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Original scientific paper

A Multi-Objective Decision-Making Approach for Network Stability Enhancement by Reconfiguration and Installation of DG and Capacitor Units Using Crow Search Algorithm

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Abstract: Network Reconfiguration (NR) is an efficient and essential methodology for minimizing power loss (Pl). However, NR is still critically challenging due to its complexity, nonlinearity, and large-scale optimization problem. This work introduces an innovative approach to enhance the Distribution Network (DN) stability and reliability. It addresses a simultaneous optimizing technique within different limits and constraints related to network power flow and voltage limits. It optimizes Distribution Reconfiguration (DR), Distributed Generation Sizing and Location (DG_SL), and shunt Capacitor Sizing and Location (CAP_SL). The main objectives are reducing Pl in the network, improving the Voltage Stability Index (VSI), and improving distribution efficiency. The Analytic-Hierarchy Process (AHP) and Crow Search Algorithm (CSA) are used as the foundation for a Multi-Objective Decision-Making Approach (MODMA). Simulations on IEEE 33 and 69 bus networks were run using MATLAB software to assess the viability of the suggested approach. This study obtains efficient output results and a positive impact on the distribution through the DR, DG_SL, and CAP_SL optimization. This appears through the system Pl reduction. For the IEEE 33-bus system, the reductions in Active Power Loss (Ploss) and Reactive Power Loss (Qloss) are 94.494% and 93.294%, respectively, whereas, for the IEEE 69-bus system, they are 97.097% and 94.412%, respectively. In contrast, the minimum bus voltage for the IEEE 33-bus system improved to 0.9926 p.u. and for the IEEE 69-bus system to 0.9912 p.u. For more validation, by comparing a part of the obtained results with other articles.

Keywords: Distribution reconfiguration; Shunt capacitor sizing and location; Distributed generation sizing and location; Power loss; Voltage Stability index; Optimization technique.

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1 Introduction

Electricity is vital for humanity since all technologies are based on it. Electricity is generated from a power system of generation, distribution, and transmission. The distribution area causes the Pl because of the current flowing through the distribution branches. Studies [1, 2] mentioned that loss through the distribution is greater than the transmission system. Thus, most works look forward to minimizing the losses through the distribution system (DS). Where Pl minimizing process improves the power quality and system efficiency [3, 4].

Recently, several techniques were used to enhance the quality of the modern system. DG_SL is one of these techniques. DG sizing means the optimal active power generation obtained from the DG power generator unit, while DG location means the optimal siting of generation units within the DS and mostly situated near the demand [5 – 7]. DG_SL technique was used to enhance the system voltage and reduce the total Pl as conducted in [8, 9]. Thus, the optimal output and location of DGs within the network are critical and vital to ensuring the power system operates effectively [10]. In [11], a hybrid approach using a Genetic Algorithm (GA) and a Particle Swarm Optimization (PSO) algorithm was presented to minimize apparent loss and enhance voltage regulations. The authors in [12] proposed a new approach based on the VSI and differential evolution method to evaluate the power system security and reliability, Voltage System (VS) enhancement, and Pl. In [13], a renewable energy DG development which handled Pl, voltage profile (VF), DG costs, energy consumption, and pollutant emissions was presented.

Network Reconfiguration is the most common technique that is used to modify the performance of the modern network such as enhancing the voltage quality, reducing Pl, and balancing the load [14]. The reconfiguration process is performed by changing the switches' status of the distribution by closing and opening the sectionalizing and tie switches while keeping the radiality of the network, maintaining the loads fed and connected and system voltage within the limitations [15]. The DR method is critical and essential since it is a large-scale and nonlinear optimization problem that is also subject to some constraints and limitations [16]. Thus, a lot of works seek to develop efficient methods to deal with this issue [17]. The DR process aims to enhance the stability and reliability of the system, reduce loss, enhance system voltage, balance the system load, and isolate the fault area [18 – 21]. Different meta-heuristic methods (MHM) were reviewed to solve DR issues according to literature works. In [22], the cuckoo search algorithm (CSA) was addressed to reduce Pl and enhance the VF. CSA was presented in [23] to minimize total Pl. The coyote-optimization algorithm in [24] and the firefly algorithm (FA) in [25] were presented to modify the system's features. In [26], cloud theory was used to improve distribution reliability. In [27], the salp swarm method was used to reduce Pl. In [28], several MHMs were

presented to enhance network performance and reduce Pl. In [29], the sin–cos algorithm was addressed to improve Voltage Stability besides minimizing Pl. In [30], the authors proposed a dataset method to reduce the search complexity for optimal discretized DR. In [31], the authors presented a method to solve the combinatorial optimization and reduce the complexity search problems using a grey wolf optimizer (GWO).

Integrated DG into the network is another technique that used to enhance the operation system of the modern network. In [32], the work presented a review of the simultaneous DR problem with DG to handle the loss and voltage volatility. In [33], the authors addressed multi-objective methods of integrating DG into the DR to reduce pollution gas emissions, Pl, and operation costs. In [34], a mixed-particle swarm optimization (MPSO) methodology was used to improve system voltage and reduce loss. This methodology used the standard PSO and binary particle swarm algorithms to enhance the methodology efficiency in determining the best output. In [35], the work presented a hybrid GWO and PSO methods to solve the DR issue including conventional and renewable DG units. The hybrid optimizer achieved better outputs than the individual one. In [36, 37], the researchers presented a simultaneous optimal DR with optimal wind turbine and photovoltaic panel locations to improve the network reliability and reduce Pl cost. In [38], a new approach was proposed to determine the optimal switching sequence that changes the network's initial configuration to the optimal configuration. This approach aims to enhance the VF and reduce the loss during real-time switching sequence operation.

Integrated shunt capacitor unit (CAP) to the DN is another technique that was used to enhance the modern network's system operation [39]. CAP sizing means the optimal reactive power generation obtained from the CAP power generator unit, while CAP location means the optimal siting of generation units within the DS [40]. Integrated CAP units into the network reduces the voltage fluctuations, the Pl, and the operating costs, and enhances the overall VF since CAP provides reactive power [41]. Several optimization methods have been reviewed for DR considering CAP sizing and location. In [42], simulated annealing and harmony search algorithms used to solve the DR and CAP_SL problems. In [43, 44], the same problem was resolved using an ant colony algorithm, GA, and the Big Bang approach. In contrast, the authors of [45] overcome the same issue by combining PSO with GWO. These projects' primary goals were to lower the costs associated with the investments, yearly losses, switching, and upkeep and operation. In [46], the research presented a new methodology to reduce energy loss using a GA. That aims to find the optimal CAP_SL and optimize the loop selection sequence. The presented method was tested through several load patterns.

A modern study addressed improving the operation of islanded networks when generation and load imbalances occur. This was achieved through the

optimal allocation of distributed generators and capacitors, and power factor adjustment, with the aim of reducing losses and improving the utilization of available energy sources [47]. While [48] reviewed the most prominent optimization strategies used for the simultaneous allocation of distributed generators and capacitor banks in distribution networks. It focused on technical and economic aspects, outlining challenges and future research directions. In [49], the study focused on determining the optimal locations and sizes of distributed generators using a multi-objective approach to achieve voltage optimization, loss reduction, and increased operational efficiency of the distribution network. The study in [50] presented a planning approach based on the advanced MOPSO algorithm to determine the optimal distribution of renewable energy sources in radial distribution networks, aiming to improve operational performance and reduce losses.

Different from the published research reviewed previously, this work addressed two essential contributions:

In the face of increasing global energy demand and the rapid transition toward sustainable smart grids, traditional optimization methods often fall short. However, most previous studies have considered Distribution Reconfiguration (DR), DG allocation, and capacitor placement separately or partially, which fails to capture the complex interactions within modern radial distribution networks (RDN). Therefore, an efficient unified optimization framework is still needed to simultaneously handle these variables while addressing global technical challenges such as improving voltage stability and reducing power losses under strict operational constraints. This work bridges this gap by introducing an innovative simultaneous approach for DR, DG_SL, and shunt CAP_SL. The secondary contribution is the simultaneous combination of the DR and DG_SL. Both contributions utilize a Multi-Objective Decision-Making Approach (MODMA) based on the Analytic-Hierarchy Process (AHP) and Crow Search Algorithm (CSA). The primary goal is to minimize power loss (Pl), maximize the Voltage Stability Index (VSI), and ensure long-term network reliability, thereby enhancing overall distribution efficiency in alignment with modern industrial standards. The paper sections are arranged as follows: The Problem Formulation is illustrated in Section 2. The proposed methodology is detailed in Section 3. The Results and Discussion are discussed in Section 4. The Conclusions are summarized in Section 5.

2 Problem Formulation

In this section, the proposed methodology is adapted to determine the network configuration, the DG sizing and location, and the CAP sizing and location. The major aim is to get the minimum Ploss and Qloss and the best VSI that enhances the system's stability and reliability. That is done under different

technical constraints and limitations related to network power flow and voltage limits. The problem can be formulated based on the MODMA approach using the following equations:

$$Minimize_F = \left(w_1 \, Ploss + w_2 \, Qloss + w_3 \, SI \right), \tag{1}$$

where w_1, w_2, and w_3 are the weight factors of the fitness (F). The terms of the fitness must be unitless, as follows:

$$Ploss = \frac{P_{loss}^{R}}{P_{loss}^{0}}, \tag{2}$$

$$P_{loss} = \sum_{N=1}^{M} \left(R_N \times \left| I_N \right|^2 \right), \tag{3}$$

where Ploss is the real power loss, P_{loss}^{R} is the real power loss after DR, P_{loss}^{0} is the real power loss before DR, R_N is the branch N resistance, I_N is the current through branch N, N is the branch number, and M is the other branch number.

$$Q_{loss} = \frac{Q_{loss}^{R}}{Q_{loss}^{0}}, \tag{4}$$

$$Q_{loss} = \sum_{N=1}^{M} \left(X_N \times \left| I_N \right|^2 \right), \tag{5}$$

where Q_{loss} is the imaginary power loss, Q_{loss}^{R} is the imaginary power loss after DR, Q_{loss}^{0} is the imaginary power before DR, and X_N is the branch N reactance.

The Voltage Stability Index (VSI) is examined to be maximized. That is looked to find the weakest bus voltage in the network which causes VS problems when load variation. The expression of the VSI Index is as follows [51]:

$$VSI = \left| V_s \right|^4 - 4 \times \left\{ P_r X_{ij} - Q_r r_{ij} \right\}^2 - 4 \times \left\{ P_r r_{ij} - Q_r X_{ij} \right\}^2 \times \left| V_s \right|^2 \geq 0, \tag{6}$$

where V_s is the sending bus voltage in pu, P_r and Q_r are the power load in the active and reactive form at the bus receiving end in pu, respectively, r_{ij} and X_{ij} are the resistance and reactance of the line $i - j$ in pu, respectively.

During the stability operation of the system, the value of the VSI index must be greater than zero for each bus. This means buses become more stable when the value of the VSI index becomes closer to one for all buses. Thus, the bus having the lowest value of VSI (the weakest bus) will be considered in the fitness function. To integrate the VSI index into the fitness function, the modified index (SI) is taken as follows:

$$SI = \frac{1 - \min(VSI)}{\max(VSI)}, \tag{7}$$

where max(*VSI*) and min(*VSI*) are the buses that have the highest and lowest values of VSI, respectively.] In this case, the SI term of fitness function also becomes unitless. Now the fitness function is harmonious and easily minimizes the Ploss and Qloss, and improves the VSI to enhance the system's stability and reliability.

The proposed method which represents the DR, DG_SL, and CAP_SL must fulfill these limitations and constraints, as follows:

Power constraints

The first one is the power injection constraint, which prevents the power flow from the DG and CAP units to the main grid since it causes protection problems, as shown in the following formulas [52]

$$\sum_{i=1}^{k} P_{DG,i} < \sum_{n}^{nbus} \left(P_{Load\,n}\right) + P_{loss}, \tag{8}$$

$$\sum_{i=1}^{k} Q_{CAP,i} < \sum_{n}^{nbus} \left(Q_{Load\,n}\right) + Q_{loss}, \tag{9}$$

where $P_{\mathrm{DG,i}}$ is the active power of the DG, $Q_{\mathrm{CAP,i}}$ is the reactive power of the CAP, k is the DG number, and nbus is the bus number.

The second one is the power balance constraint. This constraint achieves the equilibrium principle. This means the power demand must be equal to the power supply. In other words, the active power supplied must equal the sum of the Ploss and active power load. In addition, the reactive power supplied must equal the sum of the Qloss and reactive power load as shown by the following equations [52]:

$$\sum_{i=1}^{k} P_{DG,i} + P_{Sub} = P_{Load} + P_{loss}, \tag{10}$$

$$\sum_{i=1}^{k} Q_{CAP,i} + Q_{Sub} = Q_{Load} + Q_{loss}, \tag{11}$$

where P_{Load_n} and Q_{Load_n} are active and reactive power of the load, respectively, and P_{Sub} and Q_{Sub} are the active and reactive power of the main substation, respectively.

DG constraints

$$P_i^{\min} \le P_{DG,i} \le P_i^{\max}, \tag{12}$$

where $P_i^{\max}$ and $P_i^{\min}$ are the suitable limits of the DG.

CAP constraints

$$Q_i^{\min} \le Q_{CAP,i} \le Q_i^{\max}, \tag{13}$$

where $Q_i^{\max}$ and $QP_i^{\min}$ are the suitable limits of the CAP.

Voltage limits

$$V_{\min} \le V_{bus} \le V_{\max}, \tag{14}$$

where V_{bus} is the bus voltage, and $V_{\min}$ and $V_{\max}$ are the bus' acceptable maximum and minimum voltage limits, respectively.

All voltages of the system's bus must be between 0.95 p.u and 1.05 p.u (±5% of rated value) [53].

Network topology constraint

One of the most essential constraints is the topology constraint which aims to make the network in a radial form. The radial form is characterized by its simplicity in design and maintenance which in turn reduces the cost of operational and construction costs [54, 55].

Load constraint

All branches must be supplied from the grid.

3 Proposed Approach

This section presents a novel method for simultaneously determining the optimal DR integrated with the optimal sizing and location of the DG and CAP units in the planning mode. To ascertain the multi-objective function weight factors, the AHP method is employed. The CSA technique is employed to determine the optimal DR configuration, DG's-SL, and CAP's-SL. The strategy is to increase VSI, decrease Qloss, and decrease Ploss to enhance the DN system's stability and reliability.

3.1 Analytic-Hierarchy Process (AHP)

AHP is offered as a performance planner with numerous criteria that can be implemented [56]. The AHP, as addressed in [57] is a productive method for making decisions while handling complex, multi-attributed, unstructured problems [58]. Depending on how severe the system index is, AHP is utilized to calculate weight factors for several operating indices. **Table 1** displays the AHP relative relevance matrix for several indexes.

Table 1

Relative importance matrix.

Definition Importance	Number Rate	Decimal Reciprocal
Equal	1	1
Moderate	3	0.3333
Strong	5	0.2000
Very strong	7	0.1429
Extreme	9	0.1111

The weight factors estimation is presented in **Table 2** based on the matrix scale arrangement. Fig. 1 presents the AHP approach steps.

3.2 Crow Search Algorithm (CSA)

The crow search algorithm is a population-based metaheuristic that draws inspiration from nature. Technique addressed by A. Askarzadeh in 2016 [59]. It

imitates the social interactions and clever behaviors of the crow. Crows dwell in groups or flocks and hide their food in various locations. When necessary, even after several months, these perceptive crows can collect the hidden food since they have memorized the hiding spots. It is known that crows steal each other and purloin the other birds' food once they leave. Then crows can find the safest way to save their food from thieves and avoid being victims in the future. Crows are sentient birds that can recognize faces and coordinate their movements in anticipation of an intruding visitor [60, 61].

The CSA technique principle is as follows [62]:

1. Crows are a flock animal.
2. Crows can learn where they hide food.
3. Crows engage in purloining, following one another.
4. Crows guard their secret stockpiles against theft.

Table 2

Weights from the AHP approach.

Criteria	Ploss	Qloss	VSI	Total = Sum (Each Row)	Weight = Total/Sum
Ploss	1	5	7	13	0.7447
Qloss	0.2	1	1.4	2.6	0.1489
VSI	0.1429	0.7143	1	1.8572	0.1064
Sum				17.4572	1

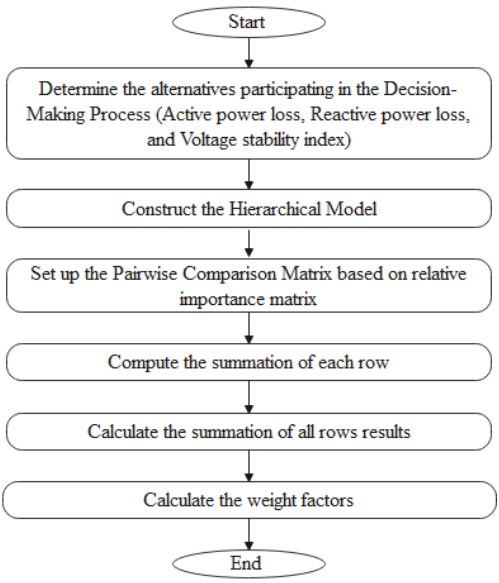


Fig. 1 – *AHP approach flowchart.*

The implementation steps of the proposed methodology (DR, DG_SL and CAP_SL) using CSA are as follows:

Step 1: Initialize the optimization problem and determine the CSA alterable parameters

Determine the optimization problem, the decision variable, and the limitations and constraints. Set the population number of crows (flock size = N), the maximum iterations number ($t_{\max}$), the awareness probability (AP), and the flight length (fl).

Step 2: Set the DN parameters such as lines' resistance and reactance values, and the initial values of the buses' voltages.

Step 3: Insert the weight factors calculated from the AHP approach into the fitness function formula.

Step 4: Initialize the crows' position.

Assume X_i^t presents the position of each crow i in t-th iteration as follows:

$$\begin{aligned} X_i^t = {} & SW_{i,1}^t, SW_{i,2}^t, \ldots, SW_{i,n}^t, DG_L_{i,1}^t, DG_L_{i,2}^t, \ldots, DG_L_{i,q}^t, \\ & DG_S_{i,1}^t, DG_S_{i,2}^t, \ldots, DG_S_{i,q}^t, CAP_L_{i,1}^t, CAP_L_{i,2}^t, \\ & \ldots, CAP_L_{i,m}^t, CAP_S_{i,1}^t, CAP_S_{i,2}^t, \ldots, CAP_S_{i,m}^t. \end{aligned} \tag{15}$$

where SW is the tie switch, DG is the distributed generation, CAP is the shunt capacitor, (i = 1, 2,…, N), (t = 1, 2,…, $t_{\max}$), n is the dimension of switch, q is the dimension of DG, m is the dimension of CAP, DG_L is the location of DG, DG_S is the size of DG, CAP_L is the location of CAP, CAP_S is the size of CAP. Each crow X_i^t are randomly located in a d-dimensional search space and present a possible solution to the optimization problem.

Step 5: Initialize the crows' memory.

Let m_i^t presents the memory of each crow i in t-th iteration as follows:

$$\begin{aligned} m_i^t = {} & m_{SW\,i,1}^{\;t}, m_{SW\,i,2}^{\;t}, \ldots, m_{SW\,i,n}^{\;t}, m_DG_L_{i,1}^t, m_DG_L_{i,2}^t, \ldots, \\ & m_DG_L_{i,q}^t, m_DG_S_{i,1}^t, m_DG_S_{i,2}^t, \ldots, m_DG_S_{i,q}^t, \\ & m_CAP_L_{i,1}^t, m_CAP_L_{i,2}^t, \ldots, m_CAP_L_{i,m}^t, m_CAP_S_{i,1}^t, \\ & m_CAP_S_{i,2}^t, \ldots, m_CAP_S_{i,m}^t. \end{aligned} \tag{16}$$

Step 6: Evaluate the value of the fitness.

Use the load flow code based on the Newton–Raphson methodology to calculate the value of Ploss and Qloss, and Max and Min values of the distribution buses' voltages. Then evaluate the fitness using (1) for each crow in the matrix (15).

Step 7: Update new position.

Suppose crow i wants to update its position. Crow i follows crow j for example (any one of the flock crows) without knowing crow j and as a result

crow i discovers the hidden position of the crow j foods. Thus, the position of crow i is updated based on the following expression:

$$X_i^{t+1} = X_i^t + \left(r_i * fl_i^t * (m_j^t - X)\right), \tag{17}$$

where X_i^{t+1} is the new or the updated position of crow i at $(t + 1)^{\text{th}}$ iteration, r is a random value with a uniform distribution between 0 and 1, and fl_i^t is flight length at $(t + 1)^{\text{th}}$ iteration. Now if crow i follows crow j and crow j observes that crow i follows it. Thus, crow j tries to fool crow i by moving randomly. This way can be presented based on the following formula:

$$X_i^{t+1} = \begin{cases} X_i^t + \left(r_i * fl_i^t * (m_j^t - X_i^t)\right), & \text{if } r_j \geq AP_j^t; \\ \text{A random position}, & \text{otherwise}; \end{cases} \tag{18}$$

where AP_j^t is the awareness probability of crow j at t-th iteration. This process (step 7) is repeated for all crows.

Step 8: Check the feasibility of updating (new) positions.

All new positions for all crows are checked to verify that it is under all limitations and constraints of the optimization process. Update the crow position if the new position of the crow is feasible. If the new position exceeds any of the limitations or constraints, the failed position changes with a feasible one from the initial position.

Step 9: Evaluate the fitness of the updated positions (new).

Calculate the fitness for each crow's new position.

Step 10: update the memory.

Compare the new position with the memorized position. Update the crow's memory with the new one if the crow's new position fitness is better than the crow's memorized position fitness. Otherwise, it will not change its memory. The updating memory is as following expression:

$$m_i^{t+1} = \begin{cases} X_i^{t+1}, & \text{if } f(X_i^{t+1}) \geq f(m_i^t); \\ m_i^t, & \text{otherwise}; \end{cases} \tag{19}$$

where $f(.)$ is the fitness value.

Step 11: Check the termination criterion.

Repeat steps 7 to 10 until reaching the $t_{\max}$. After meeting the termination criterion, the optimal solution (best position) that achieves the minimum function for the optimization problem is saved. The distribution's new configuration, the sizes and placements of the DG and CAP, the fitness, VSI, Ploss, and Qloss values, and the minimum and maximum bus voltages are all displayed in the optimal solution. The flow chart of the proposed methodology (DR, DG_SL and CAP_SL) using CSA has been depicted in Fig. 2.

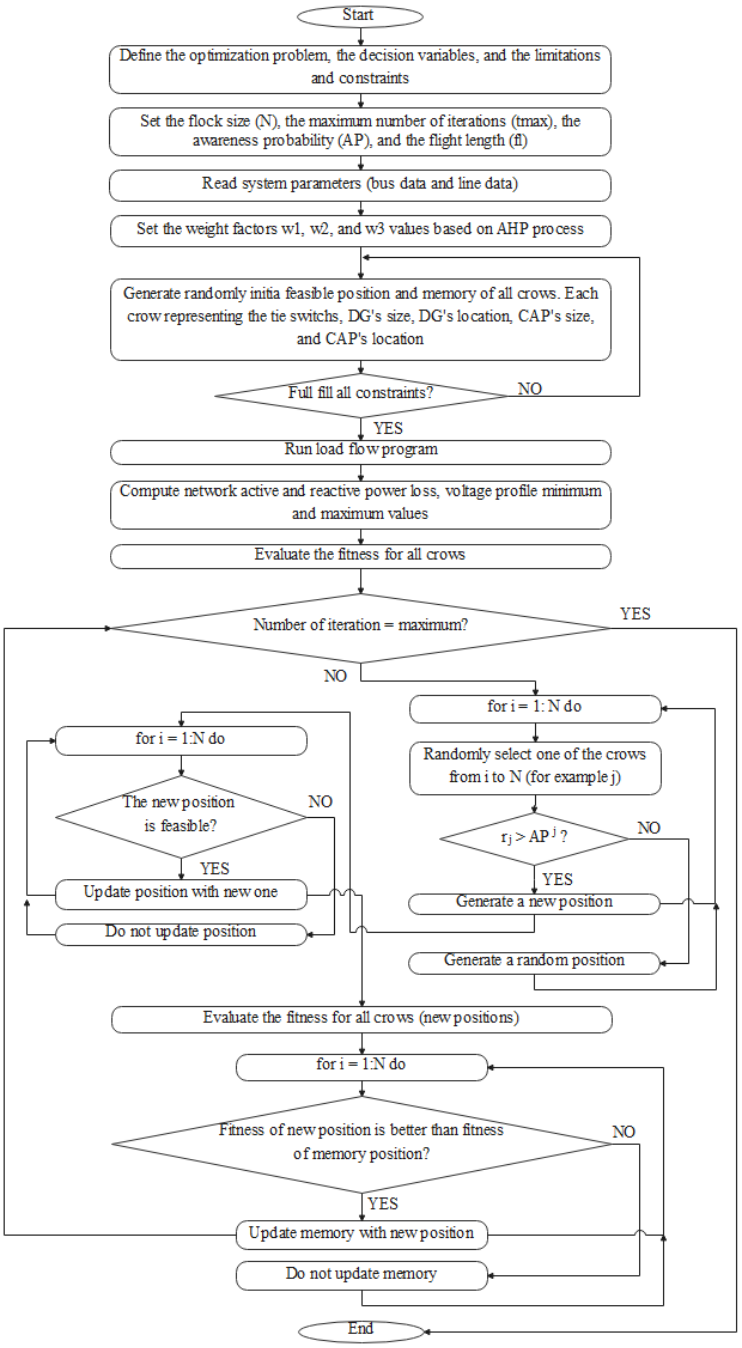


Fig. 2 – *Flow Chart of the DR and DG_SL and CAP_SL using CSA.*

4 Results and Discussion

The proposed approach is assessed by conducting an evaluation using different DNs. MATLAB software is used to run the simulation. Single-line diagrams of the typical IEEE 33 and 69 bus test networks are shown in Figs. 3 and 4. Both networks run at 12.66 kV base voltage and 100 MVA base apparent power. The five tie switches in the IEEE 33-bus distribution test system configuration are 33, 34, 35, 36, and 37. The second column of **Table 3** displays the IEEE 33-bus system's initial data. The five tie switches in the IEEE 69-bus distribution test system setup are numbered 69, 70, 71, 72, and 73. The second column of **Table 4** displays the IEEE 69-bus system's initial data. More detailed information, such as buses' power load, and the line's resistance and reactance are reported in [63, 64] for both test systems.

To showcase the power of the proposed approach, the following scenarios are considered:

First Scenario: The base case (Initial configuration).

Second Scenario: DR is performed simultaneously with DG_SL.

Third Scenario: DR is performed simultaneously with DG_SL and shunt CAP_SL.

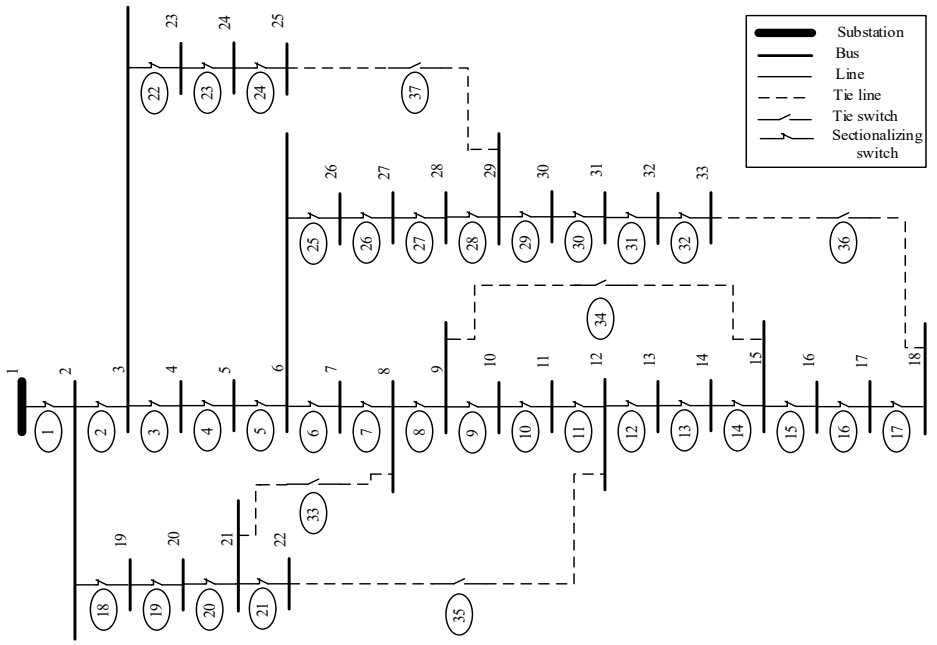


Fig. 3 – *The IEEE 33-bus radial system.*

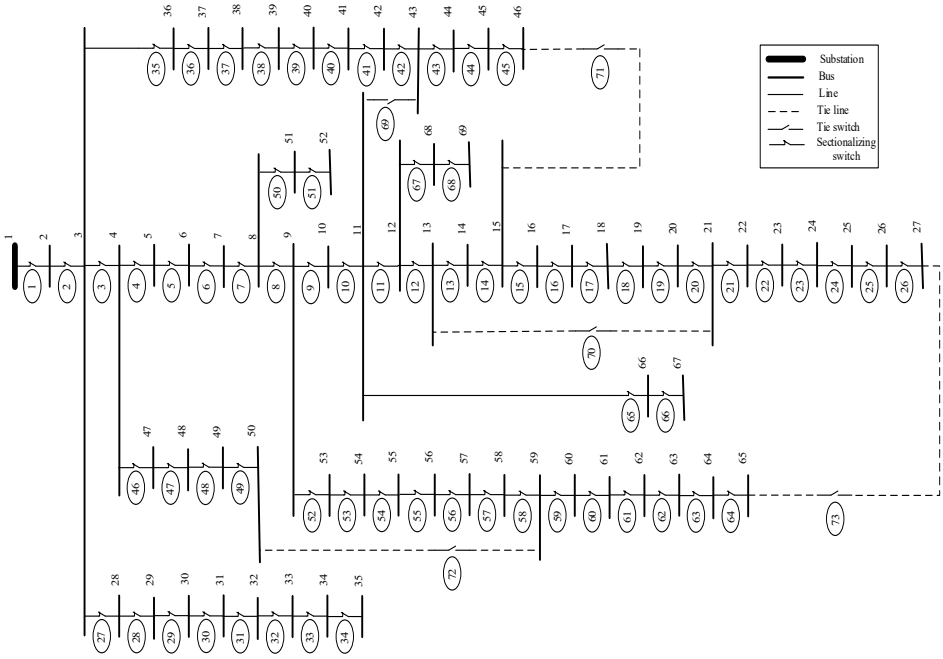


Fig. 4 – *The IEEE 69-bus radial system.*

4.1 Influence of the proposed approach on the network performances

As noted previously, the proposed approach seeks to find the simultaneous optimal DR integrated with optimal DG's-SL and optimal CAP's-SL under the planning mode using the CSA technique integrated with the AHP approach. To validate the influence of the proposed approach, the impact of the proposed approach was evaluated on the Pl, VF, and optimization performance.

4.1.1 Impact of the proposed approach on power loss

Minimizing Pl reduces the total power consumed from the main source and improves the system's efficiency. **Table 3** shows the obtained results of the IEEE 33-bus network for the different scenarios. The first scenario represents the initial case (second column). The second scenario represents the simultaneous DR with DG_SL (third column). The third scenario represents the simultaneous DR with DG_SL and CAP_SL (fourth column). Both Scenarios 2 and 3 will be compared with Scenario 1 (initial case). The first compared item is the tie switch (normal open switch). From the results, the tie switches of the first scenario are 33, 34, 35, 36, and 37. The optimal solution of the second scenario changed the tie switches to 34, 11, 31, 28, and 33. The optimal solution of the third scenario changed the tie switches to 31, 27, 35, 11, and 33. The next compared item is the DG_SL. It was recommended that the DG be a 2 MW mini-hydro generator. DGs

were not incorporated into the original network in the first scenario. In the second scenario, buses 25, 8, and 18 were selected as the DG locations. The DG sizes were 1.369077 kW, 0.685816 kW, and 0.772853 kW, respectively. In the third scenario, buses 7, 25, and 18 were designated as the DG locations. The DG sizes were 1.087237 kW, 1.084151 kW, and 0.67526 kW, respectively. The CAP_SL is the next item to be compared. The CAP was suggested to be a shunt capacitor with a maximum capacity of 2 MVAR. Only Scenario 3 has integrated shunt capacitors into the network. The locations of the CAP were determined to be busses 9, 18, and 30, with respective CAP sizes of 0.415551 kVAR, 0.316684 kVAR, and 1.057874 kVAR. The fitness, which has to be minimized, is the next thing to be compared. The third scenario's fitness is 0.104546, which is lower than the second scenario's 0.476596.

Table 3
A comparison of the IEEE 33-bus network's obtained findings.

Compared Item	Scenario 1: Initial Form	Scenario 2: Proposed DR with DG_SL	Scenario 3: Proposed DR with DG_SL and CAP_SL
Tie Switch	33, 34, 35, 36, 37	34, 11, 31, 28, 33	31, 27, 35, 11, 33
DG Location (DG Sizing (MW))	NO DG	25 (1.369077)	7 (1.087237)
		8 (0.685816)	25 (1.084151)
		18 (0.772853)	18 (0.67526)
CAP Location (CAP Sizing (MVAR))	NO CAP	NO CAP	9 (0.415551)
			18 (0.316684)
			30 (1.057874)
Fitness	-------	0.476596	0.104546
Active Power Load P(kW)	3715	3715	3715
Reactive Power Load Q (kVAR)	2300	2300	2300
Ploss(kW)	202.604	51.846	**11.156**
Qloss(kVAR)	135.115	39.1	**9.061**
Ploss Reduction (%)	-------	74.41	**94.494**
Qloss Reduction (%)	-------	71.06	**93.294**
Min Bus Voltage	0.913131	0.977619	0.9926
Max Bus Voltage	1	1	1.001947
CPU time(s)	-------	2997.328	3016.953

The next compared item is Pl which is to be minimized. The system's apparent power in the first scenario is (3, 715+j 2, 300) kVA. There are 202.604 kW of Ploss and 135.115 kVAR of Qloss, respectively. The Ploss and Qloss were decreased to 51.846 kW and 39.1 kVAR, respectively, for the second scenario.

There were 74.41 % and 71.06% decreases in active and reactive losses, respectively. Reductions in Ploss and Qloss to 11.156 kW and 9.061 kVAR, respectively, were made for the third scenario. The reactive loss was reduced by 93.294 % and the active loss by 94.494 %, respectively. The minimum voltage, or weakest bus, is the next item to be compared and should be maximized. In the first scenario, the minimum voltage magnitude is 0.9092 p.u., and the maximum voltage is 1 p.u. The system min and max voltages improved to 0.977619 and 1 p.u., respectively, for the second scenario. The system min and max voltages improved to 0.9926 and 1.001947 p.u., respectively, for the third scenario. The final compared item is the CPU time (computational time). The computational time taken for 300 iterations and 100 populations were 2997.328s and 3016.953s for Scenario 2 and Scenario 3 respectively. Those times are suitable for solving complicated problems using CSA. The comparison of the findings indicates that the IEEE 33-bus network's optimal solution is obtained in the third scenario, which involves simultaneous DR with DG_SL and CAP_SL. The best values for the minimum and maximum system voltages, the most active and reactive power reduction, and the least amount of Ploss and Qloss are all part of the optimal solution.

Table 4 shows the obtained results of the IEEE 69-bus network for the different scenarios. From the results, the tie switches of the first scenario are 69, 70, 71, 72, and 73. The optimal solution of the second scenario changed the tie switches to 10, 58, 17, 13, and 63. The optimal solution of the third scenario changed the tie switches to 55, 17, 71, 72, and 8. The DG locations for the second scenario were specified for busses 61, 64, and 11, with respective DG sizes of 1.437065 kW, 0.313167 kW, and 0.802934 kW. Buses 12, 61, and 49 were designated as the DG locations for the third scenario. The DG sizes were 1.045472 kW, 1.558693 kW, and 0.659229 kW, respectively. In the third scenario, the CAP locations were assigned to busses 28, 61, and 19, with respective CAP sizes of 1.156905 kVAR, 1.155487 kVAR, and 0.340937 kVAR. The fitness of the third scenario is 0.063456 and less than the second scenario with 0.372863. The system's apparent power demand in the first scenario is (3, 801.89+j 2, 694.1) kVA. There are 224.557 kW of Ploss and 102.013 kVAR of Qloss. The Ploss and Qloss were decreased to 37.982 kW and 38.638 kVAR, respectively, for the second scenario. The decreases in Pl from reactive and active sources were 62.14% and 84.0086%, respectively. For the third scenario, Ploss and Loss were reduced to 6.519 kW and 5.7 car, respectively. Reactive loss was reduced by 94.412% and active loss by 97.097%, respectively. In the first scenario, the maximum voltage magnitude is 1 p.u. and the minimum voltage magnitude is 0.909289 p.u. The system min and max voltages improved to 0.981438 and 1 p.u., respectively, for the second scenario. The system min and max voltages improved to 0.9912 and 1.000067 p.u., respectively, for the third scenario. The computational time taken for 300 iterations and 100 populations

were 3955s and 4017s for Scenario 2 and Scenario 3 respectively. Those times are suitable for solving complicated problems using CSA. The comparison of the findings indicates that the best solution for the IEEE 69-bus network is obtained by the third scenario (simultaneous DR with DG_SL and CAP_SL). The best values for the minimum and maximum system voltages, the most active and reactive power reduction, and the least amount of Ploss and Loss are all part of the optimal solution.

Table 4

A comparison of the IEEE 69-bus network's obtained findings.

Compared Item	Scenario 1: Initial Form	Scenario 2: Proposed DR and DG_SL	Scenario 3: Proposed DR, DG_SL and CAP_SL
Tie Switch	69, 70, 71, 72, 73	10, 58, 17, 13, 63	55, 17, 71, 72, 8
DG Location (DG Sizing (MW))	NO DG	61 (1.437065)	12 (1.045472)
		64 (0.313167)	61 (1.558693)
		11 (0.802934)	49 (0.659229)
CAP Location (CAP Sizing (MVAR))	NO CAP	NO CAP	28 (1.156905)
			61 (1.155487)
			19 (0.340937)
Fitness	-------	0.372863	0.063456
Active Power Load P(kW)	3801.89	3801.89	3801.89
Reactive Power Load Q(kVAR)	2694.1	2694.1	2694.1
Ploss(kW)	224.557	37.982	**6.519**
Qloss(kVAR)	102.013	38.638	**5.7**
Ploss Reduction (%)	-------	83.086	**97.097**
Qloss Reduction (%)	-------	62.124	**94.412**
Min Bus Voltage	0.909289	0.981438	0.9912
Max Bus Voltage	1	1	1.000067
CPU time(s)	-------	3955	4017

4.1.2 Impact of the proposed approach on voltage profile

Improving the VF enhances the DN stability and reliability. The IEEE 33-bus network VF employing CSA is shown in Fig. 5 for all scenarios. The IEEE 69-bus network VF employing CSA is shown in Fig. 6 for all scenarios. The figures show that when the suggested method is used, all of the buses' voltages approach unity, and the minimum voltage of the bus improves to a respectable value. In addition, the third scenario (DR with DG_SL and CAP_SL) achieved a

VF better than the second scenario (DR with DG_SL). That means, integrating both DG and CAP units into the network reconfiguration process will improve the VF in a better way than integrating the DG unit alone.

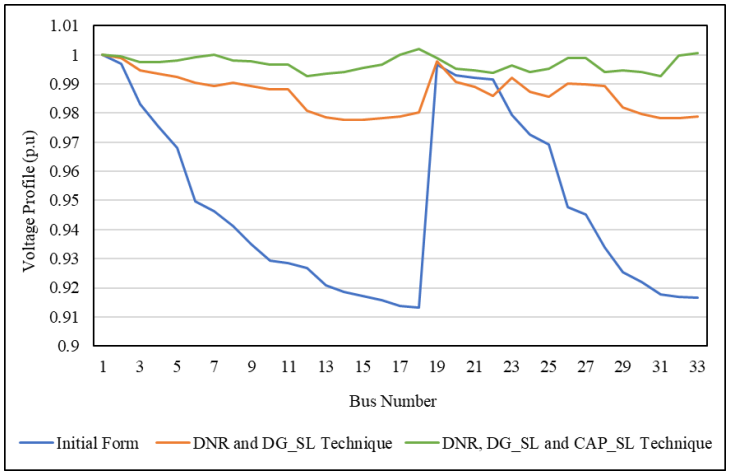


Fig. 5 – *Voltage profile curves of the IEEE 33-bus network using the suggested approach.*

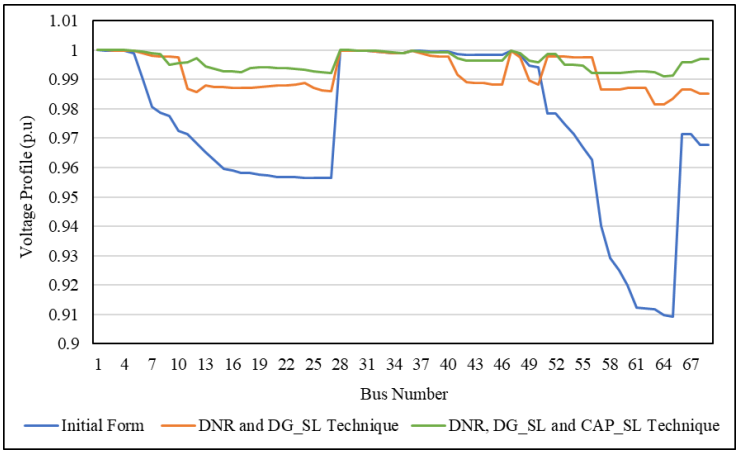


Fig. 6 – *Voltage profile curves of the IEEE 69-bus network using the suggested approach.*

4.1.3. Impact of the proposed approach on optimization performance

The overall performance was evaluated using robustness, convergence, and comparison tests. The CSA robustness was addressed after 100 times code running. The IEEE 33-bus network's robustness curves for scenarios 2 and 3 are displayed in Fig. 7. The IEEE 69-bus network's robustness curves for scenarios 2 and 3 are displayed in Fig. 8. The proposed method using CSA for each scenario

is strongly robust since all values all close together. That means the proposed method of simultaneous DR integrated with DG and CAP units makes the system more stable.

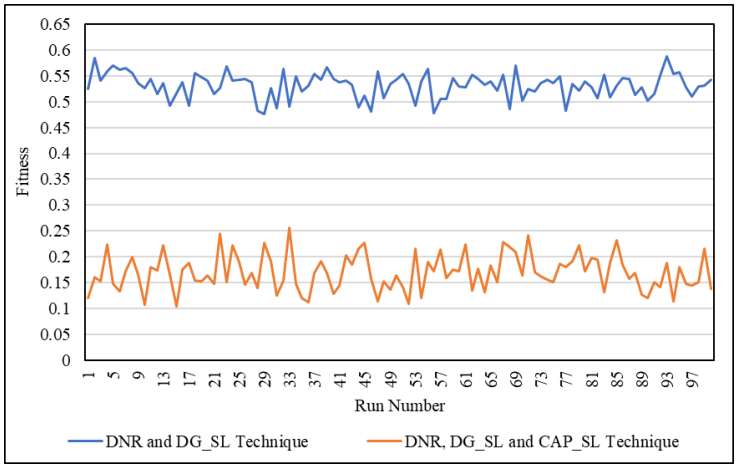


Fig. 7 – *The suggested method's robustness curves for the IEEE 33-bus network.*

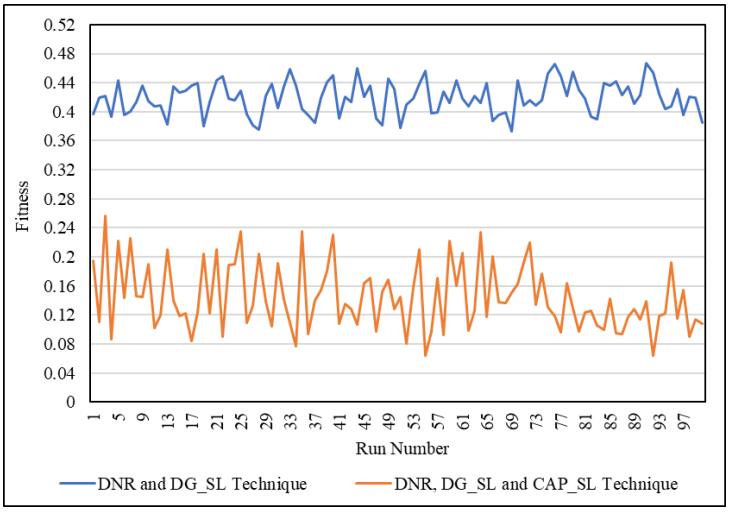


Fig. 8 – *The suggested method's robustness curves for the IEEE 69-bus network.*

The CSA robustness test statistical analysis was also evaluated. The standard deviation for the IEEE-33 bus network Scenarios 2 and 3 was computed and is shown in **Table 5**. The standard deviation for the IEEE-69 bus network Scenarios 2 and 3 was computed and presented in **Table 6**. For every scenario, the minimum,

maximum, and average values are also computed. More robustness requires the standard deviation to be near zero, as **Tables 5** and **6**'s final column demonstrates. This indicates that the CSA was strong and successful in identifying the best answers to a challenging issue.

Table 5
Statistical analysis of the 33-bus network.

Optimization Technique	Min value (Best)	Max value (Worst)	Average value (Mean)	Standard deviation (Stud)
Proposed DR and DG_SL	0.476596	0.587458	0.531452	0.024154
Proposed DR, DG_SL and CAP_SL	0.104546	0.256919	0.169653	0.034838

Table 6
Statistical analysis of the 69-bus network.

Optimization Technique	Min value (Best)	Max value (Worst)	Average value (Mean)	Standard deviation (Stud)
Proposed DR and DG_SL	0.372863	0.466845	0.419057	0.02227
Proposed DR, DG_SL and CAP_SL	0.063456	0.256655	0.143678	0.044682

For more validation, the CSA convergence was evaluated for the global optimal solution. After each scenario code has been executed 100 times, a 100 local optimal solution is thus produced. The global optimal solution is the best one from these 100 values. Fig. 9 displays the convergence of the global optimal solution for Scenarios 2 and 3 of the IEEE 33-bus network. The convergence of the global optimal solution for the IEEE 69- bus network was shown in Fig. 10 for Scenarios 2 and 3. From the curves, Scenario 3 is better than Scenario 2 since it achieved the minimum value of the fitness. In addition, the convergence test shows that the CSA technique updates its value during all iterations (300 iterations). This means the CSA technique was not trapped in the local optimal solution as other algorithms.

Additionally, the efficacy of the second contribution for the suggested method (DR and DG_SL) was compared with that of other published studies. **Table 7** displays the comparison findings for the 33-bus DN. Compared to other algorithms in **Table 7**, the CSA approach results in a 51.846 kW reduction in Pl. As a result, the reduction loss rises to the highest level (74.41%). **Table 8** displays the 69-bus DN comparison results. Compared to other algorithms in **Table 8**, the CSA approach results in a Pl of 37.982 kW less. As a result, the reduction loss (83.086%) is the largest. Compared with several existing metaheuristic algorithms, CSA provides strong global search capability, effective balance between exploration and exploitation, and improved robustness for solving highly

nonlinear optimization problems. Therefore, utilizing CSA to do simultaneous DR with DG_SL produced the best outcomes.

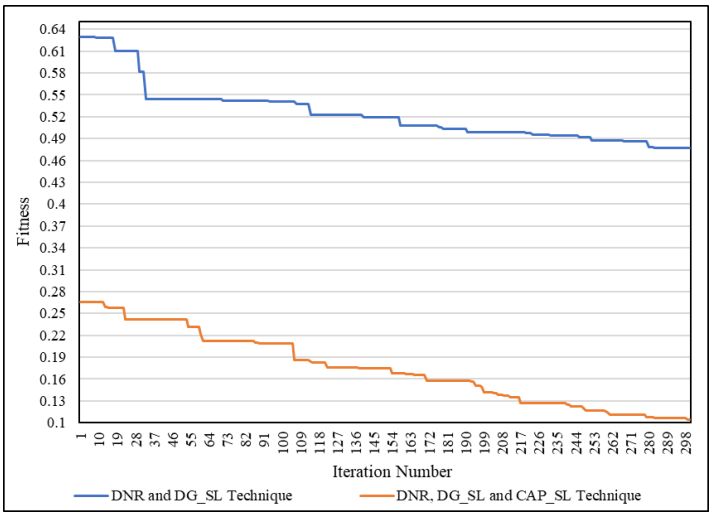


Fig. 9 – *Convergence curves for the IEEE 33-bus network using the suggested approach.*

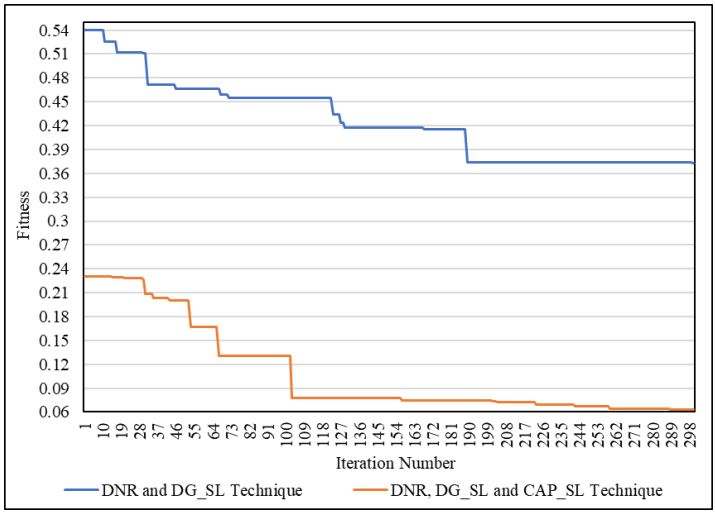


Fig. 10 – *Convergence curves for the IEEE 69-bus network using the suggested approach.*

Table 7
Comparison results of several algorithms of the 33-bus network.

Methods	Tie (Open) Switch	DG Unit Size (MW)	Min bus's Voltage (p.u)	Plods (kW)	Loss Reduction (%)
HAS [65]	7, 28, 10, 32, 14	1.668	0.97	73.1	63.9
FWA [66]	7, 32, 11, 14, 28	1.684	0.97	67.1	66.9
EP [67]	7, 32, 8, 9, 28,	1.964	0.97	73.97	63.5
PSO [67]	7, 13, 28, 32, 10	1.7660	0.97380	72.4210	64.3
GSA [67]	7, 13, 28, 32, 9	1.7450	0.97420	72.4250	64.250
FA [67]	7, 13, 28, 32, 10	1.8250	0.975	72.3610	64.280
PSO [68]	7, 14, 28, 32, 9	2.95410	0.96110	64.910	67.960
MPSO [69]	7,14, 32, 37, 9	1.09230	0.97640	62.40	68.320
ISCA [29]	7, 14, 28. 31, 9	1.69120	-	66.810	67.030
FA [70]	7, 14, 27, 30, 35	2.6520	0.975	57.637	71.55
FA [71]	34, 28, 11, 32, 33	2.5601	0.969724	54.997	72.83
The Proposed Method by CSA	34, 11, 31, 28, 33	2.827746	0.977619	51.846	74.41

Table 8
Comparison results of several algorithms of the 69-bus network.

Methods	Tie (Open) Switch	DG Unit Size (MW)	Min bus's Voltage (p.u)	Plods (kW)	Loss Reduction (%)
GA [65]	10, 62, 15, 45, 55	2.029	0.973	46.5	73.4
RGA [65]	10, 62, 16, 14, 55	2.065	0.974	44.230	80.3
HSA [65]	69, 61, 17, 13, 58	1.872	0.974	40.3	82.1
FWA [16]	69, 55, 63, 70, 13	1.818	0.980	39.25	82.6
MPSO [69]	14, 69, 70, 58-61	2.274	0.9899	42.2	81.10
ISCA [29]	12, 63, 69, 9, 57	1.873	-	39.73	82.33
FA [71]	13, 12, 62, 10, 57	2.4012	0.98035	39.16	82.6
The Proposed Method by CSA	10, 58, 17, 13, 63	2.553166	0.981438	37.982	83.086

5 Conclusion

This paper suggests a novel, simultaneous strategy for DR with DG_SL that incorporates CAP_SL to improve the DS's stability and reliability. A Multi-Objective Decision-Making Approach (MODMA) based on the Analytic-Hierarchy Process (AHP) combined with the Crow Search Algorithm (CSA) for various scenarios was used to achieve these goals. The promising findings obtained indicate that the suggested approach is highly efficient and effective in determining the global optimal solution of the DR, optimal DG_SL, and optimal CAP_SL without going above the network power flow and voltage limits, the global optimal solution produced the lowest Ploss and Loss and the highest Voltage Stability Index. The findings validate that the suggested methodology has the potential to improve network reliability and stability while accommodating real systems with DG and CAP units. Furthermore, the outcomes demonstrate the effectiveness of CSA in finding the global optimal solution for challenging issues, including the DR, DG_SL, and CAP_SL difficulties that raise system performance. A portion of the results were also compared to those from other published articles, which demonstrated the CSA's power when compared to results obtained through the use of metaheuristic techniques.

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