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Minimizing Loss in a Larger Distribution Network by Optimal Network Reconfiguration and DG Allotment using an Advanced Adaptive Differential Evolution

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Abstract: ***Power Loss minimization at the highest extent possible in an Electrical network is more important than generating the same lost power. Recent distribution network is expanding rapidly and power loss minimization is the challenging task to the automation system. This paper presents an advanced integrated optimal method for network reconfiguration along with distributed generation allocation in the large scale distribution system with an objective of minimization of network power loss and enhancement of system voltage stability & reliability as a consequence. Linear population size reduction technique of success history based adaptive differential evolution (L-SHADE) has been applied to execute this optimization assignment. In addition to the adaptation of scaling factor (F) and the crossover rate (CR) as in the previous algorithm SHADE [13], the control parameter population size (Np), over successive generations in the algorithm, is also linearly reduced. The algorithm optimizes DG size along with corresponding location (bus number) and also reconfigures the network simultaneously. Therefore, this optimization assignment is a combination of continuous (rating) and discrete (location) variables. IEEE 119 bus standard radial distribution network has been utilized for testing. The simulation results have been compared with that of other available equivalent algorithms in the large scale distribution system and found as the best among them.***

Keywords: Larger Distribution System, Network Power Loss Minimization, Voltage Profile, Optimal Reconfiguration, Distributed Generation, L-SHADE Algorithm.

I. INTRODUCTION

Electrical distribution system receives power from the high voltage transmission system and delivers to large and complex network after stepping down to subsequent lower voltages as per the requirement of several consumers. As a consequence, the high current and wide system faces substantial power losses. Studies indicate that almost 10 to 13% of the total power generated is lost at the distribution level [1]. High distribution loss means increase in the cost of energy and poor voltage regulation of the network. Due to rapid expansion of distributed networks, the voltage stability of the distribution system also has become an important concern. To reduce the power loss and improve the voltage stability & reliability, network reconfiguration is an important optimization tool in distribution network automation systems.

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Optimal integration of distributed generations (DGs), e.g., solar photovoltaics, wind turbine, micro turbine, fuel cells, diesel generator, etc. added along with locally can boost up the capacity of the system also additionally. However careful attention is required to take care the required system constraints, i.e., power balance, bus voltage and line capacity while optimizing DG size and its location.

Power loss minimization either by network reconfiguration or by optimization of DGs had been performed in several literatures in the recent past as well. Algorithms implemented only for network reconfiguration are cuckoo search algorithm (CSA) [2], fireworks algorithm (FWA) [3], modified particle swarm optimization (MPSO) [4], modified bacterial foraging optimization algorithm (MBFOA) [5], etc. Similarly optimization assignment only by DGs implemented using genetic algorithm (GA) [6], hybrid method with ant colony optimization (ACO) and artificial bee colony (ABC) [7], analytical approach [8], etc.

However efforts had been found for very few studies for utilizing integrated approach of network reconfiguration along with distributed generation allocation and better result of loss reduction achieved. Algorithms utilized are fireworks algorithm (FWA) [9], Adaptive cuckoo search algorithm (ACSA) [10], new heuristic method (UVDA) [11]. Success history based adaptive differential evolution algorithm with progressive linear reduction of population size (L-SHADE) [15] improved the past results in comparison to other algorithms mentioned for IEEE radial distribution networks having 33 bus and 69 bus.

For this present study, L-SHADE algorithm has been used for larger distribution network. Power loss minimization has been set as the objective for simultaneous system reconfiguration and optimal siting & sizing of DGs. The algorithm optimizes DG size along with corresponding location (bus number) and also reconfigures the network simultaneously. IEEE standard 119 bus radial distribution network has been studied. Besides having many more buses, IEEE standard 119 bus distribution network has 15 loops comparing with 5 loops of 33 bus and 69 bus distribution network and therefore making the formulation much complicated, e.g., selecting appropriate bus numbers for each loop as an input for the simulation. Earlier only Adaptive cuckoo search algorithm (ACSA) [10] studied for IEEE standard 119 bus distribution network. Simulation results are found better than ACSA.

In the successive sections of this paper, mathematical model for this optimization assignment has been included in section II. Section III details the case studies with required numerical values. The algorithm steps are in section IV. Section V populates the simulation results with comparison and lastly, section VI for the conclusion.

II. MATHEMATICAL FORMULATION

The endeavor in this paper is to search for optimal reconfiguration along with DG allotment in the large scale radial distribution network. The successive subsections describe for maintaining radial nature of the same network even after reconfiguration and formulations of power flow with assumptions & constraints.

A. Network Reconfiguration

Fig.1 shows the base configurations for 119 bus system where the dotted lines represent tie switches in normally open state. Branches between buses (nodes) have been numbered with prefix '***sw***'. First of all, for applying the algorithm for optimal reconfiguration, all 15 tie switches along with all sectionalizing switches of the branches of the network are set in closed state. Therefore 15 loops (L_1 to L_{15}) are created in the network as shown in **Table–I**. Thereafter, any one switch (either tie or sectionalizing) in each loop is selected to open in such a way that any single bus (node) in the network is not isolated as well as the radial nature of the network is maintained fulfilling the essential basic requirements. The algorithm needs to execute numerous iterations to finalize the switches to be opened so that overall network power loss is minimized. This process is to be simultaneously carried out with optimized allocation of certain number and rating of DGs to the buses to obtain further better result of loss reduction.

B. Power Flow Formulations

Single line diagram of a typical radial distribution system has been shown in **Fig.2**. A set of empirical equations to compute of active & reactive power flow and bus voltages are given by [15]:

$$P_{k+1} = P_k - P_{Lk+1} - R_{k,k+1}.\frac{P_k^2 + Q_k^2}{|V_k|^2} \tag{1}$$

$$Q_{k+1} = Q_k - Q_{Lk+1} - X_{k,k+1}.\frac{P_k^2 + Q_k^2}{|V_k|^2} \tag{2}$$

$$|V_{k+1}|^2 = |V_k|^2 - 2\left(R_{k,k+1}.P_k + X_{k,k+1}.Q_k\right) + \left({R_{k,k+1}}^2 + {X_{k,k+1}}^2\right).\frac{P_k^2 + Q_k^2}{|V_k|^2} \tag{3}$$

where, P_k and Q_k are the active and reactive power flowing out of bus k; P_{Lk+1} and $Q_{Lk+1}$are the active and reactive load at bus $k+1$. $|V_k|$is the voltage magnitude of bus k .The branch between buses k and$k+1$ having resistance $R_{k,k+1}$ and reactance$X_{k,k+1}$ shall have the power loss (P_{Loss}) as follows:

$$P_{Loss}(k, k+1) = R_{k,k+1}.\frac{P_k^2 + Q_k^2}{|V_k|^2} \tag{4}$$

Accordingly, the total loss (TP_{Loss}) after summing up for all branches in the network is computed by:

$$TP_{Loss} = \sum_{k=0}^{N-1} P_{Loss}(k, k+1) \tag{5}$$

C. Assumptions

This study assumes that the DGs deliver only active power (e.g. solar photovoltaic systems, micro turbines, etc.). Hence, a DG connected to k-th bus and supplying output powerP_{DG}, the reduced loading of that bus becomes ($P_{Lk} - P_{DG}$)from P_{Lk}. During execution, the algorithm checks all feasible locations and ratings of the DGs to find the most optimum allocation so as to minimize overall network power loss.

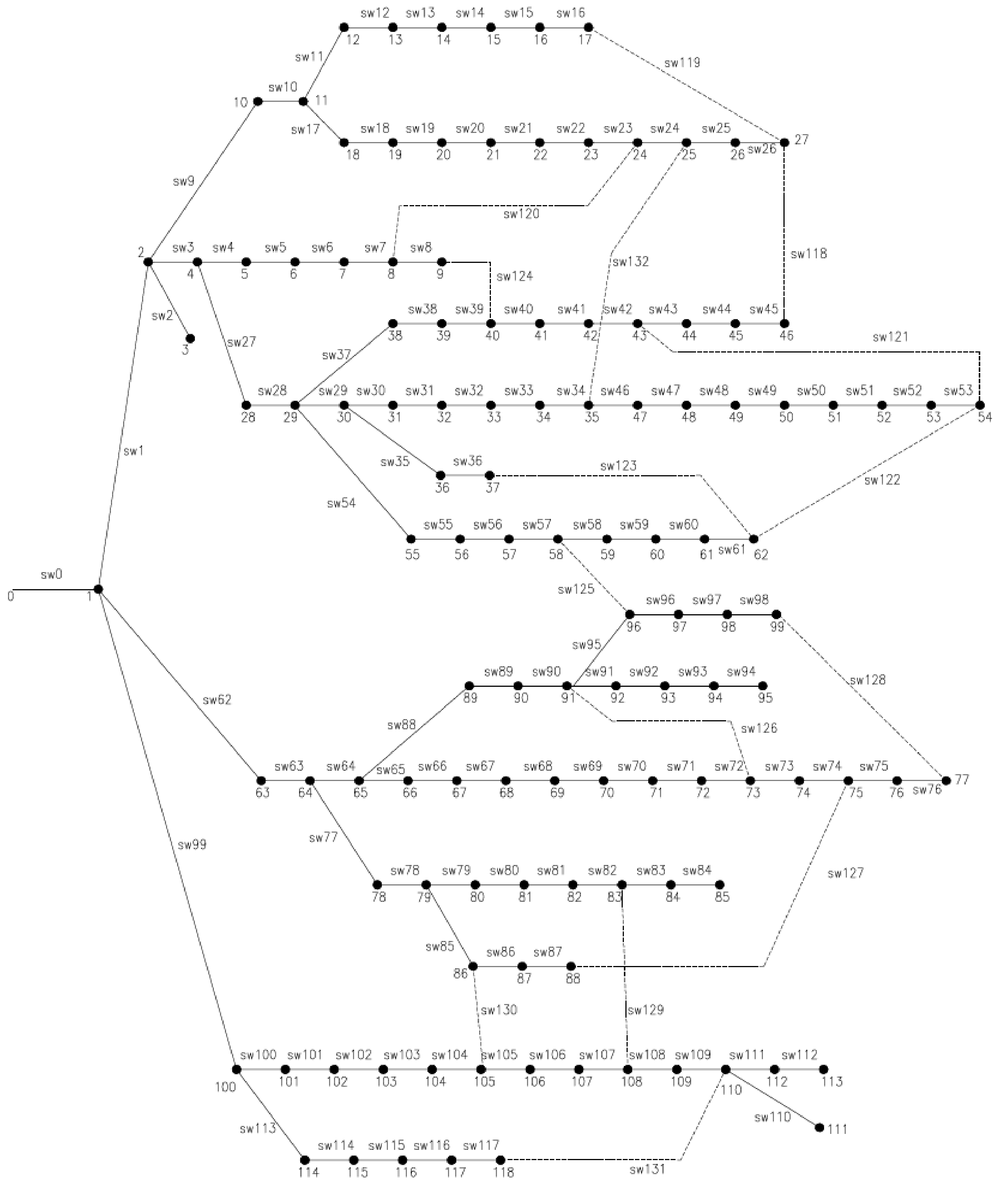

Fig.1: IEEE-119 Bus Distribution Network

D. Constraints

While execution of the algorithm, voltage $|V_k|$of any bus must be within minimum & maximum specified allowable voltage limits. Also current $|I_{k,k+1}|$flowing through any branch must be within its rated capacity.
Accordingly mathematical representation as follows:

$$V_{\min} \le |V_k| \le V_{\max} \qquad (6)$$

$$|I_{k,k+1}| \le I_{k,k+1(\max)} \qquad (7)$$

TABLE–I: Network Loops

Loops	Branches
L_1	3, 9, 10, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 37, 38, 39, 40, 41, 42, 43, 44, 45, 118
L_2	11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 119
L_3	3, 4, 5, 6, 7, 9, 10, 17, 18, 19, 20, 21, 22, 23, 120
L_4	29, 30, 31, 32, 33, 34, 37, 38, 39, 40, 41, 42, 46, 47, 48, 49, 50, 51, 52, 53, 121
L_5	29, 30, 31, 32, 33, 34, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 122
L_6	29, 35, 36, 54, 55, 56, 57, 58, 59, 60, 61, 123
L_7	4, 5, 6, 7, 8, 27, 28, 37, 38, 39, 124
L_8	1, 3, 27, 28, 54, 55, 56, 57, 62, 63, 64, 88, 89, 90, 95, 125
L_9	65, 66, 67, 68, 69, 70, 71, 72, 88, 89, 90, 126
L_{10}	64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 77, 78, 85, 86, 87, 127
L_{11}	65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 88, 89, 90, 95, 96, 97, 98, 128
L_{12}	62, 63, 77, 78, 79, 80, 81, 82, 99, 100, 101, 102, 103, 104, 105, 106, 107, 129
L_{13}	62, 63, 77, 78, 85, 99, 100, 101, 102, 103, 104, 130
L_{14}	100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 113, 114, 115, 116, 117, 131
L_{15}	3, 9, 10, 17, 18, 19, 20, 21, 22, 23, 24, 27, 28, 29, 30, 31, 32, 33, 34, 132

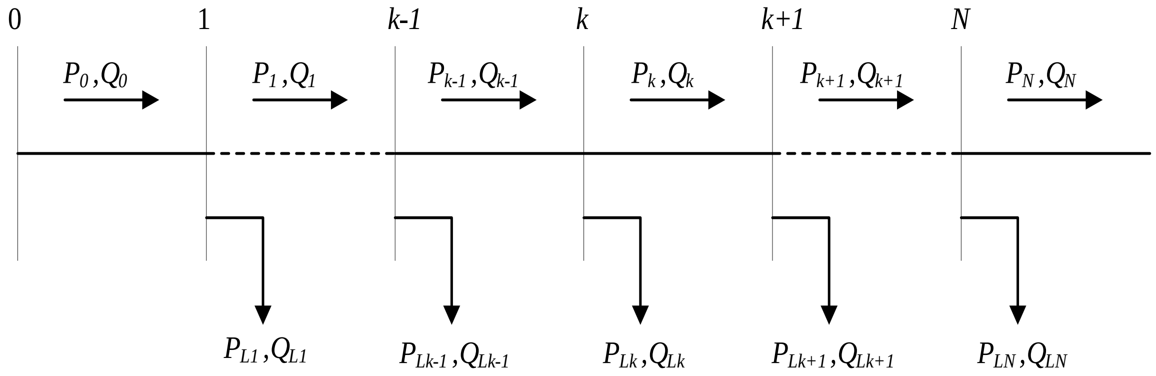

Fig.2: Single Line Diagram of a Radial Feeder

In this study, minimum allowable bus voltage for any bus has been considered as $V_{min} = 0.90$ p.u. and that of maximum as $V_{max} = 1.05$ p.u.

For branch current limits, clear guidelines are not defined for IEEE standard bus systems. However augmentation of local DGs with network reconfiguration improves the voltage profile throughout the network and therefore reduces the branch current loading. Therefore if base configuration of the network having connected load can comply the line current constraint, the new configuration after this optimization assignment will not at all violate the same constraint.

III. CASE STUDIES

The case studies executed for the IEEE standard 119 bus radial distribution network have been described under this section. Required 3 scenarios considered are network reconfiguration only, allotment of DGs only and both criteria simultaneously.

The maximum number of DGs installed for this network has been limited to three (3) considering technical and commercial feasibility. Also maximum limit of cumulative total DG rating have been chosen as 8.0 MW and that of individual DG rating as 4.0 MW taking into account the short circuit level constraint of the system components. **Table–II** is summarizing the details accordingly.

Total load demand of 119 bus distribution network is 22.71 MW and 17.04MVAr. The detailed information on load demand of the network along with line parameters are same as given in [12].

TABLE–II: Summary of Case Studies

Network	Case Study Number	Case Study Description	Total DGs	Maximum Limit of cumulative total DG Rating	Maximum Limit of individual DG Rating
119 bus	Case 1	Reconfiguration only	-	-	-
	Case 2	DG allotment only	3	8.0 MW	4.0 MW
	Case 3	Reconfiguration and DG allotment simultaneously	3	8.0 MW	4.0 MW

IV. L-SHADE ALGORITHM AND ITS APPLICATION

Differential evolution (DE) in the recent past with some adaptation and advancement has emerged as a highly efficient, effective and powerful population-based stochastic search technique to solve optimization assignments. In addition to the adaptation of scaling factor (F) and the crossover rate (CR) as in the previous algorithm SHADE [13], as a more advancement, the control parameter population size (Np), over successive generations in the algorithm, is also linearly reduced in L-SHADE [14]. This section first describes briefly the L-SHADE and next its application to solve the optimization assignment.

A. Initialization

First of all to initiate the process, an initial population (*Np* vectors having dimension *d*) of randomly generated candidate solutions within the search space specified by lower and upper bounds needs to be chosen, where the j^{th} component of the i^{th} decision vector is initialized as:

$$x_{i,j}^{(0)} = x_{min,j} + rand_{ij}[0,1](x_{max,j} - x_{min,j}) \quad (8)$$

Where i = 1 to *Np* and j = 1 to *d*. $rand_{ij}[0,1]$ is a random number between 0 and 1 and superscript '0' represents initialization.

B. Mutation

Once initialization process is done, a mutant vector $v_i^{(t)}$ at current generation *t* is generated through mutation operation corresponding to each member of population vector.

The mutation strategy selected in the current assignment is referred as'current-to-*p*best/1':

$$v_i^{(t)} = x_i^{(t)} + F_i^{(t)}.(x_{pbest}^{(t)} - x_i^{(t)}) + F_i^{(t)}.(x_{R_1^i}^{(t)} - x_{R_2^i}^{(t)}) \quad (9)$$

$x_{pbest}^{(t)}$ is selected from the top $Np \times p$ ($p \in [0,1]$) individuals of current generation, the indices R_1^i & R_2^i are selected randomly from the range [1, *Np*] and also chosen mutually exclusive. $F_i^{(t)}$is the scaling factor and is a positive control parameter for scaling the difference vectors corresponding to the i^{th} individual for the t^{th} generation. If it is found that any element $v_{i,j}^{(t)}$is not within the boundary limit $[x_{min,j}, x_{max,j}]$, the value is updated as:

$$v_{i,j}^{(t)} = \begin{cases} (x_{min,j} + x_{i,j}^{(t)})/2 \text{ if } v_{i,j}^{(t)} < x_{min,j} \\ (x_{max,j} + x_{i,j}^{(t)})/2 \text{ if} v_{i,j}^{(t)} > x_{max,j} \end{cases} \quad (10)$$

C. Crossover

Next in the crossover process, mutant vector $v_i^{(t)}$ merges its elements with the corresponding target vector $x_i^{(t)}$ to form the new vector called as trial/offspring vector and described as $u_i^{(t)} = (u_{i,1}^{(t)}, u_{i,2}^{(t)}, \ldots\ldots, u_{i,d}^{(t)}$. Binomial crossover with crossover rate $CR_i^{(t)}$ is generally adopted and is expressed as:

$$u_{i,j}^{(t)} = \begin{cases} v_{i,j}^{(t)} \text{if } j = K \text{ or } rand_{i,j}[0,1] \le CR_i^{(t)}, \\ x_{i,j}^{(t)} \text{otherwise} \end{cases} \quad (11)$$

Where K is any natural number chosen randomly in the dimension range $[1, d]$.

D. Parameter Adaptation

The parameters $F_i^{(t)}$ and $CR_i^{(t)}$ at a generation *t* are adapted as follows,

$$F_i^{(t)} = randc(\mu F_r^{(t)}, 0.1) \quad (12)$$

$$CR_i^{(t)} = randn(\mu CR_r^{(t)}, 0.1) \quad (13)$$

where $randc\left(\mu F_r^{(t)}, 0.1\right)$ & $randn(\mu CR_r^{(t)}, 0.1)$ are the values sampled from Normal and Cauchy distributions with location parameter $\mu F_r^{(t)}$ and mean $\mu CR_r^{(t)}$ respectively. The value 0.1 indicates variance and scale parameter for the corresponding distributions. $\mu F_r^{(t)}$ & $\mu CR_r^{(t)}$ are chosen randomly from the memory where the scale factors and crossover rates of successful candidates of previous generations are stored. These two values are chosen first as 0.5 and thereafter modified by weighted Lehmer mean, described in detail in [20,21].

E. Selection

After the crossover process, selection process verifies if the trial/offspring vector is going to replace the target vector at next generation *t+1* by carrying out the following comparison:

$$x_i^{(t+1)} = \begin{cases} u_i^{(t)} \text{if } f(u_i^{(t)}) \le f(x_i^{(t)}), \\ x_i^{(t)} \text{otherwise} \end{cases} \quad (14)$$

where *f(.)* is the objective function to be minimized.

F. Linear Population Size Reduction (LPSR)

In the previous algorithm SHADE [13], both scaling factor (F) and the crossover rate (CR) during evolution adapted based on their success history. As a more advancement in L-SHADE [14], the population size (Np) is also reduced for accelerating the performance.

After each generation t, the population size in the next generation t+1 is reduced by following linear equation,

$$Np(t+1) = round\left[\left(\frac{Np_{min} - Np_{ini}}{NFE_{max}}\right).NFE + Np_{ini}\right] \quad (15)$$

Np_{ini} is the population size selected initially, Np_{min} is set to 4 because the selected mutation strategy needs 4 individuals as a minimum. NFE and NFE_{max} are the present number of fitness evaluations and the maximum number of fitness evaluations respectively.

If $Np(t+1) < Np(t)$, a total of $[Np(t) - Np(t+1)]$ elements are deleted from the population [14].

G. Summary of the Algorithm

i. Input and initialization:

1. Decide & fix the value of Np_{ini}, NFE_{max}.
2. Define decision vector x.
3. Define minimum to maximum limit of x element wise.
4. Create random initial population as per equation (8).
5. Set generation counter t = 0, dynamic population size $Np(t) = Np_{ini}$, evaluation counter $NFE = 1$ and control parameters $F_r^{(0)} = CR_r^{(0)} = 0.5$.

ii. Algorithm loop:

1. Estimate $f(x_i^{(t)})$, i.e. TP_{Loss} as per equation (5) for $x_i^{(t)}$ where i = 1 to Np.
2. Increase counter NFE by Np i.e. $NFE = NFE + Np$.
3. **while** termination criteria $NFE < NFE_{max}$ **do**
4. **for** i = 1 to Np **do**

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5. Adapt control parameters $F_i^{(t)}$ and $CR_i^{(t)}$ as per equations (12) & (13).
6. Perform mutation to generate vector $v_i^{(t)}$ as per equation (9).
7. Perform crossover to generate element $u_{i,j}^{(t)}$ as per equation (11).
8. Evaluate $f(u_i^{(t)})$ i.e. TP_{Loss} as per equation (5) for $u_i^{(t)}$. Increase evaluation counter NFE by 1 i.e. $NFE = NFE+1$.
9. Select best fit individuals for next generation. If, $f(u_i^{(t)}) \leq f(x_i^{(t)})$, $x_i^{(t+1)} = u_i^{(t)}$; else $x_i^{(t+1)} = x_i^{(t)}$.

   End **for** loop.

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10. Update population size for next generation $Np(t+1)$ as per LPSR strategy in equation (15).
11. Increase generation counter $t = t$+1. Go to step 2 of algorithm loop.

For the mentioned case studies, various parameters of L-SHADE have been summarized in **Table-III**.

TABLE–III: Parameters of L-SHADE

Parameter	Case No.	Value
Dimension of optimization assignment, d	Case 1	15
	Case 2	6
	Case 3	21
Initial population size, Np_{ini}	Case 1 & 2	100
	Case 3	120
Maximum number of fitness evaluations, NFE_{max}	Case 1 &2	20,000
	Case 3	25,000

Case 1 is only for reconfiguration of the network. Since there are 15 loops as per **Fig.1** and any one switch (either tie or sectionalizing) in each loop is selected to open, therefore there will be total 15 decision variables under the optimization assignment for this case study. Case 2 is only for optimal sizing & siting of 3 DGs. The algorithm will check for suitable 3 buses in the network. Therefore 3 decision variables are for sizing for 3 DGs and 3 other variables for their locations (buses), in total 6 decision variables for this case study. Lastly case 3 is for network reconfiguration and allotment of DGs simultaneously, summing up the decision variables of case 1 & 2, it becomes 21. Since for case 3, number of variables is higher, initial population sizes and numbers of fitness evaluations have been selected higher accordingly as summarized in **Table-III**. However these parameters for all the case studies have been finally selected after many trials of the algorithm.

V. RESULTS AND COMPARISONS

This section analyzes the results after simulation utilizing L-SHADE algorithm. Each case has been run many times and satisfactory results have been found among different runs. **Table-IV** presents the comparison summaries between present study and similar past study. The favorable loss magnitude obtained from comparable algorithms has been marked in bold for easy reference and clear understanding. Also in the table, selected ratings of DGs have been mentioned and corresponding bus numbers have been provided in bracket.

In study **case 1**, only for network reconfiguration, algorithm L-SHADE achieves much considerable loss reduction of 47.86% comparing with 32.86% of ACSA [10]. This result is really significant and proves the efficiency of L-SHADE algorithm in selecting proper tie and sectionalizing switches to reconfigure such larger network without isolating any single bus. Also selecting appropriate bus numbers for each loop as an input for the simulation is also important.

In **case 2,** only for DG sizing & location optimization, L-SHADE algorithm achieves power loss reduction of 48.31% comparing with 49.11% of ACSA [10].

However selection of cumulative total ratings of DGs needs to be accounted. L-SHADE achieves this loss reduction with DGs of 8.0 MW in total while ACSA [10] utilized more than 9.1 MW.

In **case 3** for network reconfiguration and DG allocation simultaneously, L-SHADE algorithm achieves loss reduction of 56.79% comparing with 53.96% of ACSA [10]. This result is significant like study **case 1** and also thinking about cumulative total ratings of DGs selected. The total rating of selected DGs by ACSA [10] is close to 10.0 MW while L-SHADE optimizes with much lower 8.0 MW like **case 2**.

TABLE–IV: Summary of Results with Comparison

Network	Case No.	Case Description	Parameter	Available Optimization Algorithms	
				L-SHADE	ACSA [10]
119 bus	Base Case	Neither Reconfiguration nor DG allotment	Open switches	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132
			Real power loss (kW)	1298.09	1273.45
			Minimum bus voltage (p.u.)	0.8688	0.8678
	Case 1	Reconfiguration only	Open switches	12, 21, 33, 42, 44, 52, 59, 72, 78, 90, 96, 103, 105, 109, 124	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130
			Real power loss (kW)	**676.88**	855.04
			Loss reduction (%)	**47.86**	32.86
			Minimum bus voltage (p.u.)	0.9335	0.9298
	Case 2	DG allotment only	Open switches	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132
			Real power loss (kW)	671.04	**648.1**
			Loss reduction (%)	48.31	**49.11**
			DG sizes in MW (bus no.)	**2.61965** (50) **2.68997** (72) **2.69039** (110)	3.2664 (71) 3.1203 (109) 2.86267 (50)
			Minimum bus voltage (p.u.)	0.9503	0.9515
	Case 3	Reconfiguration and DG allotment simultaneously	Open switches	23, 25, 34, 39, 43, 50, 61, 70, 73, 75, 107, 108, 121, 125, 130	22, 25, 33, 39, 42, 58, 70, 81, 121, 122, 125, 127, 128, 130, 131
			Real power loss (kW)	**560.94**	586.24
			Loss reduction (%)	**56.79**	53.96
			DG sizes in kW (bus no.)	**2.92402** (79) **2.85062** (91) **2.22537** (110)	2.5331 (50) 3.6819 (109) 3.7043 (73)
			Minimum bus voltage (p.u.)	0.9533	0.9644

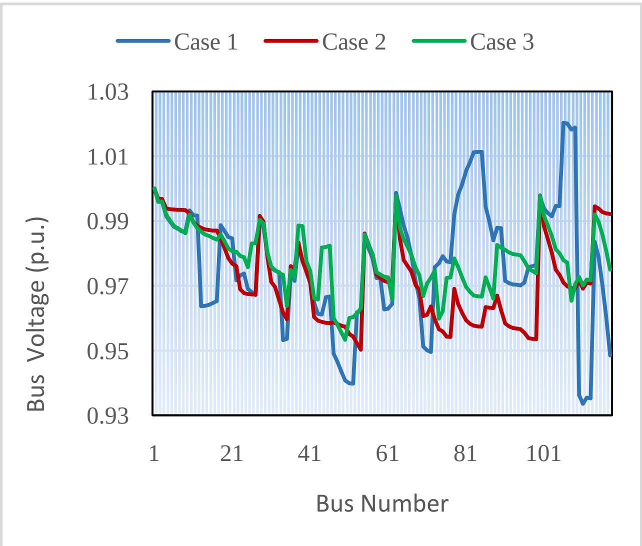

Fig. 3: Voltage Profiles of Buses for 119 Bus Systems for Case Studies

Lower DG ratings saves higher installation cost undoubtedly and relieves the system components from unforeseen higher short-circuit current. From the point of view of voltage regulation, higher DG ratings help to keep up better voltage of the network. It can be observed from **Table-IV** that minimum bus voltage is better for ACSA [10] for **case 2 & 3** for using higher cumulative total ratings of DGs selected. However, L-SHADE achieves more than 0.95 p.u. as the minimum bus voltage using much lower cumulative total ratings of DGs and also achieves the significant loss reduction which is the primary objective for the optimization assignment.

Voltage profiles for the respective buses in the network have been represented in **Fig.3** case study wise. This clearly shows the best & relatively uniform voltage profile is achieved for simultaneous reconfiguration and DG allotment.

Also voltage of the buses are within the limits specified, i.e., 0.9 p.u. to 1.05 p.u. for all case studies.

VI. CONCLUSION

This paper utilizes the L-SHADE algorithm in large scale distribution network and optimizes successfully large number of continuous and discrete variables compared to other available equivalent algorithms. The result demonstrates that simultaneous network reconfiguration and optimal sizing & siting of DGs is the best in minimization of power loss. Reducing the power loss by any more amounts is having great advantage technically and commercially. This reduces burden to the long distance transmission system and generation system as well. Also this power loss is proportionate to the heat emission in conversion and therefore enhancing the system components reliability in long term.

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