Minimizing loss in Larger Distribution Networks by Optimal Allotment of DG and Capacitor using an Advanced Adaptive Differential Evolution

Arindam Roy, Susmita Roy, Partha P. Biswas

Abstract: ***Minimization of Power Loss expenses of the rapidly expanding larger distribution network is always an attention for Electric Power Utilities. Moreover, if power loss can be minimized at the highest extent, network voltage improves inherently in overall, therefore enhancing the quality of power at the consumer end. This paper presents an integrated method for optimal allotment of distributed generation (DG) and shunt capacitor (SC) simultaneously in the largescale distribution system with the primary objective to minimize the network power loss. To perform this task of optimization, one latest algorithm named L-SHADE, linear population size reduction technique of success history based adaptive differential evolution, has been utilized. This is an advanced one of the previous Differential Evolution algorithm, namely SHADE [17] where the control parameters scaling factor (F) and the crossover rate (CR) are only adapted. In L-SHADE [18], the control parameter population size (Np) is also reduced linearly over successive generations. The algorithm optimizes the rating (continuous variable) and corresponding bus number (discrete variable) for both DG and SC. IEEE 69 bus, 119 bus standard distribution networks and a practical 83 bus distribution network have been studied. The simulation results have been compared with similar equivalent algorithms in the largescale distribution system and found as the best among them.***

Keywords: ***Power loss minimization, Larger Distribution networks, voltage profile, distributed generation, shunt capacitor, L-SHADE algorithm.***

I. INTRODUCTION

Electrical power distribution network is a large and widely scattered complex low voltage system as per consumers' requirements. Therefore, this continuously expanding network needs to carry higher current to deliver the substantial electrical power and facing significant power losses due to its inherent resistance. 10% to 13% of the power consumption is lost at the distribution level [1] as per the studies. This high distribution loss increases the cost of energy and affects the quality of power in terms of under-voltage.

The total power loss can be divided into two parts, i.e., power loss due to real power consumption and the other part due to reactive power flow because consumers are mostly reactive in nature like transformers, induction motors, power supply lines. Simultaneous installation of distributed generators and shunt capacitors near to the consumer centers in the network can minimize the overall power loss substantially.

Increase in real & reactive power generation near to the consumer end relieves the burden of the transmission & distribution lines, boosts up system capacity, improves system reliability and enhances power quality as well.

Distributed Generations are of different types. Emerging and industrialized countries are investing in renewable energy based distributed generations, e.g., solar photovoltaics, solar thermal, wind turbine, tidal & wave power, geothermal power, etc. to reduce the environmental emission. Besides, conventional internal combustion engine generators, fuel cells, micro turbine, small hydro turbine generators can be utilized. However appropriate methodology must be followed for integrating DG units along with shunt capacitors into the network so that required system parameters like bus voltage profile, line capacity, power flow, harmonic distortion, etc. are taken care. Non-appropriate allotment of these units leads to negative consequences in terms of increase in power loss, system voltage instability & reliability.

Power loss minimization in the recent past either by optimization of DGs or by SCs had been performed in several literatures. Algorithms implemented using DGs only are genetic algorithm (GA) [2], analytical approach [3], PSO & hybrid PSO [4, 5, 6], hybrid method with ant colony optimization (ACO) & artificial bee colony (ABC) [7]. Similarly, optimization assignment by SCs only are using mixed integer nonlinear programming approach [8], teaching learning based optimization [9], analytical approach [10], etc. However better result only achieved when integrated approach of optimal siting and sizing of both DGs and SCs implemented. Accordingly, algorithms utilized are analytical approach [11], PSO [12], hybrid harmony search algorithm (HSA) and particle artificial bee colony (PABC) [13], intersect mutation differential evolution (IMDE) [14], back-tracking search algorithm (BSA) [15], IPSO [16].

For this current study, L-SHADE algorithm [18] has been implemented for optimal sizing & siting of DGs & SCs simultaneously at larger distribution networks with the objective of network power loss minimization. IEEE standard 69 bus & 119 bus radial distribution network and one practical 83 bus network have been selected. In the recent time, L-SHADE has been successfully implemented for other power loss optimization assignment [19] for large scale distribution network. For this current study as well, the simulation results using L-SHADE algorithm have been found as the best among other equivalent algorithms mentioned.

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In the consecutive sections of this paper, mathematical formulation for this assignment with assumptions & constraints has been included in section II. Section III mentions the case studies with ratings & limits. Section IV details the algorithm. Section V describes the simulation results with comparison followed by section VI for the conclusion.

II. Mathematical Formulation

The successive subsections describe Power flow formulation followed by assumptions and constraints.

A. *Power flow formulations*

Single line diagram of a typical simple radial distribution system has been represented in **Fig.1**.

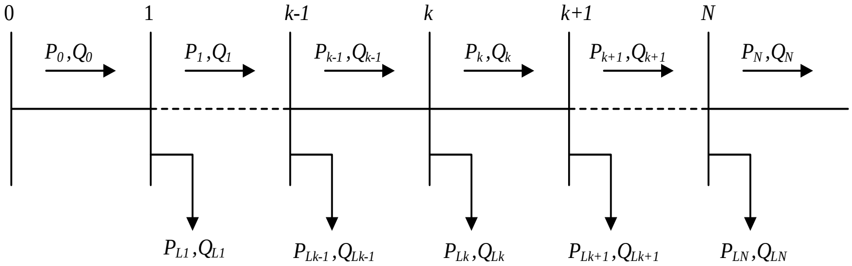

Fig.1: Single line diagram of a radial feeder

The active & reactive power flow and bus voltages can be calculated by empirical equations as given by [19]:

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

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

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

where, $|V_k|$ representing the voltage magnitude of bus k; P_k and Q_k being the real & reactive power flowing out of bus k; P_{Lk+1} & Q_{Lk+1}being the real & reactive load at bus $k+1$. $R_{k,k+1}$& $X_{k,k+1}$being the resistance & reactance of the line section between buses k & $k+1$ and P_{Loss} representing the power loss of the same line section.

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

Accordingly, $TP_{Loss}$is the total loss after summing up for all line sections in the network,

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

B. *Assumptions*

In this study, it is assumed that the DGs deliver real power only. Therefore, a DG connected to k-th bus having real load $P_{Lk}$and delivering power P_{DG}, the net loading of k-th bus becomes $(P_{Lk} - P_{DG})$. Similarly, a SC of rating Q_{SC} connected to j-th bus having inductive load Q_{Lj}, the net reactive loading of the j-th bus becomes $(Q_{Lj} - Q_{SC})$. The algorithm during execution checks all practical locations and ratings of the DGs & SCs to find the most optimum allotment so that overall power loss is minimized.

C. *Constraints*

During execution of the algorithm, voltage $|V_k|$ of any bus of the network must be within minimum & maximum allowable voltage limits specified and the current $|I_{k,k+1}|$ flowing through any branch must not exceed its rated capacity,

$$V_{min} \leq |V_k| \leq V_{max} \tag{6}$$

$$|I_{k,k+1}| \leq I_{k,k+1(\max)} \tag{7}$$

In this study, following bus voltage limits have been considered,
$V_{min} = 0.90$ p.u. and $V_{max} = 1.05$ p.u.
For branch current limits of IEEE standard bus systems, there is no clear guidelines defined. However proper integration of DGs & SCs in the network reduces the burden of the branches and the branch current loading reduces automatically. Therefore, if the network is having connected load can comply the line current constraint, it will not at all violate the same constraint after this optimization assignment.

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III. CASE STUDIES

The optimization assignment has been performed for 3 larger distribution networks. IEEE standard 69 bus & 119 bus radial network and one practical 83 bus network have been selected.

A. IEEE standard 69 bus network

Fig.2 shows the 69 bus network having 68 branches. Total load demand of the network is 3.8 MW and 2.69 MVAr. The detailed information of bus wise load data along with electrical parameters of the interconnecting line sections are as specified in [20]. Few case studies as listed in **Table–I** have been chosen judiciously considering technical and commercial viability, these also include the studies done by equivalent algorithm at the recent past for comparison.

TABLE–I : Summary of Case Studies for 69 bus network

Network	Case Study Number	Case Study Description	No. of DGs	Range of rating for individual DG	Max limit of cumulative total DG rating	No. of SCs	Range of rating for individual SC	Max limit of cumulative total SC rating
69 bus	Case 11	1 DG + 1 SC	1	0.2 – 2.25 MW	2.25 MW	1	0.2 – 2.69MVAr	2.69MVAr
	Case 12	2 DGs + 2 SCs	2	0.2 – 2.0 MW	2.8 MW	2	0.2 – 2.0MVAr	2.69MVAr
	Case 13	3 DGs + 3 SCs	3	0.2 – 2.0 MW	2.8 MW	3	0.2 – 2.0MVAr	2.69MVAr
	Case 14	3 DGs + 4 SCs	3	0.2 – 2.0 MW	2.8 MW	4	0.2 – 2.0MVAr	2.69MVAr
	Case 15	4 DGs + 4 SCs	4	0.2 – 2.0 MW	2.8 MW	4	0.2 – 2.0MVAr	2.69MVAr

B. IEEE standard 119 bus network

Fig.4 shows the 119 bus network having 118 branches. Total load demand of the network is 22.71 MW and 17.04MVAr. The detailed information of bus wise load data along with electrical parameters of the interconnecting line sections are as specified in [21]. Few case studies as listed in **Table–II** have been chosen judiciously considering technical and commercial viability, these also include the studies done by equivalent algorithm at the recent past for comparison.

TABLE–II : Summary of Case Studies for 119 bus network

Network	Case Study Number	Case Study Description	No. of DGs	Range of rating for individual DG	Max limit of cumulative total DG rating	No. of SCs	Range of rating for individual SC	Max limit of cumulative total SC rating
119 bus	Case 21	1 DG	1	0.2 – 4.0 MW	4.0 MW	-	-	-
	Case 22	3 DGs	3	0.2 – 4.0 MW	12.0 MW	-	-	-
	Case 23	1 DG + 6 SCs	1	0.2 – 4.0 MW	4.0 MW	6	0.2 – 2.5 MVAr	15.0 MVAr
	Case 24	4 DGs + 4 SCs	4	0.2 – 2.5 MW	10.0 MW	4	0.2 – 2.5 MVAr	10.0 MVAr

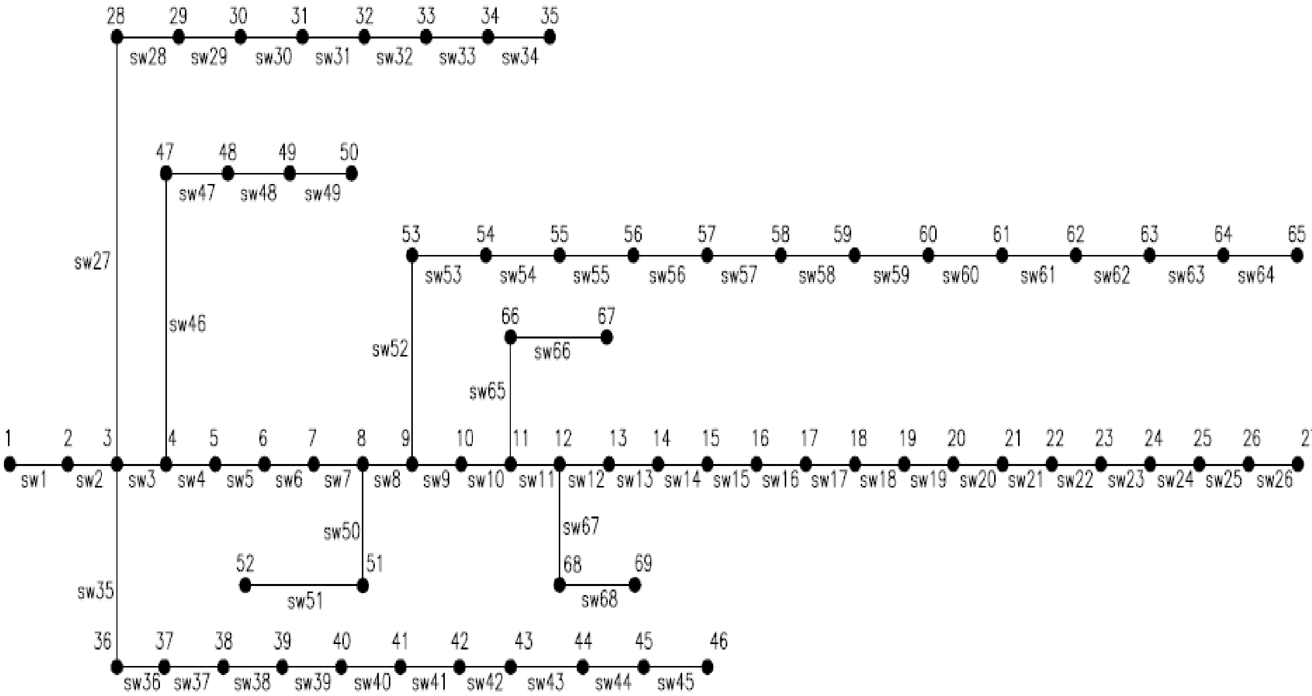

Fig. 2: IEEE 69 bus distribution network

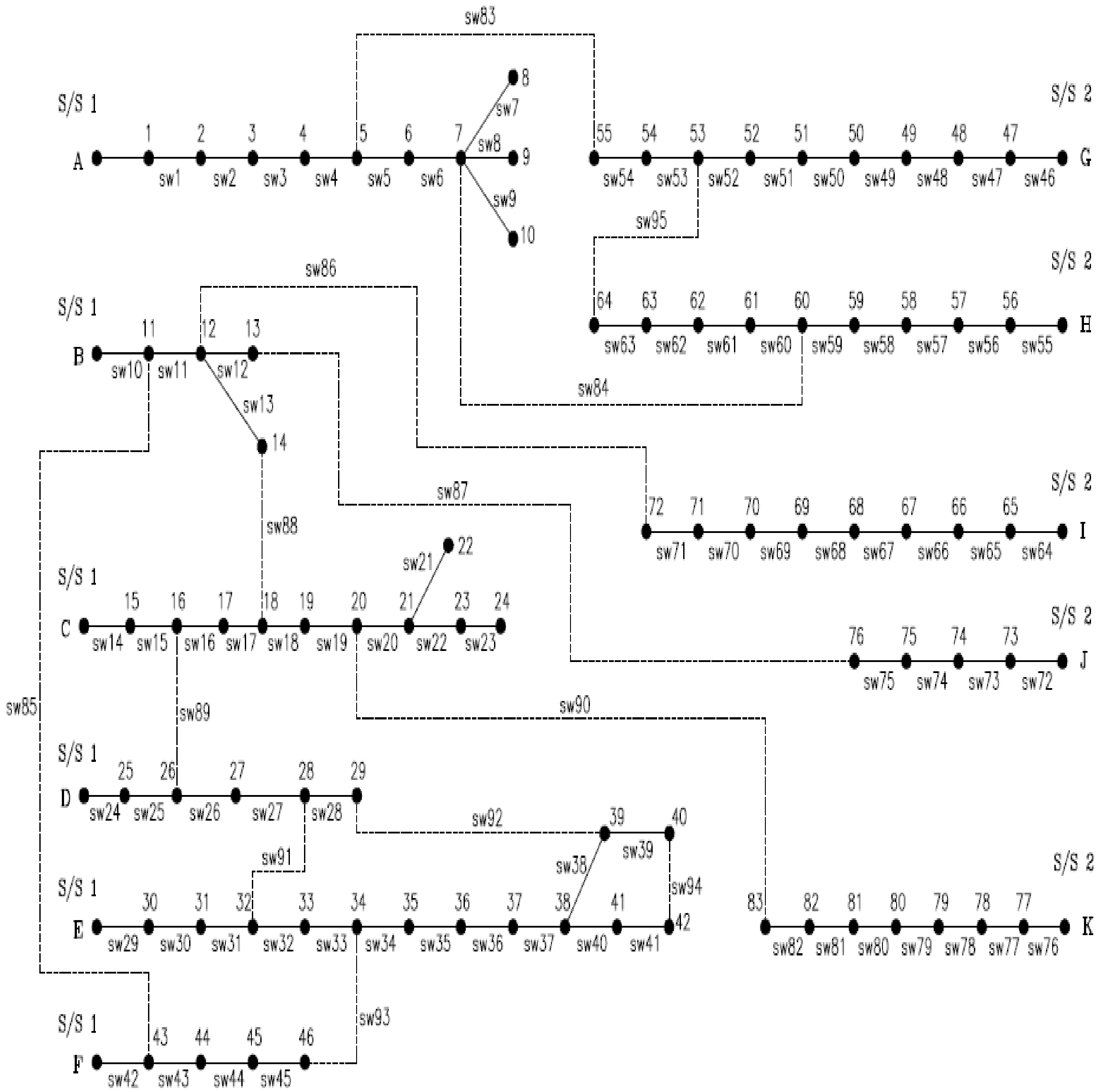

Fig. 3: IEEE 83 bus distribution network

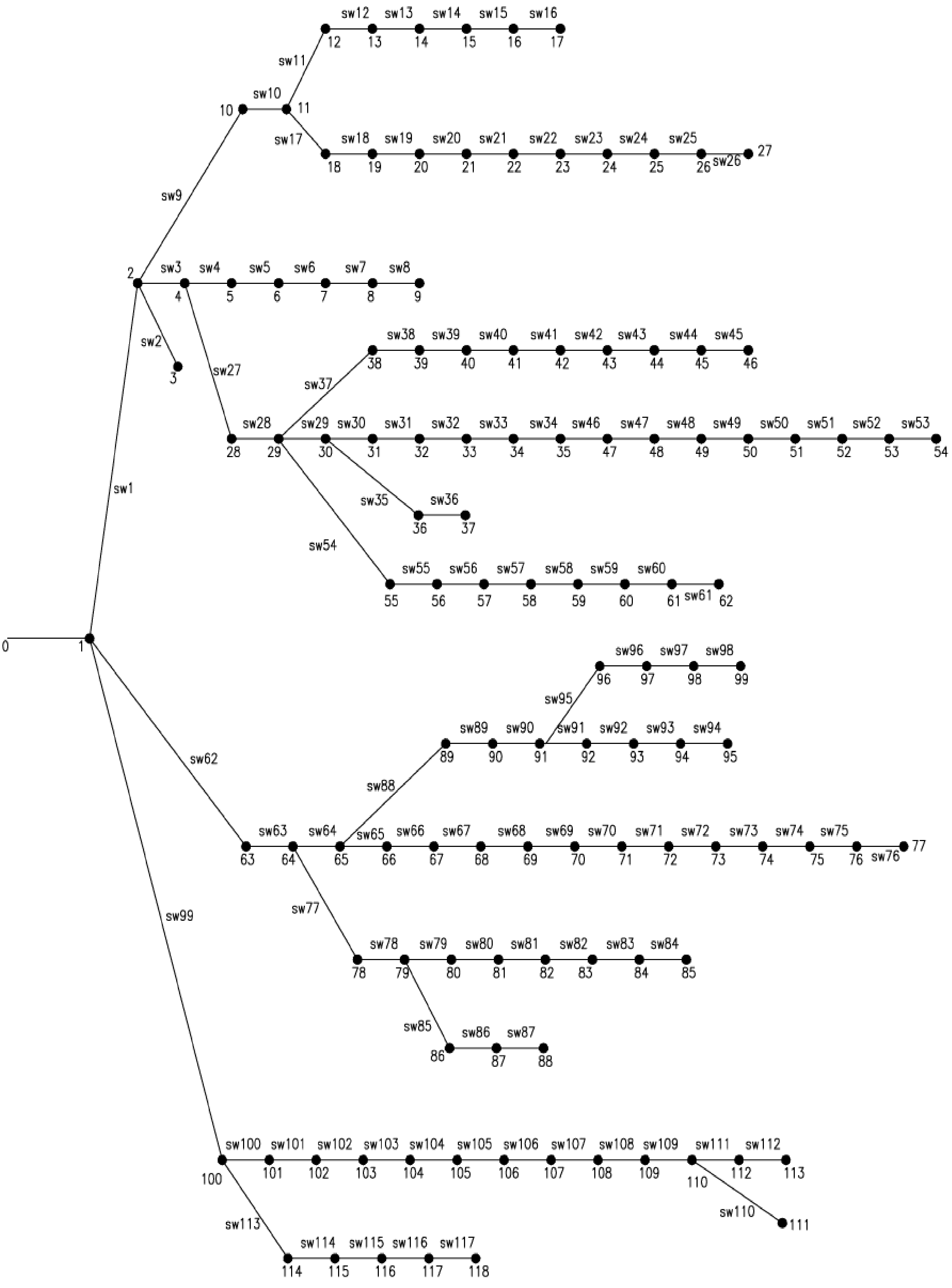

Fig. 4: IEEE 119 bus distribution network

C. *83 bus practical TPC network*

Fig.3 represents a practical 11.4kV distribution network of Taiwan Power Company (TPC). The network consists of 11 feeders, 83 normally closed switches and 13 normally open switches (sw83 to sw95). Total load demand of the network is 28.35 MW and 20.70 MVAr. The detailed information of bus wise load data along with electrical parameters of the interconnecting line sections are as specified in [22]. Loss minimization using reconfiguration studied in [22, 23, 24]. But in this current study, loss minimization studied using simultaneous allotment of DGs and SCs for the base configuration with tie-switches sw83 to sw95 remaining open. Since this network is having higher loading than IEEE standard 119 bus distribution network even, relatively more number of DGs and SCs have been considered.

TABLE–III : Summary of Case Studies for 83 bus TPC network

Network	Case Study Number	Case Study Description	No. of DGs	Range of rating for individual DG	Max limit of cumulative total DG rating	No. of SCs	Range of rating for individual SC	Max limit of cumulative total SC rating
83 bus	Case 31	4 DGs + 4 SCs	4	0.2 – 3.0 MW	12.0 MW	4	0.2 – 3.0MVAr	12.0 MVAr
	Case 32	6 DGs + 6 SCs	6	0.2 – 2.0 MW	12.0 MW	6	0.2 – 2.0MVAr	12.0 MVAr

IV. L-SHADE ALGORITHM AND ITS APPLICATION

Differential evolution (DE), a population based stochastic optmization algorithm, is getting advanced and highly efficient in the recent years by some adaptation time to time to solve optimization assignments. SHADE [17] is the success history based adaptive DE where the scaling factor (F) and the crossover rate (CR) are adapted automatically during the process of evolution. In L-SHADE [18], as a further advancement, the control parameter population size (Np) is also linearly reduced over successive generations. This section briefs the L-SHADE first and then describes its application for the optimization assignment.

A. *Initialization*

Firstly, to initiate the DE process, an initial population of decision vectors (*Np*) having individual dimension *d* for probable solutions generated randomly within the search space specified by lower and upper bounds. Accordingly, the initialization of j^{th} component of the i^{th} decision vector is as below:

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

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*

After initialization process, a mutant vector $v_i^{(t)}$ for the current generation *t* is generated for individual member of population vector through mutation operation.

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

$$v_i^{(t)} = x_i^{(t)} + F_i^{(t)} * \left(x_{pbest}^{(t)} - x_i^{(t)}\right) + F_i^{(t)} * \left(x_{R_1^i}^{(t)} - x_{R_2^i}^{(t)}\right) \qquad (9)$$

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

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

C. *Crossover*

Next in the crossover operation, the mutant vector $v_i^{(t)}$ merges its elements with the corresponding target vector $x_i^{(t)}$ and forms the new vector called as trial/offspring vector which is 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 commonly adopted and expressed as:

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

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

D. *Parameter Adaptation*

At a generation t, both parameters $F_i^{(t)}$ and $CR_i^{(t)}$ are adapted as follows,

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

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

where $randc(\mu F_r^{(t)}, 0.1)$ & $randn(\mu CR_r^{(t)}, 0.1)$ are the values from Normal and Cauchy distributions with location parameter $\mu F_r^{(t)}$ and mean $\mu CR_r^{(t)}$ respectively. The value 0.1 is the variance and scale parameter for the corresponding distributions. $\mu F_r^{(t)}$ & $\mu CR_r^{(t)}$ are chosen randomly from the memory where those of successful candidates of past generations are stored. These two values are initialized first as 0.5 and thereafter modified by weighted Lehmer mean [17, 18].

E. *Selection*

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

$$x_i^{(t+1)} = \begin{cases} \mathrm{u}_i^{(t)} \text{if } f\left(\mathrm{u}_i^{(t)}\right) \leq f\left(x_i^{(t)}\right), \\ x_i^{(t)} \text{otherwise} \end{cases} \quad (14)$$

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

F. *Linear population size reduction (LPSR)*

In the previous algorithm SHADE [17], scaling factor (F) and the crossover rate (CR) are adapted during evolution based on their past success history. With further advancement in L-SHADE [18], the population size (Np) is also dynamically reduced for accelerating the performance.

After any generation *t*, the population size (Np)in the next generation *t*+1 is reduced by following linear equation,

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

The initial population size Np_{min} is set to 4 because the selected mutation strategy needs 4 individuals as a minimum. NFE and NFE_{max} are the present 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.

G. *Summary of the Algorithm*

i. Input and initialization:
1. Decide the value of Np_{ini} & NFE_{max}.
2. Define decision vectors x.
3. Define minimum to maximum limit of x for all its elements.
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 $\mu F_r^{(0)} = \mu CR_r^{(0)} = 0.5$.

ii. Algorithm loop:
1. Calculate $f\left(x_i^{(t)}\right)$, 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 $f\left(u_i^{(t)}\right)$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, $f\left(\mathrm{u}_i^{(t)}\right) \leq f\left(x_i^{(t)}\right)$, $x_i^{(t+1)} = u_i^{(t)}$; 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, i.e., *t* = *t*+1. Go to step 2 of algorithm loop.

For the case studies of **Table-I, II & III**, various parameters of L-SHADE have been summarized in **Table-IV**.

TABLE–IV : Parameters of L-SHADE

Parameter	Case No.	Value
Dimension of optimization assignment, *d*	All Cases	2 x (No. of DGs + No. of SCs)
Initial population size, Np_{ini}	All Cases except Case 32	100
	Case 32	120
Maximum number of fitness evaluations, $NFE_{\max}$	All Cases except Case 32	20,000
	Case 32	25,000

Any Case Study is for optimal sizing & siting of DGs & SCs. The algorithm will check for suitable buses in the network for each DG and/or SC. Therefore, one decision variable is for sizing for each DG/SC and another variable is for its location (bus), in total, 2 decision variables for each DG/SC in any case study. Since for case 32, number of variables is relatively higher, initial population sizes and numbers of fitness evaluations have been chosen higher as summarized in **Table-IV**. However, these parameters have been finally selected for all the case studies after many trials of the algorithm.

V. RESULTS AND COMPARISONS

This section analyzes the simulation results utilizing L-SHADE algorithm. Each case study as mentioned in section III has been run several times and reasonable results have been found among different runs with negligible variations.

A. *IEEE standard 69 bus network*

Table-V presents the summary result for 69 bus network and shows the comparison with similar available past studies done with equivalent algorithms. The favorable loss magnitude from comparable algorithms has been marked in **bold** for clear understanding. Also selected ratings of DGs & SCs have been mentioned in the table with corresponding bus numbers in bracket alongwith. It is very clear from result of all the case studies that L-SHADE algorithm in comparison with any other available algorithms for the available cases studied at the past can efficiently allocate the DGs & SCs suitably meeting the system constraint to achieve comparatively lower loss figure. Specifically, for case 12 with 2 DGs & 2 SCs, loss figure brings down to nearly 50% extra than the only available IMDE algorithm result with similar rating of equipment.

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If the number of DGs and SCs are increased as shown for case 13, 14 & 15, further loss reduction can be achieved. However, this may always not be beneficial to increase number of such equipment in the network. Case 13 with 3 DGs & 3 SCs is coming up with lower loss than case 14 having more equipment, i.e., 3 DGs & 4 SCs, evenif cumulative total equipment ratings are similar. Therefore, option for case 14 can be avoided.

Fig.5 shows voltage profiles for various case studies (except case 14) performed for the 69 bus radial distribution network. The profile is becoming more uniform when number of DGs and SCs are increased, even for case 12 with 2 DGs & 2 SCs than for case 11 with 1 DG & 1 SC and most uniform for case 15 with 4 DGs & 4 SCs. However, careful judgment is necessary for technical and commercial viability before adding more number of equipment.

TABLE–V : Summary of Results with Comparison for 69 bus network

Network	Case Study Description	Parameter	Available Optimization Algorithms			
			L-SHADE	IMDE [14]	PSO [12]	IPSO [16]
69 bus	Base Case (No DG / SC)	Real power loss (kW)	225	224.59	225	225
		Min bus voltage (p.u.)	0.9092	0.9102	0.9092	0.9092
	Case 11 (1 DG + 1 SC)	Real power loss (kW)	**23.17**	-	25.90	-
		DG size in MW (bus no.)	1.828 (61)	-	1.566 (61)	-
		SC size in MVAr (bus no.)	1.301 (61)	-	1.401 (61)	-
		Min bus voltage (p.u.)	0.9725	-	0.970	-
	Case 12 (2 DGs + 2 SCs)	Real power loss (kW)	**7.20**	13.83	-	-
		DG size in MW (bus no.)	1.735 (61), 0.522 (17)	1.738 (62), 0.479 (24)	-	-
		SC size in MVAr (bus no.)	1.238(61), 0.353 (17)	0.109 (63), 1.192 (61)	-	-
		Min bus voltage (p.u.)	0.9943	0.9915	-	-
	Case 13 (3 DGs + 3 SCs)	Real power loss (kW)	**4.25**	-	-	4.37
		DG size in MW (bus no.)	1.674 (61), 0.495 (11), 0.379 (18)	-	-	0.557 (11), 0.321 (21), 1.672 (61)
		SC size in MVAr (bus no.)	1.195 (61), 0.375(11), 0.231(21)	-	-	0.3 (11), 0.3 (18), 1.2 (61)
		Min bus voltage (p.u.)	0.9943	-	-	0.9943
	Case 14 (3 DGs + 4 SCs)	Real power loss (kW)	**4.32**	-	-	-
		DG size in MW (bus no.)	1.674 (61), 0.495 (11), 0.379 (18)	-	-	-
		SC size in MVAr (bus no.)	0.8 (61), 0.265 (18), 0.322 (66), 0.37 (64)	-	-	-
		Min bus voltage (p.u.)	0.9943	-	-	-
	Case 15 (4 DGs + 4 SCs)	Real power loss (kW)	**3.26**	-	-	-
		DG size in MW (bus no.)	1.675 (61), 0.3 (21), 0.3 (11), 0.269 (12)	-	-	-
		SC size in MVAr (bus no.)	1.195 (61), 0.515 (50), 0.374 (11), 0.23 (21)	-	-	-
		Min bus voltage (p.u.)	0.9971	-	-	-

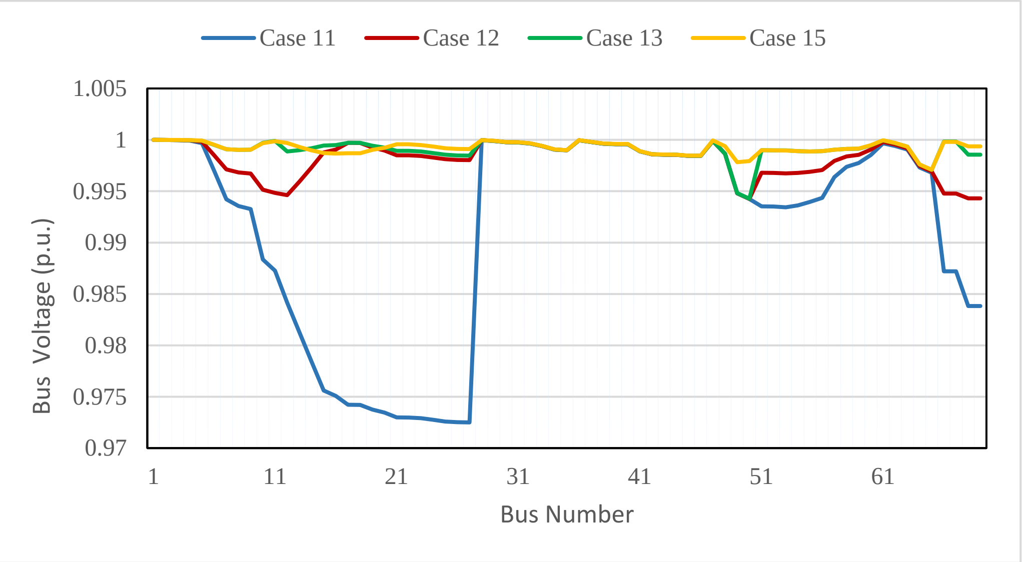

Fig.5: Voltage profiles of buses for 69 bus system for case studies

B. IEEE standard 119 bus network

Now for more larger network having 119 buses also, L-SHADE algorithm can efficiently allocate the DGs and/or SCs complying the system constraint to achieve comparatively lower loss figure as presented in **Table-VI** summary results.

The comparison has been done with the only available past study result using Hybrid algorithm. Case 21 with 1 DG achieves similar loss figure but with lower DG rating. Case 22 with 3 DGs achieves 10 kW less loss figure even with lower cumulative total DG rating, i.e., 8.98 MW, unlike 9.4 MW in Hybrid algorithm. Similarly, Case 23 with 1 DG & 6 SCs achieves 46 kW less loss figure even with overall lower cumulative total DG & SC rating. Lower Equipment rating undoubtedly saves higher installation cost. Comparing between case 21 & case 23, it can be noticed very importantly that much lower loss figure can be achieved for case 23 where DGs and SCs are used simultaneously.

If the number & rating of DGs & SCs are chosen judiciously, substantial loss reduction can be achieved as shown for case 24 with 4 DGs & 4 SCs. **Fig.6** shows voltage profiles for various case studies for the 119 bus network. The profile is becoming more uniform for case 24 when DGs and SCs are more evenly rated and distributed throughout the entire network.

TABLE–VI : Summary of Results with Comparison for 119 bus network

Network	Case Study Description	Parameter	Available Optimization Algorithms	
			L-SHADE	Hybrid [13]
119 bus	Base Case (No DG / SC)	Real power loss (kW)	1298.09	1298.1
		Min bus voltage (p.u.)	0.8688	0.8688
	Case 21 (1 DG)	Real power loss (kW)	**1016.76**	1016.77
		DG size in MW (bus no.)	2.978 (71)	3 (71)
		Min bus voltage (p.u.)	0.9053	0.9052
	Case 22 (3 DGs)	Real power loss (kW)	**667.29**	677.74
		DG size in MW (bus no.)	2.883 (50), 2.978 (71), 3.12 (109)	2.95 (71), 3.25 (47), 3.2 (108)
		Min bus voltage (p.u.)	0.9541	0.9474
	Case 23 (1 DGs + 6 SCs)	Real power loss (kW)	**595.73**	641.61
		DG size in MW (bus no.)	2.918 (71)	2.65 (73)
		SC size in MVAr (bus no.)	1.535 (40), 1.126 (96), 2.5 (50), 2.33 (110), 1.485 (74), 1.63 (80)	4.4 (28), 2.9 (34), 1.85 (70), 1.2 (86), 0.5 (85), 2.35 (110)
		Min bus voltage (p.u.)	0.9315	0.9317 (112)
	Case 24 (4 DGs + 4 SCs)	Real power loss (kW)	**271.54**	-
		DG size in MW (bus no.)	2.489(50), 2.5(110), 1.81(96), 2.431(73)	-
		SC size in MVAr (bus no.)	2.312(110), 2.5(50), 1.612(74), 1.755(80)	-
		Min bus voltage (p.u.)	0.9603	-

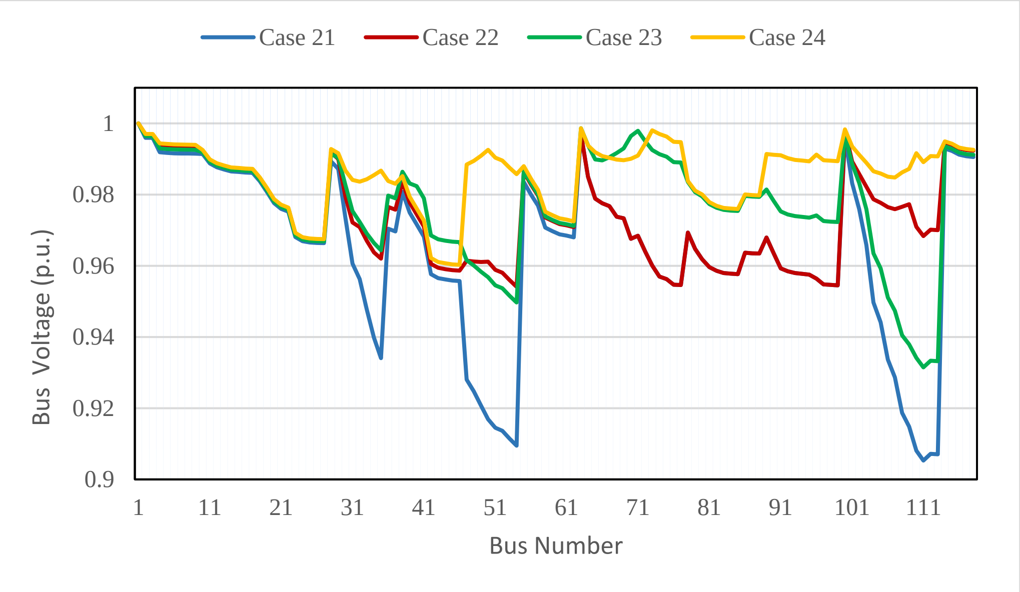

Fig.6: Voltage profiles of buses for 119 bus system for case studies

C. 83 bus practical TPC network

Table-VII presents the summary result for case studies for a practical network having 83 buses. Case 31 with 4 DGs & 4 SCs achieves 218.12 kW loss figure in comparison with 531.99 kW for the base case without any DG and SC. Network's minimum voltage is also improved from 0.9285 p.u. to 0.9651 p.u. However, case 32 brings down to much lower loss figure of 152.48 kW using more uniform distribution of DG and SC. Case 32 uses 6 DGs & 6 SCs but cumulative total equipment rating have been kept same as shown in **Table-III**. However due to practical installation and commercial constraints, the number of equipment also needs to be restricted judiciously. The result of case 32 can be implemented for the TPC network to minimize the network loss, boost up system capacity and network reliability.

Fig.7 shows bus voltage profiles for both cases. The profile is more uniform for case 32 also when DGs and SCs are more evenly rated and distributed throughout the entire network.

TABLE–VII : Summary of Results with Comparison for 83 bus TPC network

Network	Case Study Description	Parameter	Available Optimization Algorithms
			L-SHADE
83 bus	Base Case (No DG / SC)	Real power loss (kW)	531.99
		Min bus voltage (p.u.)	0.9285
	Case 31 (4 DGs + 4 SCs)	Real power loss (kW)	218.12
		DG size in MW (bus no.)	3(79), 2.517(71), 2.959(33), 2.998 (6)
		SC size in MVAr (bus no.)	1.917 (71), 2.546 (79), 2.382 (32), 2.254 (6)
		Min bus voltage (p.u.)	0.9651
	Case 32 (6 DGs + 6 SCs)	Real power loss (kW)	152.48
		DG size in MW (bus no.)	2 (19), 2(34), 2 (53), 2(81), 2(6), 2(71)
		SC size in MVAr (bus no.)	1.997 (79), 2 (33), 1.75 (52), 2 (7), 1.776 (19), 1.934 (71)
		Min bus voltage (p.u.)	0.9675

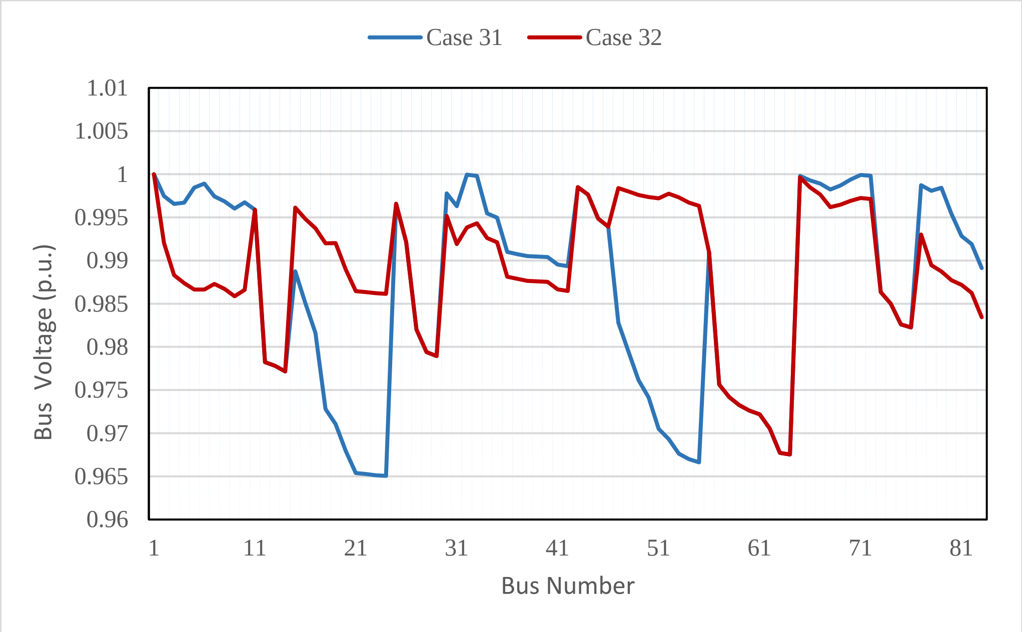

Fig.7: Voltage profiles of buses for 83 bus TPC network for case studies

For all case studies, voltage of the buses is found within the specified limits (0.9 p.u. to 1.05 p.u.) as shown in **Fig.** 5, 6 & 7.

VI. Conclusion

This paper successfully implements the L-SHADE algorithm in the larger distribution systems and optimizes efficiently the large number of continuous (rating) and discrete variables (bus number). The results clearly highlight that optimal sizing & siting of DGs & SCs simultaneously rather than individually is the best in power loss minimization and comparing with available other algorithms in the recent past. Reduction of the network power loss by any more amounts is commercially advantageous. Technically this reduces burden to the overall network and boost up network capacity as well. Besides this lost power dissipates as heat and saving the same enhances the system components reliability in long term. The system voltage profile has also improved significantly.

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