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Network Loss Minimization with Voltage Profile Considerations through Optimal Allocation of Distributed Generation using Particle Swarm Optimization Techniques

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Abstract: **Adverse impact of large fossil fuel based conventional generation plants on the environment and the challenge of fulfilling the growing demand for electrical power has generated interest in usage and installation of distributed generation. Emerging renewable energy technologies offer possibilities for using small scale generation sources not only for standalone systems but also for supplying the surplus power to the grid. However optimal location and sizing of distributed generation unit is crucial for improving the voltage profile and minimizing the network losses. This paper presents an analysis of three particle swarm optimization (PSO) techniques for optimal sizing and location of a single distributed generation unit in an IEEE 14 bus system and the effect on the network losses and voltage profile is presented.**

1. INTRODUCTION

Liberalized Electricity markets, constraints on installation of new distribution and transmission setup and environmental effects of emissions have been the motivation behind recent interest in Distributed Generation (DG) for the power systems. Advances in the technology of power electronics, small scale generators, and energy storage devices for transient backup have also accelerated the penetration of DG into electric power generation plants [1].

There are several technologies for DG ranging from conventional ones like combustion turbines, combined cycles etc. to Renewable ones including wind, solar, photovoltaic and fuel cells. Although renewable sources eliminate or reduce emissions but have relatively low efficiencies, high costs, and intermittency [2], [3].

Modeling of DG units has been done as synchronous generators, and induction generators for combustion turbines, geothermal plants and wind turbines or small scale hydro power respectively. DG units have also been modeled as power electronics based inverter generators for photovoltaic (PV) plants and fuel cells [4], [5]. Loss reduction is the focus of most utilities as it directly impacts the economy and quality of power supply. Therefore in this paper loss reduction is the primary objective with the bus voltage deviations being the secondary one. A method based on genetic algorithm (GA) has been proposed for determination of location and size of DG [6], [7]. New modified methods based on GA are proposed in [8, 9].GA is well suited for multi objective optimization as it can lead to near optimal solutions but suffers from the limitation of larger computational time requirement. An exact formula for loss based on analytical approach is presented for a single DG in [10]. A methodology based on Tabu Search (TS) is proposed for optimally locating DG units to minimize power losses in [11]. Falaghi and Haghifam have given a method for DG source allocation using Ant Colony Optimization (ACO) in [12].Discrete PSO and optimal Power Flow (OPF) has been used for placing optimal sized DG in [13] whereas combined GA and PSO hybrid has been implemented in [14].

This paper has evaluated the optimal location and sizing of a single DG required for fulfilling the objectives of loss reduction and bus voltage deviation reduction. Two cases have been considered for this purpose wherein first loss reduction alone is taken as the objective and then bus voltage deviations are considered alongside loss reduction.

2. PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization is one of the most popular heuristic search algorithms which emerged through study of social learning of birds or fishes [15]. It is a swarm based intelligence technique developed by Eberhart and Kennedy [base] in 1995. Analogous to swarm populations of animal herds a population of random sets of solutions known as particles are initialized. Each particle moves through the search space and corresponding to it's position 'fitness' is calculated in each iteration which is simply the objective function value for the particular particle or solution set.

Based on the evaluation of this 'fitness' the particle position update is carried out by calculating the velocity corresponding to it. This velocity depends on various parameters assigned to the particle such as inertia weight, acceleration factors, and personal best positions as well as global best positions attained till the current iteration. The velocity and position equations for the PSO are given as:

$$V_{pq}^{k+1} = \omega \times V_{pq}^{k} + c_1 \times r_1 \times \left(Pbest_{pq}^{k} - X_{pq}^{k}\right) + c_2 \times r_2 \times \left(Gbest_{pq}^{k} - X_{pq}^{k}\right) \quad (1)$$

$$X_{pq}^{k+1} = X_{pq}^{k} + V_{pq}^{k+1} \quad (2)$$

Where, p = 1, 2, …, S and q = 1, 2, …D. S is the swarm size and D is the dimension of the search space.

ω is the inertia weight factor, X_{pq}^{k} is the position at the k^{th} iteration of the p^{th} particle of dimension q. V_{pq}^{k} is the velocity at the k^{th} iteration of the p^{th} particle of dimension q. c_1, c_2 are the acceleration factors. r_1 and r_2 are random numbers of uniform distribution. $Pbest_{pq}^{k}$ is the best position of the p^{th} particle of dimension q upto k^{th} iteration. $Gbest_{pq}^{k}$ is the best position of the whole group of particles of dimension q upto k^{th} iteration.

2.1 Linearly Decreasing Inertia Weight Strategy (LVIW PSO)

The concept of inertia weight was not present in the Basic PSO given by Eberhart and Kennedy [16]. Inertia weight as a factor was first presented by shi and Eberhart in [17] where they used a constant value of inertia. Larger or smaller values of inertia can favour global or local search respectively. Thus in [18] linearly decreasing inertia weight strategy was proposed having improved ability for optimal convergence.

$$\omega^{k+1} = \omega_{\max} - \left(\frac{\omega_{\max} - \omega_{\min}}{k_{\max}} \times k\right) \quad (3)$$

Where ω^{k+1} is the inertia weight for the iteration $k+1$, $k_{\max}$ is the maximum number of iterations. $\omega_{\max}$ is the maximum inertia weight, and $\omega_{\min}$ is the minimum inertia weight.

2.2 Natural Exponent Inertia Weight Strategy

Natural exponent decrement of inertia weight was presented in [19] by chen et .al. these strategies namely e1 PSO and e2 PSO have faster convergence at the starting stage of the search process. Bansal et al. in [15] have discussed the performance of various inertia weight strategies. e1 PSO has been used in this paper for evaluation and it's inertia weight equation is given as [16]:

$$\omega^{k+1} = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \times \exp\left(\frac{-k}{(k_{\max}/10)}\right) \quad (4)$$

2.3 Time Varying Acceleration Coefficients Strategy (TVAC PSO)

Acceleration coefficients c_1 and c_2 affect the cognitive and social components of the searching process [20]. For any iteration $k+1$ the cognitive acceleraton c_1^{k+1} and social acceleration c_2^{k+1} is given by:

$$c_1^{k+1} = \left(c_{1\min} - c_{1\max}\right)\frac{k}{k_{\max}} + c_{1\min} \quad (5)$$

$$c_2^{k+1} = \left(c_{2\max} - c_{2\min}\right)\frac{k}{k_{\max}} + c_{2\max} \quad (6)$$

Where $c_{1\min}$ and $c_{1\max}$ are the minimum and maximum values of cognitive acceleration respectively. $c_{2\min}$ and $c_{2\max}$ are the minimum and maximum values of social acceleration respectively.

3. PROBLEM FORMULATION

To achieve loss minimization, a single DG is modelled here as a generator bus [21]. The primary objective for optimization is the following function:

$$\min P_{Loss} = \sum_{k=1}^{l} Loss_k \quad (7)$$

Where, P_{Loss} is the total active power loss in the network, l is the total number of transmission branches, loss is the power loss at k branch. Additionally, $SSEV$ (Sum of Squared Error Voltages) is taken up as the second objective for minimization where voltage magnitude of k^{th} bus is denoted by $|V_k|$.

$$\min SSEV = \sum_{k=1}^{N} \left(|V_k| - 1.00\right)^2 \quad (8)$$

To optimize both the objectives the concept of weight factor is used .The combined objective CO is defined as follows:

$$\min CO = w_1 \times P_{Loss} + w_2 \times SSEV \tag{9}$$

Where w_1 and w_2 are weight factors respectively and sum of the weight factors is equal to one.

The constraints for this formulated objective are as follows:

$$\sum_{k=1}^{N} P_{Gk} = \sum_{k=1}^{N} P_{Dk} + P_L \tag{10}$$

$$|V_k|^{\min} \leq |V_k| \leq \ |V_k|^{\max} \tag{11}$$

$$P_{DG}^{\min} \leq P_{DG} \leq P_{DG}^{\max} \tag{12}$$

P_{Gk} is the total generated active power at the j^{th} bus. P_{Dk} is the total demand of active power at the j^{th} bus. N is the number of buses in the system. $|V_k|^{\max}$ and $|V_k|^{\min}$ are the maximum and minimum permissible voltage magnitudes. $P_{DG}^{\max}$ And $P_{DG}^{\min}$ are the maximum and minimum active power generation considered for the DG installation.

4. RESULTS AND DISCUSSIONS

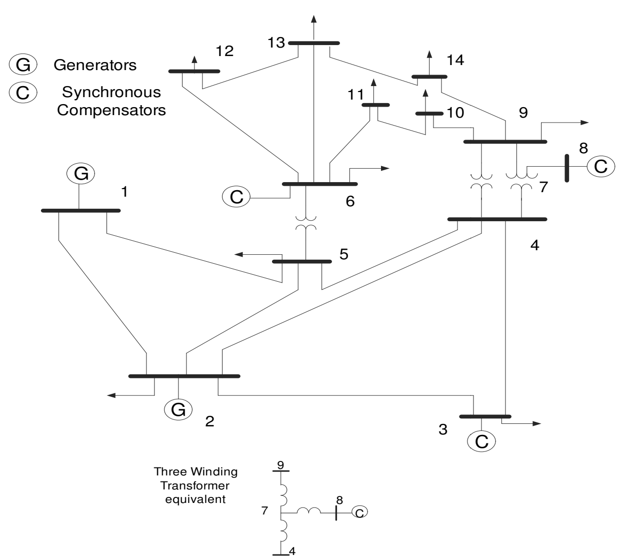

Figure 1. IEEE 14 Bus System

The standard IEEE 14 bus system as shown in Figure 1 has two generators at bus number 1 and 2. Generator at bus number 1 is assumed to be slack bus for load flow purposes. The generator at bus number 2 is of rating 40 MW. Moreover three voltage controlled buses having synchronous condensers are present at bus locations 3, 6, 8. All other buses are load buses. Out of the three transformers connected in the system one is a three winding transformer which connects bus number 4, 7, and 8, 9.The maximum and minimum limit for the active power generation of DG has been taken as 20MW and 0 MW respectively. For the inertia weight maximum and minimum a value has been taken as 0.9 and 0.4 respectively. For the TVAC PSO acceleration factors $c_{1\min}$ and $c_{2\min}$ are taken as 0.2 while $c_{1\max}$ and $c_{2\max}$ have a value of 2.5. Two cases have been considered for the optimal allocation of DG.

In the first case only real power loss is taken as the objective. Table 1 shows the optimal location and size obtained for all the three techniques along with the effect on power loss and total voltage deviation. Figure 2 shows the total bus deviation for the applied strategies compared to the condition without DG while Convergence characteristics have been shown in figure 3

Table 1. Case I: DG Location, Sizing and Effects

DG Placing Strategy	LVIW PSO	e1 PSO	TVAC PSO	No DG
DG Output (MW)	40.00000	40.00000	40.00000	-
Bus No.	3	3	3	-
Power loss (MW)	8.97428	8.97428	8.97428	13.59292
Power loss Reduction (%)	33.97827	33.97827	33.97827	-
SSEV(pu)	0.02906	0.02906	0.02906	0.02890
SSEV Reduction (%)	-0.55363	-0.55363	-0.55363	-

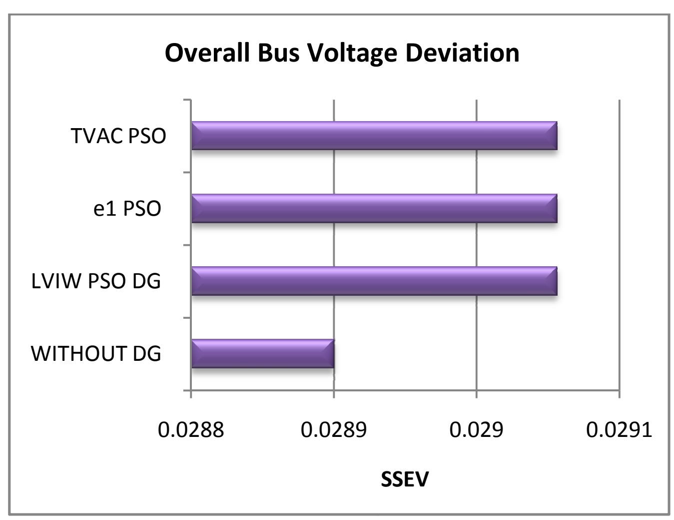

Figure 2. Case I: Overall Bus Voltage Deviation

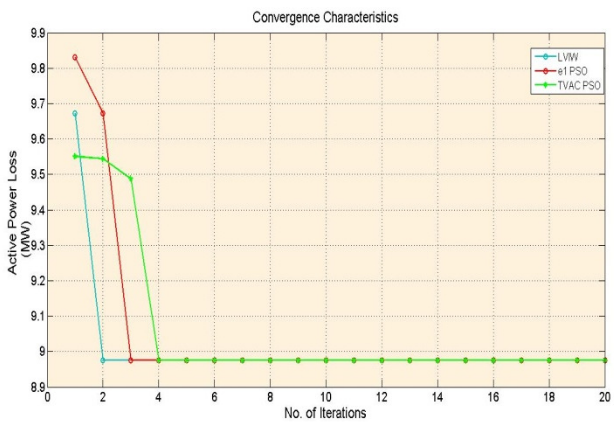

Figure 3. Case I: Convergence characteristics

Table 2. Case II: DG Location, Sizing and Effects

DG Placing Strategy	LVIW PSO	e1 PSO	TVAC PSO	No DG
DG Output (MW)	40.00000	40.00000	40.00000	-
Bus No.	7	7	7	-
Power loss (MW)	9.83054	9.83054	9.83054	13.59292
Power loss Reduction (%)	27.67896	27.67896	27.67896	-
SSEV(pu)	0.01648	0.01648	0.01648	0.02890
SSEV Reduction (%)	42.97577	42.97577	42.97577	-

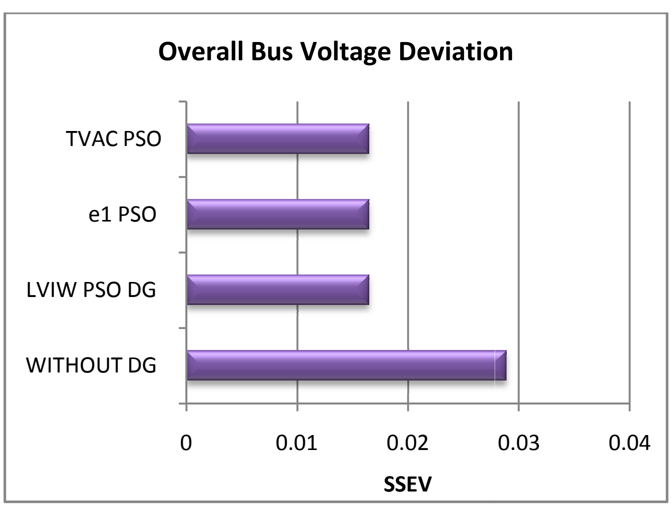

Figure 4. Case II: Overall Bus Voltage Deviation

Since Taking active power loss as the only objective has increased the overall bus voltage deviations therefore the second case is considered where SSEV is taken as the second objective to be minimized. The weight factor w_1 and w_2 taken for active power loss and SSEV are 0.5 and 0.5 respectively. Table 2 shows the results for DG location and size while figure 4 and 5 show the improvement in voltage deviations and convergence characteristics for the case II respectively.

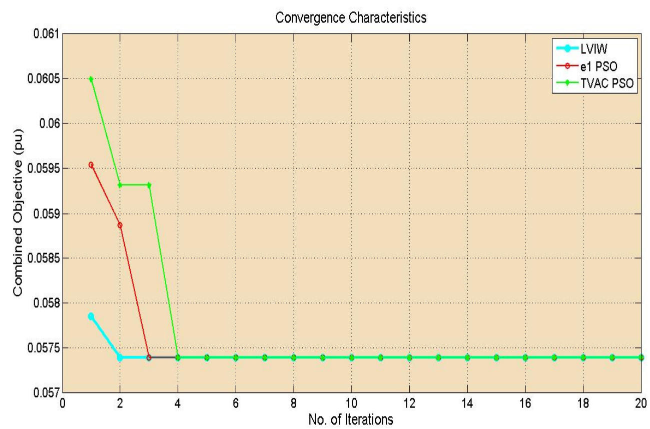

Figure 5. Case II: Convergence characteristics

5. CONCLUSION

The three PSO strategies evaluated in this paper have obtained similar optimal results for the IEEE 14 bus system. Optimal location and sizing with only loss minimization as objective reduced active power losses significantly but the total bus voltage deviation increased. This limitation was resolved by including SSEV as the second objective for minimization. The scope for further work would include implementation on larger bus systems with reactive power considerations.

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