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Optimal Integration of Distributed Generation for Power Loss Reduction and Voltage Profile Enhancement using Small Population Particle Swarm Optimization

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Research Article

Abstract

In this paper, a meta-heuristic Small Population Particle Swarm Optimization (SPPSO) is proposed for Distributed Generation (DG) integration with the objective of power loss reduction and system voltage profile improvement. One of the major setbacks of classical particle swarm optimisation (PSO) is its computational complexity and the SPPSO is employed to address this setback. The classical PSO is also implemented in this study to provide a realistic and feasible comparison for the performance of the two algorithms (Classical PSO & SPPSO) in optimal DG integration problem. The algorithms are tested on two standard 33 and 69 bus radial distribution systems. In each test network, two scenarios are considered for DG sizing and location; DG operation at unity power factor (fit and forget approach) and DG operation at pre-specified practical power factor less than unity. The SPPSO algorithm finds the optimal or near optimal solution to the problem at less computational cost associated with the use of the classical version of the algorithm. The connection of DG to 33bus network reduced the power loss by 47.40% at unity p.f and 67.71% at 0.85 lagging p.f. While, for the 69bus, the reduction in power loss at unity power factor and 0.85 p.f are respectively 63.11% and 89.4%. Thus, demonstrating the benefits accrue to Distribution Network Operators to operate their generators at a pre-specified practical power factors less than unity.

Keywords
Classical PSO; Distributed Generation; Small Population PSO; Power system optimization; Voltage support

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1. Introduction

Central power stations for electricity generation are always sited closed to their energy sources, thus are naturally located far away from load centers. Therefore, they are characterized by environmental impacts (such as carbon dioxide emission), high cost of Transmission and Distribution (T&D) upgrades, long gestation period for new plant stations and exposure of the transmission facilities to natural hazard such as wind, snow and storm. The last decade has seen an increased penetration level of Distributed Generation (DG) in in the power distribution networks. Unarguable, this has brought a tremendous alteration to the structure of a typical distribution system. Onsite generation and ancillary of supports are tenable from Distributed generation energy technologies at substations. These include reactive power enhancement of voltage profile, peak load shaving, power loss reduction, and congestion management (Chowdhury, *et al*., 2009).

The problem of DG integration is known to be a combinatorial nonlinear problem that requires the determination of the optimal or near optimal overall combination of locations and capacities (Neeraj, et al., 2015) in a network made up of n buses. Arriving at the best solution is a significant effort beyond the reach of manual searches not even for a small distribution network. The optimum placement and sizing problem is done to achieve different objectives. In Prasanna, et al., (2017) a hybrid technique based on PSO is proposed for placing distributed generation with optimal power injections on power distribution systems for loss reduction. The technique involves calculating the optimal P (real power) and Q (reactive power) injections of DG system. The modelling of DG bus as PQ injection, will results in uncontrolled Q injection. Thus, alter the voltage profile along the feeder and decrease the power flow in the HV/MV transformer thus, decreasing the load compensation (Maurizio, *et al.*, 2014).

An application of Bat algorithm for optimal allocation of Solar based distributed generators is presented in Sudabattula and Kowsalya (2016) for minimizing distribution network power losses. In Korra and Vivekananda, (2020), the Siting and Sizing of DG and Shunt Capacitor Banks in Radial Distribution System Using Constriction Factor Particle Swarm Optimization, to alleviate the power losses, revamp the voltage profile, inflate the voltage stability index, shrink the total voltage deviation, and acquire more energy savings is presented. The DG integration is based on the fit and forget approach with the reactive power support for the system provided by the shunt capacitor. In addition, the computational complexity associated with the metaheuristics algorithms used in the comparisons were not considered.

In Pushpendra, et al., (2020) a hybrid Elephant Herding Optimisation (EHO)-PSO method is proposed to solve the DG allocation problem of distribution systems. The study considered single and multiple DG locations at unity and non-unity power factor based on multi-objective. The objective functions considered are power loss minimization, voltage deviation minimization, and voltage stability improvement. However, the DG locations are preselected in multiple DG integration thus, the obtained solutions might not be optimal.

A heuristic approach for the planning of Distributed Generator (DG) to minimize annual system energy loss is proposed in Manoj, et al. (2017). The optimization tool is based on PSO and time-varying characteristics of electrical load demand was considered to mimic real load scenario in the electrical distribution system. The study considered both the fit and forget approach and the operation of DG at non unity factor. The DG at non-unity power factor was operated to inject uncontrolled reactive power support resulting in an appreciable energy loss reduction but with the consequence of violating the voltage limits constraints.

Genetic and Ant Colony algorithms for optimal distributed generation allocation and sizing is presented in Yousef, et al., (2020) with the objective of diminishing the power losses and improving the system voltage.

The effectiveness of PSO in solving the optimal DG placement problem has been reviewed in Niazi and Lalwani, (2017). The PSO methods categorized were the simple PSO method, advanced PSO method, hybrid PSO method and other methods combined with PSO. It was evident from the study that the nature and complexity of the problem to be solved can help in determining the PSO variants to be used.

In most of these reviewed studies, the complexity of the PSO algorithms in terms of the computational cost are not considered. Thus, drawing conclusion on the performance between any two metaheuristics algorithms without an objective function evaluations make such comparisons infeasible (Maurice, 2006). The computational cost of an algorithm is a very important factor not just for online operations but also, to free computer time.

This paper presents a DG optimum sizing and location study based on a variant PSO algorithm SPPSO. The major aim of which is to enhance network power loss reduction and voltage profile by considering DG reactive power capability. This SPPSO algorithm significantly reduces the execution time in terms of function evaluations and accelerates convergence. The study is carried out on 33 and 69-bus benchmark networks showing significant reductions in power loss and improvement in the system voltage profile.

The main contributions of this study are:

• The implementation of the SPPSO algorithm to address issue of Computational complexity associated with the classical PSO. To the best knowledge of the authors, the algorithm is first reported in this study for optimal DG integration. Its implementation allows realistic and valid comparison of the results and performance of the two algorithms considered.

• The consideration of DG reactive power capability in accordance with the IEEE standard 1547 for DG interconnection. Thus, demonstrating the benefits accrue to Distribution Network Operators to operate their generator in a non-fit and forget approach.

2. Problem Formulation

The optimal sizing and placement of DG problem formulation presented in this paper involve minimizing the total real power loss of the distribution system for efficient operation of the power system.

The IEEE standard 1547 for DG interconnection shows that DG with a capacity less than 10 MW may not to take part in network regulation at a node of common coupling and should operate at predefined power factor (Meena, *et al.*, 2017). Therefore, in this study Connection of a DG unit to a bus is modeled as a negative PQ load at unity power factor or a minimum pre-define leading power factor of 0.85 (generating VArs).

The objective function to be optimized can be written as:
Minimize

$$P_{Loss} = \sum_{l=1}^{L} Loss_l = \sum_{l=1}^{L} (P_{i\to j}^{l} + P_{j\to i}^{l}) \tag{1}$$

where:
P_{Loss} is the total real power loss in the network, L is the total number of branches, $Loss_l$ is the power loss at branch l, $P_{i\to j}^{l}$ is the active power flow injected into branch l from bus i and $P_{j\to i}^{l}$ is the active power flow injected into branch l from bus j.

Subject to the constraints:

$$\sum_{i=1}^{n} P_{Gi} = \sum_{i=1}^{n} P_{Di} + \mathbf{P_{Loss}} \tag{2}$$

$$|\mathbf{V}_i|^{\min} \le |\mathbf{V}_i| \le |\mathbf{V}_i|^{\max} \tag{3}$$

$$|\mathbf{I}_{ij}| \le |\mathbf{I}_{ij}|^{\max} \tag{4}$$

Equations (2), (3) and (4) show power, voltage and line current constraints, respectively.
where:
n is the total number of nodes, L is the total number of branches, P_{Gi} is the real power generated at bus i and P_{Di} is the real power demand at bus i. $|\mathbf{V}_i|^{\min}$ and $|\mathbf{V}_i|^{\max}$ are the minimum and maximum allowable voltages at node i. $\mathbf{I}_{ij}$ is

the current between nodes i and j and $\left|\mathbf{I}_{ij}\right|^{\max}$ is the maximum allowable line current between nodes i and j.

The constraint on power balance requires that the total generation of power from the grid and distributed energy resources must be equal to the summation of load demand and power losses of the system. This constraint is normally enforced by the power flow algorithm.

It is intuitive that DG placement leads to voltage rise and thermal rating effects with the consequences of spreading across the entire network. Supplying customers within a specified voltage limits is an obligation which every distribution network operator must fulfil. This voltage limits is typically around ±5% of nominal (Jenkins et. *al*., 2010). Thus, violations of these constraints may result in reverse power flow from DG source and overloading of network branches which are undesirable for efficient distribution network operation.

The power loss reduction is evaluated from the 'per-unit line loss reduction' (*PULR*) defined as the ratio of loss reduction (*LR*) to the line loss without DG (LL_{woDG}) and is given by Equation (5). The *LR* is the difference in the line loss reduction with and without DG. While the percentage of line loss reduction is given by Equation (6) (Chiradeja, 2005).

$$PULR = \frac{LR}{LL_{woDG}} \tag{5}$$

$$\%LR = PULR * 100 \tag{6}$$

The cost function is computed using MATPOWER AC power flow with network data modeled as in Zimmerman, *et al.*, (2011). MATPOWER can solve distribution system power flow and have been used in Musa, *et al.*, (2016).

3. Small Population Particle Swarm Optimisation

PSO is a cooperative population based stochastic optimization technique based on the behavior of swarms such as fish schooling and bird flocking developed by Kennedy and Eberhart in 1995 (Yuhui, 2004). Instead of using evolutionary operators to manipulate individuals as in other evolutionary computation algorithms such as GAs, each individual in a PSO swarm moves in the search space with a velocity which is dynamically adjusted according to its own previous experience and the experience of other members of the swarm. Each particle keeps track of its coordinates in the search space associated with the best fitness it has achieved so far (p_{best}) and the overall best value, and its location, obtained so far by any particle in the population (g_{best}). Each particle moves towards its p_{best} and g_{best} locations with each time step in accordance with the following velocity and position equations:

$$V_{id}^{k+1} = w^k \cdot v_{id}^k + c_1 \cdot rand_1 \cdot (pbest_{id} - x_{id}^k) + c_2 \cdot rand_2 \cdot (gbest - x_{id}^k) \tag{7}$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{8}$$

where: v_{id}^k and x_{id}^k are the current velocity and position, respectively, of the i^{th} particle along a given dimension at iteration k, V_{id}^{k+1} and x_{id}^{k+1} are the new velocity and position, respectively, of the i^{th} particle along a given dimension at iteration k+1, rand_1 and rand_2 are random numbers between 0 and 1, p_{besti} is the best position to-date of particle i, g_{best} is the global best position of the group to-date, c_1, c_2 are constants (weighting functions) determining the relative influences of p_{besti} and g_{best} and w is an inertia constant (or weighting function) determining the relative influence of the particle's own velocity. d is the number of dimensions in the search space.

In this algorithm implementation, PSO with a varying inertia w (Yuhui, 2004; Riccardo, et al., 2007) is employed. For the k^{th} iteration, the value of w is given by:

$$w_k = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} \cdot k \tag{9}$$

where, w_{min} and w_{max} are the minimum and maximum weights, respectively, and k_{max} is the maximum allowable number of iterations before the search is aborted. This allows the particles to move freely within the search space at the beginning of the search process while giving greater significance to p_{besti} and g_{best} during the later stages of the search.

If the search space is not infinite, it is necessary to confine the search space to prevent a particle leaving the search space all together. A simple mechanism for such confinement is represented by equation (10) (Maurice, 2006):

$$x_{id}^k \notin \left[x_{\min}, x_{\max}\right] \Rightarrow \begin{cases} v_{id}^k = 0 \\ x_{id}^k < x_{\min} \Rightarrow x_{id}^k = x_{\min} \\ x_{id}^k > x_{\max} \Rightarrow x_{id}^k = x_{\max} \end{cases} \tag{10}$$

The particle velocity may also be limited to a maximum value v^{max}.

The SPPSO is a classical PSO algorithm using a small population (Das, *et. al*., 2008) based on concept of algorithm regeneration. The algorithm regeneration was introduced to give the particles the ability to keep carrying out the search despite a small population. The particles are regenerated after every N iterations retaining their previous global best (*gbest*) and personal best (*Pbest*) fitness values and positions. The selection of the value of N is crucial in the realizing an efficient SPPSO algorithm. If the value of N is low, the new particles may be regenerated too quickly and in turn disturb the search process. Thus the particles will move erratically in search space. On the other hand, if the particles are regenerated at a higher value of N the search process will be delayed. Randomizing the positions and velocities of the particles every *N* iterations aids the particles in avoiding local minima and finding the global minimum.The regeneration concept drastically reduces the number of evaluations required to find the best solution and each evaluation is less computational intensive compared to the classical PSO algorithm.

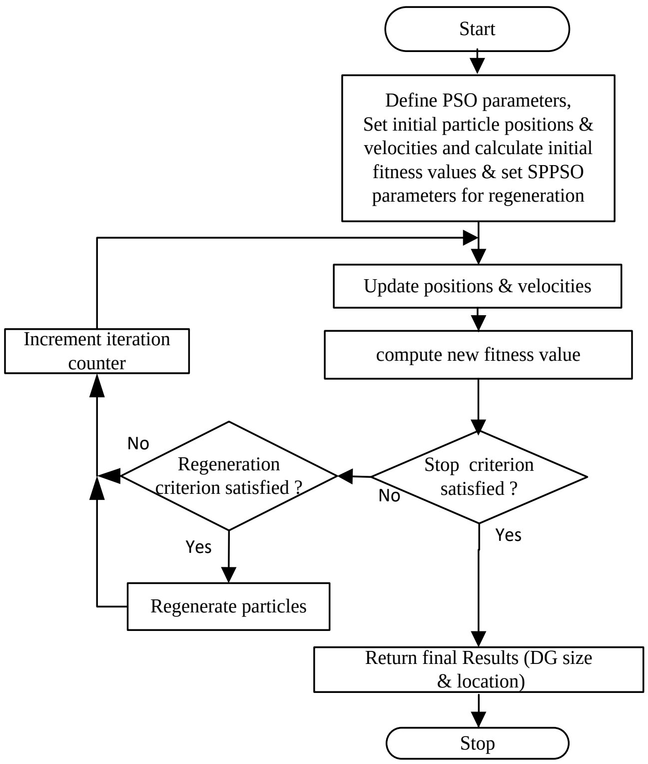

Figure 1: SPPSO algorithm flow chart

In Das, *et al*., (2008) the algorithms was used for the Design of Multiple Optimal Power System Stabilizers. A survey of the available literature shows that the algorithm has not been used for problem of optimal DG integration.

Thus, in this paper, the algorithm is employed to solve the DG placement and sizing problem. This study involves a solution vector X in a three-dimensional search space represented as $X_i = (x_{i1}, x_{i2}, x_{i3})$. For a single distributed generator placement problem considered in this study, x_1, x_2, x_3 represent generator location, generator output power and VArs respectively. The SPPSO algorithm implementation flow chart is shown in Figure 1.

4. Test Scenarios and Simulation Results

The proposed SPPSO algorithm is tested on two standard benchmark networks commonly used by researchers (Abu-Mouti and El-Hawary, 2011; Acharya, et al., 2006; Baran and Wu, 1989a; Baran and Wu, 1989b; Amin & Ehsan, 2008; Shukla, et al., 2010) for power system optimization problems.

4.1 Test Case Systems

Network I: This proposed test system is a 12.66 kV 33bus primary radial distribution system with one feeder substation, 32 busses and 5 tie lines (Amin & Ehsan, 2008) as shown in Figure 2. The total substation load is 3.72MW and 2.3MVAr. The network power loss and reactive power loss are 0.211MW (about 6% of the total load) and 0.14MVAr, respectively as summarized in Table 1.

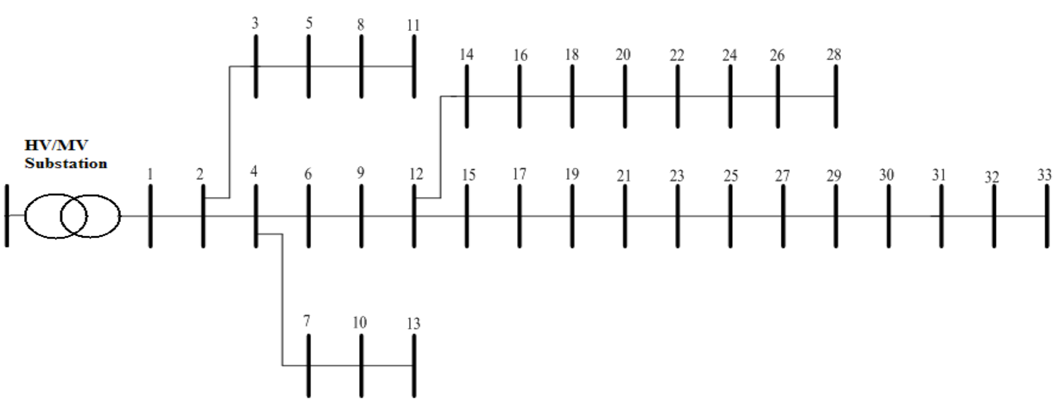

Figure 2: Single line diagram for 33 bus distribution system I (Amin & Ehsan, 2008)

Network II: This is a 12.66-kV radial distribution system comprising one sub-station, 7 laterals, 69 nodes and 68 branches including normally open tie lines (Baran and Wu, 1989*)* as shown in Figure 3.

The details for both networks can be obtained from Amin & Ehsan, (2008) & Baran and Wu, (1989a). The maximum and minimum voltage limits for this study are set to 1.06 p.u. and 0.94 p.u for all nodes of both networks. In both test networks, the voltages at some nodes are lower than the minimum limit of 0.94p.u. The allocation of DG would normally be expected to improve the voltage profile of the network. Thus, making the current study a single objective function.

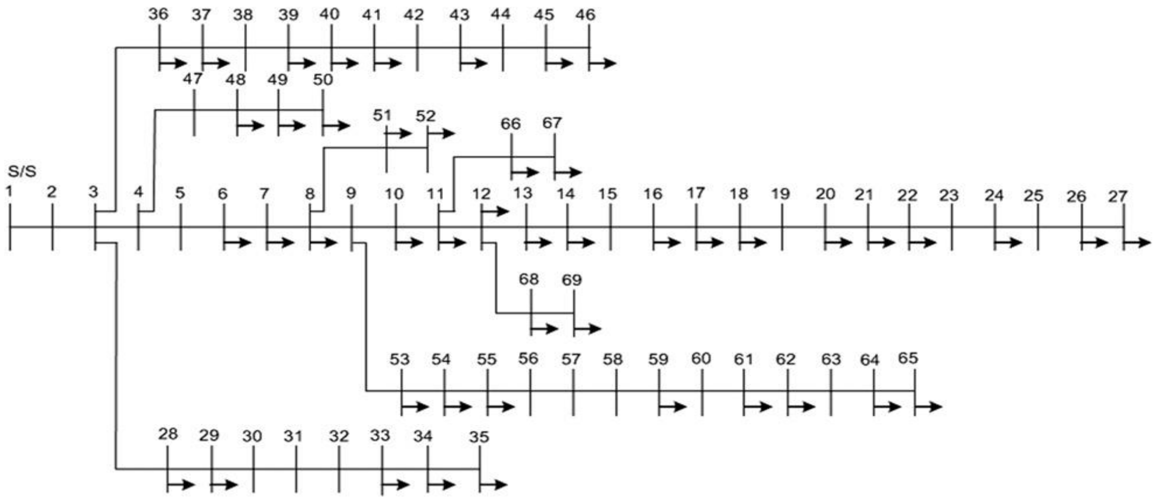

Figure. 3: Single line diagram for 69 bus distribution system II (Baran and Wu, 1989a)

4.2 Simulation Results

In these optimization studies, DG sizes are considered in the range 0kW to 5MW. DG output reactive power is considered within the range 0 to a pre-specified maximum value corresponding to the minimum operating power factor of the machine. For a grid connected generator, this corresponds to operation at its continuous power output rating at a range of possible lagging power factors up to a maximum reactive power output limited by the current rating of the stator or rotor windings.

Table 1: summary of results base case (No DG)

System Parameters	Test systems	
	33- bus network	**69- bus network**
Real Power Loss (MW)	0.2112	0.225
Reactive Power Loss (MVAr)	0.1432	0.102
Min bus voltage (pu)	0.9040	0.9090
Max bus voltage (pu)	1.000	1.000
Total Real Load (MW)	3.72	3.802
Total Reactive Load (MVAr)	2.30	2.690

For each benchmarking network two scenarios are considered. The first is with the generator operated at unity power factor (PF) and the second when operating with a minimum lagging power factor of 0.85. Results of the optimization process for unity power factor operation are presented in Tables 2 & 3, using a swarm population of 20 particles for the classical PSO and 20 particles (with only 5 selected at each iteration for evaluation) for the SPPSO with *N* (no of iteration before regeneration occurs) selected as 10 and a stop criteria of 50 iterations where the objective function value remains within a margin of 10^{-9} or a maximum number of 1000 iterations.

Tables 4 & 5 show the corresponding results for operation with a minimum lagging power factor of 0.85. The results are compared with those obtained from the classical version of the PSO algorithm. The required number of function evaluations for SPPSO is reduced by 24.3%, 19.2%, 21.5% and 23.0% for scenarios in Tables 2, 3, 4 and 5 respectively compared with the standard PSO. The results are based on average values with ten independent runs of the algorithms. Nevertheless, both algorithms obtained the same quality of solutions, but with SPPSO requiring lesser no of objective function evaluations.

Table 2: Summary of results: optimal size and location for 33-bus network DG operating at unity power factor

System Parameters	Algorithms	
	Classical PSO	**SPPSO**
DG optimum bus location	12	12
DG real power generated (MW)	2.5909	2.5909
Average no of iterations	117	350
Average no. of function evaluations	2318	1750
Real Power loss (MW)	0.1111	0.1111
Reactive Power Loss (MVAr)	0.0817	0.0817
Percentage power loss reduction (%)	47.40	47.40
Maximum bus voltage (pu)	1.000	1.000
Minimum bus voltage (pu)	0.9423@ bus 33	0.9423 @ bus 33
Average voltage (pu)	0.9720	

Table 3: Summary of results: optimal size and location for 69-bus network DG operating at unity power factor

System Parameters	Algorithms	
	Classical PSO	**SPPSO**
DG optimum bus location	61	61
DG real power generated (MW)	1.8726	1.8726
Average no of iterations	116	374
Average no of function evaluations	2314	1870
Real power loss (MW)	0.0831	0.0831
Reactive power loss (MVAr)	0.0405	0.0405
Percent power loss reduction (%)	63.10	63.10
Maximum bus voltage (pu)	1.000	1.000
Minimum bus voltage(pu)	0.968 @ bus 27	0.968 @ bus 27
Average voltage (pu)	0.9874 pu	

Table 4: Summary of results: optimal size and location for 33-bus network DG operating at minimum pf of 0.85

System Parameters	Algorithms	
	Classical PSO	**SPPSO**
DG optimum bus location	12	12
DG real power generated (MW)	2.6382	2.6382
DG reactive power generated (MVAr)	1.635	1.635
Average no of iterations	125	413.5
Average no of function evaluations	2632	2067.5
Real power loss (MW)	0.0682	0.0682
Reactive power loss (MVAr)	0.0551	0.0551
Percentage power loss reduction (%)	67.71	67.71
Maximum bus voltage (pu)	1.001	1.001
Minimum bus voltage (pu)	0.958 @ bus 33	0.958 @ bus 33
Average voltage (pu)	0.9828	

From Tables 4 & 5 it is evident that significant benefits in loss reduction and improved network voltage profiles were obtained for both networks when DG is operated to support the reactive power requirement of the network (compared with its operation at unity PF, see Tables 2 & 3). For the 33bus network, the connection of the generator reduced the power loss by 47.40% with a minimum bus voltage of 0.942pu when operating at unity power factor, whereas a loss reduction of 67.71% was achieved with the generator operating at a power factor of 0.85 lagging with a corresponding minimum bus voltage of 0.958pu. The best of the mean voltage (0.9828) was obtained with the case of DG operating and injecting reactive power support to the network (scenario II, 33bus).

Table 5: Summary of results: optimal size and location for 69-bus network DG operating at minimum power factor of 0.85

System Parameters	**Algorithms**	
	Classical PSO	**SPPSO**
DG optimum bus location	61	61
DG real power generated (MW)	1.9040	1.9040
DG reactive power generated (MW)	1.180	1.180
Average no of iterations	122	386.6
Average no of function evaluations	2510	1933
Real power loss (MW)	0.0238	0.0238
Reactive power loss (MVAr)	0.0146	0.0146
Percentage power loss reduction (%)	89.40	89.40
Maximum bus voltage (pu)	1.001	1.001
Minimum bus voltage (pu)	0.973 @ bus 27	0.973 @ bus 27
Average voltage (pu)	0.9916	

In the 69-bus network, a power loss reduction of 63.11% was achieved with a minimum bus voltage of 0.968pu for DG operation at unity PF, while 89.42% loss reduction was obtained with 0.973pu minimum bus voltage when the DG is allowed to operates at a lagging power factor of 0.85. The best of the mean voltage (0.9916) was obtained with the case of DG operating and injecting reactive power support to the network (scenario II, 69bus).

Figures 4 and 5 show the network bus voltage profiles for operating at unity and 0.85 PF for both 33bus and 69bus networks. The improvement obtained through the connection of the optimally sized and located DG is evident especially when allowed to provide network voltage support.

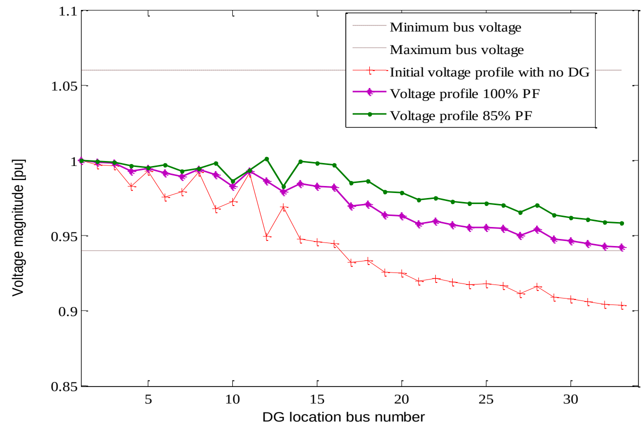

Figure. 4: 33-bus network voltage profile improvement for a single optimally sized DG at optimal location (bus 12)

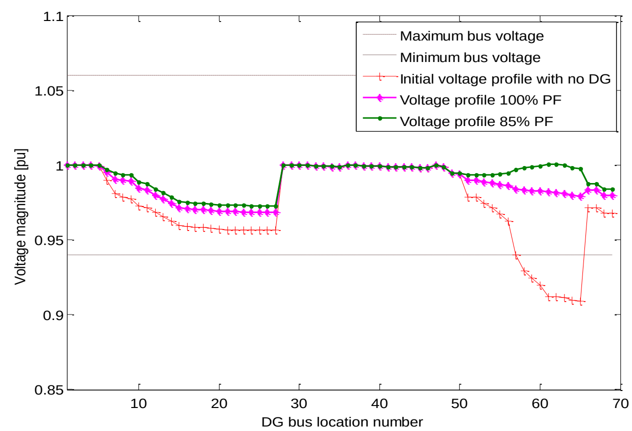

Figure. 5: 69-bus network voltage profile improvement for a single optimally sized DG at optimal location (bus 61)

To allow direct comparisons of the results (not in terms of algorithms computational complexity) obtained from the SPPO algorithm with previously published solutions obtained using analytical techniques (Acharya, et al., 2006), GAs (Shukla, et al., 2010), and the ABC algorithm (Abu-Mouti and El-Hawary, 2011) a simple test case using the 69-bus network was also considered. The optimization studies in Abu-Mouti and El-Hawary, (2011), Acharya, et al., (2006) and Shukla, et al., (2010) were limited to the single objective function of minimizing network losses (Scenario I, with DG operation at unity PF). Table 6 shows the optimal solutions (in terms of network loss reduction) achieved by all four methods. The results obtained from the four methods are identical in terms of the optimal location of the DG unit. But the application of SPPSO resulted in 63.1% power loss reduction compared to the three other algorithms.

Table 6: Comparison of optimal DG size and location for 69-bus network scenario I (unity p.f) with previous studies

System Parameters	**Algorithms**			
	Analytical method *(Acharya,* et al.*, 2006)*	GA *(Shukla, et al., 2010*)	ABC Algorithm *(Abu-Mouti and El-Hawary, 2011*),	Proposed SPPSO
Optimum bus location	61	61	61	61
Optimum DG size (MW)	1.810	1.827	1.900	1.873
Percent MW loss reduction (%)	62.86	62.91	62.97	63.10

5. Conclusion.

An application of power system optimization tool based on a variant PSO (SPPSO) algorithm to solve the problem of optimal DG integration in power network has been implemented in this paper. This proposed algorithm was tested on two standard 33 and 69 bus medium voltage radial distribution networks and results are compared with those obtained when using the classical version of the PSO algorithm. Two DG operating regimes were considered: The first is for operation at unity power factor and the second is for operation at a minimum power factor of 0.85 lagging. In all cases, the SPPSO algorithm was found to be effective in solving the optimization problem converging to an optimum DG size and location with lesser number of objective function evaluations compared to classical PSO. Thus, overcoming the problem of computational complexity associated with the classical PSO in terms of objective function evaluation. The results also show improvement in the system voltages when the DG is allowed to provide reactive power support. Thus, it can be concluded that the network power loss reduction for DG integration exercise is dependent on the operating power factor of the DG. Higher power loss reduction figures were obtained when operating at lagging power factors compared to unity operating power factor.

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