Minimization of Network Losses by Optimal Placement and Sizing of DG using Flower Pollination Algorithm

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Abstract - Reliable *and Quality power supply to the consumer is the major objectives of power system planner. Recent trends in the power system infrastructure enhancement, increases the efficiency in the system operation and control. One among them is the advancement in the usage of Distributed Generation (DG) which helps to provide more flexible power transaction within the system utilities. The proposed scheme in this paper explored the features of Distributed Generation in achieving the objective of network loss minimization by optimally sizing and placing the DG within the security limits. Nature based Flower pollination algorithm (FPA) has been applied to extract the best exploration and exploitation balanced solution. The proposal has been tested with the two radial distribution system networks such as 33 and 69 bus systems with Unity and Variable Power Factor(VPF) DG. Solution based comparison of FPA with the standard Genetic Algorithm (GA) and Particle Swarm Optimization(PSO) algorithm depicts the system stability by reducing the network loss at the greater extent.*

Keywords: **Distributed Generation (DG), Flower Pollination Algorithm (FPA), PSO, GA, Variable Power factor (VPF)**

1. INTRODUCTION

Effective production and maintenance in terms of supplying sustainable power supply to the customer utility is the main focus of a power systems planner. With the advent of smart technologies in the power system planning and control, the structure of power system has been remodelled and invited more number of market participants in electricity market. The competiveness in the electricity market makes the system utilization at the higher level which makes the system security at the most vulnerable position. Hence there is a great challenge in maintaining power balance during the load variations. The optimal usage of distributed generations (DG) helps to provide solution in achieving greater power balance in terms of generation, transmission and distribution of electricity in the power system network. Thanks to Griffin et.al and Ackermann et.al [1-2] for adopting the distribution generation (DGs) in a power system which will resolve any power shortage problem by directly connecting the DGs to distribution network or to customer side (Load Center). It also improves the following parameters of power system network such as power quality, continuous power supply and security, constant bus voltage profile, voltage stability during load variations. Recent years there are larger possibilities of renewable and non- renewable DGs of different capacities such as solar, wind, diesel, gas and micro turbines are available for power integration however the benefit depends on the location and sizing of the DGs. Wang et al. (2004) have shown that improper allocation not only costs heavier power loss but also collapsed the system operation [3]. It is mandatory to choose the optimal location as well as sizing for the reliable operation. DGs placement and sizing is considered as non-linear programming for minimizing the power losses. There are multitudes of classical literatures [4-5] available for analytical based solution for this problem Das et al., Willis et al. and Acharya et al. are noted among them. Introduction of meta-heuristic algorithms for computing complex power system problem have invaded in the region of optimal location and sizing problem. Acharya et al. [6] and Zhu et al. [7] have approached this problem using popular nature inspired GA algorithm. Evolutionary programming (EP) has been exploited by the De sauza et al. [8], Cano have used Fuzzy systems[9], Ant Colony optimization (ACO) has been proposed by Favuzza et al. [10], Srinivasa rao et al. have made use of the plant growth simulation [11], Bee Colony optimization algorithm (BCO) as a tool for solving optimal DG allocation and sizing problem has been exploited by Abu-mouti et al. [12]. A hybrid algorithm of GA with PSO has been utilized for optimal placement of DG Moradi et al. [13].

Minimizing the technical aspects of power losses [14] while improving the voltage profile is achieved independently by Abou et.al, Khalesi et al. [15]. In this paper, it is proposed to minimize the network losses by optimal placement and sizing of DG using a nature inspired Flower Pollination Algorithm(FPA) in distributed system. The effectiveness of the algorithm is tested using standard IEEE 33 and 69 bus radial distribution system networks. To attain the real time system results, DGs with various power factors are also considered and the results are recorded. The effectiveness of this algorithm is compared using the test results taken from standard GA and PSO algorithms.

2. MATHEMATICAL FORMULATION

2.1 Objective Function:

Best solutions of minimizing the real power loss of the distribution system are extracted by means of formulating the problem as per detail given below.

Minimization of (F) is the Objective function.

The network loss of the system is defined as follows

$$F = \sum_{i=1}^{NB} P_{Gi} - P_{Di} - V_{Si} V_{Ri} Y_i cos\,(\delta_{Si} - \delta_{Ri} + \theta_i) \quad (1)$$

Where P_{Gi} is the i^{th} generator bus real power, P_{Di} is the i^{th} bus real power load demand value, V_{Si} and V_{Ri} are the i^{th} bus connected branch's sending and receiving end voltages, Y_i and θ_i are the admittance magnitude and phase angle of the i^{th} bus connected branch, δ_{Ri} , δ_{si} are the receiving and sending end voltage angle of the i^{th} bus connected branch . NB is the total number of bus in radial distribution system (RDS). Conventional real power loss is obtained using Newton Raphson's power flow methodology.

2.1.1 Constraints

The above single objective problem needs to be solved by satisfying the following static operational limit values.

Constraint I: Voltage Limit Constraint

$$V_{i\,min} \le V_i \le V_{imax} \quad (2)$$

Constraint II: DG Capacity Constraint

$$P_{DGmin} \le P_{DG} \le P_{DG\,max} \quad (3)$$
$$Pf_{min} \le Pf \le Pf_{max} \quad (4)$$

Reactive power formulation of the distribution generation from the real Power is given as below

$$Q_{DG} = (P_{DG}).\tan(\,Cos^{-1}(Pf)\,) \quad (5)$$

Constraint III: Power balancing Constraints

$$P_{Gi} - P_{Di} - V_i \sum_{i=1}^{N} V_j Y_{ij}\ Cos(\ \theta_{ij} - \delta_i + \delta_j) = 0 \quad (6)$$
$$Q_{Gi} - Q_{Di} - V_i \sum_{i=1}^{N} V_j Y_{ij}\ Sin\,(\ \theta_{ij} - \delta_i + \delta_j) = 0 \quad (7)$$

Where V_{imin} and V_{imax} are the minimum and maximum permissible voltage at i^{th}bus, P_{DGmin} and P_{DGmax} are the minimum and maximum permissible real power value of each DG capacity, P_{Gi} and Q_{Gi} are the real and reactive power from DG in p.u, Pf_{min} and Pf_{max} are the minimum and maximum permissible power factor value of each DG capacity, P_{Di} and Q_{Di} are the real and reactive power load demand in p.u, V_i and V_j are the voltage magnitude at the i^{th} and j^{th} bus in p.u, δ_i and δ_j are the voltage angle at the i^{th} and j^{th} bus in p.u, N is the total number of bus in distributed system, Y_{ij} is the magnitude of admittance matrix and θ_{ij} is the angle of admittance matrix between i^{th} and j^{th} buses in p.u.

2.2 Optimization Algorithm structure

The objective of achieving the minimised network loss in the Distribution System (DS) with the optimal allocation of pre-determined number of DG's without violating the system operation limits as given in the previous section , Stochastic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Flower Pollination Algorithm (FPA) are used to solve this optimization problem. The structure of the FPA optimization algorithm has been explained as follows

2.2.1 Flower Pollination Algorithm structure

Flower Pollination Algorithm (FPA) is a nature inspired stochastic algorithm recently came to lime light for solving hard nonlinear optimization problems. It is proposed by Xin-She Yang in 2012, is based on flower pollination behaviour. Pollination may occur from pollen of same flower or of different flowers in same plant or between flowers of different genus, the former is known as self-pollination, and the latter is known as cross pollination. Biotic pollination known as global pollination initiated by the bats, bees, birds, insects and flies which can fly a long distance. So it has characteristics of Levy flight jumps as Levy flight distribution, one of the control parameter. The pollination process is dictated by four mandatory rules such as 1) Global pollination is biotic and pollen carrying agents do the Levy flights 2) Self-pollination is abiotic and termed as local pollination 3) Reproduction probability is attributed to flower constancy and depends on the similarity of the two flowers involved 4) p ∈ [0, 1], is assumed as switch probability which controls both local and global pollination.

The pollination and reproduction of the fittest is given as below

$$v_i^{t+1} = v_i^t + L(v_i^t - d_*) \quad (8)$$
$$L \sim \frac{\mu\Gamma(\mu)\sin(\pi\mu/2)}{\pi\pi}\frac{1}{s^{1+\mu}} \quad (s>>s_o>0) \quad (9)$$

Where v_i^t is the pollen i or solution vector v_i at iteration t, and d_* is the current best solution found among all solutions at the current generation/iteration. L is the strength of the pollination, which is a step size. Pollinators can move over a long distance with various distance steps known as Levy flight distribution. $\Gamma(\mu)$ is the standard gamma function, and this distribution is valid for large steps s > 0. In all our simulations, we have used $\mu = 1.5$ and $s \in [0, 10]$. L > 0 is assumed for Levy distribution. The local pollination and flower constancy can be represented as

$$v_i^{t+1} = v_i^t + \varepsilon\left(v_j^t - v_k^t\right) \quad (10)$$

Where, v_j^t and v_k^t are pollens from the different flowers of the same plant species. This essentially mimics the flower constancy in a limited neighbourhood. Mathematically, if v_j^t and v_k^t comes from the same species or selected from the same population, this become a local random walk if we draw 'ε' from a uniform distribution in [0, 1]. Pollination activities in FPA algorithm can occur at both local and global scale. Flowers at closer proximity are more likely to pollinate compared to flowers at distance, so switch probability or proximity probability 'p' to vary between p = 0.5(initially) to 0.8.The value of p = 0.8 works better for most applications. The flow chart of FPA is given in fig.1

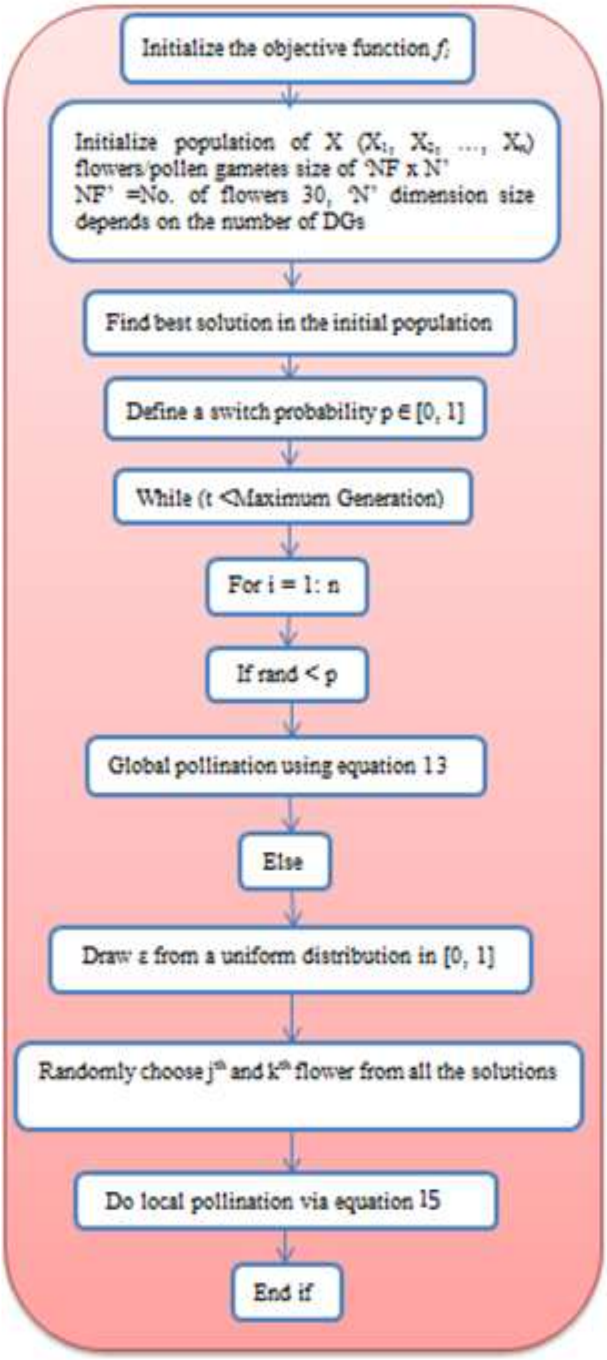

Fig1. Flower Pollination Algorithm Flow chart

3. RESULT AND DISCUSSION

The proposed single objective formulation has been implemented with the help of two standard radial distribution test systems 33bus and 69bus. The 33 bus radial distribution test system has 32 branches with the total system load of 3.72 MW and 2.3 MVAR. The initial system power loss of the 33 bus system is 210.908 kW and the reactive power loss is 143 kVAR. The system voltage base is 12.66 kV and the base apparent power is 10 MVA. The second test system is the 69 bus radial distribution test system with the total system load of 3.80 MW and 2.69 MVAR. The initial system power loss of the 69 bus system is 224.9 kW and the reactive power loss is 102.1 kVAR. Both 33 bus and 69 bus radial distribution system data are taken from the literature by Moradi et al. (2012). GA, PSO and FPA based optimization algorithms are used to extract the best optimized solution by means of finding best distributed generation site and sizing.

Three best locations for DG placement have to be identified and the best sizing for each DG should be less than 2000 KW has been assumed. In this proposed work, DG power generation with both unity and variable leading power factors are optimized to achieve the reduced network loss. In DGs with variable power factor optimization, the power factor is also taken as control parameter along with location and DG sizing. MATLAB simulation of FPA, PSO and GA algorithms for the 33 and 69 bus RDS test system have been conducted with the DG's unity and variable operational power factors. The simulation results have been recorded and the details are provided below with the explanation.

3.1 Simulation results of single objective problem formulation with unity power factor DGs

The most excellent optimum location and sizing to extract the best real power loss is identified by means of implementing the three algorithms such as GA, PSO and FPA. The simulation results of the three algorithms are recorded and it is provided in the Table 1 and Table 2 for the 33 and 69 bus RDS test system respectively.

Table 1 GA, PSO and FPA based optimization results for 33 bus RDS

RDS Test system	Algorithm	Bus No	Sizing in kW	F in per unit	Fitness in per unit
33 BUS	FPA	13	1054	1.0388	0.45568
		29	1847		
		24	1314		
	PSO	13	1054	1.0391	0.45566
		29	1850		
		24	1319		
	GA	29	1865	1.0398	0.45617
		24	1324		
		14	1024		

Table2. GA, PSO and FPA based optimization results for 69 bus RDS

RDS Test system	Algorithm	Bus No	Sizing in kW	F in per unit	Fitness in per unit
69 BUS	FPA	18	591	1.0235	0.4411
		55	772		
		61	1994		
	PSO	17	551	1.0236	0.4411
		55	842		
		61	1980		
	GA	61	1155	1.0251	0.4421
		14	808		
		62	999		

It is inferred from the Table 1 and Table 2 that the FPA provides best minimized network loss (F) in 33 bus and 69 bus test radial distributed systems. The FPA provides better solution compared to the GA and PSO.

3.1.1 Optimization algorithm's performance measures

The statistical measures such as mean, best, standard deviation of the three algorithms for the two test systems are recorded in the Table 3 by conducting 20 different trials. It is inferred from the statistical performance Table 3 that the optimal solutions of FPA for the two test system is better compared to GA and PSO and also the number of iterations for extracting best solution using FPA is better than compared to GA and PSO for all the test system. The above is obvious from the three algorithm's convergence graph in Figure 2 and Figure 3 for the 33 bus and 69bus respectively. The solution of the FPA has been compared with that of the combined GA/PSO based methodology proposed in the literature by Moradi et al. (2012). It is inferred from the result that the FPA based solution provides better extraction of minimized network loss compared to the combined GA/ PSO based methodology.

The above percentage comparison of real power loss from the base case for the FPA based proposed problem formulation and the combined GA/PSO based problem formulations are depicted in the Figure 4.

Table 3. Statistical measures of GA, PSO and FPA

Test System	Algorithm	Minimum	Mean	Maximum	Standard Deviation	No of Iteration for convergence
33 Bus	FPA	0.45568	0.4582	0.4618	0.00175	380
	PSO	0.45566	0.4594	0.4621	0.00181	500
	GA	0.45617	0.4589	0.4626	0.00197	610
69 Bus	FPA	0.4411	0.4488	0.4549	0.00510	450
	PSO	0.4411	0.4618	0.4688	0.00626	590
	GA	0.4421	0.4624	0.4709	0.00690	860

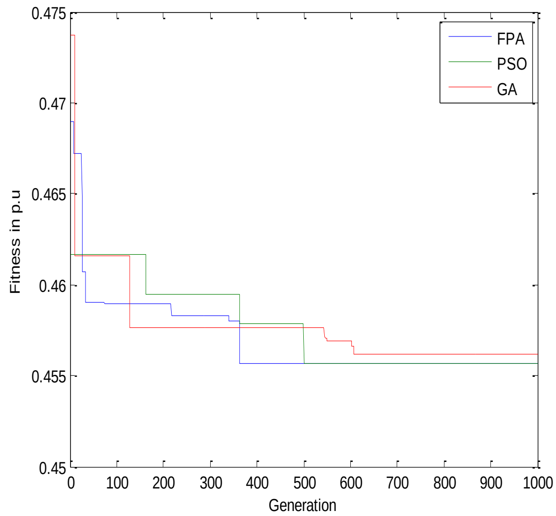

Fig.2. GA, PSO and FPA based optimization convergence graph for 33 bus RDS

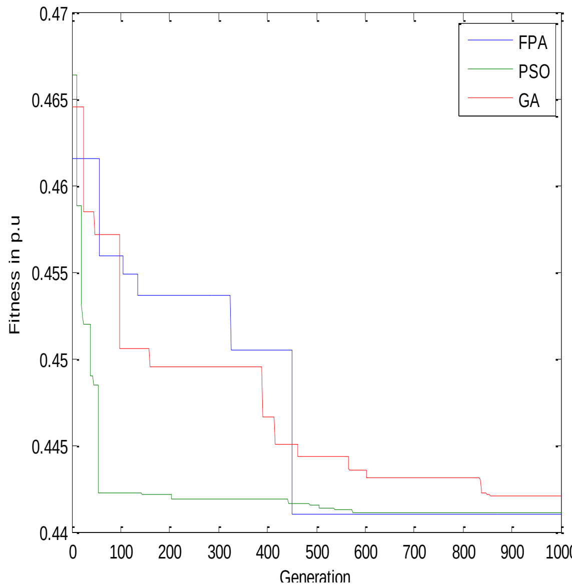

Fig3. GA, PSO and FPA based optimization convergence graph for 69 bus RDS

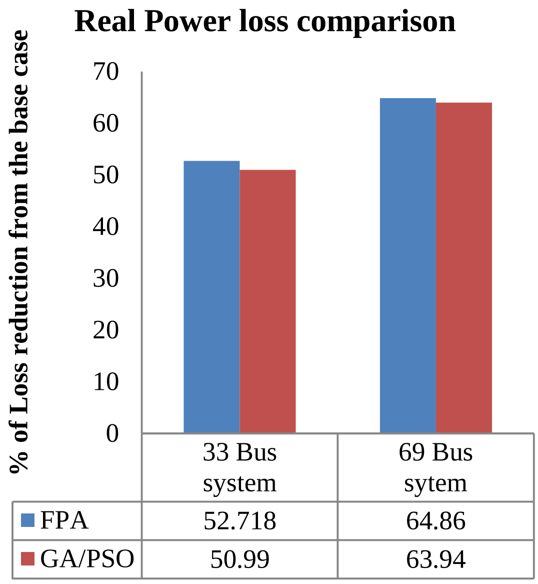

Fig.4. Combined GA/PSO and FPA based real power loss(reduction) comparison

3.2 Simulation results of single objective problem formulation with variable power factor DGs

The proposed single objective problem is solved by finding the optimal sites and their respective sizing of DG with the help of finding optimal power factor within the specified limit. DGs with the variable power factor based optimal sizing and location to achieve the best optimal solutions are extracted and it is recorded in the Table 4 and Table 5 for the 33 and 69 bus RDS system respectively. The convergence graph for the three optimization algorithms simulations are depicted in the figure 5 and 6. It is inferred from the graphs that the FPA based optimal solution extraction solution converges faster compared to that of GA and PSO. It is inferred from the table 4 & 5 that FPA based simulation provides the improved solutions compared to that of GA and PSO simulations. The statistical measures such as mean, best, standard deviation of the three algorithms for the two test systems are recorded in the Table 6 by conducting 20 different trials. It is inferred from the Table 6 that the optimal solutions of FPA for the two test system is better compared to GA and PSO and also the number of iterations for extracting best solution using FPA is better than compared to GA and PSO for all the test system.

Table 4 GA, PSO and FPA based optimization results for 33 bus RDS

RDS Test system	Algorithm	Bus No	Sizing in kW	F in per unit	Fitness in per unit
33 B	FPA	24	994	0.0120	0.4211
		30	1048		
		13	756		
	PSO	13	696	0.0134	0.4218
		30	1046		
		24	957		
	GA	13	688.	0.0142	0.4214
		30	1137		
		24	928		

Table5. GA, PSO and FPA based optimization results for 69 bus RDS

RDS Test system	Algorithm	Bus No	Sizing in kW	F in per unit	Fitness in per unit
69 BUS	FPA	61	1616	0.00500	0.4114
		19	323		
		12	487		
	PSO	21	345	0.00466	0.4112
		11	532		
		61	1674		
	GA	61	1673	0.00427	0.411
		67	391		
		21	372		

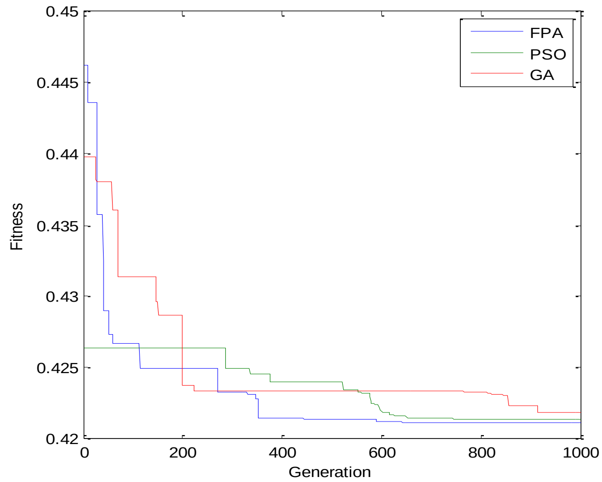

Fig. 5 Variable power DG based optimization Convergence graph for 33 bus RDS

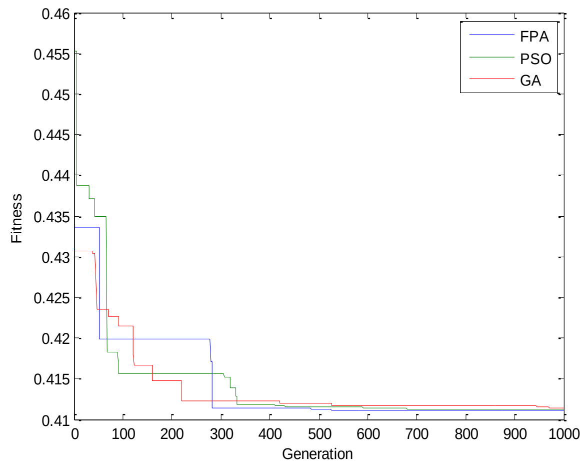

Fig.6 Variable power DG based optimization Convergence graph for 69 bus RDS

Table.6 Variable power factor DG based optimization algorithm's statistical measures

Test System	Algorithm	Minimum	Mean	Maximum	Standard Deviation	No of Iteration for convergence
33 Bus	**FPA**	0.411	0.4115	0.412	0.00034	520
	PSO	0.4112	0.4119	0.412	0.00036	680
	GA	0.4114	0.4123	0.413	0.00051	980
69 Bus	**FPA**	0.4211	0.4223	0.424	0.00060	620
	PSO	0.4218	0.4224	0.424	0.00077	750
	GA	0.4214	0.4224	0.424	0.00066	950

3.3 Variable and unity power factor DGs optimization solution comparison

It is obvious from simulation results that the real power loss solution extracted from variable power factor DG optimization gets largely improved when comparing with the unity power factor DG optimization. The percentage improvement of reduction in power loss from the base case for the 33 and 66 bus RDS test systems are depicted in the fig.7 and fig.8.

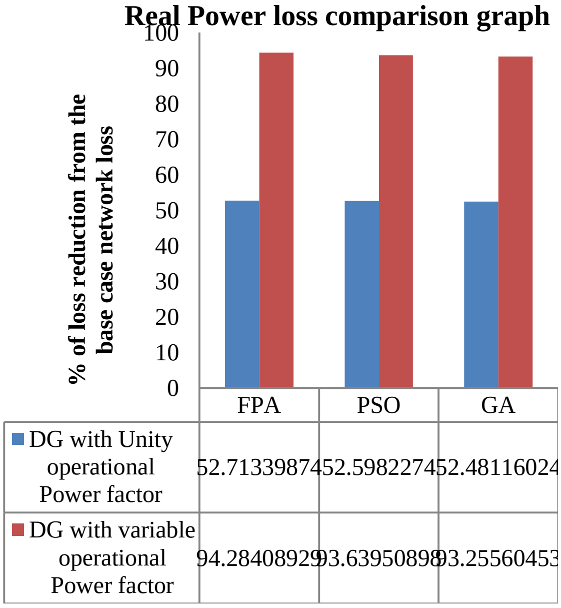

Fig.7 Variable power factor DG and unity power factor DG based real power loss comparison for 33 Bus RDS

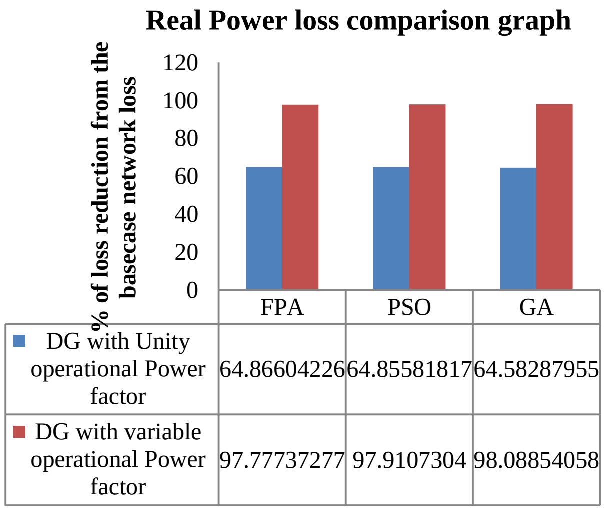

Fig .8 Variable power factor DG and unity power factor DG DG based real power loss comparison for 69 bus RDS

4. CONCLUSION

This paper projects the application of DG in extracting the network loss minimization by optimally determining the placement and sizing of DG with unity and variable power factor by considering the system security limits. From the simulation results, it is evident that the proposed optimization problem extracts the better solutions. Also it is concluded that the application of FPA in solving the proposed optimization provides the most definite solution by maintaining the good balance in exploring the global minima and exploiting the local minima.

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