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Multiobjective Optimization Of Capacitor Banks Placement In Distribution Networks Using Particle Swarm Optimization (PSO) And Differential Evolution (DE)

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Abstract: Reactive power flow compensation is widely employed in power grids to reduce active power losses and enhance the Voltage Stability Margin (VSM). Typically, the optimal placement of capacitor banks at each node can be determined using multi-objective optimization methods. This paper proposes a new optimization algorithm in which the objective function simultaneously considers the minimization of power losses and the maximization of voltage stability margin. Particle Swarm Optimization (PSO) and Differential Evolution (DE) are applied to find the optimal solution. The performance of these methods is evaluated on both radial and meshed network configurations. The results demonstrate that DE and PSO show higher robustness and better fitness for large-scale and meshed networks, compared to Genetic Algorithms (GA).

Keywords: Power grid, Multiobjective optimization, Particle Swarm Optimization and Differential Evolution (DE), Active power losses, Voltages Stability Margin

I- INTRODUCTION

The stressing operation condition imposed by the deregulated electricity market favor nowadays the economic benefits over the technical aspects of operation. This leads, in many cases, to pushing the HV transmission power systems beyond their optimal operation conditions and closer to their stability and security limits, which has a direct effect upon the operation conditions of the subsequent distribution networks. To counter balance this inconvenience, the distribution need often to employ compensation measures and restore the normal operation of their system. Static VAR compensation and capacitor banks are often used for this purpose [9].

Most of previous work have just informed some different methods for placement capacitor banks, with the aim to optimize active power losses, bus voltage levels, and power factor or investment costs ([1], [2], [3]). The latest approaches involve multiobjective optimization, such as maximizing energy utilization, feeder power loss reduction and power factor correction [3] bus voltage profile improvement and feeder power loss reduction [4], optimal capacitor bank placement by using genetic Algorithms and network reconfiguration ([5],[9]). These approaches use a wide array of algorithms, such as simulated annealing [4], sensitivity analysis methods [8], heuristic methods or artificial intelligence ([3], [5]).

In this paper, a new method for capacitor banks placement is verified, which uses multiobjective optimization for active power loss reduction and bus voltage stability improvement, and where a standard Particle Swarm Optimization (PSO) and

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Differential Evolution (DE) algorithm determines the optimal solution. For computing the power losses, the Newton-Raphson load flow algorithm is used. For assessing the voltage stability, the Voltage Stability Margin (VSM) proposed in ([6], [9]) is used. For each objective, different weights are considered and the result are discussed. The method is tried on a real radial MV distribution feeder from the Romanian power system [9] and on the meshed IEEE-30 bus test system [7].

II- PROPOSED OPTIMIZATION METHODOLOGIES

A- Particle Swarm Optimization algorithm (PSO)

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique inspired by the social behavior of bird flocking or fish schooling [13]. Each solution, called a particle, represents a point in the search space and has an associated velocity. Particles move through the space by updating their positions based on their own best-known solution and the global best solution found by the swarm. The velocity update is influenced by cognitive and social components, balancing exploration and exploitation. At each iteration, particles evaluate the objective function and adjust their positions to improve their fitness. The process continues iteratively until a predefined stopping criterion, such as the maximum number of iterations or convergence of the objective function, is met.

B- Differential Evolution Algorithm (DE)

The Differential Evolution (DE) algorithm is a population-based stochastic optimization technique widely used for solving continuous and nonlinear optimization problems [11]. It operates through a parallel search mechanism over the solution space and is inspired by evolutionary principles. In DE, each solution is represented as a real-valued vector, and its quality is evaluated using an objective (fitness) function. New candidate solutions are generated through differential mutation, where the weighted difference of randomly selected individuals is added to another individual, followed by a crossover process to increase population diversity. A selection mechanism then compares the trial solution with the target solution, retaining the one with better fitness. This mutation–crossover–selection process is iteratively repeated over successive generations until a predefined stopping criterion is satisfied.

C- Voltage Stability Margin (VSM)

The Voltage Stability Margin (VSM) is a voltage stability index projected and used in [6] for distribution radial networks in order to compute the system's distance to voltage collapse, by finding the weakest branch in the system with regard to voltage stability (the branch with the highest voltage drop). For each feeder in the system, VSM is calculated with:

$$\mathrm{VSM} = \prod_{i=1}^{n_b} L_i \quad (1)$$

Where L_i the linear loading index of branch i and n_b is is the total number of branches that make the feeder.

For each branch, the loading index is computed with:

$$L_i = \left(2.\frac{V_k}{V_j}.\cos\left(\delta_j - \delta_k\right) - 1\right)^2 \quad (2)$$

Where V_j, V_k, δ_j and δ_k are the bus voltage magnitudes and angles for branch i, with the assumption that bus j is closer to the source than bus k.

If the system has more than one feeder, the global VSM is the lowest feeder VSM value.

D- Problem formulation

Particle Swarm Optimization (PSO) and Differential Evolution (DE) founds the best solution of the problem, namely the optimal distribution of a limited stock of capacitor banks (CBs) among buses. The fitness function (FF) used to assess the optimality of a solution is

$$\mathrm{FF}=\alpha.\mathrm{VSM} + \mathrm{K}.\beta(.\frac{1}{loss}) \quad (3)$$

Where α and β are the weight, VSM is the Voltage Stability Margin computed using eq. (1) and eq. (2) and loss is the value of active power losses in the network, computed using the Newton-Raphson load flow method. K is a scaling factor between VSM and losses and its value is computed for the case when no compensation is used in the network. PSO and DE optimized for FF maximization, while losses need to be minimized, so $\frac{1}{loss}$ is used in eq. (3).

For testing the method, two different network types were used. The first is a radial 20/0.4kV distribution network with a feeder consisting of 10MV branches and 10MV/LV transformers. Its one line diagram and technical data are presented in Fig.3 (a) and the bus, branch data, as well as the transformer data associated with this radial network, are presented in reference [9]. Capacitor Banks can be placed only at the LV buses and their rating is 5 KVAR. Losses and VSM are evaluated for all the buses and branches. For computing the VSM, voltage are scaled to the 20kV level using the transformers ratio [9].

The second network is the meshed IEEE 30bus 132/33kV test system. The capacitor banks can be placed only at buses 10, 12, 14-26, 29 and 30 (the 33 kV section). The HV and compensator bus are excluded. The KVAR rating of CBs is 150. Losses are evaluated only on the area where compensation is allowed, while VSM is computed for the entire system. [9]

The limit of the capacitor banks stock was set as 40 for the radial system is characterized in the fig.3 (a) and at 60 for the meshed is represented in fig.3 (b) [9].

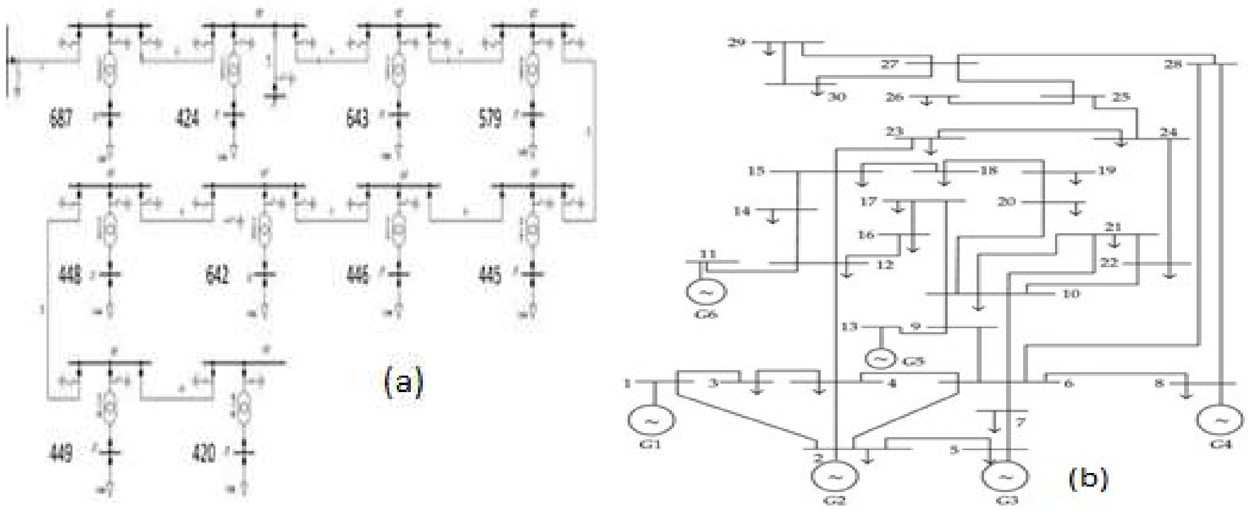


Fig 3: (a)- one-line diagram of the radial 10bus, (b)- meshed networks IEEE 30bus

III- RESULTS AND DISCUSSION

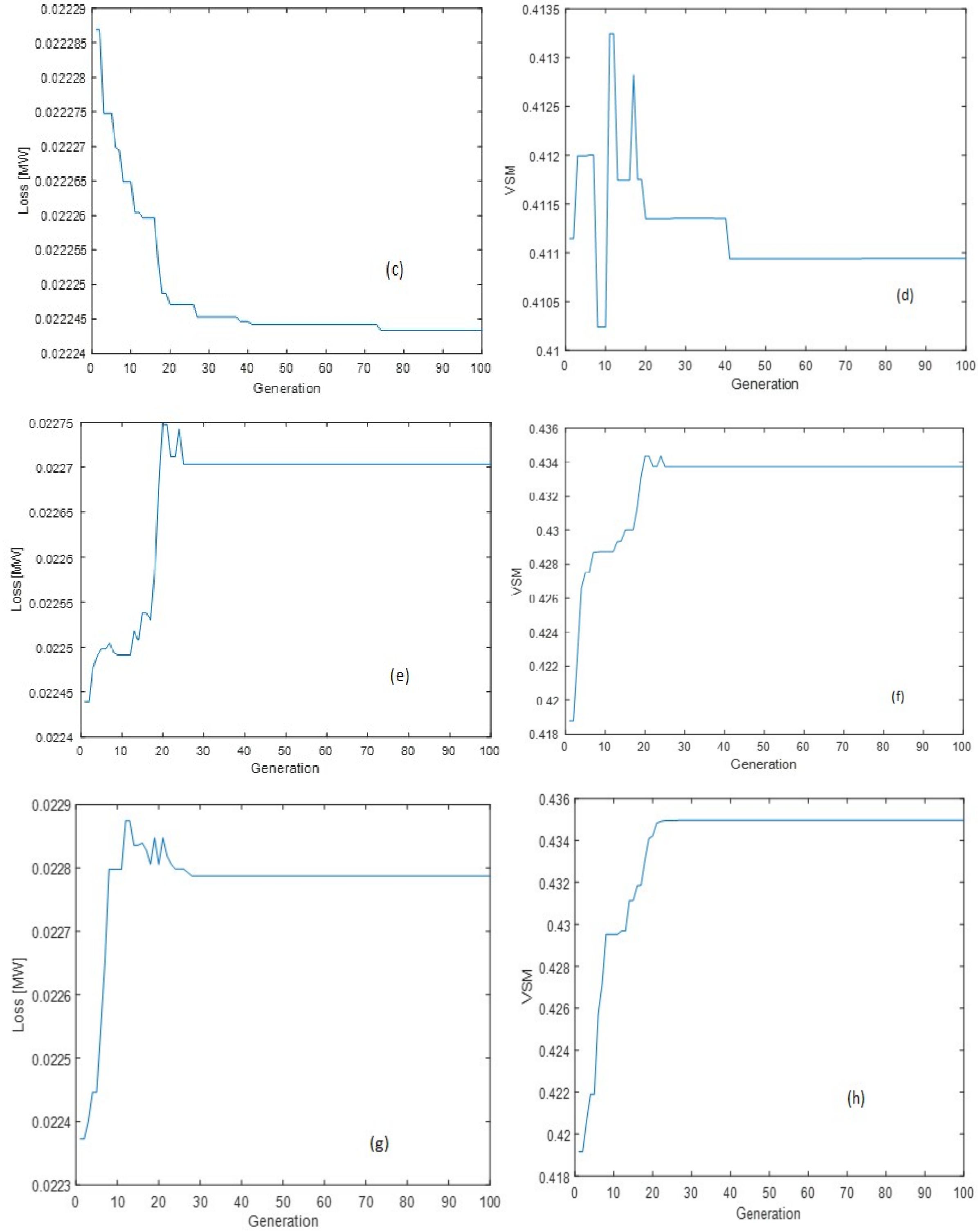
A- *Results for the radial network IEEE 10bus by PSO*

Table IV shows the distribution of capacitor banks according to the weights (α andβ) associated with each objective. When losses are given more weight, the capacitor banks are dispersed throughout the network with peaks of 8 and 9 at nodes 449 and 445, respectively, which are located near the end of the supply node. When the VSM weights gradually increase and the loss weights decrease, the 40-capacitor banks tend to concentrate at the extreme nodes of the network.

Table IV: Optimal CBs placement by PSO found for the radial network IEEE 10bus with different weights of objectives

$\propto$ VSM	β Loss	FF	Losses (MW)	VSM	Optimal CBs placement by PSO									
0	1	0.3973	0.0222	0.4109	4	3	0	3	2	4	4	8	9	3
0.1	0.9	0.3989	0.0223	0.4153	5	4	0	1	3	4	3	6	9	5
0.2	0.8	0.4011	0.0223	0.4213	7	6	0	0	0	4	4	2	10	7
0.3	0.7	0.4039	0.0224	0.4268	10	8	0	0	0	4	0	0	9	9
0.4	0.6	0.4074	0.0225	0.4300	11	10	0	0	0	1	0	0	7	11
0.5	0.5	0.4115	0.0227	0.4337	13	12	0	0	0	0	0	0	2	13
0.6	0.4	0.4162	0.0228	0.4350	14	13	0	0	0	0	0	0	0	13
0.7	0.3	0.4256	0.0228	0.4350	14	13	0	0	0	0	0	0	0	13
0.8	0.2	0.4256	0.0228	0.4350	14	13	0	0	0	0	0	0	0	13
0.9	0.1	0.4303	0.0228	0.4350	14	13	0	0	0	0	0	0	0	13
1	0	0.4350	0.0228	0.4350	15	13	0	0	0	0	0	0	0	12

Figures (c)-(h) indicate the variations in losses and VSM in the radial network for extreme cases (optimizing only for losses or VSM) and balanced optimization (weights for losses and VSM are 0.5). These figures represents that the two objectives are not achieved simultaneously. Indeed, when the losses are at their minimum, the VSM does not reach its maximum value. Similarly, when the VSM reaches 0.4268 or more, the losses begin to increase significantly. For a balanced optimization between losses and VSM, neither objective reaches its optimal value (see Figures (c), (h)).



Figures (c-h): Optimization for Radial network IEEE 10bus by PSO: (c)- losses evolution when optimizing only losses, (d)- VSM evolution when optimizing only losses, (e)- loss evolution when optimizing 50% losses and 50% VSM, (f)- VSM evolution when optimizing 50% losses and 50% VSM, (g)- loss evolution when optimizing only VSM and (h)- VSM evolution when optimizing only VSM

B- *Results for the radial network IEEE 10bus by DE*

The optimal placement of (CBs) using Differential Evolution (DE) for the IEEE 10-bus radial network, under different objective weightings, is presented in Table V. When the optimization is performed with a Voltage Stability Margin (VSM) weight of 0 and a Loss weight of 1, the optimal CB placement obtained by DE is distributed across all buses up to the weighting combination VSM = 0.3 and Loss = 0.7. Starting from the weighting combination VSM = 0.4 and Loss = 0.6, the optimal CB placement determined by DE becomes concentrated within the network feeder.

Table V: Optimal CBs placement by DE found for the radial network IEEE 10bus with different weights of objectives

$\propto$ VSM	β Loss	FF	Losses (MW)	VSM	Optimal CBs placement by DE									
0	1	0.3973	0.0222	0.4105	4	3	0	3	1	4	4	9	9	3
0.1	0.9	0.3989	0.0223	0.4164	6	4	0	1	3	3	4	5	9	5
0.2	0.8	0.4012	0.0223	0.4218	7	6	0	0	2	4	4	1	9	7
0.3	0.7	0.4040	0.0224	0.4261	9	8	0	0	1	3	2	0	8	9
0.4	0.6	0.4074	0.0225	0.4294	11	9	0	0	0	2	1	0	6	11
0.5	0.5	0.4115	0.0227	0.4337	13	11	0	0	0	0	0	0	2	14
0.6	0.4	0.4162	0.0228	0.4350	14	12	0	0	0	0	0	0	0	14
0.7	0.3	0.4209	0.0228	0.4350	14	13	0	0	0	0	0	0	0	13
0.8	0.2	0.4256	0.0228	0.4350	14	13	0	0	0	0	0	0	0	13
0.9	0.1	0.4303	0.0228	0.4350	14	13	0	0	0	0	0	0	0	13
1	0	0.4350	0.0228	0.4350	15	13	0	0	0	0	0	0	0	12

Figures (i)-(n) indicate the variations in losses and VSM in the radial network for extreme cases (optimizing only for losses or VSM) and balanced optimization (weights for losses and VSM are 0.5). These figures show that the two objectives are not achieved simultaneously. Indeed, when the losses are at their minimum, the VSM does not reach its maximum value. Similarly, when the VSM reaches 0.4294 or more, the losses begin to increase significantly. For a balanced optimization between losses and VSM, neither objective reaches its optimal value (see Figures (i), (n)).

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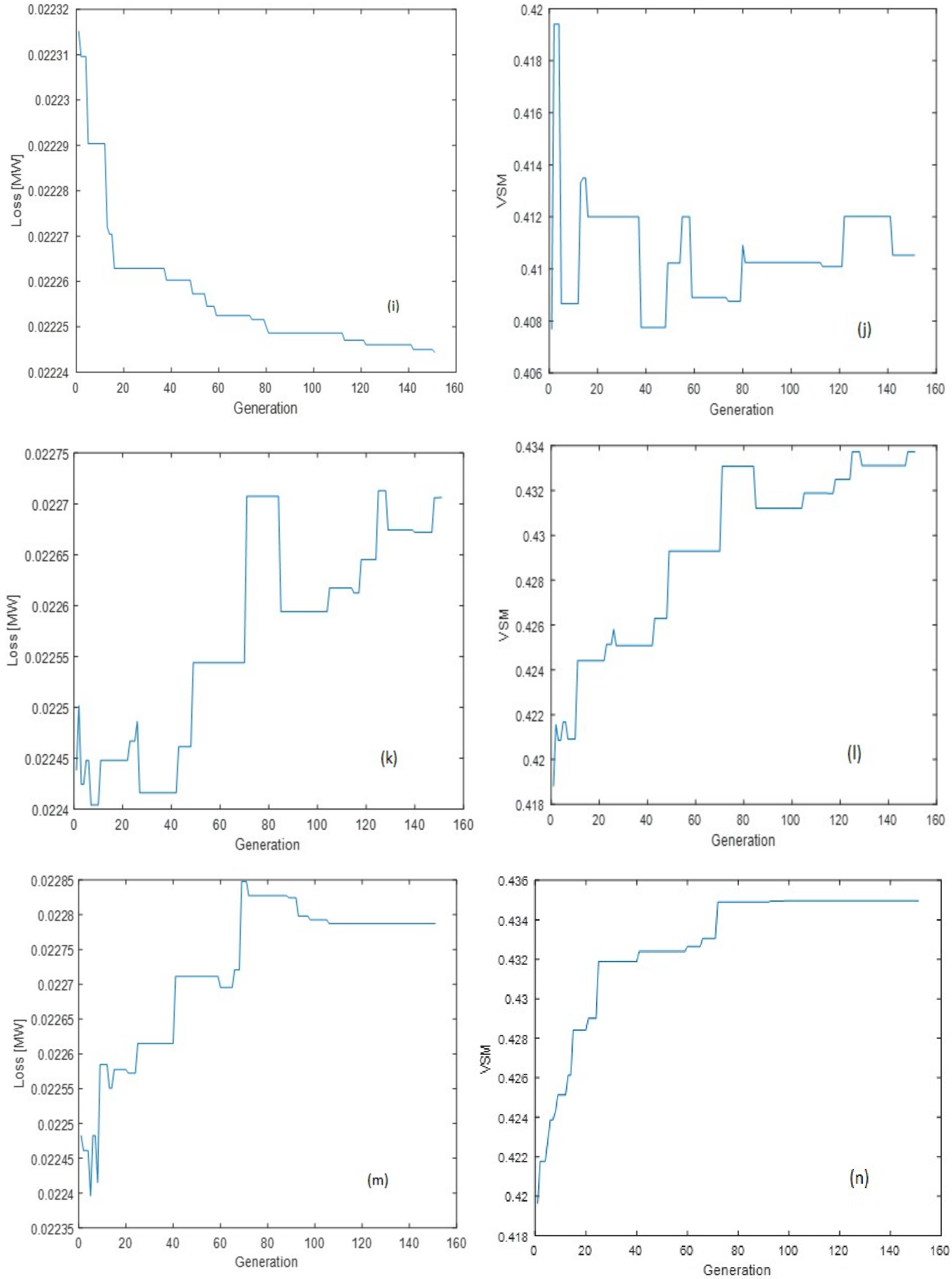

Figures (i-n): Optimization for Radial network IEEE 10bus by DE: (i)- losses evolution when optimizing only losses, (j)- VSM evolution when optimizing only losses, (k)- loss evolution when optimizing 50% losses and 50% VSM, (l)- VSM evolution when optimizing 50% losses and 50% VSM, (m)- loss evolution when optimizing only VSM and (n)- VSM evolution when optimizing only VSM

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C- *Results for the meshed network IEEE 30bus by PSO*

As shown by the table VI and Figures (o)-(t), the distribution of capacitor banks in the 30-node meshed network differs from the previous case. Specifically, when only losses are optimized, the voltage stability of the network becomes low. Conversely, to optimize VSM, the losses are not minimal. Both quantities are significantly reduced when VSM is optimized. To optimize losses (for β=0 and α=1), the capacitor banks are placed mainly at nodes 19, 21, and 23 with enormous loads. Furthermore, when VSM is optimized to be greater than the losses, the largest number of capacitor banks are found at nodes 24, 26, and 30, where the reference calculation conditions are without reactive power compensation and the voltages are the lowest. In addition, for VSM=0.6 and Loss=0.4, the capacitor bank locations are found at nodes 19, 26, and 30. In all cases, the VSM remains much lower than that of the radial network.

Table VI: Optimal CBs placement by PSO found for the meshed network IEEE-30Bus with different weights of objective

$\propto$ VSM	β Loss	FF	Losses (MW)	VSM	Optimal CBs placement by PSO															
					10	12	14	15	16	17	18	19	20	21	23	24	25	26	29	30
0	1	0.1346	0.7444	0.1504	0	0	0	0	0	0	0	12	0	29	10	9	0	0	0	0
0.1	0.9	0.1366	0.7581	0.1762	0	0	0	0	0	0	0	10	0	0	10	13	0	15	0	12
0.2	0.8	0.1414	0.7653	0.1832	0	0	0	0	0	0	0	0	4	0	0	23	0	15	6	12
0.3	0.7	0.1467	0.7641	0.1828	0	0	0	0	0	0	0	6	0	0	0	21	0	15	6	12
0.4	0.6	0.1518	0.7660	0.1833	0	0	0	0	0	0	0	0	0	0	0	27	0	15	6	12
0.5	0.5	0.1570	0.7660	0.1833	0	0	0	0	0	0	0	0	0	0	0	27	0	15	6	12
0.6	0.4	0.1605	0.7694	0.1806	0	0	0	0	0	5	0	22	0	0	0	0	0	15	6	12
0.7	0.3	0.1675	0.7656	0.1833	0	0	0	0	0	0	0	0	2	0	0	25	0	15	6	12
0.8	0.2	0.1728	0.7660	0.1833	0	0	0	0	0	0	0	0	0	0	0	27	0	15	6	12
0.9	0.1	0.1780	0.7660	0.1833	0	0	0	0	0	0	0	0	0	0	0	27	0	15	6	12
1	0	0.1833	0.7660	0.1833	0	0	0	0	0	0	0	0	0	0	0	27	0	15	6	12

Figures (o)-(t) designate the variations in losses and VSM in the meshed network for extreme cases (optimizing only for losses or VSM) and balanced optimization (weights for losses and VSM are 0.5). These figures show that the two objectives are not achieved simultaneously. Indeed, when the losses are at their minimum, the VSM does not reach its maximum value. Similarly, when the VSM reaches 0.1762 or more, the losses begin to increase significantly. For a balanced optimization between losses and VSM, neither objective reaches its optimal value (see Figures (o), (t)).

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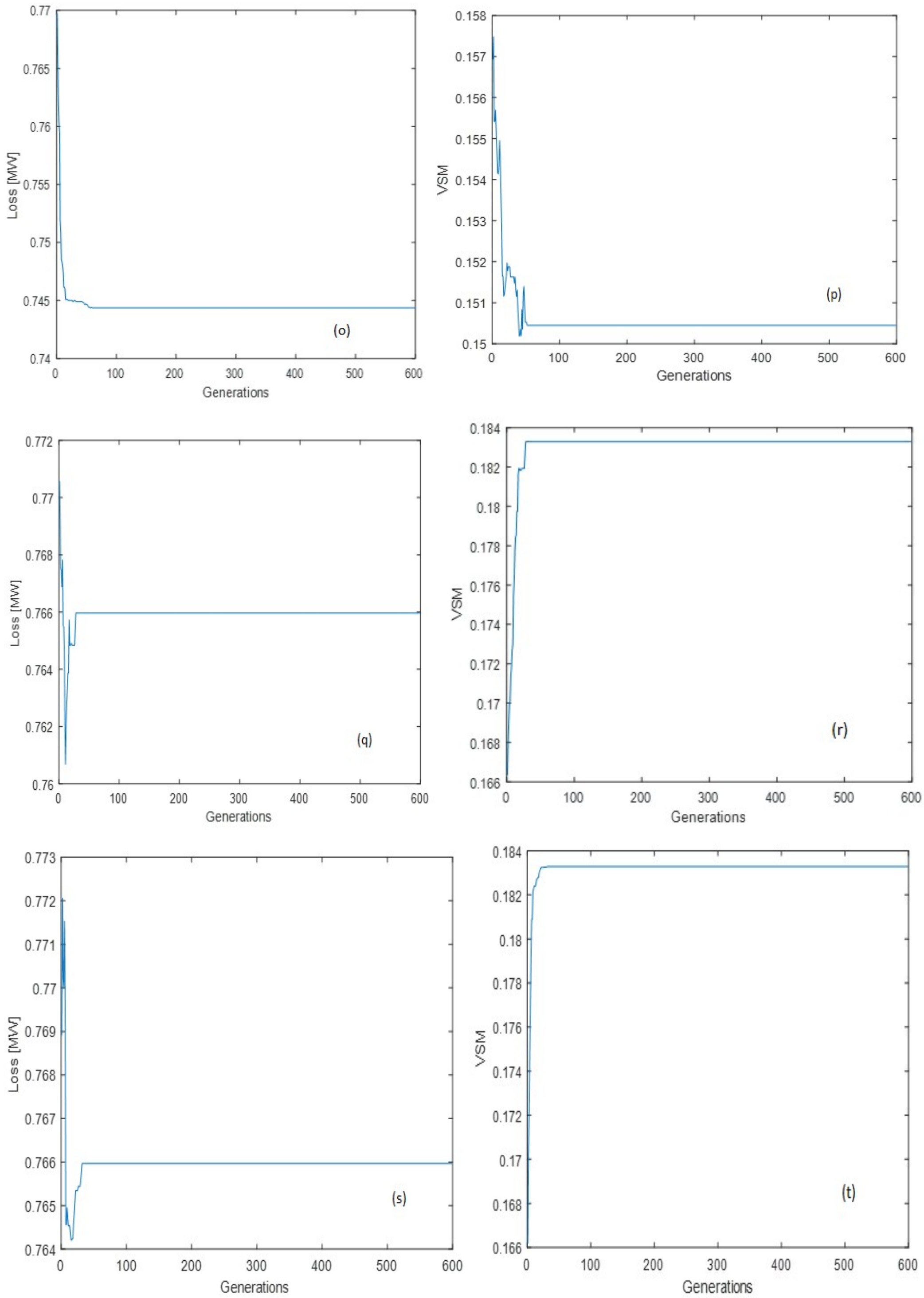

Figures (o-t): Optimization for meshed network IEEE-30 Bus by PSO: (o)- losses evolution when optimizing only losses, (p)- VSM evolution when optimizing only losses, (q)- loss evolution when optimizing 50% losses and 50% VSM, (r)- VSM evolution when optimizing 50% losses and 50% VSM, (s)- loss evolution when optimizing only VSM and (t)- VSM evolution when optimizing only VSM

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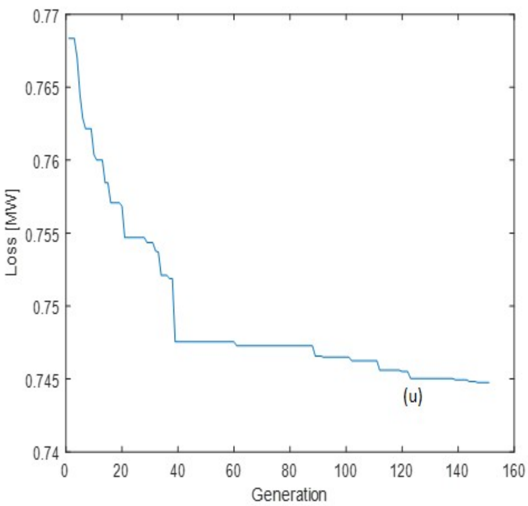
D- Results for the meshed network IEEE 30Bus by DE

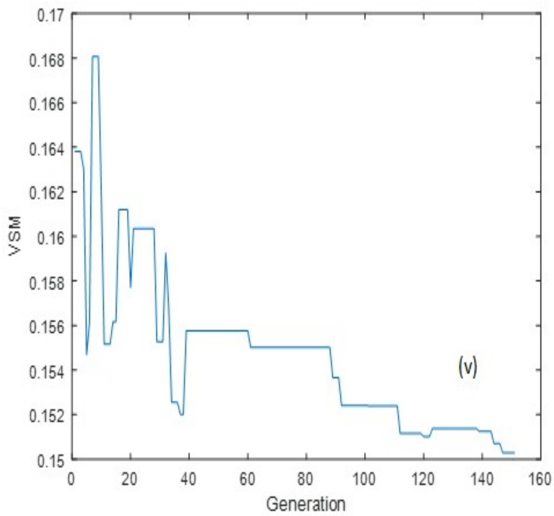
The Differential Evolution (DE) algorithm was used to determine the optimal allocation of Capacitor Banks (CBs) in the IEEE-30 system under various objective weight configurations. When the Voltage Stability Margin (VSM) was to set to 0 and the loss minimization weight to 1, buses 19, 21, and 23 were selected for BC installation, corresponding to locations with significant load levels. For VSM = 0.1 and loss = 0.9, the optimal allocation expanded to buses 19, 21, 24, 26, and 30. As the emphasis on voltage stability increased (VSM = 0.2 and loss = 0.8), the CB were shifted to buses 24, 26, and 30, which under the reference conditions without reactive power compensation and show the lowest voltages magnitudes. This allocation trend persisted up to VSM = 1 and loss = 0, indicating that voltage stability becomes the dominant criterion when given greater weight. No CBs installations were selected for buses 10 to 18, regardless of the weight configuration.

Table VII: Optimal CBs placement by DE found for the meshed network IEEE 30bus with different weights of objectives

$\propto$ VSM	β Loss	FF	Losses (MW)	VSM	Optimal CBs placement by DE															
					10	12	14	15	16	17	18	19	20	21	23	24	25	26	29	30
0	1	0.1345	0.7448	0.1503	0	0	0	0	0	0	0	9	3	31	10	7	0	0	0	0
0.1	0.9	0.1365	0.7572	0.1741	0	0	0	0	0	0	0	10	1	9	3	12	0	15	0	10
0.2	0.8	0.1414	0.7631	0.1818	0	0	0	0	0	0	0	6	1	3	2	15	0	15	6	12
0.3	0.7	0.1466	0.7640	0.1827	0	0	0	0	0	0	0	7	2	0	0	18	0	15	6	12
0.4	0.6	0.1518	0.7648	0.1831	0	0	0	0	0	0	0	2	4	0	0	21	0	15	6	12
0.5	0.5	0.1571	0.7653	0.1832	0	0	0	0	0	0	0	0	4	0	0	23	0	15	6	12
0.6	0.4	0.1623	0.7651	0.1832	0	0	0	0	0	0	0	1	3	0	0	23	0	15	6	12
0.7	0.3	0.1675	0.7656	0.1833	0	0	0	0	0	0	0	0	2	0	0	25	0	15	6	12
0.8	0.2	0.1728	0.7660	0.1833	0	0	0	0	0	0	0	0	0	0	0	27	0	15	6	12
0.9	0.1	0.1780	0.7660	0.1833	0	0	0	0	0	0	0	0	0	0	0	27	0	15	6	12
1	0	0.1833	0.7660	0.1833	0	0	0	0	0	0	0	0	0	0	0	27	0	15	6	12

Figures (u)-(z) indicate the variations in losses and VSM in the meshed network for extreme cases (optimizing only for losses or VSM) and balanced optimization (weights for losses and VSM are 0.5). These figures show that the two objectives are not achieved simultaneously. Indeed, when the losses are at their minimum, the VSM does not reach its maximum value. Similarly, when the VSM reaches 0.1741 or more, the losses begin to increase significantly. For a balanced optimization between losses and VSM, neither objective reaches its optimal value (see Figures (u), (z)).





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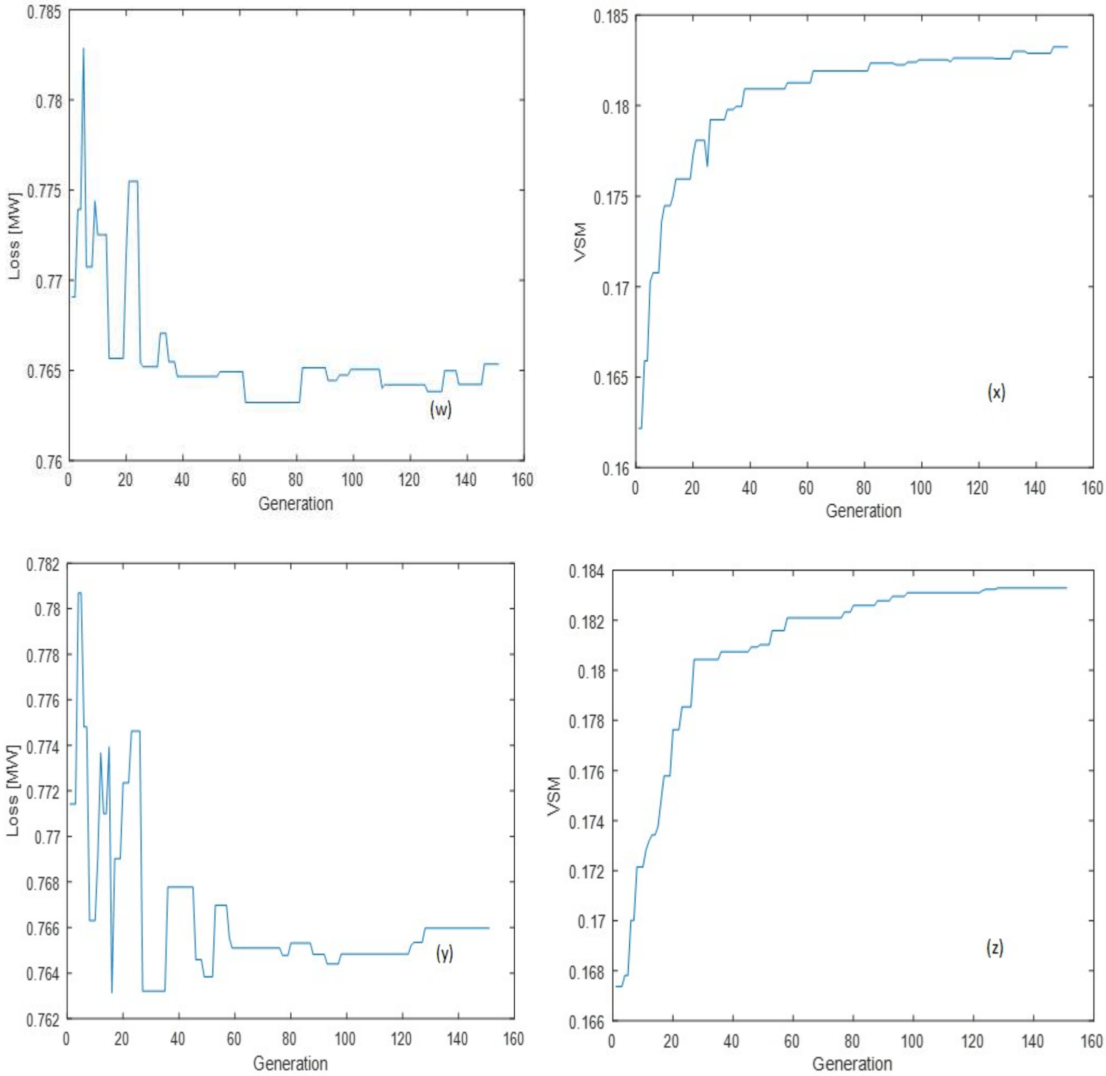

Figures (u-z): Optimization for meshed network IEEE 30bus by DE: (u)- losses evolution when optimizing only losses, (v)- VSM evolution when optimizing only losses, (w)- loss evolution when optimizing 50% losses and 50% VSM, (x)- VSM evolution when optimizing 50% losses and 50% VSM, (y)- loss evolution when optimizing only VSM and (z)- VSM evolution when optimizing only VSM

E- *Evaluation of FF given by AG [6], DE and PSO methods*

The GA [9], DE, and PSO algorithms were initialized using the same population Np = 100 and executed five independent times to evaluate stability, robustness, and statistical variability. For all three methods, the number of capacitor banks (CBs) was fixed: 40 units for the IEEE 10-bus radial network and 60 units for the IEEE 30-bus meshed network. In DE, the population size was set to Np = 100, with a mutation factor of 0.5 and crossover rate of 0.5, and the maximum number of generations was 150. In PSO, the inertia weight decreased linearly from w_{max} = 0.5 to w_{min} = 0.2, with cognitive and social coefficients c_1 = 0.8 and c_2 = 1.5, and a maximum of 100 iterations. The resulting objective function (FF) values for the radial and meshed network are reported in Table VIII and Table IX, respectively.

Table -VIII: Fitness Function Evaluation for the radial IEEE 10-Bus Test System based on AG [6], DE and PSO algorithms

α	β	Try no	AG [6]	DE	PSO
0	1	1	0,3956	0,3973	0,3973
		2	0,3956	0,3973	0,3973
		3	0,3956	0,3973	0,3973
		4	0,3956	0,3973	0,3973
		5	0,3956	0,3973	0,3973
		average	0,3956	0,3973	0,3973
α	β	Try no	AG [6]	DE	PSO
0.5	0.5	1	0,4969	0,4115	0,4115
		2	0,4969	0,4115	0,4115
		3	0,4969	0,4115	0,4115
		4	0,4969	0,4115	0,4115
		5	0,4969	0,4115	0,4115
		average	0,4969	0,4115	0,4115
α	β	Try no	AG [6]	DE	PSO
1	0	1	0,4350	0,435	0,435
		2	0,4350	0,435	0,435
		3	0,4350	0,435	0,435
		4	0,4350	0,435	0,435
		5	0,4350	0,435	0,435
		average	0,4350	0,435	0,435

Table IX: Fitness Function Evaluation for the meshed IEEE 30-Bus Test System based on AG [6], DE and PSO algorithms

α	β	Try no	AG [6]	DE	PSO
0	1	1	0,149	0,1346	0,1346
		2	0,149	0,1345	0,1346
		3	0,149	0,1345	0,1346
		4	0,149	0,1345	0,1346
		5	0,149	0,1345	0,1346
		average	0,149	0.13452	0,1346
α	β	Try no	AG [6]	DE	PSO
0.5	0.5	1	0,2218	0,1571	0,1571
		2	0,2218	0,1571	0,1571
		3	0,2218	0,1571	0,157
		4	0,2218	0,157	0,1571
		5	0,2218	0,157	0,1571
		average	0,2218	0.15706	0.15708
α	β	Try no	AG [6]	DE	PSO
1	0	1	0,1794	0,1833	0,1833
		2	0,1794	0,1833	0,1833
		3	0,1794	0,1833	0,1833
		4	0,1794	0,1833	0,1833
		5	0,1794	0,1833	0,1833
		average	0,1794	0,1833	0,1833

Tables VIII and IX report the power flow (FF) optimization results for the IEEE 10-bus radial and IEEE 30-bus meshed networks using Genetic Algorithm (GA[6]), Differential Evolution (DE), and Particle Swarm Optimization (PSO). Each result represents the average of five independent runs.

For the IEEE 10-bus radial network, all methods converge reliably with negligible variation across runs. FF values are nearly identical in single-objective dominant cases, indicating limited dependence on the optimization technique. Under balanced weighting, GA [6] yields higher FF values, while DE and PSO show identical and more consistent performance.

For the IEEE 30-bus meshed network, DE and PSO consistently achieve lower FF values than GA [6] in most cases, particularly under balanced objective weighting, demonstrating superior performance for larger and more complex systems. GA [6] performs competitively only in the single-objective dominant scenario. Across all cases, DE and PSO show nearly identical behavior.

Overall, the results confirm the robustness and stability of all three methods. However, DE and PSO demonstrate superior fitness for meshed and large-scale power networks, while GA [6] shows greater sensitivity to objective weighting and network topology.

IV- CONCLUSION

This paper analyzed optimal capacitor bank placement in radial and meshed distribution networks considering power loss reduction and voltage stability improvement. Results confirm the existence of a trade-off between these objectives. For the IEEE 10-bus system, GA [6], DE, and PSO show comparable performance, while for the IEEE 30-bus system, DE and PSO consistently outperform GA [6]. Overall, DE and PSO demonstrate higher robustness and suitability for large-scale and meshed networks.

References

[1] M. H. Haque, "Capacitor placement in radial distribution systems for loss reduction," *International Journal of Science and Technology*, vol. 146, no. 5, pp. 501-505, 1999.

[2] A. Pourshafie et al., "Optimal reactive power compensation in a deregulated distribution network," in *Proceedings of the 44th International Universities Power Engineering Conference (UPEC)*, Sept. 2009, pp. 1-6.

[3] A. M. Sharaf and A. El-Gammal, "A multiobjective multi-stage particle swarm optimization MOPSO search scheme for power quality and loss reduction on radial distribution system," *in International Conference on Renewable Energy and Power Quality (ICREPQ'09)*, Valencia, Apr. 2009.

[4] M. Hadi et al., "Optimal Placement with Different Number of Capacitor Banks for Voltage Profile Improvement and Loss Reduction based on Simulated Annealing," *IJCT*, vol. 2, no. 4, pp. 390-394, 2011.

[5] S. Medeiro, "Simultaneous capacitor placement and reconfiguration for loss reduction in distribution networks by a hybrid genetic algorithm," in *IEEE Congress on Evolutionary Computation (CEC)*, June 2011, pp. 2178-2185.

[6] M. H. Haque, "A Linear Static Voltage Stability Margin for Radial Distribution Systems," in *IEEE Power Engineering Society General Meeting*, Montreal, Oct. 2006.

[7]. University of Washington, "Power Systems Test Case Archive," [Online]. Available: http://www.ee.washington.edu/research/pstca. [Accessed: 19-Dec-2025].

[8] RANDRIAMBOLOLONA F. V., RAKOTOARIMANANA L. G., and RANDRIAMANANTANY Z. A., "Influencing factors on losses in electric power distribution," in *Proceedings of the HEPMAD 2017 Conference*, 2017.

[9] RAKOTOARIMANANA L. G., G. Mihai, and O. Ovidiu, "Multiobjective Optimization of Capacitor Banks Placement in Distribution Networks," in *Latest Advances in Information Science, Circuits and Systems, WSEAS*, 2012.

[10] L. Al-Bahrani, M. Al-Kaabi, and J. Al Hasheme, "Solving Optimal Power Flow Problem Using Improved Differential Evolution Algorithm," *International Journal of Electronic Engineering & Telecommunications*, vol. 11, no. 2, March 2022.

[11] R. Muthukumar and K. Thanushkodi, "Opposition Based Differential Evolution Algorithm for Capacitor Placement on Radial Distribution System," *Journal of Electrical Engineering & Technology*, vol. 9, no. 1, pp. 45-51, 2014.

[12] L. Al-Bahrani, M. Al-Kaabi, M. Al-Sasdi, and V. Dumbrava, "Optimal power flow based on differential evolution optimization technique," *U.P.B. Scientific Bulletin, Series C*, vol. 82, no. 1, pp. 378-388, 2020.

[13] M. Bhavani and K. A. Murugan, "Capacitor Placement On Radial Distribution System Using Particle Swarm Optimization," *International Journal of Advanced Information Science and Technology (IJAIST)*, vol. 4, no. 1, January 2015.