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Novel Real Valued Improved Coral-Reef Optimization Algorithm for Optimal Integration of Classified Distributed Generators

LOKESH K. YADAV[1,2], MITRESH K. VERMA[1], and PUNEET JOSHI[2]
[1]Department of Electrical Engineering, IIT (BHU) Varanasi, Varanasi-(221005) UP, India
[2]Department of Electrical Engineering, Rajkiya Engineering College Ambedkar Nagar, Ambedkar Nagar-(224122) UP, India

Corresponding author: Lokesh K. Yadav (e-mail: lokeshky@recabn.ac.in).

ABSTRACT In recent times, Distributed Generation (DG) penetration, especially, through Renewable Energy Sources (RES) has been growing immensely due to marginal carbon footprints. Furthermore, they make system more reliable by minimizing the voltage deviation of the distribution network. Nevertheless, to exploit the DGs in the best manner, they need to be sited and rated optimally. Diverse solutions exist for the problem mainly classified as: analytical approaches, classical non-linear optimization algorithms and meta-heuristic methods. With the objective of minimizing power loss, this manuscript proposes a novel hybrid meta-heuristics approach: Particle Swarm Optimization-Coral Reef Optimization (PSO-CRO) for identifying an optimum positioning and rating of Type-1, Type-2 & Type-3 DGs (at 0.82 optimal power factor) in IEEE 33, 69 & 118 bus Radial Distributed System (RDS). Furthermore, the results from the proposed hypothesis are compared with its prevalent peers, namely, PSO, CRO, Gravitational Search Algorithm (GSA), PSO-GSA and PSO-Grey Wolf Optimization (PSO-GWO) etc. The results of the proposed algorithm are also compared with the results of GAMS/CONOPT commercial solver. The simulation results prove the robustness, higher efficacy and faster convergence of the proposed method when applied to larger distribution systems.

INDEX TERMS radial distribution network, power loss minimization, optimal DG integration, coral reef optimization (CRO), particle swarm optimization (PSO).

I. INTRODUCTION

An electrical power network consists of a transmission system and a distribution system. A distribution network is usually a radial or weekly connected ring type system that draws power from a single generator bus and transmits it to individual load buses. Such type of structures have high R/X ratio which results in high power loss as well as low voltage profile [1]–[3]. Additionally, industrial loads often cause dramatic load variations that causes voltage collapses.

Preventive measures like "feeder reconfiguration" [4], [5] and "capacitor bank/DG placement" [6] may be employed to reduce high power loss and low voltage profile respectively. Distribution systems have various tie-switches which may be opened/closed in such a manner that the power loss is minimized which inherently improves voltage profile.

Generally, low rating renewable energy sources come in the category of DGs. They have emerged as the alternative solution to power loss and voltage regulation problems in RDS. Proper sizing and placing of DGs reduces total active power loss [7] and improve the voltage profile of each bus [8]. DGs can be employed to inject the appropriate type of power as enlisted in table I. DGs may also be utilized for reliability augmentation and future investment deferral on the system equipment.

Contemporarily most power system optimization problems are being catered through metaheuristic algorithms. Numerous applications of metaheuristic optimization approaches in power system include optimal DG integration [9], network reconfiguration [10], optimal phasor measurement unit (PMU) placement [11], optimal scheduling of generators [12], [13], real time economic dispatch with DGs [14], [15] and VAR compensation [16].

Essentially, DGs integration problem encapsulates the optimal siting and sizing of utility owned DGs in RDS. The

List of abbreviations

Symbol	Description	Symbol	Description
P_{Loss}	system active power loss	P_a	active power at bus a
Q_a	reactive power at bus a	P_b	active power at bus b
Q_b	reactive power at bus b	α_{ab}, β_{ab}	loss coefficients
δ_a, δ_b	voltage angles at bus a and b respectively	V_a	voltage in pu at bus a
V_b	voltage in pu at bus b	r_{ab}	resistance of the line connecting bus a and b
x_{ab}	reactance of the line connecting bus a and b	z_{ab}	impedance of the line connecting bus a and b
$P^T_{G,grid}$	total active power injected though grid	$P^T_{G,DG}$	total active power injected through DG
$P^T_{D,load}$	total active power demand by the connected loads	P^T_{Loss}	total system active power loss
$Q^T_{G,grid}$	total reactive power injected though grid	$Q^T_{G,DG}$	total reactive power injected through DG
$Q^T_{D,load}$	total reactive power demand by the connected loads	Q^T_{Loss}	total system reactive power loss
$S^T_{D,load}$	total apparent power demand by the connected loads	S^T_{Loss}	total system apparent power loss
V_{min}, V_{max}	minimum and maximum voltage limit	I_k, I_k^{rated}	current and rated current of branch k
P^{T-1DG}	size of Type-1 DG	Q^{T-2DG}	size of Type-2 DG
S^{T-3DG}	size of Type-3 DG	$\wedge$	$N \times M$ reef grid
ρ_0	the ratio of free and occupied squares	F_b	broadcast spawners
1-F_b	brooders	F_d	fraction of corals are depredated
g_{best}	global best solution	k	number of attempts given to a larva to settle
w	Inertia weight	c_1, c_2	individual cognition and social learning parameter

problem is extremely complex and non-linear in nature. The problem can be postulated as single or multi objective by considering the power loss minimization, voltage profile improvement, network reinforcement, cost minimization, reliability enhancement, and reduction of environmental emissions pertaining to techno-economic benefits. [17], [18] . Copious methodologies are available for the said problem in the scripts like analytical approach, classical non-linear optimization algorithms and bio-inspired approaches [19].

Bio-inspired algorithms used for the for DG allocation and sizing problem include particle swarm optimization (PSO) [20], improved PSO (IPSO) [21], genetic algorithm (GA) [22], hybrid GA-PSO algorithm [23], harmony search algorithm (HS) [24], big bang-big crunch algorithm (BBBCA) [25], [26], grey wolf optimization (GWO) [27], Genetic Algorithm-Tabu Search (GA-TS) [28], Artificial Bee Colony (ABC) [29] and PSO & shuffled frog leaping algorithm (PSO-SLF) [30] etc.

A. LITERATURE REVIEW

Most researchers use power loss minimization as the fitness function for the problem of optimal siting & sizing of DG. [31] utilized GA-PSO to optimize the size of DG and also determine the site of the same by taking active, reactive power loss & voltage deviation as an weighted fitness function and the results were compared with GA and PSO individually with DG and without DG. In [32] , authors proposed a mixed integer conic programming (MICP) model to find the optimal type, size and site of DG to minimize the cost in several aspects objective function, investment, production, CO_2 emission and load shedding for various cases like when considering only gas turbine generation, wind turbine and energy storage device (ESD), PV generation, intermittent of DG and ESD and considering all alternatives. The proposed approach is directly applied to the application. In [33] Coyote Optimization Algorithm (COA), a two stage optimization approach has been employed for optimal zero power factor DG integration in 123-bus IEEE network. Voltage regulator tap and power loss minimization has been taken as objective function. Results has been compared with that of classical mixed-integer nonlinear programming, GA, PSO and GWO. A hybrid of empirical discrete metaheuristic & steepest descent method is proposed in [34] to solve problem of optimal DG location-allocation by minimizing power loss. Qualitative and quantitative analysis in terms of efficiency, convergence & robustness has been carried out on 34-bus IEEE network. Optimal planning of only Type-1 DG has been presented in the paper. An improved parameter PSO and sequential quadratic programming (SQP) has been proposed in [35] for optimal planning of individual and multiple Type-1 DGs with the aim of minimizing active power loss. The results are tested over 33 & 69-bus IEEE networks. The novel quasi-op-positional chaotic symbiotic organisms search algorithm has been proposed in [36]. The aim is to minimize system power loss and place the multiple Type-1 and Type-2 DGs with appropriate size at optimal location in 33 & 69-bus IEEE networks. Every optimization algorithm may not be suitable for finding the optimal solution of each type of DG. Uniform Voltage Distribution Algorithm (UVDA) proposed in [37] is not suitable for optimal siting and sizing of Type-2 DG. Authors in [38] came up with new hybrid of Cuckoo Search technique & Grasshopper Optimization Algorithm for optimal planning of Type-1 DG. The objective function adopted is weighted sum of loss, voltage deviation and cost of DG power generated. Single and multi-objective based improved harris hawks optimization algorithm has been presented in [39] for optimal integration of unity pf, 0.95 lead pf and optimal pf DGs in 33 & 69-bus IEEE networks. An improved eco system based optimization approach is implemented by the authors in [40] for optimal integration of unity pf, fixed pf & optimal pf DGs in 33 & 69-bus IEEE networks.

B. CONTRIBUTION AND PAPER ORGANIZATION

Radial distribution system has large R/X ratio that results in high power loss during power transmission. Now-a-days optimally placed distributed generators (DGs) are utilised to generate power in decentralised manner to compensate the power loss in the distribution system. Several work has been reported in literature on optimal placement of distributed generators for loss minimization. These methodologies may broadly be classified as analytical approaches and meta-heuristic approaches. Analytical approaches are found most accurate in solving optimal DG integration problem but the major drawback is that these are not suitable for large power system networks [41]. The drawback of the analytical approaches has been overcome by classical non-linear optimization algorithms. But such optimization algorithms generally get stuck at local minima and fail to find optimal solution [41].

Lately, meta heuristic optimization techniques have been employed by several researchers for a variety of optimization problems. The convergence and efficacy of the metaheuristic approaches can further be improved by hybridizing two optimization techniques. This motivated authors of the paper to propose a new metaheuristic approach for optimal placement of DGs by hybridizing particle swarm optimization (PSO) and coral reef optimization (CRO). The exploration capability of PSO and the exploitation capability of Coral reef optimization (CRO) approach enables the proposed metaheuristic approach to avoid local minima and reach global optimal solution. Convergence and accuracy of the effectiveness of PSO-CRO is tested over five test functions recommended by IEEE. Further, the applicability of the approach is demonstrated on 33, 69 and 118-bus IEEE networks for optimal integration of Type-1, Type-2 and Type-3 DGs. Also, the results obtained by the proposed approach for Type-1, Type-2 and Type-3 DGs are compared with PSO, CRO, GSA, PSO-GSA, PSO-GWO, GAMS/CONOPT commercial solver [42] and some other existing work reported in the literature. Investigations carried out on three test systems shows the preeminence of proposed approach over existing approaches.

The paper has been structured as follows. Section II provides an overview of DG classification based on of active/reactive power absorption/dispatch to/from grid. Section III provides mathematical outlook of the problem. Section IV depicts the fundamentals of the proposed method. Section V confers the results of the various methods for Type-1, Type-2 & Type-3 DGs on both 33, 69 & 118 bus systems and critically compares the results. Statistical analysis proves the superiority of the proposed approach over PSO & CRO. Simulation results depict the optimal size of DGs, system power loss corresponding to the optimal DG size and voltage profile for 33, 69 & 118 bus IEEE networks. Section VI summarizes the method's conceptual and programming simplicity, fastness and efficacy and its ability to identify the optimal solution in all types of RDS.

II. DG CATEGORIZATION

Table 1 categorizes different types of DGs where " + " sign indicates injection of real/reactive power to the system, whereas, " − " sign indicates absorption of these. Zero indicates neither injection nor absorption.

Distributed generators having unity power factor and injecting only active power to the power system (like PV cell and fuel cell) falls into category of Type-1 DG. Zero power factor DGs (like KVAr compensator, synchronous condensers and capacitors) inject only reactive power to the power system and falls in Type-2 category of DGs. Distributed generators with leading power factor such as diesel genset that injects both active and reactive power to the power system network fall into the category of Type-3 DG. Type-4 DG injects active power to the power system and absorbs reactive power. Such type of DGs operate at lagging power factor. Wind turbines/wind energy generator or induction generators operating at fixed speed fall under the category of Type-4 DG. However, Doubly Fed Induction Generator (DFIG) can either absorb or deliver reactive power to the grid. Wind turbine driven DFIG operating at leading power factor and injecting reactive power to the grid can be considered as Type 3 DG instead of Type 4.

TABLE 1: Categorisation of DGs

DG type	Real power	Reactive power	Examples
Type-1	+	0	PV arrays, fuel cells
Type-2	0	+	Synchronous condensers, capacitors
Type-3	+	+	Diesel genset, wind turbines driven DFIG operating at leading power factor
Type-4	+	-	Wind turbines/induction generators at fixed speed and operating at lagging power factor

In this work, optimal placement of Type-1, Type-2 and Type-3 DGs have been contemplated.

III. PROBLEM FORMULATION

It is imperative to provide a suitable allocation of DG with appropriate size as the improper siting and sizing of DGs in distribution network causes increased power loss, operating cost, reduces energy transmission and under utilization of resources. The main objective of the proposed approach is to minimize total active power loss at maximum load condition subject to various constraints like load flow equations, voltage constraints, current constraints and DG size constraints of the buses.

The objective function is to be minimize active power loss [43] by optimally placing and sizing the DG in a given radial distribution system. Mathematically, it is represented as:

$$f = min(P_{Loss}) \tag{1}$$

where, P_{Loss} is the loss due to resistance in the distribution feeder. The power loss in a network is given by equation (2) [43].

$$P_{Loss} = \sum_{a=1}^{n}\sum_{b=1}^{n}(\alpha_{ab}(P_aP_b + Q_aQ_b) + \beta_{ab}(Q_aP_b - P_aQ_b)) \tag{2}$$

The expression represented by equation (2) shows the loss as a function of active and reactive power injected at each bus in the network, n denotes the number of buses in the network, α_{ab} and β_{ab} are the loss coefficients. These loss coefficients are calculated as per following:

$$\alpha_{ab} = \frac{r_{ab}}{V_a V_b} cos(\delta_a - \delta_b) \tag{3}$$

$$\beta_{ab} = \frac{r_{ab}}{V_a V_b} sin(\delta_a - \delta_b) \tag{4}$$

and,

$$\bar{z}_{ab} = r_{ab} + jx_{ab} \tag{5}$$

where $\bar{z}_{ab}$, r_{ab} and x_{ab} represent impedance, resistance and reactance,respectively, of line connecting buses a and b and, $\bar{V}_i = V_i \angle \delta_i$ represents complex voltage at bus i.

Objective function given by equation (1) is to be minimized subjected to:

1) System power balance equality constraints,

$$P^T_{G,grid} + P^T_{G,DG} - P^T_{D,load} = P^T_{Loss} \tag{6}$$

where, $P^T_{G,grid}$ is total active power injected though grid, $P^T_{G,DG}$ is total active power injected through DG, $P^T_{D,load}$ is total active power demand by the connected loads and P^T_{Loss} is total system active power loss. Similarly:

$$Q^T_{G,grid} + Q^T_{G,DG} - Q^T_{D,load} = Q^T_{Loss} \tag{7}$$

where, $Q^T_{G,grid}$ is total reactive power injected though grid, $Q^T_{G,DG}$ is total reactive power injected through DG, $Q^T_{D,load}$ is total reactive power demand by the connected loads and Q^T_{Loss} is total system reactive power loss.

2) Voltage constraints,

$$V_{min} \leq V_a \leq V_{max} \tag{8}$$

where, V_a is the voltage in per unit (pu) at bus 'a', V_{min} and V_{max} are the minimum and maximum permissible voltage limits.

3) Current constraint,

$$I_k \leq I_k^{Rated} \tag{9}$$

where, I_k^{Rated} is rated permissible branch current in branch k.

4) DG size constraints,

For Type-1 DG

$$P^{T-1DG} \leq P^T_{D,load} + P^T_{Loss} \tag{10}$$

where, P^{T-1DG} is the size of Type-1 DG.

For Type-2 DG

$$Q^{T-2DG} \leq Q^T_{D,load} + Q^T_{Loss} \tag{11}$$

where, Q^{T-2DG} is the size of Type-2 DG.

For Type-3 DG

$$S^{T-3DG} \leq S^T_{D,load} + S^T_{Loss} \tag{12}$$

where, S^{T-3DG}, $S^T_{D,load}$ and S^T_{Loss} represent size of Type-3 DG, total MVA demand in the system and total MVA loss in the system, respectively.

The exact values of maximum capacity of Type 1, Type 2 and Type 3 DG are calculated as 3.931 MW, 2.435 MVAr and 4.624 MVA, respectively for IEEE 33 bus system and 4.025 MW, 2.793 MVAr and 4.899 MVA, respectively for IEEE 69 bus system. Also, maximum capacity of Type 1, Type 2 and Type 3 DG for IEEE 118 bus system are calculated as 24.007 MW, 18.019 MVAr and 30.017 MVA respectively. Considering practical considerations, maximum capacity of Type 1, Type 2 and Type 3 DG were taken as 4 MW, 2.5 MVAr and 4.5 MVA, respectively for IEEE 33 bus system, and 4 MW, 3 MVAr and 5 MVA, respectively for IEEE 69 bus system and 4 MW, 4 MVAr and 5 MVA respectively for IEEE 118 bus system. The maximum capacity of each type of DG for the three test systems considered in this work have been shown in Appendix.

IV. OPTIMAL SITING & SIZING OF DGS

A novel hybrid meta-heuristic optimization technique PSO-CRO is proposed for optimal integration of classified DGs. The proposed approach exhibits improved performance, flexibility in decision making, intelligence and high scalable property over conventional optimization approaches. PSO-CRO is flexible in decision making and it determines the alternate optimal solutions for a problem. On the contrary, conventional algorithm's flexibility in decision making depends on the user's understanding over problem. Intelligence in the proposed approach involves a bottom-up approach, which generates simple basic rules, whereas in conventional algorithm rules generation is problem dependent. Improved CRO approach is highly scalable but conventional algorithms are scalable up to certain extend. Less computational time, cost effectiveness, ease of programming and lesser mathematical complexity are the advantages of improved CRO approach over conventional optimization methods.

This section presents the application of the proposed PSO-CRO approach for finding optimal location and size of DG for minimum system active power loss. It is apparent from equation (2) (in Section III) that real power loss (P_{Loss}) is a function of power injected by DG placed at same bus. Thus, injected power as well as location of DG can be varied by proposed approach to get minimum real power loss in the network. The proposed approach provides information in the form of optimal size and location of DG. In this work Type 1, Type 2 and Type 3 DGs are optimally integrated in 33, 69 and 118 bus IEEE networks to minimize objective function, using PSO-CRO approach. To minimize the objective function variables in the decision vector considered in the system are given below:

$$D_{var} = [DG_{loc} \qquad DG_{size}] \tag{13}$$

where, decision variables DG_{loc} and DG_{size} are the DG location and DG size.

Both the decision variables (DG_{loc} and DG_{size}) are initialized randomly and updated at each iteration. Location and size of each Type of DGs are optimized by the proposed optimization technique. Optimal location and size of DG is selected for which the system active power loss (i.e. objective function) is minimum. By utilizing this approach the optimal locations of Type-1, Type-2 and Type-3 DGs are computed and presented in result and discussion section for 33, 69 and 118 bus IEEE networks.

The general approach for optimally siting and sizing of DGs is shown in the Fig. 1.

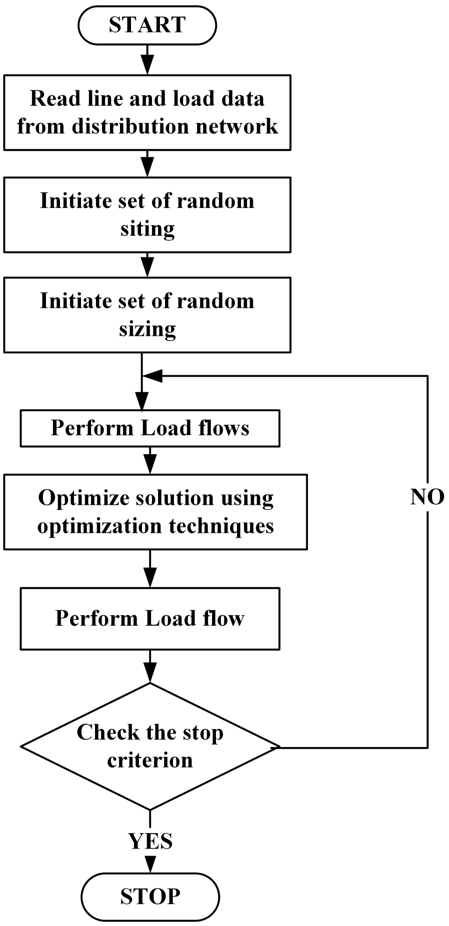

FIGURE 1: General approach for optimal siting & sizing of DG

A. PROPOSED NOVEL APPROACH: PARTICLE SWARM OPTIMIZATION-CORAL REEF OPTIMIZATION (PSO-CRO)

The proposed algorithm provides a co-evolutionary hybridization of Particle Swarm Optimization and Coral Reef Optimization techniques [44]. The methodology blended the high exploration capability of PSO with the excellent exploitation proficiency of Coral Reef Optimization. It is termed as co-evolutionary as both the algorithms run in tandem to achieve the solution for a given optimization problem.

The following section describes the salient features of the novel (PSO-CRO).

The flowchart for optimal planning of DG using PSO-CRO is shown in Fig. 2. The pseudocode for the proposed approach is shown in the Fig. 4.

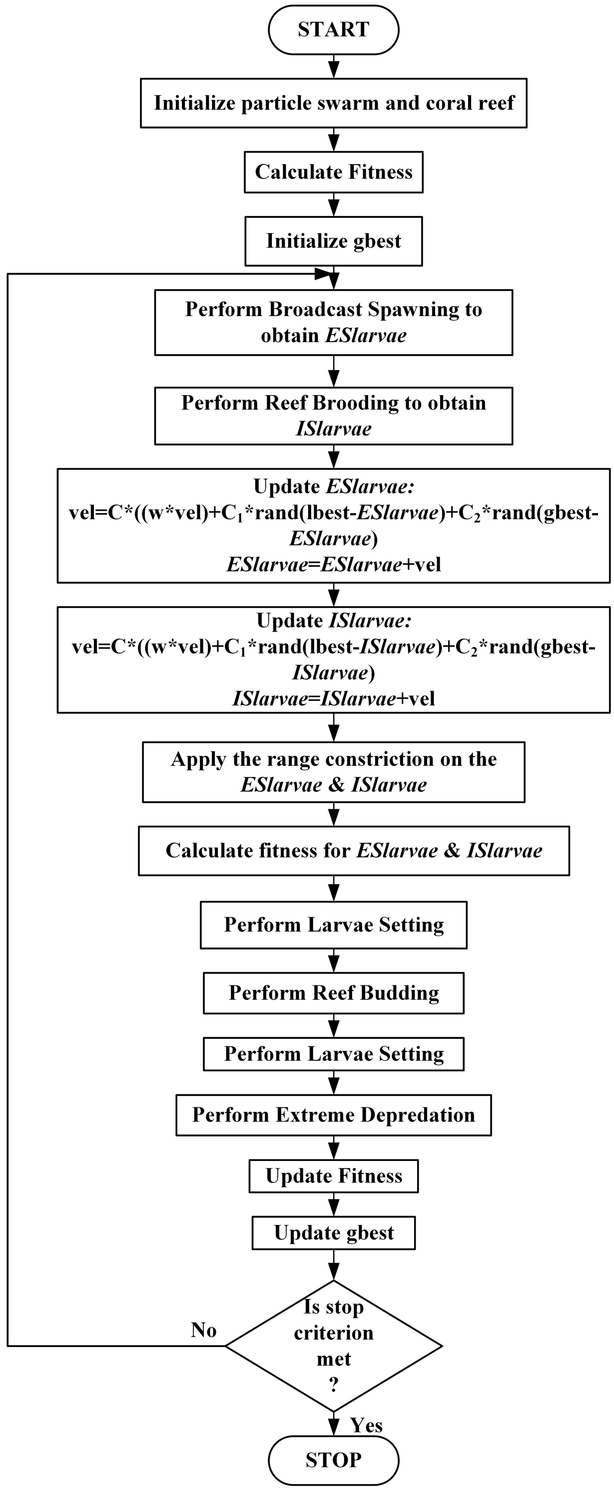

FIGURE 2: Flowchart for optimal siting & sizing of DG using PSO-CRO

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1) Corals and Reef Formation

The corals belong to the Cnidaria phylum. Hundreds of such corals form a reef. Thus, let ∧ represent an N × M reef grid. It is assumed that each block (n, m) of the grid is able to house a coral $E_{i,j}$, representing the different feasible solutions of a given problem.

2) Problem Initialization

Initially some squares of ∧ are set to be occupied by corals and some are left empty. This ratio of the free and the occupied squares is represented by $0 < \rho_0 < 1$. Consider Fig. 3, for a grid of 5×5 size, the shaded squares indicate existence of a coral and the hole represents absence of them. The occupied places are 14 and the non-occupied are 11. Thus, $\rho_0 = 11/14$, which is approximately equal to 0.785. Each feasible solution is accompanied with its health, which is the value of the objective function when the solution is substituted into the given function. It is imperative that for a maximization problem, solutions that have better health survive, whereas, weaker solutions perish gradually.

FIGURE 3: Coral and empty spaces in a reef

Subsequently, a second phase of reef formation through reproduction is carried out which includes modelling of sexual reproduction (broadcast spawning and brooding) and the asexual reproduction (budding). Lastly, the new corals fight for their place in the reef modelled by the depredation process.

3) Global Best Solution

The exploration feature of the PSO has been incorporated to improve the efficiency of the CRO. Once the fitness is determined, the global best variable is used to retain the value of the solution that generates the best fitness value. Later this value is used to improve the quality of the solutions generated through sexual reproduction.

4) Sexual Reproduction

(a) External Sexual Reproduction (Broadcast Spawning): This phenomenon involves a two-step approach explained as follows:

(1) In any given iteration *i*, a fraction of the corals is selected as the broadcast spawners. This fraction is denoted by, F_b, and and the remaining $(1 - F_b)$ reproduce through brooding.

(2) The spawners are selected using the fitness proportionate approach to form couples, which then form a larva through crossover.

(b) Internal Sexual Reproduction (Brooding): The $(1 - F_b)$ brooders form larvae by a random mutation process.

5) Larvae Setting

The larvae generated through any of the above mentioned processes now try to settle in the reef. The setting process of larvae depends on its fitness value. If the reef space is empty, the larvae simply occupies it, but if another coral preoccupies the square then the one with a better fitness value gets the space. A larva is given k attempts to search and settle in a square in the grid. The larvae perishes if it fails in k attempts.

6) Asexual Reproduction

In Budding, firstly, all the corals are sorted based on their fitness values out of which a fraction F_a imitates itself to form new larvae that again try to settle in the grid.

7) Depredation

The depredation process involves the elimination of weaker solutions in the group. After the reproduction process is completed, a fraction F_d of the corals in the reef are depredated and fresh empty spaces are formed.

The above mentioned process is repeated until the stopping criteria satisfies. The algorithm for the complete method is given below.

8) Algorithm

Step 1. Initialization

Initially, parameters of both CRO and PSO are initialized. Size of the reef is selected as per the problem's requirement and the corals (feasible solutions) are randomly initialized and settled into the reef.

Step 2. Fitness evaluation

Fitness for each coral in the reef is evaluated by substituting the value of each individual set of solutions in the objective function.

Step 3. G_{best} Updation

The solution that has best fitness value is stored in the g_{best} variable.

Step 4. Broadcast Spawning

Randomly selected corals depending on the value of F_b are selected as the spawners. Amongst these spawners pairing is done for the crossover process, and a spawner is allowed to parent a larva only once in an iteration. The couple selection is done using the roulette-wheel selection approach. The pseudocode code for this is given in the Fig. 5 below.

Step 5. Reef Brooding

The $(1 - F_b)$ corals reproduce asexually by means of a random mutation process. These larvae then fit for settlement in the reef.

The pseudocode code for Reef Brooding is given in the Fig.

Start PSO-CRO
Initialize particle swarm and coral reef
Calculate fitness
Initialize *gbest*
While (stopping criterion is not met)
  For *bus= 1 to n*
  Perform **Broadcast Spawning** to obtain *ESlarvae*
  Perform **Reef Brooding** to obtain *ISlarvae*
  Update *ESlarvae:*

$$vel = C*\begin{pmatrix}(w*vel)+C_1*rand*(lbest-ESlarve)\\ +C_2*rand*(gbest-ESlarve)\end{pmatrix}$$

  ESlarve=ESlarvae+vel
  Update *ISlarvae:*

$$vel = C*\begin{pmatrix}(w*vel)+C_1*rand*(lbest-ISlarve)\\ +C_2*rand*(gbest-ISlarve)\end{pmatrix}$$

  ISlarve=ISlarvae+vel
  Apply the range constriction on the *ESlarvae & ISlarvae*
  Calculate fitness for *ESlarvae & ISlarvae*
  Perform **Larvae Setting**
  Perform **Reef Budding**
  Perform **Larvae Setting**
  Perform **Extreme Depredation**
  Update reef fitness
  Update *gbest*
  End For
End While
Stop PSO-CRO

FIGURE 4: Pseudocode for the proposed PSO-CRO Method

Start Broadcast Spawning
Divide Spawners into two groups
Generate *ESlarvae*

$$ESlarvae1 = spawners1*(1-mask)*\frac{(1-B)}{2}+spawners2*mask*\frac{(1+B)}{2}$$

$$ESlarvae2 = spawners1*(1-mask)*\frac{(1+B)}{2}+spawners2*mask*\frac{(1-B)}{2}$$

$$ESlarvae = [ESlarvae1; ESlarvae2]$$

Stop Broadcast Spawning

FIGURE 5: Pseudocode for Broadcast Spawning

6 below.
The larvae are then updated through the g_{best} information as well to enhance their quality.
Step 6. Fitness evaluation
The fitness for each larva formed either by broadcasting or by brooding is evaluated.
Step 7. Larvae setting
Randomly selecting a position in the reef, the larvae try to settle in the reef. If the (n, m) square is empty the larva will settle irrespective of its fitness value. If the (n, m) is already occupied, the larva can only settle, if it has a better fitness value than the coral residing there. A maximum of k attempts is given to a larva to try to occupy a space in the reef, in case of failure the larva perishes.
The pseudocode for larvae setting is shown in the Fig. 7 below.
Step 8. Reef Budding
In budding all the corals in the reef are sorted as a function

Start reef brooding
Select (1-F_b) brooders randomly
Set eta=0.2
M=max(brooders)
m=min(brooders)
  for all brooders
    if M=m
    then S=M
    else S=abs(M-m)
    End if
Generate random no. r
    if r≥0.5
    then $D=(1-2*r)^{1/(eta+1)}$
    else $D=(1-2*r)^{1/(eta+1)}-1$
    End if
  larvae=brooders+S*D
End for loop
Stop reef brooding

FIGURE 6: Pseudocode for the proposed Reef Brooding

Start Larvae Setting
Arrange all larvae randomly
Each larva is assigned a place in the reef to settle
  for each larva
    if the reef is empty
    then larva occupies
    End if
    if the place is occupied
    then if the larva is better than the coral it occupies the space
    End if
Otherwise, a larva is discarded after 3 unsuccessful attempts
  End for
Stop Larvae Setting

FIGURE 7: Pseudocode for larvae setting

of their fitness value, and a fraction F_a duplicates itself and tries to settle in a different position in the reef by following the larvae setting process.
The pseudocode for reef budding is shown in the Fig. 8 below.

Start Reef Budding
Select those reefs which have occupied space & their fitness
Sort them in descending order of fitness
Select F_a reef as larvae
Stop Reef Budding

FIGURE 8: Pseudocode for Reef Budding

Step 9. Depredation
At the end of each reproduction stage, F_d fraction of corals get eliminated, generally that have the worst health in the reef.
The pseudocode for depredation is shown in the Fig. 9 below.

If the stopping criteria is met the process may be terminated else, it is repeated from step 3.

To inspect the performance of the metaheuristic techniques the standard test functions are used. Few of them with mathematical equations are shown in [40]. In accordance authors have selected five standard test function listed in Table 2 to assess the performance of proposed algorithm in

Start depredation
1: Sort the corals in ascending order based on their fitness
2: Generate random number 'ρ' for each coral
3: for all corals
4: if P>P_d
5: then eliminate the coral
6: End if
7: End for
Stop depredation

FIGURE 9: Pseudocode for Depredation

respect of quality and convergence: Sphere (F_1), Rosenbrock (F_2), Rastrigin (F_3), Ackley (F_4) and Griewank (F_5).

Numeric value-based approach is used to inspect the comparative performance assessment of proposed algorithm as compared with PSO and CRO techniques. In this way quality of the solution is measured by mean/average and standard deviation (SD) values. Table 3 sum up the convergence profile of the three optimization techniques (PSO-CRO, PSO and CRO) for five different test functions. The proposed PSO-CRO approach is better as compared to CRO and PSO, irrespective of all test function due to lower value of mean and SD values. To assess the search capability of the proposed approach over PSO and CRO, simulations are carried out for dimension (D=5) and is shown in Fig. 10. The result shows that the proposed algorithm has better convergence characteristic over PSO and CRO.

TABLE 2: Representation of test functions

Test function	Formulation	Characteristics	Range	f_{min}
Sphere	F_1=$\sum_{i=1}^{D} x_i^2$	US	[-100 100]	0
Rosenbrock	F_2=$\sum_{i=1}^{D-1} 100(x_{i+1}-x_i^2)^2$+$(1-x_i)^2$	UN	[-30 30]	0
Rastrigin	F_3=10D+$\sum_{i=1}^{D} (x_i^2 - 10cos2\pi x(i))$	MS	[-5.12 5.12]	0
Ackley	F_4=$-20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right)-\exp\left(\frac{1}{D}\sum_{i=1}^{D} cos2\pi x_i\right)+20+\exp 1$	MN	[-32 32]	0
Griewank	$F_5 = \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D} cos(\frac{x_i}{\sqrt{i}})+1$	MN	[-600 600]	0

TABLE 3: Comparative performance assessment of proposed algorithm on test functions

Functions	Techniques	Best value	Worst value	Average	SD
F_1	PSO-CRO	0	5.74E-78	4.42E-24	3.12E-23
	CRO	2.26E-16	0.713385	1.43E-02	0.100882
	PSO	6.10E-19	0.000482	1.03E-05	6.82E-05
F_2	PSO-CRO	9.15E-08	1.29E-07	1.54E-07	1.24E-07
	CRO	0.01066	3.991414	2.83E-01	0.940966
	PSO	3.73E-05	0.000935	2.28E-04	0.000129
F_3	PSO-CRO	0	7.11E-15	7.58E-08	8.67E-09
	CRO	0.01818	8.9546	1.89043	1.585944
	PSO	1.63E-07	0.99498	2.22901	1.964816
F_4	PSO-CRO	8.88E-16	7.99E-15	4.09E-15	1.79E-15
	CRO	5.12E-05	0.001508	5.39E-04	0.000336
	PSO	4.39E-05	0.000347	1.90E-04	9.78E-05
F_5	PSO-CRO	0	8.88E-16	5.52E-15	1.42E-14
	CRO	5.73E-07	0.001274	0.000589	0.000328
	PSO	5.73E-07	0.000128	1.03E-05	9.60E-06

V. RESULT AND DISCUSSION

A. 33-BUS IEEE NETWORK

The first test system is the 33-bus IEEE network on which the proposed approach and other optimization algorithms are tested for the problem optimal siting and sizing of individual Type-1, Type-2 & Type-3 DG. This system is loaded with 3.72 MW of real power, 2.3 MVAr of reactive power. It has 33 buses and 32 branches as shown in Fig 11. On performing the load flow, the real and reactive power loss is 210.9983 kW and 135.14 kVAr, respectively [32]. Table 4 presents the median for 50 runs of optimal allocation and sizing problem using PSO-CRO, PSO, CRO, GSA, PSO-GSA, PSO-GWO and CONOPT SOLVER of GAMS for Type-1, Type-2 & Type-3 DG. Also, various other methods in literature are compared with the proposed approach.

The proposed PSO-CRO approach gives better optimal solution than PSO, CRO, GSA, PSO-GSA, PSO-GWO & CONOPT SOLVER etc. Also, the median value of optimal size of DGs for 50 runs computed through PSO-CRO approach is near to the exact solution. The statistical analysis over optimal solutions by PSO, CRO & PSO-CRO techniques is discussed in the further subsection.

1) Statistical Analysis

Statistical analysis has been applied to further validate the approach. Fig. 12, 13 & 14 depict the box plot of 50 runs for optimal DG size in 33 bus IEEE network with respect to Type-1, Type-2 & Type-3 DG, respectively.

In context to the Fig. 12, 13 & 14 it is observed that the proposed method has the best performance as, the median (shown in Table 5) of the method is closest to the exact solution (shown in Table 6) of the problem. Additionally, there are no outliers for the proposed method in any case, which indicates that it very rarely gets trapped into the local minima. Also, the Q1 and Q3, boundaries of the box, are very near to Q2 (median) which indicates that the proposed method gives the answer with minimum deviation when not able to converge onto the exact solution.

Table 5 shows the first quartile (i.e. Q1), second quartile/median (i.e. Q2) and third quartile (i.e. Q3) values with respect to PSO, CRO and PSO-CRO algorithm for Type-1, Type-2 & Type-3 DG.
Table 6 shows the exact DG size for each type (i.e. type-1, type-2 & type-3) in 33 bus IEEE network. The exact size of each DG type is calculated through bisection method.

2) Simulation results

The power loss minimization analysis with the help of PSO-CRO algorithm, Fig. 15 presents the optimum DG size of Type-1, Type-2 & Type-3 DGs at each bus in 33 bus IEEE network. Figure 16 gives the system power loss corresponding to optimal DG size of Type-1, Type-2 & Type-3 DGs at each bus in 33 bus IEEE network. . Among the all-optimum DG sizes, the most suitable value is the one which corresponds to minimum system power loss. At 6^{th} bus the system power loss is found minimum for Type-1 and Type-3 DGs but for Type-2 DG at bus number 30, the system power loss is found minimum. After individual integration of various type of DGs with optimal value at appropriate bus, Fig. 17 shows improved voltage scenario as compared to the

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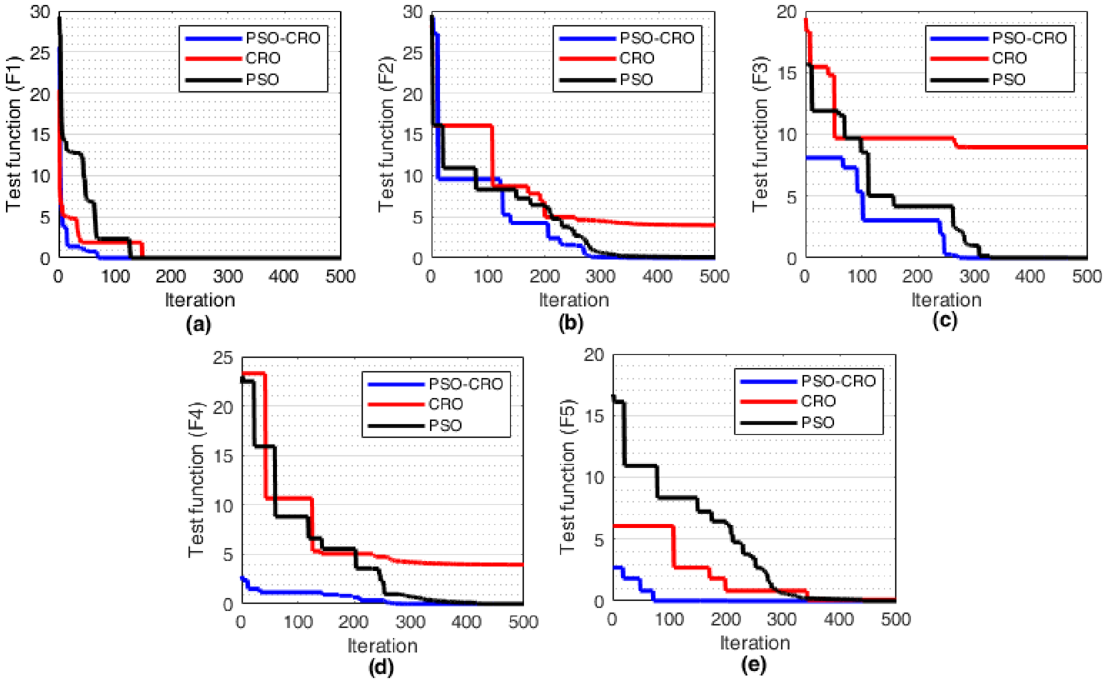

FIGURE 10: Convergence characteristic comparison of PSO-CRO, CRO & PSO on linear scale for dimension D=5 **(a)** Sphere, **(b)** Rosenbrock, **(c)** Rastrigin, **(d)** Ackley, **(e)** Griewank

TABLE 4: Performance analysis of optimal DG integration in 33 bus IEEE network

Method	Type-1 DG			Type-2 DG			Type-3 DG		
	Bus No.	DG Size (MW)	Power loss (kW)	Bus No.	DG Size (MVAr)	Power loss (kW)	Bus No.	DG Size (MVA)	Power loss (kW)
Proposed (PSO-CRO)	6	2.5751	110.9856	30	1.2559	150.8992	6	3.0985	67.0088
PSO	6	2.5338	111.0738	30	1.2483	151.3820	6	3.0650	67.8965
CRO	6	2.5950	111.0302	30	1.2625	151.3794	6	3.1404	67.8894
GSA	6	2.2564	111.1422	30	2.3334	151.3788	6	2.9252	67.8831
PSO-GSA	6	2.5902	111.0299	30	1.2579	151.3787	6	3.1061	67.8738
PSO-GWO	6	2.5973	111.0306	30	1.2614	151.3791	6	3.1082	67.8739
CONOPT SOLVER [42]	6	2.5655	111.0000	30	1.2578	150.9980	6	3.0785	67.8000
HGWO [45]	6	2.5900	111.0180	30	1.2580	151.3600	6	3.1600	67.8550
Hybrid [46]	6	2.4900	111.1700	30	1.2300	151.4100	6	3.0280	67.9370
MINLP [45]	6	2.5900	111.0180	-	-	-	6	3.1050	67.8550
EA OPF [47]	6	2.5900	111.0200	-	-	-	6	3.1190	67.8600
EA [47]	6	2.5300	111.0700	-	-	-	6	3.1190	67.8700
IA [42]	6	2.6000	111.1000	-	-	-	6	3.1070	67.9000
Exhaustive OPF [47]	6	2.5900	111.0200	-	-	-	-	-	-

'-' represents the type of DGs are not considered in the corresponding reference

TABLE 5: First quartile (i.e. Q1), second quartile/median (i.e. Q2) and third quartile (i.e. Q3) values for 33 RDS.

DG Type	33 bus IEEE network								
	PSO			CRO			PSO-CRO		
	Q3	Q2	Q1	Q3	Q2	Q1	Q3	Q2	Q1
Type-1	2.6056	2.5776	2.5446	2.6052	2.5816	2.5342	2.5835	**2.5751**	2.5574
Type-2	1.2756	1.2467	1.2273	1.2675	1.2526	1.2426	1.2585	**1.2559**	1.2522
Type-3	3.0718	3.1006	3.1383	3.1261	3.1046	3.0915	3.1065	**3.0985**	3.0894

TABLE 6: Exact DG size

33 bus IEEE network	
DG Type	**Exact DG size**
Type-1	2.5940
Type-2	1.2590
Type-3	3.0999

case when there is no DG present in the system. Fig. 17 shows that by optimal integration of Type-3 DG in the system gives better improvement in the voltage profile as compared to the rest of the DGs types.

The average computational time for 50 runs for each case

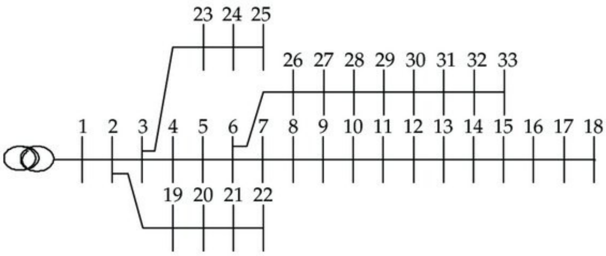

FIGURE 11: 33 bus IEEE network

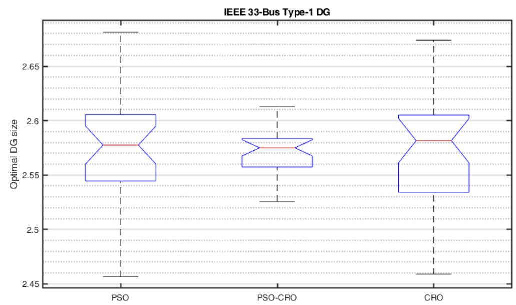

FIGURE 12: Box plot for Type-1 DG

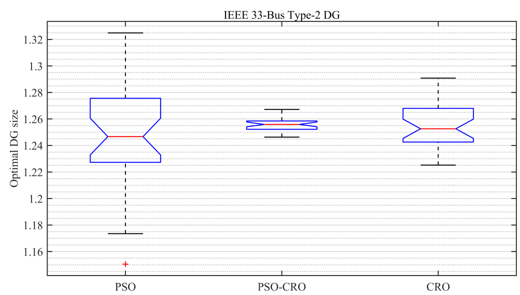

FIGURE 13: Box plot for Type-2 DG

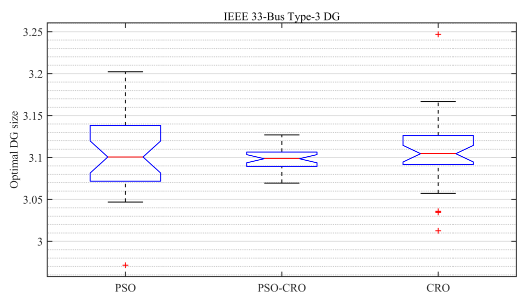

FIGURE 14: Box plot for Type-3 DG

for 33 bus IEEE network is computed and displayed in Table 7. It is observed from Table 7 that proposed PSO-CRO based optimization approach results in least computational time over some existing metaheuristic optimization approaches under optimal integration of all the three types of DGs considered in this work.

TABLE 7: Average computational time for 33 bus IEEE network.

33 bus IEEE network			
Optimization technique	Computational time (Sec.)		
	Type-1 DG placement	Type-2 DG placement	Type-3 DG placement
PSO	5.8151	5.1301	5.1446
CRO	9.4136	9.2273	9.3019
GSA	13.1209	13.4714	13.5001
PSO-GSA	12.4822	12.8619	13.0482
PSO-GWO	5.1706	5.2592	5.1528
PSO-CRO	1.8402	1.8991	1.8896

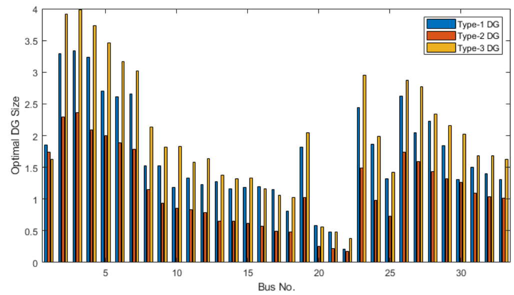

FIGURE 15: Optimal size of DGs at each bus in 33-bus IEEE network using PSO-CRO

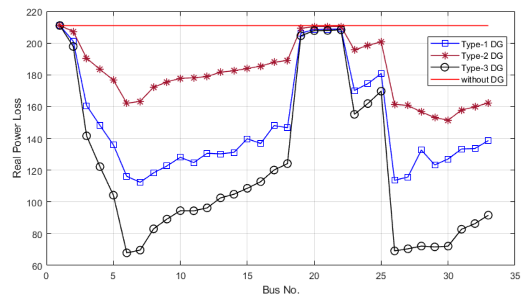

FIGURE 16: System power loss for optimal DG size at each bus in 33-bus IEEE network using PSO-CRO

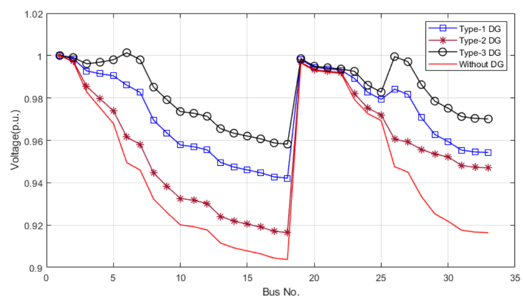

FIGURE 17: Voltage profile of 33-bus RDS with and without DGs using PSO-CRO

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B. 69-BUS RADIAL DISTRIBUTION SYSTEM

The second test bed is 69 bus IEEE network on which the proposed approach and other optimization algorithms are tested for optimal siting and sizing of individual Type-1, Type-2 & Type-3 DGs. This system is loaded with 3.80 MW of real power, 2.69 MVAr of reactive power (Fig. 18). Power flow study shows that the real and reactive power is 225.002 kW and 102.525 kVAr, respectively [32]. Table 8 presents the median for 50 runs obtained from the proposed approach PSO-CRO, PSO, CRO, GSA, PSO-GSA, PSO-GWO and CONOPT SOLVER of GAMS for Type-1, Type-2 & Type-3 DGs. Also, various other methods in literature are compared with the proposed approach.

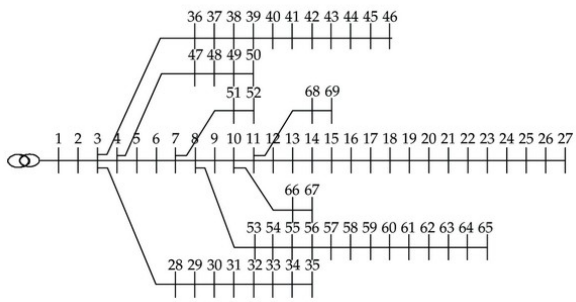

FIGURE 18: 69 bus IEEE network

The proposed PSO-CRO approach gives better results than PSO, CRO, GSA, PSO-GSA, PSO-GWO & CONOPT SOLVER etc. Also, the median value of optimal size of DGs for 50 runs computed through PSO-CRO approach is nearest to the exact solution. The statistical analysis over optimal solutions by PSO, CRO & PSO-CRO techniques is elaborated further in the following subsection.

1) Statistical analysis

Fig. 19, 20 & 21 depict the box plot of 50 runs for optimal DG size in 69 bus IEEE network with respect to Type-1, Type-2 & Type-3 DGs, respectively.

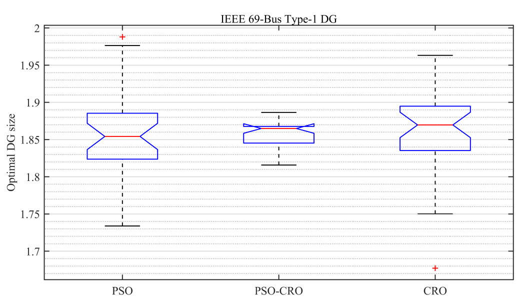

FIGURE 19: Box plot for Type-1 DG

In context to the Fig. 19, 20 & 21, it is observed that the proposed method has the best performance. As the median (shown in Table 9) of the proposed method is nearest the exact solution (shown in Table 10) of the problem.

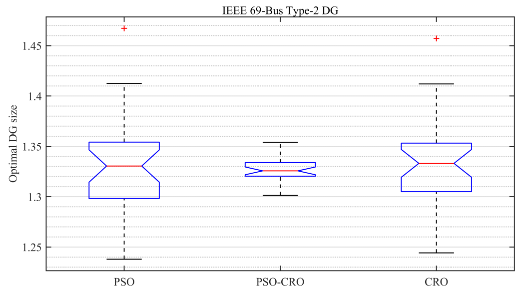

FIGURE 20: Box plot for Type-2 DG

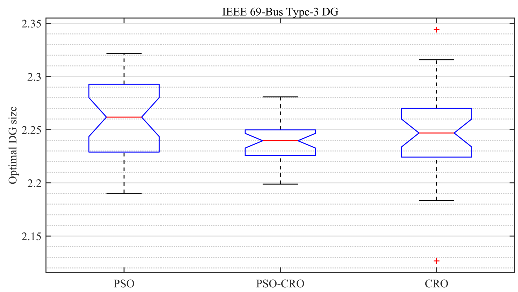

FIGURE 21: Box plot for Type-3 DG

Table 9 shows the first quartile (i.e. Q1), second quartile/median (i.e. Q2) and third quartile (i.e. Q3) values with respect to PSO, CRO and PSO-CRO algorithm for Type-1, Type-2 & Type-3 DGs.

Table 10 shows the exact DG size for each type (i.e. type-1, type-2 & type-3) in 69 bus IEEE network. The exact size of each DG type is calculated through bisection method.

2) Simulation results

By the power loss minimization analysis with the help of PSO-CRO algorithm, Fig. 22 presents the optimum DG size of Type-1, Type-2 & Type-3 DGs at each bus in 69 bus IEEE network. Fig. 23 gives the system power loss corresponding to optimal DG size of Type-1, Type-2 & Type-3 DGs at each bus in 69 bus IEEE network. At 61^{st} bus the system power loss is found minimum for Type 1, Type 2 and Type 3 DGs. After individual integration of various type of DGs with optimal value at appropriate bus, Fig. 24 shows improved voltage scenario as compared to the case when there is no DG present in the system. Fig. 24 shows that by optimal integration of type 3 DG in the system gives better improvement in the voltage profile as compared to the rest type of the DGs.

The average computational time for 50 runs for each case for 69 bus IEEE network is computed and displayed in Table 11. It is observed from Table 11 that proposed PSO-CRO based optimization approach results in minimum computational time compared to some other existing metaheuristic optimization approaches under placement of all the three types of DGs considered in the work.

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TABLE 8: Performance analysis of optimal DG integration in 69 bus IEEE network

Method	Type-1 DG			Type-2 DG			Type-3 DG		
	Bus No.	DG Size (MW)	Power loss (kW)	Bus No.	DG Size (MVAr)	Power loss (kW)	Bus No.	DG Size (MVA)	Power loss (kW)
PSO-CRO	61	1.8666	83.0014	61	1.3285	151.9934	61	2.2396	24.0011
PSO	61	2.0264	84.0400	61	1.3965	152.5922	61	2.2392	24.1675
CRO	61	1.9627	84.2092	61	1.3625	152.4525	61	2.2400	24.1676
GSA	61	3.0758	84.3900	61	1.6827	152.4034	61	2.5448	24.1720
PSO-GSA	61	1.8685	83.9013	61	1.3272	152.4033	61	2.2386	24.1675
PSO-GWO	61	1.8572	83.9058	61	1.3282	152.4214	61	2.2405	24.1676
CONOPT SOLVER [42]	61	1.8877	83.1500	62	1.3080	152.6790	61	2.2626	23.1200
CPLS [42]	61	1.8500	83.1500	-	-	-	61	2.2000	27.9100
HGWO [45]	61	1.8720	83.2220	61	1.3300	152.0410	61	2.2460	23.1600
Hybrid [46]	61	1.1810	83.3720	61	1.2900	152.1020	61	2.2000	23.9200
MINLP [45]	61	1.8700	83.2220	-	-	-	61	2.2440	23.1600
EA OPF [47]	61	1.8700	83.2300	-	-	-	61	2.2290	23.1700
EA [47]	61	1.8780	83.2300	-	-	-	61	2.2900	23.2600
Exhaustive OPF [47]	61	1.8700	83.2300	-	-	-	-	-	-

'-' represents the type of DGs are not considered in the corresponding reference

TABLE 9: First quartile (i.e. Q1), second quartile/median (i.e. Q2) and third quartile (i.e. Q3) values for 69 RDS

DG Type	69 Bus RDS								
	PSO			CRO			PSO-CRO		
	Q3	Q2	Q1	Q3	Q2	Q1	Q3	Q2	Q1
Type-1	1.8854	1.8542	1.8237	1.8949	1.8697	1.8353	1.8677	**1.8666**	1.8453
Type-2	1.3542	1.3304	1.2982	1.3532	1.3331	1.3048	1.3339	**1.3285**	1.3204
Type-3	2.2927	2.2618	2.2289	2.2701	2.2469	2.2242	2.2498	**2.2396**	2.2257

TABLE 10: Exact DG size

69 bus IEEE network	
DG Type	**Exact DG size**
Type-1	1.8699
Type-2	1.3199
Type-3	2.2298

TABLE 11: Average computational time for 69 bus IEEE network.

69 bus IEEE network			
Optimization technique	**Computational time (Sec.)**		
	Type-1 DG placement	**Type-2 DG placement**	**Type-3 DG placement**
PSO	33.9360	33.9799	35.0513
CRO	62.8101	62.9990	62.9647
GSA	43.1392	43.1562	45.0636
PSO-GSA	42.4069	42.0382	42.1048
PSO-GWO	33.7171	35.4585	34.3210
PSO-CRO	8.1376	8.2098	8.2408

C. 118-BUS RADIAL DISTRIBUTION SYSTEM

The third test bed is 118 bus IEEE network on which the proposed approach and other optimization algorithms are tested for optimal siting and sizing of individual Type-1, Type-2 & Type-3 DGs. This system is loaded with 22.709 MW of real power, 17.041 MVAr of reactive power (Fig. 25). Load flow shows that the real and reactive power loss is 1298.0916 kW and 978.736 kVAr, respectively [48]. Table 12 presents the median for 50 runs obtained from the proposed approach PSO-CRO, PSO, CRO, GSA, PSO-GSA, PSO-GWO and CONOPT SOLVER of GAMS for Type-1, Type-2

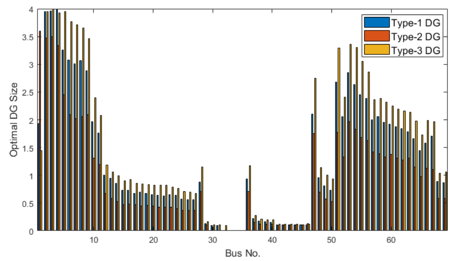

FIGURE 22: Optimal size of DGs at each bus in 69-bus IEEE network using PSO-CRO

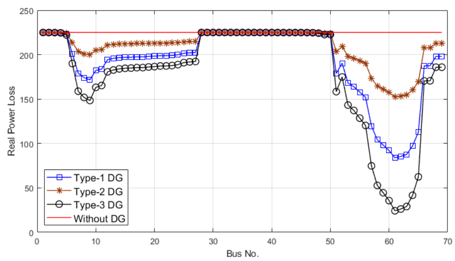

FIGURE 23: System power loss for optimal DG size at each bus in 69-bus IEEE network using PSO-CRO

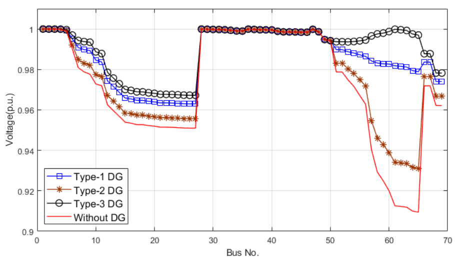

FIGURE 24: Voltage profile of 69-bus RDS with and without DGs using PSO-CRO

& Type-3 DGs. Also, various other methods in literature are compared with the proposed approach for Type-1, Type-2 & Type-3 DGs. The proposed PSO-CRO approach gives better

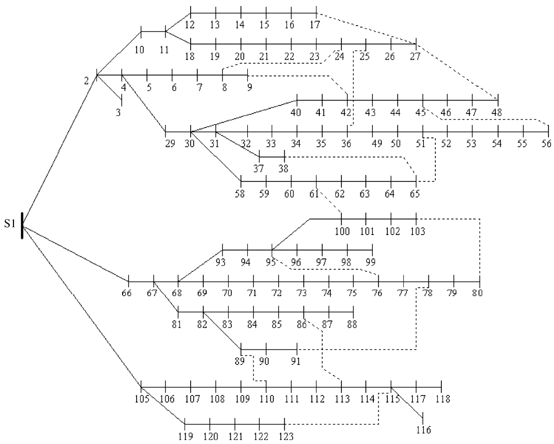

FIGURE 25: 118 bus IEEE network

objective value than PSO, CRO, GSA, PSO-GSA and PSO-GWO. Besides, the median value of optimal size of DGs for 50 runs computed through PSO-CRO approach is near to the exact solution. The statistical analysis over optimal solutions by PSO, CRO & PSO-CRO techniques is discussed in the further subsection.

1) Statistical analysis

Fig. 26, 27 & 28 depict the box plot of 50 runs for optimal DG size in 118 bus IEEE network with respect to Type-1, Type-2 & Type-3 DGs respectively.

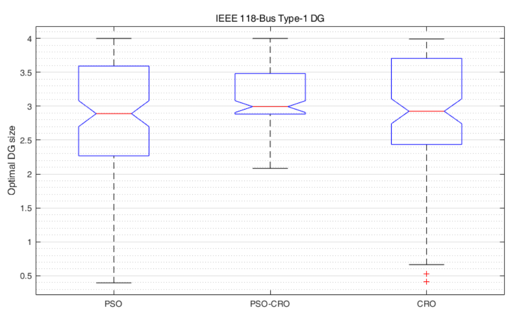

FIGURE 26: Box plot for Type-1 DG

In context to the Fig. 26, 27 & 28, it is observed that the proposed method has the best performance. As the median

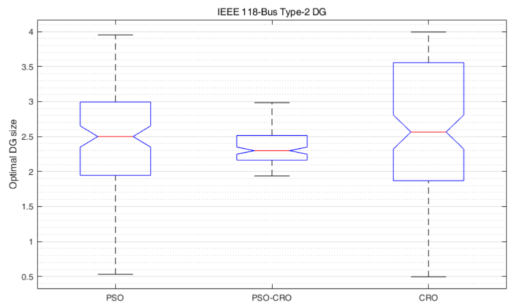

FIGURE 27: Box plot for Type-2 DG

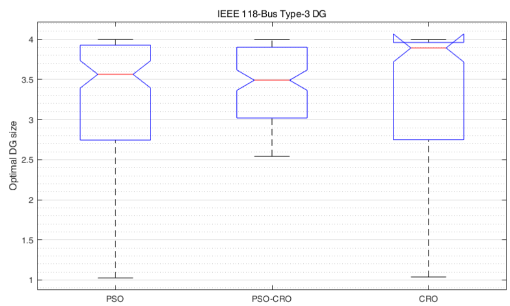

FIGURE 28: Box plot for Type-3 DG

(shown in Table 13) of the proposed method is nearest to the exact solution (shown in Table 14) of the problem.

Table 13 shows the first quartile (i.e. Q1), second quartile/median (i.e. Q2) and third quartile (i.e. Q3) values with respect to PSO, CRO and PSO-CRO algorithm for Type-1, Type-2 & Type-3 DGs.

Table 14 shows the exact DG size for each type (i.e. type-1, type-2 & type-3) in 118 bus IEEE network. The exact size of each DG type is calculated through bisection method.

2) Simulation results

The power loss minimization analysis with the help of PSO-CRO algorithm, Fig. 29 presents the optimum DG size of Type-1, Type-2 & Type-3 DGs at each bus in 118 bus IEEE network. Fig. 30 gives the system power loss corresponding to optimal DG size of Type-1, Type-2 & Type-3 DGs at each bus in 118 bus IEEE network. At 71^{st} bus the system power loss is found minimum for type 1 and type 3 DGs. The optimal solution for type 2 DG is found at 110^{th} bus. After individual integration of various type of DGs with optimal value at appropriate bus, Fig. 31 shows improved voltage scenario as compared to the case when there is no DG present in the system. Fig. 31 shows that by optimal integration of type 3 DG in the system gives better improvement in the voltage profile as compared to the rest types of the DGs.

The average computational time for 50 runs for each case for 118 bus IEEE network is computed and displayed in Table 15.

TABLE 12: Performance analysis of optimal DG integration in 118 bus IEEE network

Method	**Type-1 DG**			**Type-2 DG**			**Type-3 DG**		
	Bus No.	DG Size (MW)	Power loss (kW)	Bus No.	DG Size (MVAr)	Power loss (kW)	Bus No.	DG Size (MVA)	Power loss (kW)
PSO-CRO	71	3.0073	824.8902	110	2.3000	916.9917	71	3.4861	746.9887
PSO	71	2.9200	825.0315	110	2.4902	917.0693	71	3.5568	747.2363
CRO	71	2.9839	825.1003	110	2.5629	918.1537	71	3.8937	747.5961
GSA	71	3.9014	825.0089	110	3.5435	917.0991	71	2.9635	747.2769
PSO-GSA	71	2.8497	825.0101	110	2.5366	917.1537	71	3.8766	747.2283
PSO-GWO	71	2.9987	825.1100	110	2.4344	917.0897	71	3.9846	747.2296
CONOPT SOLVER [42]	79	3.0212	885.1465	114	2.7392	934.4086	68	4.3033	747.0005
HSA-PABC [49]	70	3.0500	1021.0900	-	-	-	-	-	-
SOS [49]	70	3.0482	1021.0890	-	-	-	-	-	-
WOA [49]	113	2.7040	1092.4600	-	-	-	-	-	-
PIPSO-SQP [49]	72	2.9785	1016.8000	-	-	-	-	-	-

'-' represents the type of DGs are not considered in the corresponding reference

TABLE 13: First quartile (i.e. Q1), second quartile/median (i.e. Q2) and third quartile (i.e. Q3) values for 118 RDS

DG Type	**118 Bus RDS**								
	PSO			**CRO**			**PSO-CRO**		
	Q3	**Q2**	**Q1**	**Q3**	**Q2**	**Q1**	**Q3**	**Q2**	**Q1**
Type-1	3.5920	2.9200	2.2678	3.7048	2.9839	2.4362	3.4823	**3.0073**	2.8838
Type-2	2.9939	2.4902	1.9452	3.5568	2.5629	1.8681	2.5150	**2.3000**	2.1628
Type-3	3.9285	3.5568	2.7451	3.9615	3.8937	2.7494	3.9026	**3.4861**	3.0212

TABLE 14: Exact DG size

118 bus IEEE network	
DG Type	**Exact DG size**
Type-1	3.0038
Type-2	2.3400
Type-3	3.4999

TABLE 15: Average computational time for 118 bus IEEE network.

118 bus IEEE network			
Optimization technique	**Computational time (Sec.)**		
	Type-1 DG placement	**Type-2 DG placement**	**Type-3 DG placement**
PSO	185.3673	185.8833	185.9187
CRO	376.9396	376.8467	376.7964
GSA	368.6843	368.8502	370.5487
PSO-GSA	203.6566	203.8932	205.5787
PSO-GWO	248.3372	245.7584	396.2382
PSO-CRO	153.5437	153.2579	153.3583

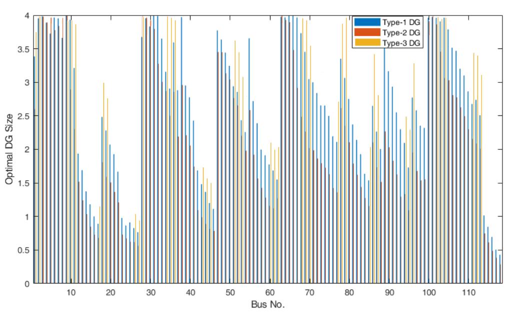

FIGURE 29: Optimal size of DGs at each bus in 118-bus IEEE network using PSO-CRO

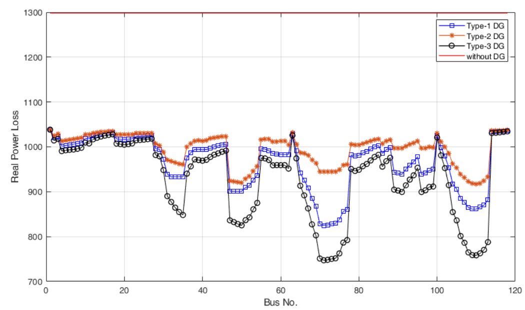

FIGURE 30: System power loss for optimal DG size at each bus in 118-bus IEEE network using PSO-CRO

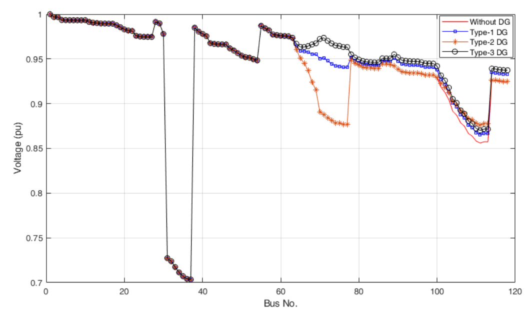

FIGURE 31: Voltage profile of 118-bus RDS with and without DGs using PSO-CRO

VI. CONCLUSION

This manuscript proposes a novel optimization algorithm that hybridizes PSO and CRO to overcome the disadvantages of classical non-linear optimization techniques. High exploration capability of PSO and excellent exploitation proficiency of CRO has been utilized to develop the novel optimization method. It enables the proposed metaheuristic approach not to get trapped at local minima (i.e. the main drawback of classical non-linear optimization techniques) and gives global optimal solution. The proposed method is tested for its convergence rate on various standard test functions. Convergence rate of the proposed approach is found better as compared to PSO and CRO method.

Investigations for optimal placement of Type-1, Type-2 and Type-3 DGs on IEEE 33, 69 and 118 bus test systems have been carried out in the paper and showed proposed approach to be more effective compared to existing approaches. Statistical results showed that the proposed method has the best performance, as the median of the proposed method is nearest to the exact solution of the problem. Additionally, there are no outliers for the proposed method in any case, which indicates that it very rarely gets trapped into the local minima. Also, the Q1 and Q3, boundaries of the box, are very near to Q2 (median) which indicates that the proposed method gives the answer with minimum deviation when not able to converge onto the exact solution.

Simulation of PSO-CRO has been carried out in the MATLAB software. Simulation results of the proposed approach present the optimal DG size and location for which system power loss is minimum. In IEEE 33 bus system the optimal solution (i.e. location and size) for Type-1, Type-2 and Type-3 DGs are 6^{th} bus (2.5751 MW), 30^{th} bus (1.2559 MVAr) and 6^{th} bus (3.0985 MVA), respectively. In IEEE 69 bus system the optimal solution (i.e. location and size) for Type-1, Type-2 and Type-3 DGs are 61^{st} bus (1.8666 MW), 61^{st} bus (1.3285 MVAr) and 61^{st} bus (2.2396 MVA), respectively. In IEEE 118 bus system the optimal solution (i.e. location and size) for Type-1, Type-2 and Type-3 DGs are 71^{st} bus (3.0073 MW), 110^{th} bus (2.3000 MVAr) and 71^{st} bus (3.4861 MVA), respectively.

The proposed method is found better based on accuracy, computational time and convergence rate as compared to PSO and CRO. The proposed method is compared and tested on 33, 69 and 118-bus IEEE networks against metaheuristic algorithms, namely, CRO, PSO, GSA, PSO-GSA & PSO-GWO as well as on the GAMS/CONOPT commercial solver, and some other existing approaches. It is observed that proposed approach yields better results for optimal DGs placement compared to existing approaches considered in this work. In future research, the PSO-CRO approach might be tested on multi-objective function for optimal DG integration in radial distribution network as well as meshed system. Further research may also consider placement of Type-4 DGs using proposed PSO-CRO based approach.

APPENDIX

Simulation parameters in PSO-CRO							
Population size=50	Maximum iterations=100						
$\wedge = 55$	$\rho_0 = \frac{11}{14} = 0.785$	$F_b = 0.9$	$F_a = 0.01$	$F_d = 0.1$	$K = 3$	$w = 0.5$	$C_1 = C_2 = 1$
DG maximum capacities							
33-bus IEEE Network	$Type - 1DG = 4MW$	$Type - 2DG = 2.5MVAr$	$Type - 3DG = 4.5MVA$				
69-bus IEEE Network	$Type - 1DG = 4MW$	$Type - 2DG = 3MVAr$	$Type - 3DG = 5MVA$				
118-bus IEEE Network	$Type - 1DG = 4MW$	$Type - 2DG = 4MVAr$	$Type - 3DG = 5MVA$				

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LOKESH K. YADAV received the M.Tech. degree in control system from the National Institute of Technology Patna, India, in 2014, and the B.Tech. degree in electrical and electronics engineering from Uttar Pradesh Technical University, Lucknow, India, in 2011. He is currently pursuing the Ph.D. degree in electrical engineering with the Indian Institute of Technology (Banaras Hindu University), Varanasi, India. He is also an Assistant Professor with the Department of Electrical Engineering, Rajkiya Engineering College, Ambedkar Nagar, Uttar Pradesh, India. His research interests include renewable energy integration in radial distribution systems, optimization techniques, and voltage stability analysis of power systems.

MITRESH K. VERMA received his B.Sc (Eng.) degree in Electrical Engineering from Regional Engineering College, Rourkela (presently National Institute of Technology, Rourkela), India in 1989, M.Sc (Eng.) degree in Electrical Engineering from Bihar Institute of Technology, Sindri, India in 1994 and PhD degree in Electrical engineering from Indian Institute of Technology (IIT), Kanpur, India in 2005. He is currently working as Professor in Electrical Engineering Department at Indian Institute of Technology (BHU), Varanasi, India. His current research interests include voltage stability studies, application of FACTS controllers, power quality, wide area monitoring system and smart grid.

PUNEET JOSHI is currently Assistant Professor with the Department of Electrical Engineering, Rajkiya Engineering College, Ambedkarnagar (U.P.), India. He received B.E. in Electrical Engineering from G. B. Pant Engineering College, Pauri Garhwal, Uttarakhand, India in 2008. He received M. Tech. degree in Electrical Engineering from G. B. Pant university of Agriculture & Technology, Pant Nagar, Uttarakhand, india in 2012. He completed PhD degree in Electrical Engineering from G. B. Pant university of Agriculture & Technology, Pant Nagar, Uttarakhand, india in 2018. His research interests include renewable energy integration in radial distribution system, optimization techniques MPPT, multulevel interter.