comparative analysis shows that the proposed algorithm was more efficient in minimizing power losses and enhancing the voltage profile of the system.

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1. INTRODUCTION

The distribution system (DS) is the final stage in the construction and planning electrical power system, which delivers the power between the transmission and end-user consumer. Transmission networks operate in loops/radial structures and distribution networks always operate in radial structure to reduce the short circuit currents. Distribution network reconfiguration (DNR) is defined as the process of varying the topological arrangement of distribution feeders by changing the open/closed status of sectionalizing and tie switches concerning system constraint and satisfying the operator objectives. The most common practice methods used by researchers widely for power loss (PL) reduction and voltage profile improvement in DS is network reconfiguration (NR) and DGs integration in DS [1,2]. Generally, distribution networks/systems are reconfigured to minimize the system PL and relieve overload. However, dynamic loads in the system may increase total system loads; it may be higher than its generation capacity sometimes, making it difficult to relieve the load on the feeders. Due to this problem system voltage profile may not be enhanced to the required level. Therefore, to meet the desired level of load demand, DGs have to be installed to enhance voltage profile and supply continuous power to customers.

The main objectives of DNR were to reduce system PL, load balancing and improve voltage profile and voltage stability of the system. Furthermore, many researchers have implemented optimization techniques such as Analytical, Heuristic, Meta-heuristic, AI and Hybrid methods to minimize system PL. These methods may also be used to improve system power transmission reliability and provide a continuous power supply for the varying load. Analytical techniques use distinct switching and sensitivity computation methods for changing the network's topology structure by closing and opening switches in a loop. Similarly, Metaheuristic, AI techniques and hybrid methods implemented by researchers are also widely used for solving network reconfiguration and DGs allocation problems simultaneously for minimization of system PL and voltage profile improvement. The drawback of metaheuristics methods is it takes more computation time and iterations to search and generate an optimal solution for the problem considered compared to analytical techniques. On the other hand, these methods can handle large datasets' complex issues and solve single/multi-objective functions with high accuracy and convergence.

Merlin and Back [3], in the year 1975 have implemented a discrete branch and bound technique to solve the DNR problem to minimize feeder loss by satisfying the system constraints. Civanlar et al. [4] have proposed a switch exchange method to solve the NR problem and developed a simple formula to estimate PL reduction for a particular topology structure obtained by opening and closing a specific switch in loops. In the past decade of literature, many metaheuristic techniques have been proposed by the researchers to find the optimal solution for the DNR problem separately without DGs allocation, with an aim to minimize active PL and enhance the voltage profile of system. Some of the most popularly used metaheuristic algorithms to solve DNR problem alone with different objective functions are listed as Refined genetic algorithm[5], Harmony search algorithm[6], Minimum current circular-updating mechanism method[7], Discrete PSO algorithm[8], Improved adaptive imperialist competitive algorithm[9], Catfish PSO algorithm[10], Fireworks algorithm[11], Enhanced genetic algorithm[12], NSGA-II algorithm[13], Cuckoo search algorithm[14], Genetic algorithm with varying population size[15], Runner-root algorithm[16], Biased random key genetic algorithm[17], Binary PSO algorithm[18], Modified culture algorithm[19], Feasibility-preserving evolutionary optimization[20], graphically-based network reconfiguration[21]. Moreover, this algorithm needs many control parameters to be tuned for each problem to obtain an optimal solution. Therefore, these approaches have been used extensively to solve large-scale complex problems to obtain better solutions.

Besides, various research studies in the literature have made a tremendous effort to find the optimal location and sizing of DGs in the DS by applying different approaches with an aim to improve the performances and voltage profile of DS. DGs allocation in an optimal location and suitable sizes may minimize active power loss and improve the system voltage profile and power quality. Many meta-heuristic algorithms have been introduced to solve DG allocation problems for last decades, such as genetic algorithm and particle swarm optimization [22], modified bacterial foraging optimization algorithm [23], analytical approach [24], invasive weed optimization algorithm [25], quasi-oppositional teaching-learning based optimization [26], intelligent water drop algorithm [27], Krill herd algorithm [28], Flower Pollination algorithm [29], Shuffled Bat algorithm [30], Stud Krill herd Algorithm [31], hyper-spherical search algorithm [32], one rank cuckoo search algorithm [33], symbiotic organism search-based method [34], stochastic fractal search algorithm [35], combined evolutionary algorithm [36], mutated salp swarm algorithm [37], Multi-Objective Hybrid Teaching–Learning Based Optimization-Grey Wolf Optimizer [38], coyote optimization algorithm (COA) and electrical transient analyzer program (ETAP)[39], improved spotted hyena algorithm [40]. These methods are easy to implement and widely used in the DS to obtain a global optimum solution with less computation time. In this context, a hybrid CS-GWO algorithm is used to find the optimal allocation of DGs and suitable sizes to minimize active PL and improve voltage profile. This algorithm's obtained results are better than various optimization methods in literature such as HSA, GA, RGA, FWA and UVDA.

2. RELATED WORKS

In past works, it is observed that DNR and optimal allocation of DGs in RDSs are generally studied independently. Integration of these sub-problems together and solving them concurrently may lead to more advantages to DS operators. There are very few works in the literature dealing with the DNR and optimal allocation and sizing of DGs simultaneously for minimizing active PL. Performing DNR using available switches in loops can reduce PL, improve voltage regulation, relieve feeder loading, and improve system reliability. Implementing DNR and DG allocation simultaneously in DS has been more effective for active PL reduction and voltage profile improvement in RDSs than other methods. This method may also enhance the system performance, quality and reliability. In this paper, both DNR and DG allocation problem is solved simultaneously by applying a hybrid CS-GWO algorithm to obtain a desired optimal solution.

Various effective optimization algorithm have been implemented by researchers in literature for solving DNR and DGs allocation problem simultaneously are listed as: Harmony search algorithm [41], hyper-cube ant colony optimization algorithm [42], Fireworks Algorithm [43], modified plant growth simulation algorithm [44], adaptive cuckoo search[45], binary particular swarm optimization algorithm [46], enhanced evolutionary algorithm [47], uniform voltage distribution based constructive reconfiguration algorithm[48], discrete artificial bee colony algorithm [49], Harmony search algorithm (HSA) and particle artificial bee colony algorithm (PABC) [50], hybrid Grey Wolf Optimizer (GWO)-Sine Cosine Algorithm (SCA)[51], hybrid Particle Swarm Optimizer (PSO)-ant colony optimization (ACO) [52], comprehensive teaching-learning-based optimization algorithm [53], Grey Wolf Optimizer (GWO) and Particle Swarm Optimizer (PSO)[54], Strength Pareto Evolutionary Algorithm 2 [55], adaptive shuffled frogs leaping algorithm [56], Particle swarm optimization (PSO) and Dragonfly algorithm (DA) [57], Stochastic fractal search algorithm [58], Mixed Particle Swarm Optimization [59], Symbiotic Organism Search Algorithm [60], Equilibrium optimization algorithm [61], Harris Hawks Optimization [62], Meta-heuristic matrix moth–flame algorithm [63], Bacterial Foraging with Spiral Dynamic (BF-SD) algorithm [64], chaotic stochastic fractal search algorithm[66], Modified Selective particle swarm optimization (SPSO) method[73], Grasshopper optimization algorithm (GOA)[74], Grid based Multi-Objective Harmony Search Algorithm (GrMHSA)[75], Modified Whale Optimization (MOWOA) algorithm and fuzzy decision-making method[77], Fuzzy Expert System (FES) method[78], Manta-Ray Foraging Optimization (MRFO) algorithm[79], Rider Optimization Algorithm[80]. The summary of recently published works on DNR considering DG problems in the literature above discussed is provided clearly in Appendix Table A1.

Researchers in the past and recently published works have already implemented various methods for solving network reconfiguration problems and DGs placement in DS separately, considering some constraints and assumptions. But few works have been published in solving DNR problems simultaneously considering DGs. So, we have focused on this area of research to work using hybrid metaheuristics algorithms to solve DNR problems considering DGs and Renewable energy sources and capacitor placement to obtain an optimal solution within a short duration of convergence time.

The above algorithms mentioned by researchers have also yielded better results. Still, a minor variation will be in the convergence time of the solution depending on algorithm performances and control parameters. For example, it is observed that the Grey wolf optimizer (GWO) algorithm updates the positions of wolves by random search, and the highest fitness value is computed. Thus, the random search's fitness value may lead to weak global search ability and fall easily into the optimum local region, mainly when performed on large-dimensional data sets. On the other hand, the cuckoo search (CS) algorithm is used to update the nest's positions using a levy flight search to avoid this problem. This search method can quickly find the random best positions of birds very rapidly by changing birds' directions with sudden turns.

Due to this CS algorithm feature, the solution obtained can quickly jump from the current area to other areas to get an optimal solution less competitively. Based on this advantage, the CS algorithm is integrated into the GWO algorithm to obtain a better optimal solution for optimization problems.

In this context, the significant contribution of this paper is highlighted as follows:

- The application of a hybrid CS-GWO algorithm is introduced to solve the DNR problem considering DGs allocation simultaneously for the first time.
- In this context, voltage deviation at load buses and percentage voltage improvement are also calculated.
- The proposed method is applied, tested successfully on standard IEEE 33-bus and 69-bus systems for different scenarios.
- Further, the proposed method's results are compared with other metaheuristic algorithms existing in the literature (such as FWA, RGA, GA, HSA, ACSA, UVDA, MPGSA, SFS, EOA, IEOA) to evaluate the performance of the algorithm.

The remaining of the paper is arranged according to the following: Section 2, Describe the problem formulation. The implementation of the hybrid CS-GWO algorithm and pseudocode along with a flowchart to solve the DNR problem considering DGs simultaneously is presented in Section 3. Section 4 explains test results and a comparative analysis of the proposed technique with existed techniques were discussed on different IEEE test systems considered. The study is concluded in Section 5.

Nomenclature

$P_{Loss}(m, m+1)$: Loss in the line connecting buses $m \; and \; m+1$

$P_{TL,Loss}$: Total active power loss of the DS

$P'_{Loss}(m, m+1)$: Loss in the line connecting buses m and $m+1$ after DNR
$P'_{TL,Loss}$: Total active power loss of the DS after DNR
ΔP_{Loss}^{RE} : Net power loss before and after DNR
ΔP_{Loss}^{DG} : Power loss due to DG installation
R_m : resistance of the line section between buses m and $m+1$
X_m : reactance of the line section between buses m and $m+1$
ΔV_D : Voltage deviation al load buses
V_m : Voltage at bus m
P_m : Real power flowing out of bus m
P'_m : Real power flowing out of bus m after DNR
Q_m : Reactive power flowing out of bus m
Q'_m : Reactive power flowing out of bus m after DNR
V'_m : Voltage at bus m after DNR

3. PROBLEM FORMULATION

The problem of DNR and optimal allocation of DGs simultaneously is to find the optimal radial structure of the network and the best location and sizing of DGs to minimize total active power loss, voltage deviation and improve the voltage profile of DS. In this work, five different scenarios were considered to solve the DNR problem considering DG installation simultaneously in order to estimate the effectiveness of the proposed hybrid CS-GWO algorithm.

3.1. *Objective functions*

The main objective of this work is to minimize the active PL, voltage deviation and improve voltage profile of the system considering DGs while satisfying all the system operating constraints.
Mathematically, the DNR problem considering DGs installation simultaneously is formulated as follows:

$$f = \min.\ (X + Y) \tag{1}$$

Where, X = ($\Delta P_{Loss}^{RE} + \Delta P_{Loss}^{DG}$) and $Y = \Delta V_D$ (ΔV_D =Voltage deviation at load buses)

PL in the DS is real and reactive power. In a balanced RDS, which has m branches, the power loss connecting buses m and $m+1$ were calculated using Equation 2 [65].

$$P_{Loss}(m, m+1) = R_m * \frac{(P_m^2 + Q_m^2)}{|V_m|^2} \tag{2}$$

The total active power loss, $P_{TL,Loss}$ of DS is calculated by summating losses in all branches using Equation (3).

$$P_{TL,Loss} = \sum_{m=1}^{n} P_{Loss}(m, m+1) \tag{3}$$

3.2. *Reduction of power loss using DNR*

DNR is a technique used for finding the best possible network topology of the DS that will minimize the PL. Simultaneously, specified operating constraints such as the current capacity of the feeder, system voltage profile, and radiality structure of the DS must be satisfied. The total PL of a line section linking busses between m and $m+1$ after the DNR is calculated using Equation (4).

$$P'_{TL,Loss} = \sum_{m=1}^{n} P'_{Loss}(m, m+1) \tag{4}$$

where $P'_{TL,Loss}$ Represents the summation of losses in all branches after the accomplishment of DNR, written as in equation (5).

$$P'_{Loss}(m, m+1) = R'_m * \frac{(P'^2_m + Q'^2_m)}{|V'_m|^2} \tag{5}$$

The net PL reduction ΔP_{Loss}^{RE} In DS are computed using Equation (6), i.e., the difference of power loss value before and after DNR.

$$\Delta P_{Loss}^{RE} = \sum_{m=1}^{n} P_{TL,Loss}(m, m+1) - \sum_{m=1}^{n} P'_{TL,Loss}(m, m+1) \tag{6}$$

3.3. *Reduction of power loss using DG installation*

Installing DGs in DS at the optimal location and proper size results in several advantages: reducing line losses, peak demand shaving, improving voltage profile, reducing environmental impacts, and reducing the burden on lines. Consider an RDS with M_L branches, DG is located at node m, and γ be set of branches linking the source and node m. Let us assume that the DG generate active power (P_G) to the system, and reactive power (Q_G) supplied or consumed from the system depending upon the source of the DG. Thus, real power and reactive current flows in the system will alter the apparent power components of the present branch set.

Total apparent power at m^{th} node is calculated using Equation (7).

$$S = S_{Dm} = \sum(P_{Dm} + jQ_{Dm})\ m = 1,2,3 \dots . n \tag{7}$$

And the current at m^{th} node was computed using Equation (8).

$$I_D = I_{Dm}^{without\ DG} = \left(\frac{S_{Dm}}{V_m}\right)^* \tag{8}$$

To integrate the DG model in the network, the apparent power demand at m^{th} node, where a DG unit is located is obtained using the Equations (9)

$$P_{Dm}^{with\ DG} = P_{Dm}^{without\ DG} - P_{Gm}^{DG} \tag{9}$$

The DG power at m^{th} node was calculated using Equation (10).

$$S_{DGm} = \sum(P_{Gm}^{DG}\ \pm jQ_{Gm}^{DG})\quad m = 1,2,3 \dots \dots . . n \tag{10}$$

Then the total new apparent power at m^{th} node was calculated using Equation (11).

$$[S] = [S_{Dm}] - [S_{DGm}] \tag{11}$$

The new current at m^{th} node is computed using Equation (12).

$$I_D = I_{Dm}^{with\ \ DG} = \left(\frac{S_{Dm} - S_{DGm}}{V_m}\right)^* \tag{12}$$

By using the new current I_DObtained from Equation (12) and the power losses reduction due to DG installation were calculated using Equation (13).

$$\Delta P_{Loss}^{DG} = \sum I_D^2 * R_m \tag{13}$$

The total power loss reduction due to DNR considering DGs installation simultaneously in RDS is calculated as

$$X = (\ \Delta P_{Loss}^{RE} + \Delta P_{Loss}^{DG}) \tag{14}$$

3.4. *Voltage deviation at load buses*

The voltage deviation (ΔV_D) of the network structure is computed using the eq. (15) as [66]:

$$\Delta V_D = \ V_{refe} - V_{min} \tag{15}$$

Where V_{refe} : represents the prespecified voltage magnitude at load bus m (V_{refe} =1.0 p.u) and V_{min} : represents minimum bus voltage

- **Constraints**

Considering the DNR problem, the equality and inequality constraints are;

a. Voltage value should be within the specified limits for each bus:

$$V_{min} \le |V_m| \le V_{max} \tag{16}$$

where V_{min} and V_{max} represents the minimum and maximum bus voltages.

b. Current value should be within specific limits at each line:

$$|I_{m,m+1}| \le |I_{m,m+1,max}| \tag{17}$$

where $I_{m,m+1}$ represents the current between busses m and $m+1$.

c. The DG units should be sized within specific limits:

$$P_{Dm,min} \le P_{Dm} \le P_{Dm,max} \tag{18}$$

$$Q_{Dm,min} \le Q_{Dm} \le Q_{Dm,max} \tag{19}$$

where $P_{Dm,min}$ and $P_{Dm,max}$ represents the minimum and maximum power provided by DG.

d. The total power generation of the system is

$$\sum_{m=1}^{n} P_{Dm} \le\ \sum_{m=1}^{n}\left(P_m + P_{Loss(m,m+1)}\right) \tag{20}$$

e. Network must be radial structure and all loads must be supplied power after DNR.

4. Proposed Hybrid Cuckoo Search-Grey wolf algorithm for distribution network reconfiguration

4.1. *Grey wolf optimizer (GWO)*

Seyedali Mirjalili and Andrew Lewis implement the GWO algorithm to solve various optimization problems in different fields [67]. This algorithm performs the common behaviour of the grey wolves (GWs) in cooperatively hunting their prey. It is a large-scale search method centered on three optimal samples. This algorithm's main motivation is the social leadership hierarchy and the hunting mechanism of GWs in nature. Different forms of GWs used to simulate the hierarchy of leadership are alpha (α), beta (β), and delta (δ), and omega (ω). GW's hunting process is as follows; Stage 1: Includes activities like Tracking, chasing and approaching the prey. Stage 2: Consists of activities like Pursuing, encircling, and harassing the prey until it stops moving. And the final step is attacking the prey.

4.1.1. Mathematical model and algorithm

The mathematical models of the GWO algorithm are stated as follows;

(1). Social hierarchy of GWO- In this hierarchy, an appropriate solution is considered to be alpha (α), beta (β), and delta (δ) are regarded as the three best solutions, respectively. Assume omega (ω) is the remaining candidate solution. In this algorithm, hunting (optimization) is handled by alpha (α), beta (β), and delta (δ). Omega (ω) wolves move accordingly to alpha (α), beta (β), and delta (δ).

(2). Encircling Prey- GWs encircle prey during hunting. Equation (21) to Equation (27) is used for mathematically modeling the encircling behaviour of the GWs

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}\,(t)\right| \tag{21}$$

$$\vec{X}\,(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \tag{22}$$

where t denotes the current iteration, $\vec{X}$ & $\overrightarrow{X_p}$ represent the position vector of the GW and the prey, and $\vec{A}$, $\vec{C}$ represents coefficient vectors.

- The $\vec{A}$, $\vec{C}$ vectors were determined by Equations (23) and (24).

$$\vec{A} = 2\,\vec{a}.\overrightarrow{r_1} - \vec{a} \tag{23}$$

$$\vec{C} = 2.\overrightarrow{r_2} \tag{24}$$

where the components $\vec{a}$ which is linearly reduces from 2 to 0 throughout the repetition process and $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ denotes the arbitrary vectors $[0,1]$. Using Equations (21) and (22), the GW will update its position in any random location in the space around the prey.

c). Hunting- GWs can recognize and encircle the location of prey, and alpha regularly guides the hunting process. Beta (β) and delta (δ) may occasionally participate in hunting. This process is mathematically simulated by considering that alpha (α), beta (β), and delta (δ) have provided better info about the potential location of the prey. Alpha (α), beta (β), and delta (δ) are optimal solutions obtained so far during the process. The objective function in the problem is prey. Omega (ω) wolf's solution will update their location, according to the α, β, and δ locations. The hunting process is formulated using Equations (25) and (26).

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right|,\ \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right|\ ,\overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right| \tag{25}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\left(\overrightarrow{D_\alpha}\right),\quad \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\left(\overrightarrow{D_\beta}\right),\quad \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\left(\overrightarrow{D_\delta}\right) \tag{26}$$

where $\overrightarrow{D_\alpha}$, $\overrightarrow{D_\beta}$ and $\overrightarrow{D_\delta}$ are the position vectors of the GWs in the population w.r.t α, β, and δ wolves. The $\overrightarrow{C_1}$, $\overrightarrow{C_2}$and $\overrightarrow{C_3}$ were the generated arbitrary numbers in the range $[0,2]$, $\vec{X}$ is the search agents, i.e., population, $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ were the best search agents related to the optimal solutions. $\overrightarrow{A_1}$, $\overrightarrow{A_2}$ and $\overrightarrow{A_3}$ were arbitrary numbers that depend on the $\vec{a}$.

The encircling behaviour is implied to obtain the new positions of GWs using Equation (27).

$$\vec{X}(t+1) = \frac{(\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3})}{3} \tag{27}$$

Finally, alpha (α), beta (β), and delta (δ) predict the prey's location, and the remaining wolves randomly change their position around the prey. When the prey stops moving hunting, the process is ended. Alpha (α), beta (β), and delta (δ) wolves predict the feasible location of the prey throughout iterations. The $\vec{a}$ is gradually reduced from 2 to 0 to make emphatic exploration and characteristics of the algorithm. Every candidate solution updates its distance from the prey. If $|\vec{A}| > 1$, Candidate solutions move towards diverging from the prey. If $|\vec{A}| < 1$ converge near the prey. Finally, the algorithm comes to an end with satisfaction.

4.2. Integration GWO with Cuckoo search algorithm (CS)

Yang and Deb have proposed implementing a meta-heuristic algorithm known as the cuckoo search algorithm to obtain an optimal solution using a minimum no. of parameters for various optimization problems [68]. This algorithm is mainly inspired by the obligate brood parasitism of some cuckoo species. This species lay their eggs in the nests of other host birds of different species. This algorithm is combined with the unique nesting way of cuckoo birds and levy flight behaviour of birds. The levy flight style is a common feature of flight behaviours for several animals and insects. This flight style performs a smaller movement range, but it may have a minimum probability of broad range jump and vary from the activities' mean value. Due to this CS algorithm jumps out of the optimum local region.

Levy flights perform random walks in different directions, and step lengths are obtained using the levy distribution function. These Levy flights are represented by a series of straight flights, proceeded by quick turns. Levy flights are more competent in finding large-scale search areas due to the deviation of species direction much faster when compared to traditional random walks. Using the levy flight search in the cuckoo search algorithm may reduce the number of iterations in algorithm execution. And computation time to obtain an optimal solution may be reduced compared to a standard random walk.
"The CS algorithm implementation is done based on the rules explained as follow:

- Cuckoo birds select nests randomly and they only place one egg at once.
- Next, the best nests will persist in being the next generations.
- Further, the number of bird nests and the probability of egg discover are fixed. Suppose the host bird finds an outsider bird's egg. Then the host bird will leave the nest and create a new one."

The nests are updated according to the following equations during the iteration process by satisfying the above rules.

$$X_i(t+1) = x_i(t) + \alpha \oplus Levy(\lambda), i = 1,2,3, \ldots .n \tag{28}$$

Where the product $\oplus$ denotes entry-wise multiplication. $X_i(t+1)$ represents new solutions for cuckoo, i. $x_i(t)$ represents the current solutions. Since $\alpha > 0$ controls the step size and is set to 1.
The following probability distribution equation provides the Levy-flight:

$$Levy(\lambda) = t^{-\lambda}, 1 < \lambda \leq 3 \tag{29}$$

Hence, this algorithm may search solutions widely in space effectively because its step length varies with short distance finding and random long-distance walking.

4.3. Implementation of Hybrid CS-GWO for DNR and DG allocation simultaneously

It is observed that the GWO algorithm updates the positions of wolves using equation (27) by randomly search and the highest fitness value is computed. Thus, the random search's fitness value may lead to weak global search ability and fall easily into the optimum local region, mainly when performed on large-dimensional data sets. The CS algorithm updates the nest's positions using a levy flight search to avoid this problem. This search method can quickly find the random best positions of birds very rapidly by changing birds' directions with sudden turns. Furthermore, the solution obtained can soon jump from the current area to other areas to get an optimal solution less competitively due to this CS algorithm feature.

Based on this advantage, the CS algorithm is integrated into the GWO algorithm to obtain a better optimal solution for optimization problems. The GWO algorithm combined with cuckoo search was implemented by Xu, H., Liu, X., & Su, J. in 2017 as the CS-GWO algorithm to solve the optimization problems [69]. In 2020, Abhishek Gupta proposed implementing a hybrid GWO-CS algorithm to test different benchmark optimization functions and found that the performance is better in finding the optimal solution than the GWO algorithm alone [70].

The flow chart of the CS-GWO algorithm is shown in Fig. 1 and the pseudo-code explanation of the hybrid CS-GWO algorithm is as follows:

4.3.1. The pseudo-code of the CS-GWO algorithm is presented as follows [69]

Initialize the grey wolf population X_i (i = 1, 2, ..., n)
Initialize a, A, C and ρ_a
Compute the fitness of each search agent in the pack using eq. 1
Set $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ according to the fitness
$t = 0$ (iteration=0)
while *($t \leq$ Max number of iterations)*
for *wolf (each search agent)*
Update the position of the current search agent by equation 27
end for
update a, A, C
Run load flow analysis with constraints
Calculate the fitness function using equation 1
Update $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$,
For $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$
Update the position by *cuckoo search* algorithm using the Levy flight method [14] by equation 28.
If the random number $>P_a$
Random change wolf's position
Compute the fitness function and update it according to the fitness
End for
t=t+1
end while
return $\overrightarrow{X_\alpha}$ *output value*

4.3.2. Implementation of CS-GWO for DNR considering DGs installation:

Step 1: *Initialization of problem and parameters of the algorithm*
The optimization problem is specified as follows:

$$\text{Minimize } f(y) \tag{30}$$

Subjected to $y_i \in Y_i \; i = 1,2, \dots N$

Where $f(y)$ is an objective function; y is the set of each decision variable y_i; Y_i is the set of the possible range of values for each decision variable (lower and upper bound values). The decision variable in this algorithm is considered as opened switches, DGs size and Buses number. The grey wolf and cuckoo search parameters are specified in this step. The dimension of search agent=12, Number of search agents =200 wolfs, Max. iteration=100, $P_a = 0.25$ (probability of alien eggs discovery). The grey wolf-cuckoo search memory (GWCM) is a location where all the solution vectors are stored (opened switches, DGs location and size, power loss value). Here the grey wolf coefficient vectors $\vec{A}$, $\vec{C}$ will be updated based on the components $\vec{a}$ ($\vec{a} = \left[2 - \left(2 - \frac{(2*current\ iteration)}{max.iteration}\right)\right]$) which is linearly reduced from 2 to 0 throughout the repetition process and $\vec{r_1}$ and $\vec{r_2}$ denotes the arbitrary vectors [0,1].

Step2: *Initialize GWCM*
In this step, the GWCM is filled with as many randomly generated solution vectors as the grey wolf population size (wolfs =200).

$$GWCM=\begin{bmatrix} (SW_1^1\ SW_2^1\ SW_3^1\ SW_4^1\ SW_5^1) & (BN_{dg1}^1\ BN_{dg2}^1\ BN_{dg3}^1) & (P_{dg1}^1\ P_{dg2}^1\ P_{dg3}^1) & (P_{loss1}) \\ (SW_1^2\ SW_2^2\ SW_3^2\ SW_4^2\ SW_5^2) & (BN_{dg1}^2\ BN_{dg2}^2\ BN_{dg3}^2) & (P_{dg1}^2\ P_{dg2}^2\ P_{dg3}^2) & (P_{loss2}) \\ & \vdots & & \\ (SW_1^{GWP}\ SW_2^{GWP}\ SW_3^{GWP}\ SW_4^{GWP}\ SW_5^{GWP}) & (BN_{dg1}^{GWP}\ BN_{dg2}^{GWP}\ BN_{dg3}^{GWP}) & (P_{dg1}^{GWP}\ P_{dg2}^{GWP}\ P_{dg3}^{GWP}) & (P_{loss\,GWP}) \end{bmatrix} \tag{31}$$

Where $(SW_1^1\ SW_2^1\ SW_3^1\ SW_4^1\ SW_5^1)$ indicates switches opened during reconfiguration, $(BN_{dg1}^1\ BN_{dg2}^1\ BN_{dg3}^1)$ indicates the DGs installation at bus number, $(P_{dg1}^1\ P_{dg2}^1\ P_{dg3}^1)$ indicates the size of the DGs and P_{loss1} total loss value obtained for that network reconfiguration. The matrix size of GWCM is $[200 \times 12]$ including randomly generated reconfiguration loops, DGs location and size depending on the number of switches in loops, limits of DGs size.

Random generation of network reconfiguration topology considering DGs location and size

x=zeros(wolf,12);
%%% random generation of network configuration%%%
x(:,1)=randi(10,1,wolf);% number switches in loop 1
……
….
x(:,5)=randi(8,1,wolf);% 8 is number switches in loop5
%% Random generation of DGs location at different buses%%
x(:,6)=randi(33,1,wolf);
….
%% limits of DGs size power %%%
x(:,9)=randi(2000,1,wolf);
…

Step 3: Compute the fitness by using eq (1) of each search agent in the pack (each configuration randomly generated) using load flow analysis.
For $i = 1{:}\, no.search\ agents$
Calculate fitness value
End for
Set obtained $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ According to fitness.

Step 4: Initialize $iter$ =0; Then $\vec{a} = 0$ (for current iteration)
%%% main Loop%%%
$while\ (iter \le Max.iteration)$
For each search agent (each network configuration, DGs location and size)
Update the position of the current search agent by eq. (27) (based on power loss value obtained)
End for
%%%%
Update $\vec{A}$, $\vec{C}$ and $\vec{a}$ using eq. (23 and 24)
Run load flow analysis with constraints
Compute the fitness value
Update $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ according to the fitness (where $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ are best three search agents related to the optimal solution obtained during the iteration process)
The matrix size of the $\overrightarrow{X_\alpha}\ is\ [1 \times 11]$ include best network reconfiguration topology (switches to open), DGs location at bus number and size depending on minimum power loss.

Step 5: Incorporating a cuckoo search algorithm using the levy flight method to find the best configuration and DGs location and size.
For $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ obtained in step 4 are given as the input to the cuckoo search algorithm [14]
Levy flight method generates a new solution using eq. (28)
If rand> P_a
%%% controlling is sending back to GWO algorithm%%%%%
Update $\vec{A}$, $\vec{C}$ in GWO algorithm according to the random best position obtained by cuckoo search algorithm (i.e., updating wolf position according to the obtained random values $\overrightarrow{r_{P1}\ (X_{best\iota})}$and $\overrightarrow{r_{P2}\ (X_{best\iota})}$ from levy flight method)
Compute the fitness function and update it according to fitness
Compute the new position of a grey wolf using eq. (27)
Iteration= $iter$ +1
End $while$
Output alpha_score (displays the Open switches, DGs location at which bus number and DGs size)

The application of the hybrid CS-GWO algorithm for PL reduction problem and voltage profile improvement with DNR and DGs installation simultaneously is validated with the standard IEEE 33-bus test system. This test system comprises five tie switches, normally opened and represented as 33, 34,35, 36, and

37. Based on the number of tie switches, five loops have been formed as L_1 to L_5 as depicted in Fig. 2. Assume that DG units installed at buses as 18,22, and 25, as depicted in Fig. 2. DG size may change in discrete steps at the desired location during the optimization process. To obtain an optimal radial network topology, only open switches in the system need to be known.

The solution vector (SV) for DNR with DGs installation problem for all scenarios is represented from Equations (32)-(34).

$$SV=\left\{\underbrace{OS_1^1, OS_2^1, OS_3^1, OS_4^1, OS_5^1}_{BASE\ AND\ RECONFIGURATION} \rightarrow P_{LOSS}\right\} \tag{32}$$

$$SV=\left\{\underbrace{LO_1^1, LO_2^1, LO_3^1}_{lOCATION\ OF\ DGs}, \underbrace{SI_1^1, SI_2^1, SI_3^1}_{SIZE\ OF\ P+\ DGs}, \rightarrow P_{LOSS}\right\} \tag{33}$$

$$SV=\left\{\underbrace{OS_1^1, OS_2^1, OS_3^1, OS_4^1, OS_5^1}_{RECONFIGURATION}, \underbrace{LO_1^1, LO_2^1, LO_3^1}_{lOCATION\ OF\ DGs}, \underbrace{SI_1^1, SI_2^1, SI_3^1}_{SIZE\ OF\ P+\ DGs}, \rightarrow P_{LOSS}\right\} \tag{34}$$

where $OS_1^1, OS_2^1, OS_3^1, OS_4^1, OS_5^1$ are opened switches with respect to (33,34,35,36,37) and (69, 70, 71, 72,73) tie switches. LO_1^1, LO_2^1, LO_3^1 are the locations of DG units. SI_1^1, SI_2^1, SI_3^1 and SI_4^1, SI_5^1, SI_6^1 are the sizes of DG units in MW and MVAR. For the base case analysis SV, Equation (32) is used to determine the optimal solution by choosing the best-reconfigured switches open in the loop. Equation (33) is used to solve scenarios III and IV, determining the optimum location and sizing of three DG units. Equation (34) is used to solve scenario V to perform simultaneous DNR with DGs installation to reduce PL and improve minimum system voltage magnitude.

In the proposed CS-GWO method, only three control parameters need to be adjusted, including the number of wolves, the maximum number of iterations and $P_a = 0.25$ (probability of alien eggs discovery). The remaining parameters, such as switches to be opened in the loop, DG location at bus number, and DG size, are randomly selected. These parameters can easily be predetermined depending on the tested systems. The proposed method is executed independently for each scenario to obtain the optimal solution. The implemented algorithm has been coded in MATLAB R2017a software and simulated on a computer desktop with Intel Core (TM) i3 PC with 2.0 GHz of speed and 8 GB of RAM.

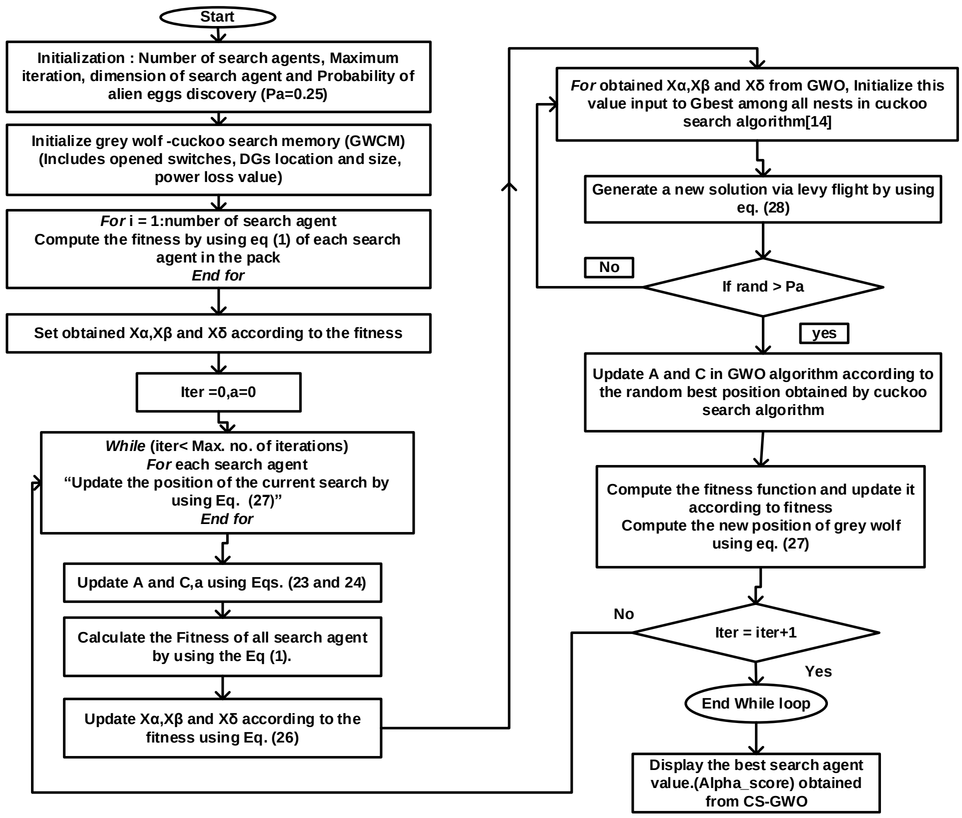

Figure 1. Flowchart of CS-GWO algorithm

5. TEST RESULTS

The standard IEEE test systems 33-bus and 69-bus systems are considered for this work to show the proposed hybrid CS-GWO algorithm's effectiveness and robustness to solve the considered problem. Different type of scenarios was considered as follows:

- Scenario I: Base case (without DNR and DGs installation).
- Scenario II: DNR is done, depending on existing switches.
- Scenario III: DGs are installed in the DS before DNR (Only DG units).
- Scenario IV: DGs are installed after the DNR.
- Scenario V: Simultaneous DNR considering DGs installation.

Test system-I: *IEEE 33-bus system*

The topology of test system-I consists of 5 tie switches from 33-37, normally opened and 32 SS from 1-32 generally closed [71]. The system load data under the base case were 3715 kW and 2300 kVAR, respectively. The range of apparent power injected by the DGs is 0 to 2 MW & 2 MVAR, respectively. The base parameters are 100 MVA, 12.66 kV. Table 1 shows the simulation results of test system 1 for different loading conditions and voltage deviation at load buses. Table 2 shows the CS-GWO algorithm's effectiveness compared with existing algorithms in obtaining optimal configuration, sizing, and location of DGs for all the scenarios considered and simulation results are presented. Fig. 2 depicts the single line diagram (SLD) of the considered test system 1 with different loop formation and DGs placement. Based on the number of tie switches, five loops have been formed as L_1 to L_5, these switches are operated during fault cases, load balance conditions and reduce system losses.

L1 = [2; 3; 4; 5; 6; 7; 33; 20; 19; 18]; L2= [9; 10; 11; 12; 13; 14; 34]; L3 = [8; 9; 10; 11; 35; 21; 33]; L4= [26; 27; 28; 29; 30; 31; 32; 36; 17; 16; 15; 34; 8; 7; 6]; L5 = [22; 23; 24; 37; 28; 27; 26; 25; 5; 4; 3]

Table 1. Results of an IEEE 33-bus RDS using GWO and CS-GWO

Scenario	Item	GWO Nominal load (1.0)	Proposed CS-GWO		
			Load levels		
			Light load (0.5)	Nominal load (1.0)	Heavy load (1.6)
Base case (Scenario I)	Open switch numbers	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37
	Power loss (kW)	202.68	47.072	202.68	575.39
	Minimum voltage (p.u.)	0.9132	0.9582	0.9130	0.8528
	ΔV_D(p.u.)	0.0868	0.0418	0.0870	0.1472
Only reconfiguration (Scenario II)	Open switch numbers	7, 9, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 32, 37
	Power loss (kW)	**139.55**	**33.269**	**139.55**	**380.45**
	Minimum voltage (p.u.)	0.9425	0.9698	0.9424	0.8640
	Loss reduction (%)	31.14	29.30	31.14	33.87
	ΔV_D(p.u.)	0.0575	0.0302	0.0576	0.1360
	Iterations	100	2	2	2
Only DG Installation (Scenario III) (P Type)	Opened switches	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37
	Size of DGs (MW), Bus number	0.7646(13) 1.2061(24) 1.1383(29)	0.3750(14) 0.5435(24) 0.5247(30)	0.7520(14) 1.096(24) 1.074(30)	1.2152(14) 1.784(24) 1.7365(30)
	Power loss (kW)	**71.82**	**17.32**	**71.40**	**190.19**
	Minimum voltage (p.u.)	0.9785	0.9903	0.9804	0.9555

	Loss reduction (%)	64.56	63.20	64.74	66.94
	ΔV_D(p.u.)	0.0215	0.0097	0.0196	0.0445
	Iterations	100	23	29	17
DG installation after reconfiguration (Scenario IV) (P Type)	Opened switches	7, 9, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 32, 37
	Size of DGs (MW), Bus number	0.9222(8) 1.0760(24) 0.9512(30)	0.2691(12) 0.7678(6) 0.2520(16)	0.9329(8) 1.0831(24) 0.9512(30)	1.4772(8) 2.6312(3) 1.4418(30)
	Power loss (kW)	**59.65**	**16.22**	**58.55**	**169.678**
	Minimum voltage (p.u.)	0.9814	0.9924	0.9855	0.9575
	Loss reduction (%)	70.56	65.54	71.16	70.51
	ΔV_D(p.u.)	0.0186	0.0076	0.0145	0.0425
	Iterations	100	45	60	65
Simultaneous reconfiguration, DG installation (Scenario V) (P Type)	Opened switches	7,14,9,15,27	33,11,34,28,30	7,10,14,28,30	19,11,14,24,29
	Size of DGs (MW), Bus number	0.7608(18) 0.7085(22) 1.1749(25)	0.4367(18) 0.5559(25) 0.4767(7)	0.7311(18) 0.8075(27) 1.4805(25)	1.17469(12) 0.9488(24) 2.0262(27)
	Power loss (kW)	**56.58**	**11.89**	**54.01**	**112.91**
	Minimum voltage (p.u.)	0.9827	0.9932	0.9865	0.9610
	Loss reduction (%)	72.08	74.73	73.35	80.37
	ΔV_D(p.u.)	0.0173	0.0068	0.0135	0.0390
	Iterations	100	40	28	40

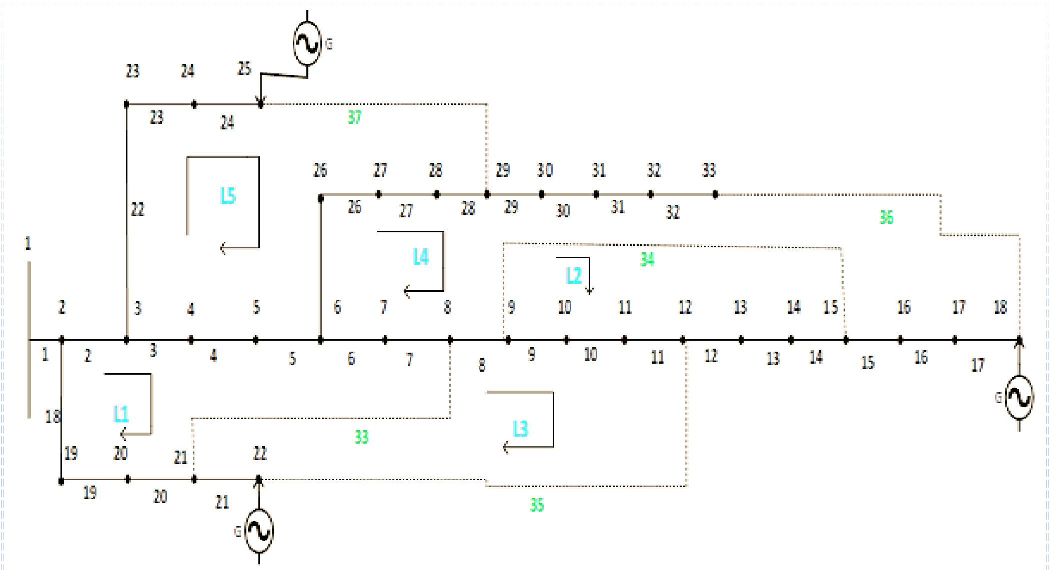

Figure 2. The IEEE 33-bus RDS, with different loops and DGs installation

To estimate the performance of the hybrid CS-GWO algorithm, the network/system is simulated at three different load levels, such as light (0.5), nominal (1.0) and heavy (1.6); simulation results obtained are presented in Table 1. From Table 1, we can infer that at light load base case, PL in the system (in kW) is 47.07, which is drastically reduced to 33.26, 17.32, 16.22, and 11.89 for scenarios II, III, IV and V, respectively. Similarly, at nominal load, base case PL (in kW) is 202.68, which is reduced to 139.55,71.40,58.55, and 54.01 for scenarios II, III, IV, and V, respectively. At heavy load, base case PL (in kW) is 575.39, which is reduced to 380.45, 190.19, 169.67, and 112.91 for scenarios II, III, IV, and V, respectively. The percentage PL reduction for scenario II to V at light load is 29.30, 63.20, 65.54, and 73.35, respectively. Similarly, at nominal and heavy load conditions is 31.14, 64.74, 71.16,74.50 and 33.87, 66.94, 70.51,80.37 respectively. These obtained results show that PL minimization using scenario-V by the proposed hybrid CS-GWO technique is maximized for all load levels, proving the proposed method's effectiveness over the other algorithms. It is observed from results that as load rises from light to heavy, enhancement in percentage PL reduction in all scenarios is nearly the same. It is pertinent from Table 1 that PL reduction and voltage profile improvement for scenario V are higher when compared to scenario IV. This Table also provides the estimated PL value (in kW) and ΔV_D (p.u.) as {202.68, 139.55, 71.82, 59.65, 56.58} and {0.0868, 0.0575, 0.0215,0.0186, 0.0173} using the GWO algorithm. From this Table, the results obtained from the hybrid CS-GWO algorithm are better than the GWO algorithm.

Furthermore, the system voltage profile (in p.u.) is being improved from 0.9582 to 0.9932 in light load condition and similarly 0.9130 to 0.9865 in nominal load; 0.8528 to 0.9610 in heavy load condition. The percentage minimum voltage improvement for scenarios II to V at the light, medium and heavy load estimated from the proposed method are 1.19,3.24,3.44,3.52; 3.11,6.87,7.35,7.45 and 1.29,10.74,10.93,11.25, respectively. From this, it is noted that the voltage profile and percentage minimum voltage improvement of the DS for scenario V is higher than in other scenarios. Incidentally, the voltage deviation (in p.u) estimated for light, nominal and heavy load for scenario I-V using CS-GWO method are 0.0418,0.0302,0.0097,0.0076,0.0068; 0.0870,0.0576,0.0196,0.0145,0.0135 and 0.1472,0.1360,0.0445,0.0425,0.0390, respectively.

Table 2. Comparison of results with other algorithms for the IEEE 33-bus system

Scenario	**Item**	**FWA [43]**	**RGA [5]**	**GA [15]**	**HSA [6]**	**ACSA [14]**	**UVDA [48]**	**MPGSA [44]**	**SFS [58]**	**Proposed CS-GWO**
Base case (Scenario I)	Opened switches	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33,34,35, 36,37
	Power loss (kW)	202.68	202.68	202.68	202.68	202.68	202.68	202.68	202.68	202.68
	Minimum voltage (p.u.)	0.9131	0.9131	0.9131	0.9131	0.9131	0.9131	0.9131	0.9131	0.9130
Only reconfiguration (Scenario II)	Opened switches	7, 9, 14, 28, 32	07,09, 14, 32, 37	33,34,9, 36,28	7, 10, 14, 32,28	7, 9, 14, 28, 32	7, 9, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 32, 37
	Power loss (kW)	**139.98**	**139.98**	**141.60**	**146.39**	**139.98**	**139.55**	**139.5**	**139.55**	**139.55**
	Minimum voltage (p.u.)	0.9413	0.9315	0.9310	0.9336	0.9410	0.9378	0.9343	0.9378	0.9424
	Loss reduction (%)	30.93	30.93	30.13	27.77	30.93	31.15	31.16	31.15	31.14
Only DG Installation (Scenario III)	Opened switches	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33,34,35, 36,37
	Size of DGs (MW), Bus number	0.5897 (14) 0.1895 (18) 1.0146 (32)	1.777	1.6044	0.1070 (18) 0.5724 (17) 1.0462 (33)	0.7798 (14) 1.251 (24) 1.3496 (30)	0.875 (11) 0.931 (24) 0.925 (29)	0.1058 (17) 0.5900 (18) 1.0812 (33)	0.7540 (14) 1.0994 (24) 1.0714 (30)	0.7520 (14) 1.096 (24) 1.074 (30)

	Power loss (kW)	**88.68**	**97.60**	**100.1**	**96.76**	**74.26**	**74.21**	**95.42**	**71.47**	**71.40**
	Minimum voltage (p.u.)	0.9680	0.9687	0.9605	0.9670	0.9778	0.962	0.9585	0.9687	0.9804
	Loss reduction (%)	56.24	51.84	50.60	52.26	63.36	63.39	52.92	64.72	64.74
DG installation after reconfiguration (Scenario IV)	Opened switches	7, 9, 14, 28, 32	07,09,14, 32, 37	33,34 9,36, 28	07,09, 14, 32, 37	7, 9, 14, 28, 32	7, 9, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 32, 37
	Size of DGs (MW), Bus number	0.5996 (32) 0.3141 (33) 0.1591 (18)	1.100	1.448	0.2686 (32) 0.1611 (31) 0.6612 (30)	1.7536 (29) 0.5397 (12) 0.5045 (16)	1.125 (30) 0.592 (15) 0.526 (12)	0.2469 (31) 0.1795 (32) 0.6645 (33)	1.0682 (24) 0.9503 (30) 0.9317 (8)	0.9329 (8) 1.0831 (24) 0.9512 (30)
	Power loss (kW)	**83.81**	**98.23**	**98.36**	**97.13**	**58.79**	**66.60**	**92.87**	**58.88**	**58.55**
	Minimum voltage (p.u.)	0.9612	0.9479	0.9506	0.9479	0.9802	0.9758	0.9482	0.9741	0.9855
	Loss reduction (%)	58.59	51.53	51.46	52.07	70.99	67.14	54.17	70.95	71.16
Simultaneous reconfiguration, DG installation (Scenario V)	Opened switches	7, 14, 11, 32, 28	07,09,12, 32, 27	7,10,28, 32,34	07,10,14, 32,28	7, 10, 13, 32, 28	7, 10, 13, 27, 32	7, 10, 14,28,31	6, 34, 11, 32, 28	7,10,14, 28,30
	Size of DGs (MW), Bus number	0.5367 (32) 0.6158 (29) 0.5315 (30)	1.774	1.9633	0.5258 (32) 0.5586 (31) 0.5840 (33)	0.4263 (32) 1.2024 (29) 0.7127 (30)	1.554 (29) 0.649 (15) 0.486 (21)	0.6311 (18) 0.5568 (32) 0.5986 (33)	0.6951 (8) 1.5718 (25) 0.6318 (13)	0.7311(18) 0.8075(27) 1.4805(25)
	Power loss (kW)	**67.11**	**74.32**	**75.13**	**73.05**	**63.69**	**57.28**	**72.23**	**55.28**	**54.01**
	Minimum voltage (p.u.)	0.9713	0.9691	0.9766	0.9700	0.9786	0.9676	0.9724	0.9724	0.9865
	Loss reduction (%)	66.89	63.33	62.92	63.95	68.57	71.74	64.36	72.73	73.35

From the obtained results, the DNR with DG installation minimizes voltage deviation closer to zero, improving voltage stability and network performance. The optimal network structure after simultaneous DNR, considering the DGs installation for scenario V, is 8,12,15,29,31 with DGs size (MW) 0.8075,0.7311,1.4805 located at buses 27,18,25 having PL of 51.01 kW respectively. The voltage profile curve for scenario I-V under nominal load is shown in Fig. 3. From this Figure, it is observed that the voltage profile for scenario V is better compared to other scenarios. The minimum voltage magnitude (in p.u) of DS is 0.9130, which is enhanced to 0.9424,0.9804,0.9855 and 0.9865 using scenarios I-V.

Table 2 represents the comparison of results obtained by hybrid CS-GWO with different algorithms such as RGA [5], HSA [6], ACSA [14], GA [15], FWA [43], MPGSA [44], UVDA [48] and SFA [58].

- For scenario II, hybrid CS-GWO optimized NR with opened switches: 7-9-14-32-37, estimated PL and minimum voltage magnitude as 139.55 kW and 0.9424 p.u, the obtained results do not vary when compared to other methods.
- For scenario III (DGs installation only) obtained optimal location and sizing (MW) of DGs at buses {14,24,30} and {0.7520,1.096,1.074} respectively. The proposed method provided the minimum PL and improved voltage profile compared with other methods.

- For scenario IV, the proposed method estimates the optimal DGs sizes (MW) of {0.9329,1.083 and 0.9512} for the installation at buses {8,24,30}. It is estimated that the PL obtained by the proposed method is minimal compared to other methods, i.e., 58.55 kW and improved voltage magnitude of 0.985 p.u.
- For scenario V, the proposed method provides optimal DNR along with DGs installation with opened switches: 8,12,15,29,31, the optimal DGs installation at buses {27,18,25} with sizes (MW) of {0.8075,0.7311,1.4805}. It is estimated that the power loss obtained in this scenario by the proposed hybris CS-GWO algorithm is minimal compared to other methods, i.e., 54.01 kW and improved voltage magnitude of 0.9865 p.u.

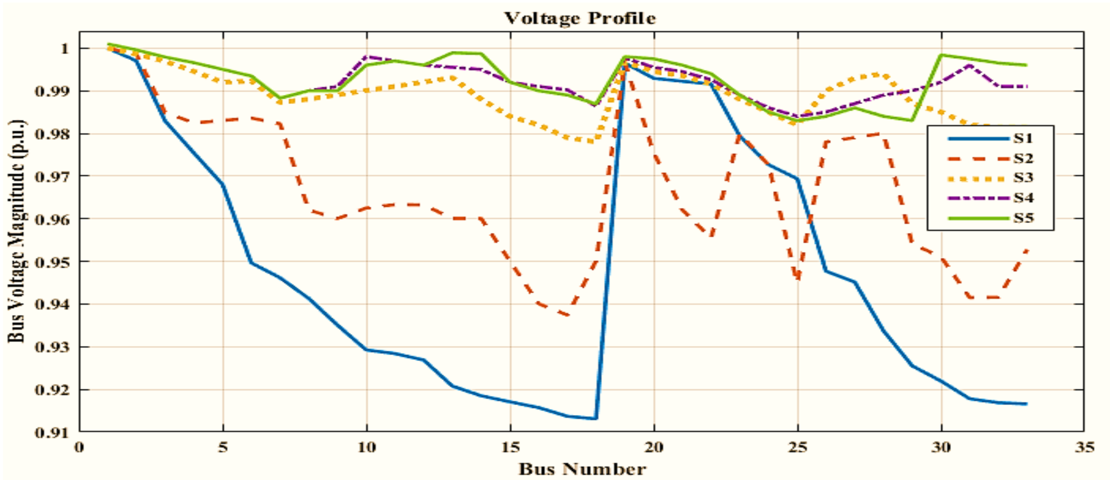

Figure 3. Voltage profile curves of an IEEE 33-bus system using hybrid CS-GWO algorithm

Convergence characteristics are also estimated for two scenarios II and V by considering the IEEE 33-bus system and depicted in Fig. 4a and 4b, respectively. In Fig. 4a, it is observed that, from the 1st iteration onwards, PL decreased from 140.77 kW to 139.55 kW for scenario II. From Fig. 4b at 30th iteration onwards, PL decreased from 60.00 kW to 54.01 kW for scenario V. From Fig. 4a, it is pertinent to note that the proposed hybrid CS-GWO technique has converged to an optimal solution after 2nd iteration for scenario II, showing that by integrating cuckoo search in GWO algorithm may find a better solution within less computation time of convergence process. Similarly, from Fig. 4b, it is found that the algorithm converges at the 28th iteration providing an optimal solution with minimum power loss in scenario V compared to other algorithms found in the exhaustive literature survey.

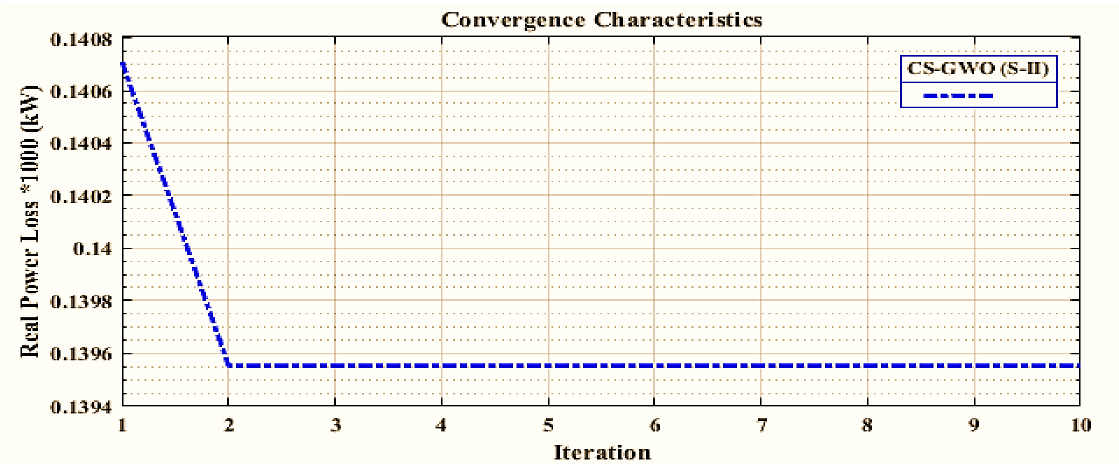

Figure 4a. Convergence characteristics for scenario II of IEEE 33-bus system using hybrid CS-GWO algorithm.

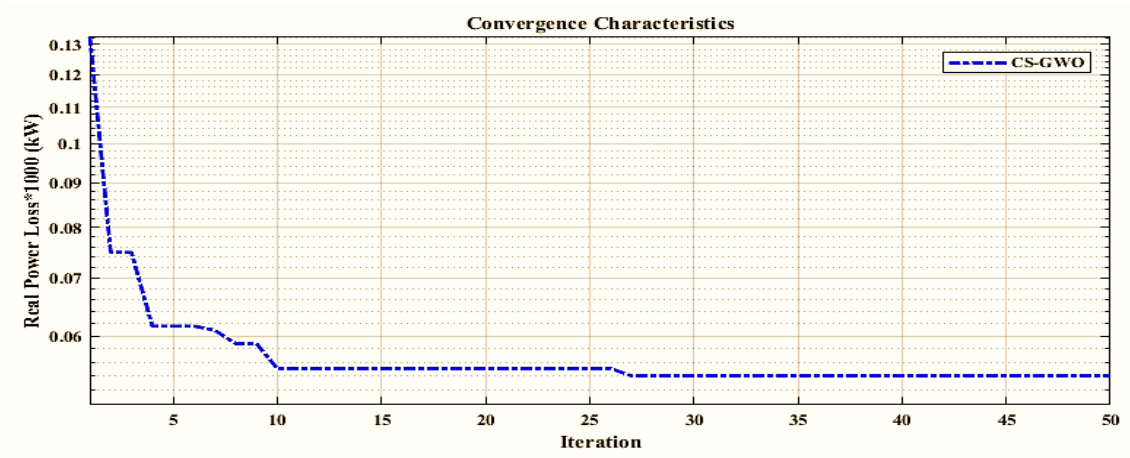

Figure 4b. Convergence characteristics for scenario V of IEEE 33-bus system using CS-GWO algorithm.

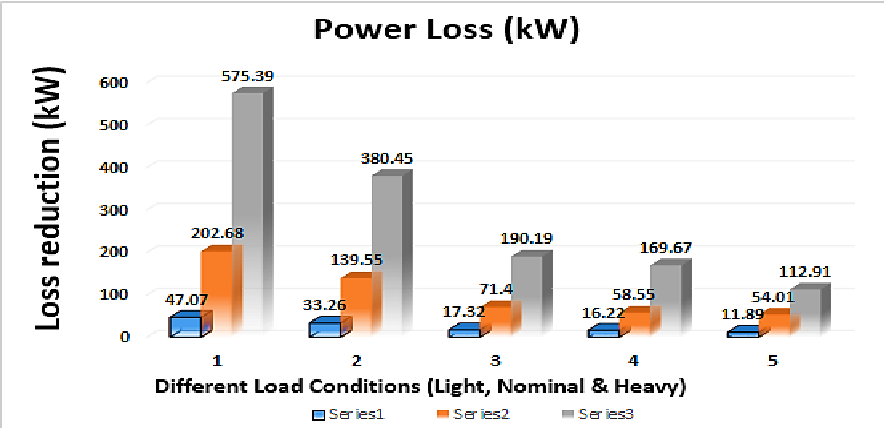

Figure 5. Power loss of an IEEE 33-bus system using hybrid CS-GWO algorithm under different loading conditions

The reduction in active PL obtained in the base case and to those obtained from different scenarios for light, nominal and heavy load conditions is represented as a bar graph in Fig. 5, From which the active PL (in kW) in the base case for nominal load is 202.68, and it is reduced drastically to 139.55, 71.40, 58.55, 51.98 for scenarios II, III, IV, V respectively. From Table 2, it is concluded that the PL reduction obtained by the proposed hybrid technique is higher than the results obtained with GA, UVDA, MPGSA, SFS, and FWA methods. From these results, the percentage PL reduction by the proposed hybrid CS-GWO method for scenarios II, III, IV, and V were 31.14%, 64.74%, 71.16%, and 74.50%, respectively. Whereas with MPGSA, UVDA and SFS, it is {31.16%, 63.39%, 67.14%, and 71.74%}; {31.15%, 52.92%, 54.17%, and 64.36%}; and {31.15%, 64.72%, 70.95%, and 72.50%} respectively. Hence the performance in terms of active PL minimization and voltage profile improvement, the proposed hybrid CS-GWO algorithm proved better performance for obtaining optimal solution when compared to the other optimization techniques.

Test system-II: IEEE 69-bus system

The topology of the test system consists of 68 SS (1-68) and 5 tie switches from (69-73) and system data were considered from [72]. The total load data under the base case were 3.80 MW and 2.694 kVAR, respectively. Table 3 shows the simulation results of test system 2 with installed DGs for different loading conditions and also computed voltage deviation ΔV_D(p.u.) at load buses. Table 4 shows the effectiveness of the hybrid CS-GWO algorithm compared with existing algorithms in obtaining optimal configuration, sizing and location of DGs for all the scenarios considered and simulation results are presented. Fig. 6 depicts the SLD of test system 2 with different loops and DGs placement. Depending on the number of tie switches, five loops have been formed as L_1 to L_5, these switches are operated during fault cases, load balancing conditions and to reduce the system losses.

L1= [3,4,5,6,7,8,9,36,37,38,39,40,41,42,35]; L2= [11,12,13,14,44,43,45]; L3 = [15,16,17,18,19,20];
L4= [21,22,23,24,25,26,59,60,61,62,63,64]; L5 = [47,48,49,53,54,55,56,57,52,46,58]

To evaluate the effectiveness of proposed method, test system 2 is also simulated at different load levels such as light (0.5), nominal (1.0), and heavy (1.6), and obtained results are conferred in Table 3. From Table 3, we can infer that base case PL in the DS (in kW) at light load is 51.60, which is reduced to 23.43, 18.14, 11.54 and 9.545 using scenarios II, III, IV, and V, respectively. Similarly, at nominal load, base case PL in the system (in kW) is 224.70, which is reduced to 98.12,70.98,36.07 and 34.28 using scenarios II, III, IV, and V, respectively. Base case PL in the DS (in kW) at heavy load is 652.45, which is reduced to 271.16, 186.30, 96.42, and 72.65 using scenarios II, III, IV, and V, respectively. The percentage loss reduction for scenarios II to V at light load is 54.59, 64.84, 77.63 and 81.50, respectively. Similarly, the percentage loss reduction for scenarios II to V at nominal and heavy load conditions is {56.33,68.39,83.94,84.74}; and {58.43,71.44,85.22,88.86} respectively.

This represents that for all load levels, PL reduction using scenario-V by the proposed hybrid CS-GWO algorithm is highest, proving the proposed method's effectiveness over the GWO method. As load level rises from light to heavy, enhancement in percentage PL reduction in all scenarios is nearly the same. It is pertinent from table 3 that reduction in PL and voltage profile improvement for scenario V is higher in comparison with scenario IV. As well as, this Table also provides the estimated PL value (in kW) and ΔV_D (p.u.) as {225.00, 98.53, 71.65, 37.07, 40.28} and {0.0908, 0.0508, 0.0220,0.0178, 0.0193} using the GWO algorithm. From this Table, the results obtained from the hybrid CS-GWO algorithm are better than the GWO algorithm.

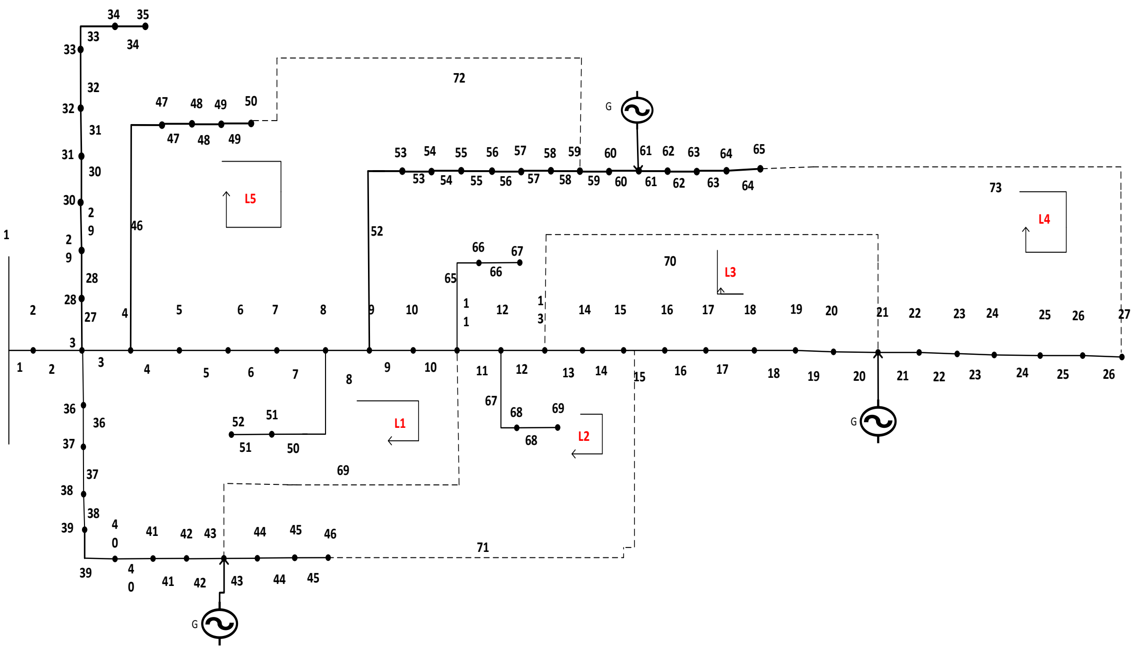

Figure 6. SLD of IEEE 69-bus RDS, with different loops and DGs placement

Furthermore, that the voltage profile (in p.u.) of the DS was improved from 0.9561 to 0.9875 in light load condition. Similarly, from 0.9094 to 0.9842 in nominal load; 0.8544 to 0.9625 in heavy load condition, respectively. The percentage minimum voltage improvement of the system for scenario II to V at light, medium and heavy load estimated from proposed method is {1.70,3.11,2.85,3.17}; {4.22,7.05,7.52,7.60} and {5.72,10.71,10.44,11.23}, respectively. From this, it is noted that voltage profile and percentage minimum voltage improvement of the DS for scenario V is the highest in comparison with other scenarios. Incidentally, the voltage deviation (in p.u) estimated for light, nominal and heavy load for scenario I-V using hybrid CS-GWO method is {0.0439,0.0273,0.0132,0.0158,0.0125}; {0.0906,0.0505,0.0216,0.0166,0.0158} and {0.1456,0.0937,0.0431,0.0459,0.0375}, respectively.

From the obtained results, the DNR with DG installation minimizes voltage deviation closer to zero, which will improve voltage stability and network performance. After simultaneous DNR, considering the DGs installation for scenario V, the network's optimal structure is 13,56,69,24,18 with DGs size (MW) as 0.3738,0.3888,1.6764 located at buses 24,32,61 having power losses of 34.28 kW and minimum voltage magnitude of 0.9842 p.u respectively. The voltage profile curve for scenario I-V under nominal load is depicted in Fig. 7. From this Figure, it is observed that the voltage profile for scenario V is better compared to other scenarios. For example, the minimum voltage magnitude (in p.u) of the DS is 0.9094, which is later enhanced to 0.9495,0.9784,0.9834 and 0.9842 using scenarios I-V.

Table 3. Results of an IEEE 69-bus RDS using GWO and hybrid CS-GWO

Scenario	**Item**	**GWO Nominal load (1.0)**	**Proposed CS-GWO Load levels**		
			Light load (0.5)	**Nominal load (1.0)**	**Heavy load (1.6)**
Base case (Scenario I)	Opened switches	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73
	Power loss (kW)	**225.00**	**51.60**	**224.70**	**652.45**
	Minimum voltage (p.u.)	0.9092	0.9561	0.9094	0.8544
	ΔV_D(p.u.)	0.0908	0.0439	0.0906	0.1456
Only reconfiguration (Scenario II)	Opened switches	69,71,14,55,61	69,20,12,55,61	69,20,12,56,61	69,20,12,58,61
	Power loss (kW)	**98.53**	**23.43**	**98.12**	**271.16**
	Minimum voltage (p.u.)	0.9492	0.9727	0.9495	0.9063
	Loss reduction (%)	56.19	54.59	56.33	58.43
	ΔV_D(p.u.)	0.0508	0.0273	0.0505	0.0937
	Iterations	60	4	3	7
Only DG Installation (Scenario III) (P Type)	Opened switches	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73
	Size of DG in MW (Bus number)	0.5147(17) 1.7798(61) 1.4710(47)	0.2618(18) 1.4373(4) 0.8752(61)	0.5202(18) 0.7509(50) 1.7644(61)	0.8531(18) 1.2536(49) 1.9008(61)
	Power loss (kW)	**71.65**	**18.14**	**70.98**	**186.30**
	Minimum voltage (p.u.)	0.9780	0.9868	0.9784	0.9569
	Loss reduction (%)	68.15	64.84	68.39	71.44
	ΔV_D(p.u.)	0.0220	0.0132	0.0216	0.0431
	Iterations	65	14	32	34
DG installation after reconfiguration (Scenario IV) (P Type)	Opened switches	69,14,70,61,57	69,14,70,61,57	69,14,70,61,57	69,13,70,61,56
	Size of DG in MW (Bus number)	0.6940(67) 0.5333(25) 1.3008(61)	0.1945(60) 0.1142(58) 0.4584(61)	0.6950(64) 0.5401(12) 1.2008(61)	0.3315(60) 1.1551(57) 1.9586(61)
	Power loss (kW)	**37.07**	**11.54**	**36.07**	**96.42**
	Minimum voltage (p.u.)	0.9822	0.9842	0.9834	0.9541
	Loss reduction (%)	83.52	77.63	83.94	85.22
	ΔV_D(p.u.)	0.0178	0.0158	0.0166	0.0459
	Iterations	80	40	45	50
Simultaneous reconfiguration, DG installation (Scenario V) (P Type)	Opened switches	10,14,15,63,57	69,20,71,57,26	13,56,69,24,18	69,70,13,57,63
	Size of DG in MW (Bus number)	0.4447(43) 0.6966(21) 1.4982(61)	0.5696(13) 0.4485(50) 1.6729(61)	0.3738(24) 0.3888(32) 1.6764(61)	0.7953(27) 1.0035(49) 1.9586(61)
	Power loss (kW)	**40.28**	**9.545**	**34.28**	**72.65**
	Minimum voltage (p.u.)	0.9807	0.9875	0.9842	0.9625
	Loss reduction (%)	82.00	81.50	84.74	88.86
	ΔV_D(p.u.)	0.0193	0.0125	0.0158	0.0375
	Iterations	80	40	40	40

Table 4 represents the comparison of results obtained by hybrid CS-GWO with different algorithms such as RGA [5], HSA [6], ACSA [14], GA [15], FWA [43], and UVDA [48].

- For scenario II, hybrid CS-GWO optimized NR with opened switches:69-20-12-56-61, with estimated PL and minimum voltage magnitude as 98.12 kW and 0.9495 p.u, is approximately close to the obtained results from other methods compared.
- For scenario III (DGs installation only), hybrid CS-GWO obtained optimal location and sizing (MW) of DGs at buses {18,50,61} and {0.5202,0.7509,1.7644}, respectively, to be installed for minimizing

power losses and improving voltage profile. As a result, the proposed method provided the minimum PL and improved voltage profile compared with other methods.

- For scenario IV, the proposed method provides the optimal DGs sizes (MW) of {0.6950,0.5401 and 1.2008} for the installation at buses {64,12,61}. The PL obtained by the proposed method in this scenario is estimated to be minimal compared to other methods, i.e., 36.07 kW and improved voltage magnitude of 0.9834 p.u.
- For scenario V, the proposed method estimates optimal DNR along with DGs installation with opened switches: 13,56,69,24,18, the optimal DGs installation at buses {24,32,61} with sizes (MW) of {0.3738,0.3888 and 1.6764}, respectively. It is assessed that the PL obtained in this scenario by the proposed method is minimal compared to other methods, i.e., 34.28 kW and improved voltage magnitude of 0.9842p.u.

Table 4. Comparison of results with other methods for the IEEE 69-bus system

Scenario	**Item**	**FWA [43]**	**RGA [5]**	**GA [15]**	**HSA [6]**	**ACSA [14]**	**UVDA [48]**	**Proposed CS-GWO**
Base case (Scenario I)	Opened switches	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73
	Power loss (kW)	**224.89**	**224.89**	**224.89**	**225.00**	**224.89**	**224.89**	**224.70**
	Minimum voltage (p.u.)	0.9092	0.9092	0.9092	0.9092	0.9092	0.9092	0.9094
Only reconfiguration (Scenario II)	Opened switches	60, 70, 14, 57, 61	69,17, 13, 55,61	69,70,14, 53,61	69,18,13, 56,61	60, 70, 14, 57, 61	69, 70, 14, 58, 61	69,20,12,56,61
	Power loss (kW)	**98.59**	**100.28**	**103.29**	**99.35**	**98.59**	**98.58**	**98.12**
	Minimum voltage (p.u.)	0.9459	0.9428	0.9411	0.9428	0.9459	0.9495	0.9495
	Loss reduction (%)	56.16	55.42	54.08	55.85	56.16	56.19	56.33
Only DG Installation (Scenario III)	Opened switches	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73
	Size of DG in MW (Bus number)	0.4085(65) 1.1986(61) 0.2258(27)	1.7868	1.9471	0.1018(65) 0.3690(64) 1.3024(63)	0.6022(11) 0.3804(18) 2.000(61)	1.410(61) 0.6040(11) 0.4170(17)	0.5202(18) 0.7509(50) 1.7644(61)
	Power loss (kW)	**77.85**	**87.65**	**88.50**	**86.77**	**72.44**	**72.626**	**70.98**
	Minimum voltage (p.u.)	0.9740	0.9678	0.9687	0.9677	0.9890	0.9688	0.9784
	Loss reduction (%)	65.39	61.04	60.66	61.43	67.79	67.72	68.39
DG installation after reconfiguration (Scenario IV)	Opened switches	69,70,14, 57,61	69,17, 16, 55,61	69,70,14, 53,61	69,18,13, 56,61	69,70,14, 57,61	69,70,14, 58,61	69,14,70,61,57
	Size of DG in MW (Bus number)	1.7254(61) 0.4666(64) 0.3686(12)	1.6396	1.7422	1.0666(61) 0.3525(60) 0.4257(58)	1.7254(61) 0.4666(64) 0.3686(12)	1.378(61) 0.6200(11) 0.7220(64)	0.6950(64) 0.5401(12) 1.2008(61)
	Power loss (kW)	**37.23**	**52.34**	**54.53**	**51.30**	**37.23**	**37.84**	**36.07**

	Minimum voltage (p.u.)	0.9870	0.9611	0.9401	0.9619	0.9870	0.9801	0.9834
	Loss reduction (%)	83.45	76.73	75.76	77.20	83.45	83.18	83.94
Simultaneous reconfiguration, DG installation (Scenario V)	Opened switches	69,70,12, 58,61	10,16, 14, 55,62	10,15,45, 55,62	69,17,13, 58,61	69, 70, 14, 58, 61	69,70,14, 58,63	13,56,69, 24,18
	Size of DG in MW (Bus number)	1.749(61) 0.1566(62) 0.4090(65)	2.0654	2.0292	1.0666(61) 0.3525(60) 0.4527(62)	0.1566(62) 1.749(61) 0.4090(65)	0.5380(11) 0.6730(17) 1.472(61)	0.3738(24) 0.3888(32) 1.6764(61)
	Power loss (kW)	**40.49**	**44.23**	**46.50**	**40.30**	**40.49**	**37.11**	**34.28**
	Minimum voltage (p.u.)	0.9873	0.9742	0.9727	0.9736	0.9873	0.9816	0.9842
	Loss reduction (%)	82.00	80.32	73.38	82.08	82.00	83.51	84.74

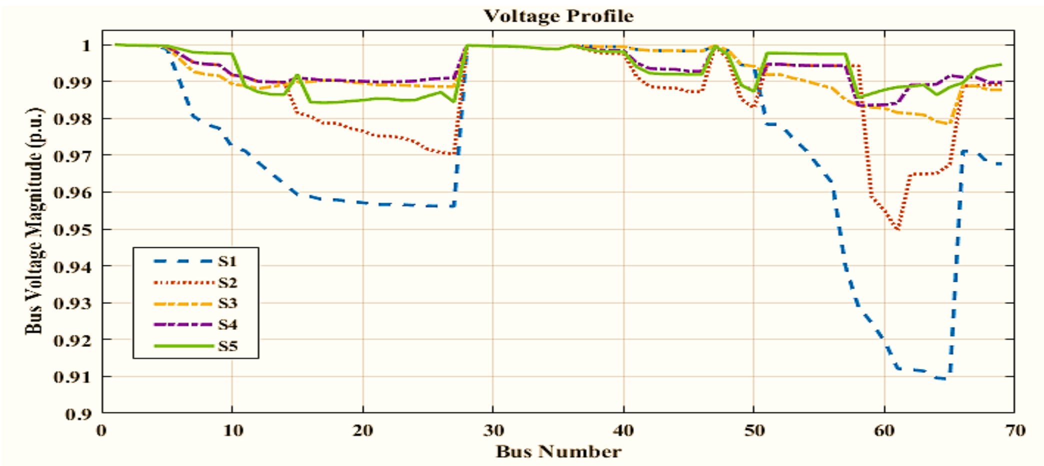

Figure 7. Voltage profile curves of an IEEE 69-bus system using hybrid CS-GWO algorithm

Convergence characteristics are also estimated for two scenarios II and V by considering the IEEE 69-bus system and depicted in Fig. 8a and 8b. From Fig. 8a at the 1st iteration onwards, PL decreased from 110.00 kW to 98.12 kW for scenario II, and from Fig. 8b at 30th iteration onwards, PL decreased from 60.10 kW to 34.28 kW for scenario V. From Fig. 8a, it is found that the proposed hybrid CS-GWO technique has converged to an optimal solution after 3rd iteration for scenario II, showing that by integrating cuckoo search in GWO algorithm may find a better solution within a short time of convergence process. Similarly, from Fig. 8b, it is found that the algorithm converges at the 30th iteration providing an optimal solution with minimum PL in scenario V in comparison with other algorithms in the literature. The reduction in active PL obtained in the base case to those obtained from different scenarios for light, nominal and heavy load conditions is represented as a bar graph in Fig. 9. It can be noticed from Fig. 9 that the active PL (in kW) in the base case for nominal load is 224.70, and it is reduced drastically to 98.12, 70.98, 36.07, 34.28 for scenarios II, III, IV, V, respectively.

From table 4, it is concluded that the PL reduction obtained by the proposed hybrid CS-GWO method is higher than that result with GA, UVDA, ACSA and FWA methods. From these results, the percentage PL reduction by the proposed hybrid CS-GWO method for scenarios II, III, IV, and V were 56.33%, 68.39%, 83.94%, and 84.74%, respectively. Whereas with GA, ACSA, UVDA and FWA, it is {54.08%, 60.66%, 75.76%, and 73.38%}; {56.16%, 67.79%, 83.45%, and 82.00%}; {56.19%, 67.72%, 83.18%, and 83.51%} and {56.16%, 65.39%, 83.45%, and 82.00%} respectively. Hence the performance in terms of active PL minimization and voltage profile improvement, the proposed hybrid CS-GWO algorithm proved better performance for obtaining optimal solution when compared to the other optimization techniques.

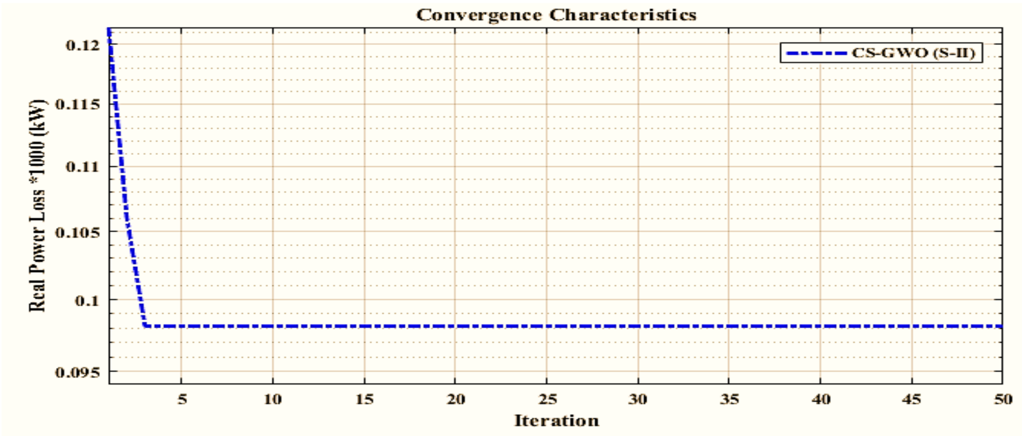

Figure 8a. Convergence characteristics for scenario II of IEEE 69-bus system using hybrid CS-GWO algorithm.

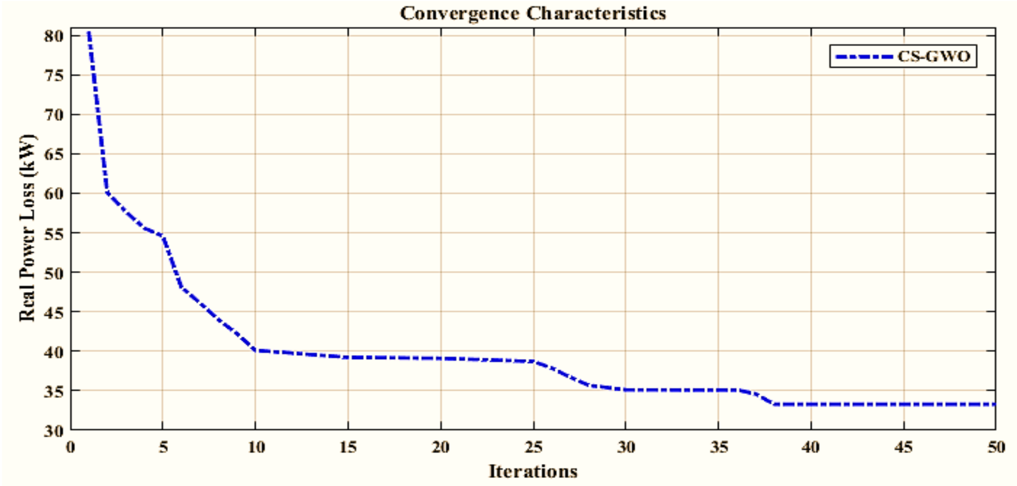

Figure 8b**.** Convergence characteristics for scenario V of IEEE 69-bus system using hybrid CS-GWO algorithm.

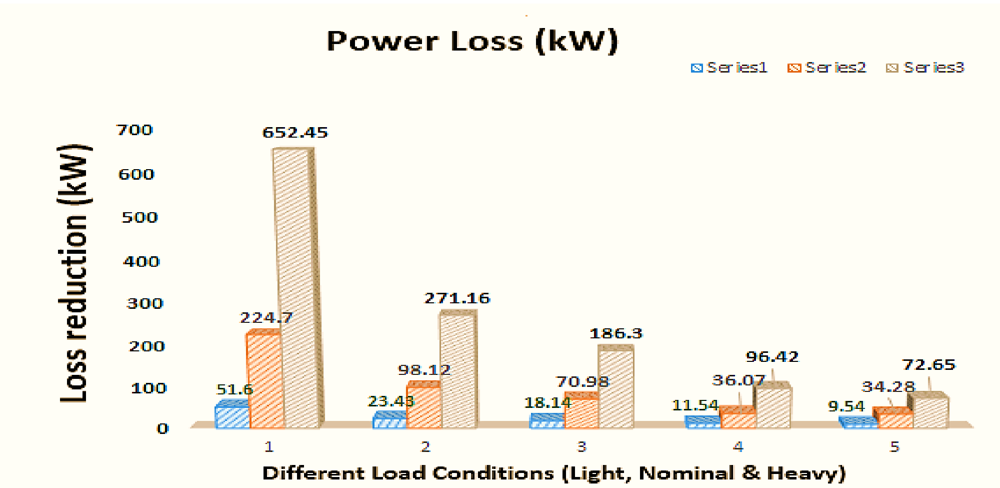

Figure 9. Power loss of an IEEE 69-bus system using CS-GWO algorithm under different loading conditions

Table 5 presents the assessment of the proposed CS-GWO algorithm for scenario V at nominal loading conditions and the results of the compared techniques. From this Table, it is observed that for scenario-V, simultaneously DNR with DG installation using the proposed algorithm has obtained an optimal solution that reduces power loss by 54.01 kW, percentage power loss by 73.35%, and enhanced minimum voltage magnitude (p.u) to 0.9865 for the 33-bus system and for the 69-bus system are 33.29kW, 85.18% and 0.9842 under nominal load. The results show the effectiveness of the proposed algorithm over the conventional GWO and other earlier methods published. Therefore, the proposed CS-GWO method can be a promising method for dealing with the simultaneous DNR problem considering DG placement.

Table 5. Assessment of obtained results with previously published optimization algorithms for the IEEE 33, 69-bus systems

Scenario	**Item**	**SFSA [58]**	**EOA [61]**	**IEOA [61]**	**GWO**	**Proposed CS-GWO**
				IEEE 33-bus system		
Simultaneous reconfiguration, DG installation (Scenario V)	Opened switches	6,34,11,32,28	8,27,33,34,36	7,10,13,27,31	7,14,9,15,27	7,10,14,28,30
	Size of DG in MW (Bus number)	0.6951(8) 1.5718(25) 0.6318(13)	1.413(29) 0.651(14) 0.165(8)	0.399(8) 0.669(17) 1.160(29)	0.7608(18) 0.7085(22) 1.1749(25)	0.7311(18) 0.8075(27) 1.4805(25)
	Power loss (kW)	**55.28**	**61.48**	**57.40**	**56.58**	**54.01**
	Minimum voltage (p.u.)	0.9724	----	0.9748	0.9827	0.9865
	Loss reduction (%)	72.73	69.66	71.67	72.08	73.35
				IEEE 69-bus system		
Scenario	**Item**	**SFSA [58]**	**EOA [61]**	**IEOA [61]**	**GWO**	**Proposed CS-GWO**
Simultaneous reconfiguration, DG installation (Scenario V)	Opened switches	69,70,12,55,26	12,18,56,63,69	10,13,57,61,70	10,14,15,63,57	13,56,69,24,18
	Size of DG in MW (Bus number)	1.1811(61) 0.3802(59) 0.3802(60)	1.463(61) 0.522(27) 0.278(66)	0.362(12) 1.400(61) 0.518(26)	0.4447(43) 0.6966(21) 1.4982(61)	0.3738(24) 0.3888(32) 1.6764(61)
	Power loss (kW)	**42.84**	**37.55**	**36.39**	**40.28**	**34.28**
	Minimum voltage (p.u.)	0.9810	----	0.9721	0.9807	0.9842
	Loss reduction (%)	80.94	83.31	83.82	82.00	84.74

6. CONCLUSION

In this paper, the proposed hybrid CS-GWO algorithm has been implemented to simultaneously solve the DNR, DGs installation problem in the RDSs to reduce active power loss and voltage profile improvement. Moreover, different scenarios aimed at system loss reduction, voltage profile improvement and minimum voltage deviation were considered here.

- They are (i) Considering DNR only (S-II), estimated PL reduction solution by hybrid CS-GWO under nominal load is 139.55 kW, along with minimum voltage magnitude and voltage deviation at load buses (p.u) is 0.9424 and 0.0576 for the IEEE 33-bus system, for the 69-bus system is 98.12 kW,0.9495 and 0.0505. Similarly, power reduction (S-V) for IEEE 33 and 69-bus systems is 54.01 kW and 34.28 kW, respectively.
- Meanwhile, for scenario-V, simultaneously DNR with DG installation have obtained an optimal solution that reduces percentage power loss by 73.35% and enhanced minimum voltage magnitude (p.u) to 0.9865 for the 33-bus system and for the 69-bus system are 84.74% and 0.9842 under nominal load.
- Additionally, the percentage voltage improvement obtained by this proposed algorithm for scenarios II and III under nominal load is 3.11 and 7.45 for the IEEE 33-bus system. Similarly, for IEEE 69 bus is 4.22 and 7.60, respectively.

- Analysis of the results obtained from the hybrid CS-GWO algorithm shows that simultaneous DNR, DG installation process in RDSs is a more effective method in minimizing system power loss and improving the system's voltage profile than results obtained by other optimization methods reported earlier in the literature.

The results obtained by the proposed hybrid CS-GWO algorithm are compared with other optimization techniques such as HSA, GA, RGA, FWA, ACSA, UVDA, SFS and MPGSA. The comparison validates the effectiveness of the proposed technique shows that it is a better and promising method than the other optimization approaches in solving DNR, DGs installation problems simultaneously. Therefore, the proposed hybrid CS-GWO algorithm may be treated as a constructive method for optimizing DNR problem for complex and large-scale RDS and optimal location and sizing of the installed DGs.

APPENDIX:

Table A1. Summary of recently published works to solve DNR problem considering DGs

Author, Year, [Ref.]	Optimization algorithm/technique	Objective function	Test system & outcome
A. M. Shaheen, et.al., 2021, [61]	Equilibrium Optimization Algorithm (IEOA)	To minimize the total power losses (TPL) and maximize the total voltage stability index (TVSI)	• IEEE 33,69 and 137-bus test system. • Obtain optimal global solutions for complex combinatorial problems. • Effective method having better controllability between exploration and exploitation.
Dieu Vo Ngoc, et.al., 2020, [66]	Chaotic Stochastic Fractal Search Algorithm (CSFSA)	To minimize the APL and improve the voltage profile.	• 33,84,119 and 136 RDSs. • Favorable method for solving complex and large-scale DNR problem. • Integration of chaos theory in SFSA has improved diffusing efficiency, updating process, and search ability.
Ayodeji Olalekan Salau et.al., 2020, [73]	Modified Selective particle swarm optimization (SPSO) method	To minimize the power loss and improve the voltage profile.	• 33 RDSs. • the proposed method has been found to be more efficient in reducing voltage deviation (VD) and power losses in the system. • the proposed algorithm was efficient in terms of reducing both the real and reactive power losses in the system.
T Jayabarathi, et.al., 2020, [74]	Grasshopper optimization algorithm (GOA)	Power loss minimization and voltage profile (VP) enhancement in RDSs under different loading conditions.	• 33,69 and 118 RDSs. • Effective method for solving complex and large-scale DNR problem in presences of D-STATCOM units and PV arrays.
Ayodeji Olalekan Salau et.al., 2020, [75]	Grid based Multi-Objective Harmony Search Algorithm (GrMHSA)	To optimally size and locate the DG on the feeder resulting in lowest total voltage deviation, total active and reactive power loss.	• Debre Markos Feeder 3. • The results showed that the total voltage deviation, active and reactive power losses are reduced to 1.479 p. u, 95.398 kW and 90.979 kVAR, respectively.
Ayodeji Olalekan Salau et.al., 2020, [76]	Grid-Based Multi-Objective Harmony Search Algorithm (GrMHSA)	To mitigate power losses and improve the voltage profile by the optimal sizing and placing of DGs in the distribution network.	• Utility feeder 4 test system. • The performance comparison of GrMHSA and MOPSO showed that GrMHSA performs better in terms of reducing voltage deviation and power losses in the system. • The results showed that the total voltage deviation, active and reactive power losses were reduced by 85.20%, 84.94%, and 85.73%, respectively.
A.Selim, et.al., 2021, [77]	Modified Whale Optimization (MOWOA) algorithm and fuzzy decision-making method	Power loss and voltage deviation (VD) minimization and voltage stability index (VSI) optimize.	• IEEE 33,69-bus test system. • Competitive optimization algorithm having minimum convergences rate. • An effective method for finding optimal DGs placement and size in the system based on the fuzzy decision-making process.
Ayodeji Olalekan Salau et.al., 2021, [78]	Fuzzy Expert System (FES) method (Fuzzy logic optimization method)	To determine the voltage regulator (VR) and capacitor placement suitability index.	• Gondar feeder in Gondar, Ethiopia (60 nodes RDS). • The results indicate that by using capacitors, 159.85KW power is saved and also in the same way all the weak bus VPs are optimized to the standard ±5% voltage deviation level. • The total real PL reduction is 38.46% using VRs and 42.316% using shunt capacitors.

Ahmad Eid, et.al., 2021, [79]	Manta-Ray Foraging Optimization (MRFO) algorithm	To reduce the total energy loss of system	• IEEE 69-bus test system. • Have capable of optimizing the size, site, and power factor of every DG along the 24-hour cycle to minimize system losses. • An effective method for finding optimal DGs placement and size in system considering time-varying demands and different operating DG power factor.
M. Khasanov, et.al., 2021, [80]	Rider Optimization Algorithm	To minimize total power and energy losses	• IEEE 33,69-bus test system. • Weibull and Beta probability distribution functions are used to characterize the variability of renewable potentials. • An effective approach for finding optimal renewable DGs placement and size in system considering time-varying load demand and probabilistic generation.
K. Balu, et.al., 2021, [81]	**Student Psychology-Based Optimization Algorithm**	To minimize APL, total voltage deviation and voltage stability index of the RDSs consider different load models.	• IEEE 33,69 and brazilian136-bus test system. • The analytic hierarchy process is used to optimize the weighting factor. • An effective method to solve the optimal multiple DG allocation problem with minimum real power loss, less computational time, and a prominent convergence rate.
I. Khonturaev, et.al., 2021, [82]	Atom Search Optimization Algorithm	To minimize power losses	• IEEE 33-bus test system. • Power loss sensitivity index method is used to find optimal buses for DGs installation. • An effective approach for finding optimal DGs placement and size in system.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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