Indian Journal of Fundamental and Applied Life Sciences ISSN: 2231– 6345 (Online)
An Open Access, Online International Journal Available at www.cibtech.org/sp.ed/jls/2015/01/jls.htm
2015 Vol.5 (S1), pp. 3321-3327/Rezaei and Ghanbari
Research Article

OPTIMIZATION OF SIZING AND PLACEMENT OF PHOTOVOLTAIC (PV) SYSTEM IN DISTRIBUTION NETWORKS CONSIDERING POWER VARIATIONS OF PV AND CONSUMERS USING DYNAMIC PARTICLE SWARM OPTIMIZATION ALGORITHM (DPSO)

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ABSTRACT
This paper presents optimization of sizing and placement of photovoltaic (PV) systems in order to utilize them in distribution systems. Output variations of such resources and consumers variations are accounted for study time to reach to actual condition. Dynamic particle swarm optimization (DPSO) is used for optimization with the aim of achieving to high convergence speed. The proposed method is validated on two sample 33 and 69-bus IEEE networks.

Keywords: *Distribution Grid-connected PV System, Optimization of Sizing and Placement, Load Variations, Produced Power Variations, Dynamic Particle Swarm Optimization Algorithm (DPSO)*

INTRODUCTION
Industrial electricity reconstruction is a situation where consumers reach to competitive resources and can select among different resources which leads to a competitive bazaar for power production resources specifically for Distribute Generations (DG) resources. Besides, there is a need for replacement of fossil fuels due to finite nature of fossil fuels and oil and environmental problem. To do this, it has to be in mind from now on to replace new resources instead of current resources and amongst these resources, PV systems is a wonderful option because it has good features like being clean and indefinite nature (Brown, 2002; Ghaebi *et al.*, 2013; Yasin and Rahman, 2006; Xi and Wenzhong, 2008).
From an economic perspective, use of this resource in the network independently would be profitable such as adjustment or postponement of capital investment in the network. Also in grid-connected conditions, other benefits would be harvested such as reducing electrical losses in the distribution system, supplying reactive power, peak shaving, reducing reserve margins, improving power quality and reliability increase(Yasin and Rahman, 2006; Xi and Wenzhong, 2008).
Determining the capacity and the placement are not independent from each other and the optimal and correct solution will be achieved only if both of these quantities are optimized together. Therefore it requires proper methods to optimize the size and location of PV systems in the distribution network, so do that the greatest losses reduction in the network is occurred by taking into account technical constraints of the problem (Lotfi and Shabanzadeh, 2012; Tamer *et al.*, 2012; Wanxing *et al.*, 2013; Dryabary *et al.*, 2010). In this paper, DPSO algorithm is used to optimize size and placement of PV system in distribution network considering output power variations of PV alongside with load variations in the time of study. To evaluate the proposed optimization method, it is validated on two sample 33 and 69bus IEEE networks with three different scenarios and the results are discussed.

Definition of optimization problem and Objective Function
Energy losses are used instead of calculating the power losses due to variations of consumed load. Therefore, objective function is considered the minimum annual energy losses according to equation (1).

$$\mathrm{O.F.} = \mathrm{Min} \quad \sum_{h=1}^{24} \mathrm{E}_{\mathrm{Loss}} \times 365 \qquad (1)$$

E_{loss} hourly energy losses (KWH)
It is assumed in the optimization for simplicity: first of all, a certain daily profile is repeated for al days of year, and second of all, connection of PV in bus is considered as negative load (PQ).

The constraints for this optimization are:
Constraint for current according to equation (2), constraint for rated line voltage range according to equation (3) where $v_i^{min} = 0.95, v_i^{max} = 1.05$ and constraint for power equilibrium according to equation (4) where P_i is injected power to the test network, P_{pvi} sum of produced active power in bus i, P_{Di} sum of required power in bus i, P_L active power losses, n number of PVs and N number of buses.

$$|I_{ij}| \leq |I_{ij}|^{max} \quad . \tag{2}$$

$$\langle V_i^{min} \leq |V_i| \leq V_i^{max} \rangle. \tag{3}$$

$$P_i + \sum_{i=1}^{n} P_{pvi} = \sum_{i=1}^{N} P_{Di} + P_L. \tag{4}$$

Voltage profile index of the distribution system consists of under-voltage or over-voltage situation in feeders of the network. Although the voltage of transmission network in terminal of generators that generates electricity is an appropriate and standard voltage profile, in the distribution feeders, which are mostly radial, and so voltage profile of the end buses of these feeders will noticeably decrease, which may have many negative impacts for consumers (Ebrahimi *et al.*, 2013).Therefore, considering the importance stated about voltage profile parameter, voltage deviation index (VDI) is determined which shows the distance from the reference voltage i.e. one per unit. Voltage deviation is a measure used to describe the amount of voltage profile that its value is calculated according to equation (5) during the day.

$$VDI = \sum_{h=1}^{24} \frac{|V_{pu,h} - 1|}{24}. \tag{5}$$

where$V_{pu.h}$ is voltage amplitude in per unit per hours.

Daily Load and PV Produced Power Variations Curve

In most previous work generally the producing power of DG and required power of load were considered constant or that one of these two is considered as variable. Therefore, to acquire an actual approximation for solution to this optimization problem, the required load is considered variable in addition to producing power of PV system.

In (Figure 1) daily load variations is considered as Demand Level Factor (DLF) that is a percentage of load consuming power. Maximum value of DLF is 13 per hours and its minimum value is 4 per hours. In the simulation program, at any hour the DLF value is multiplied by loads of test networks.

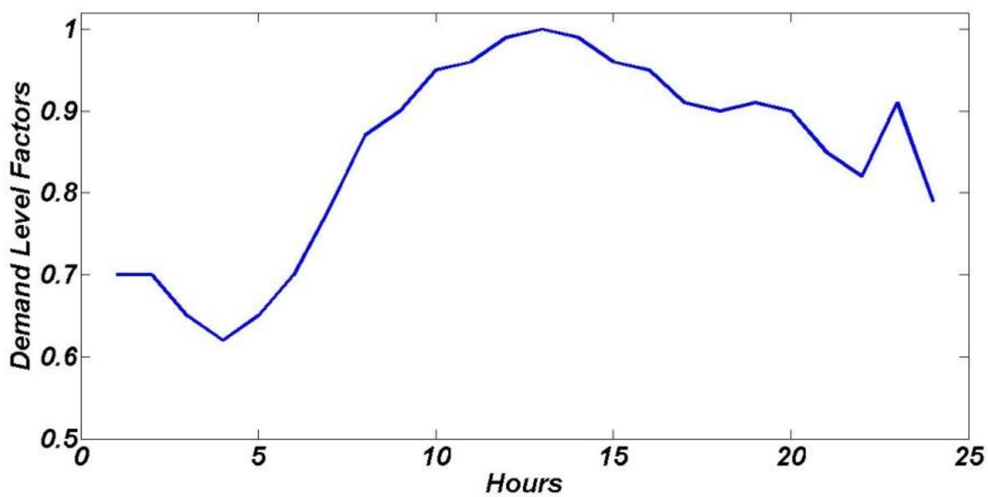

Figure 1: Daily load variations curve (Soroudi and Ehsan, 2011)

In (Figure 2) the daily producing active power variations curve of PV system is shown. In this curve power production begins at 6 and the increases, and at 12 the maximum power extracted from PV is occurred and after that the amount of power produced by PV starts to decline to find that at 19 productivity reaches to zero. In this curve produced power per hour is multiplied by 10 with respect to the reference values (Mosavi *et al.*, 2012) so as to power loss reduction can be more intuitive.

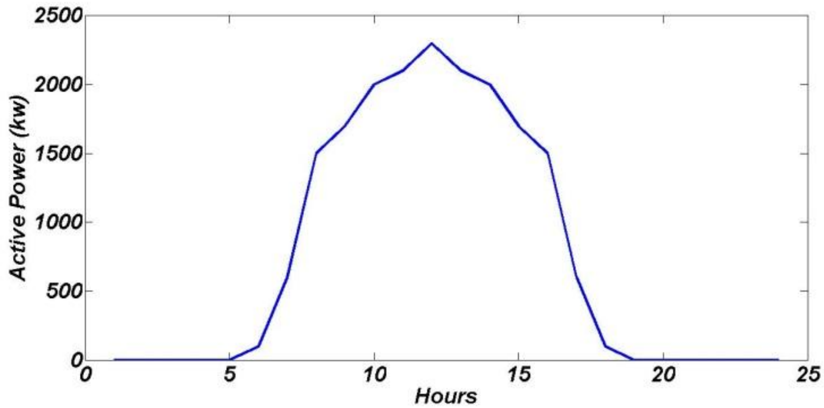

Figure 2: Daily producing active power variations curve of PV system (Soroudi and Ehsan, 2011)

Utilizing Dynamic Particle Swarm Optimization (DPSO) Algorithm Optimal Placement and Sizing of PV

4.1. Dynamic Particle Swarm Optimization (DPSO) Algorithm

Particle swarm optimization (PSO) is an accidental population-based optimization method that was first presented by Kennedy and Eberhart in 1995. PSO algorithm is inspired by social behavior of bird flocking or fish schooling. In the PSO algorithm, each solution is corresponding to a bird in the search space, considered as a particle. Each particle is consisted on three d-dimensional vectors where d is search space. For i_{th} particle we have: x^i is current location of particle, v^iparticle speed, $x^{i,best}$ best location that particle has experienced (Eberhart and Kennedy, 1995).

The algorithm is started with a random selection of location and speed for particles as initial population. Location and speed of particles are updated from previous data in each $t+1_{th}$ stage. If Z_j is j_{th} component of vector z, then the equations for location and speed of particles are as follow:

$$v_j^i[t+1] = wv_j^i[t] + c_1 r_1 (x_j^{i,best}[t] - x_j^i[t]) + c_2 r_2 (x_j^{g,best}[t] - x_j^i[t]). \qquad (6)$$

$$x_j^i[t+1] = x_j^i[t] + v_j^i[t+1]. \qquad (7)$$

In these equations, x^{gbest} is the best location found by all particles, w inertia coefficient, r_1 and r_2 random numbers in the range (0,1) with uniform distribution, and also c_1 and c_2 are learning coefficients. r_1 and r_2 makes a variety of solutions arise and this way a complete search is performed in the space. Coefficient $c_1$is learning about the experiences of each particle and coefficient $c_2$is learning experiences related to all particles that these coefficients are applied in PSO algorithm as $C_1 = C_2 = 2$.

Proper selection of inertia weight w provides a balance between global and local identification. This number is chosen constant in the conventional PSO. By changing the variable with time of this parameter, a dynamic state is added to the algorithm, which is called DPSO. In this paper, w is linearly reduced from 0.9 to 0.4during running in order to speeding up the time to convergence, and slowly continuing the path near to optimal solution (Altaf *et al.*, 2012; Hu and Eberhart, 2002).

$$w = w_{max}\left(\frac{w_{max} - w_{min}}{iter_{max}}\right).iter. \qquad (8)$$

In this relation,$iter_{max}$is maximum number of iterations, iter value of the iteration or the current production, w_{max} and w_{min} the maximum and minimum number of iterations, respectively.

Stages of Optimization

The steps for DPSO algorithm applied to the problem of optimizing the size and location of PV system in the distribution network are as follows.

Step 1) Enter the data related to lines and loads and apply buses voltage limit

Step 2) Calculate the annual energy losses in the basic state using backward/forward swept load flow. At this stage, 24 load flow programs are executed to calculate the annual energy losses and in each execution hourly energy losses are calculated considering the variations of producing power of PV and variations load and sum of energy losses in 24 hours are multiplied by 365 days of a year and after those annual energy losses are calculated.

Step 3) Location of each particle or decision variables in the optimization problem$x = \{x_{opt}, s_{opt}\}$, consists of determining the size of s_{opt} and optimum location of PV system x_{opt} with the aim of minimizing the annual energy losses.

Step 4) For each particle if the bus voltage is within the specified range objective function is calculated using the method of (stage 2), otherwise it is an inappropriate particle.

Step 5) For each particle the objective function is compared with the best personal experience. If objective function is lower than the best personal experience, the objective function is set as Pbest, and registers the location of the particle.

Step 6) Among all the particles, particles that have the least amount Pbest (the best personal experience) will be selected and introduced as Gbest.

Step 7) The speed and location of particles and inertia weight are updated using equations (6) to (8).

Step 8) If the number of iterations reaches its maximum limit, go to step 9, otherwise go to step 4.

Step 9) The best value for objective function and also the best location that is consisted of optimum placement and size of PV system with least annual energy losses are shown.

Simulation Results

In the simulation two 33 and 69-bus standard IEEE test networks are used with three different scenarios. These scenarios include the size and location optimization for one, two and three PV systems in each of the test networks. For this simulation, the initial population size of particles is considered 100 and simulation program runs 24 times a day and in each run the hourly energy losses is calculated considering the variations in producing power of PV and load variations. The sum of these hourly losses would be the amount of energy losses in 24 hours which is multiplied by 365 days of a year. In order to ensure the convergence of the objective function, simulation program is repeated 200 times for all scenarios and test networks.

Simulation Results of 33-bus Network

In (Table 1) the results of different scenarios for 33-bus network are compared with. For the first scenario of 33-busnetwork, the greatest potential recoverable power for PV is considered due to production constraints of PV. Given this limitation, bus NO. 7 is selected as the optimum location for PV installation. As seen in the table, by increasing the number of PVs for different scenarios, energy losses of 33-bus network is also reduced.

In Figure (3) the objective function for different scenarios in the first 200 iterations of the DPSO algorithm is compared with each other. It is noted from this Figure that the increase of PVs for different scenarios leads to reduction in objective function.

Table 1: Comparison of different scenarios on 33-bus network

VDI	Objective function	Total daily energy losses (MW.h)	Optimum capacity for PV (MW)	Optimum location for PV	NO. of PV
0.05154	-	3.503	-	-	-
0.02889	0.7605	0.09524	2.3	7	One
0.01956	0.6926	0.0788	1.7	29	Two
			1.275	13	
0.01773	0.668	0.06471	1.173	30	Three
			1.02	13	
			1.071	24	

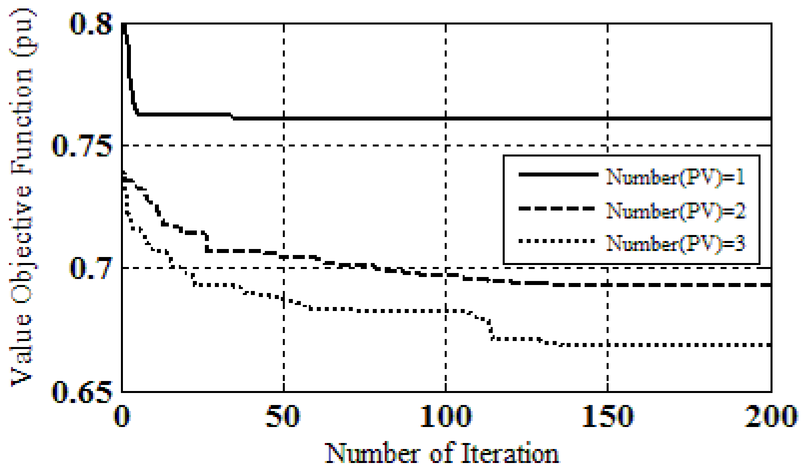

Figure 3: Comparison of objective function for different scenarios of 33-bus network

In (Figure 4) results of voltage profile for different scenarios are compared. Voltage deviation, the distance from the reference voltage (i.e. one per unit), decreases with increasing in the number of PVs for different scenarios and improves the voltage profile of buses of the network.

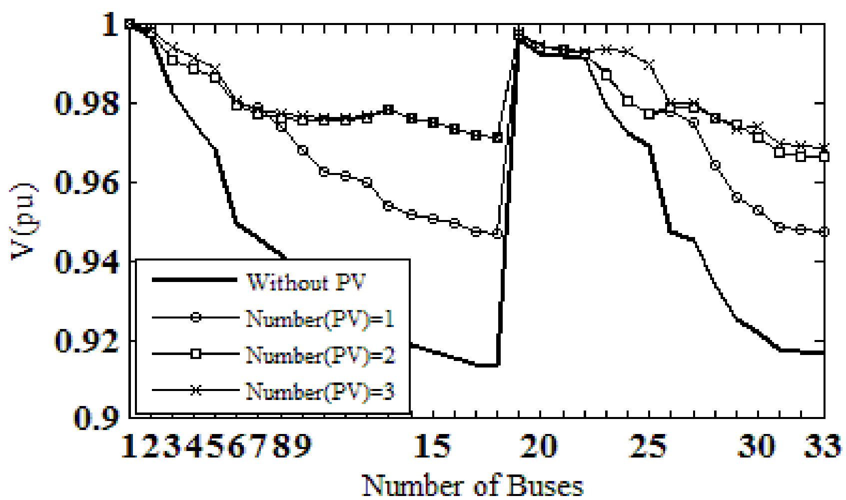

Figure 4: Comparison of the results of voltage profile improvement for different scenarios

Simulation Results of 69-bus Network

In (Table 2) results for different scenarios of 69-bus network have been compared with each other.

Table 2: Comparison of different scenarios on 69-bus network

VDI	Objective function	Total daily energy losses (MW.h)	Optimum capacity for PV (MW)	Optimum location for PV	NO. of PV
0.02662	-	3.876	-	-	-
0.01277	0.4794	2.589	2.1	61	One
0.00905	0.4649	0.06811	2.189	61	Two
			1.581	66	
0.00817	0.4577	0.06631	1.725	61	Three
			1.575	61	
			1.125	12	

For the first scenario of 69-bus network, optimal size of PV is greater than 2.3 MW but due to limitations of power produced by PV, the maximum recoverable power for PV is considered. According to distribution of load on the 69-bus network, great amount of load is seen in bus NO. 61 with respect to other buses and because of that there is great voltage drop in this bus. Therefore, to compensate for the voltage drop, this bus has been selected as the optimal location for installation of PV. In this Table, by increasing the number PV resources for different scenarios, energy losses have been decreased and this because of the fact that the production place is close to the consumers place. In (Figure 5) objective function for different scenarios of 69-bus network in the first 200 iterations of the DPSO algorithm is compared with each other. In this curve, the increase of PVs for different scenarios leads to reduction in objective function.

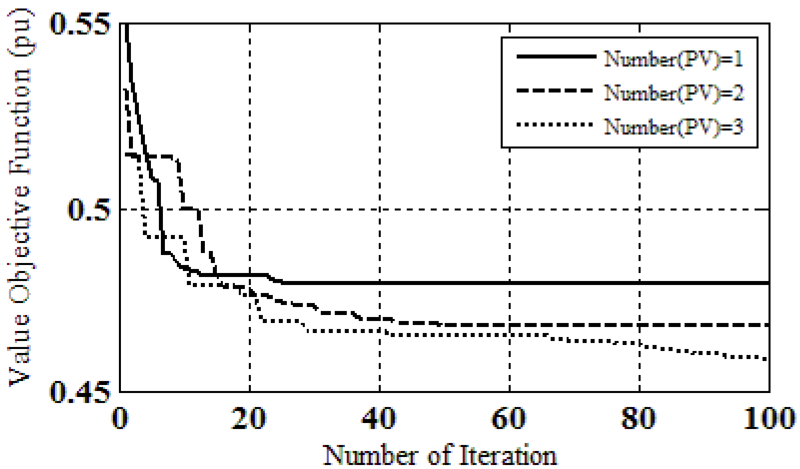

Figure 5: Comparison of objective function for different scenarios of 69-bus network

In (Figure 6) results of voltage profile for different scenarios of 69-bus network are compared. In this Figure, the increase in the number of PVs for different scenarios will improve the voltage profile results.

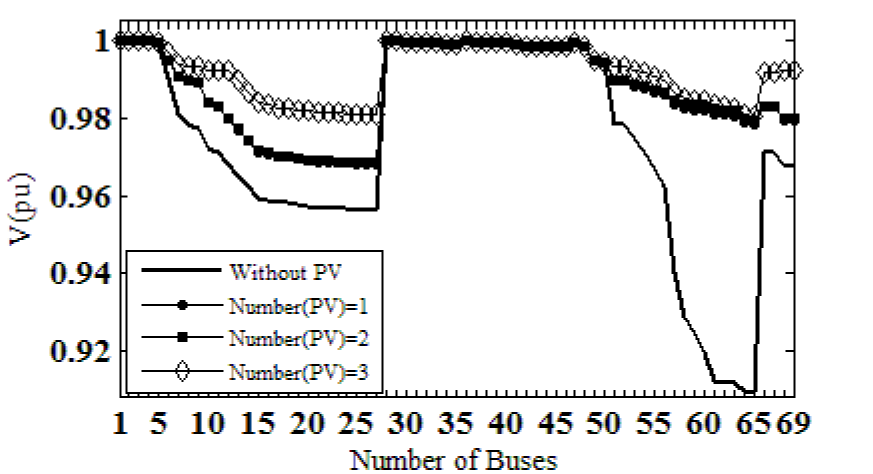

Figure 6: Comparison of the results of voltage profile improvement for different scenarios of 69-bus network

CONCLUSION

In this paper, the optimal size and placement of PV system is presented for utilizing them optimally in the distribution networks. The objective function considered is the annual energy losses. DPSO algorithm is used to reach to high speed in convergence of the problem. This program is executed on two test33 and 69-bus IEEE networks with three different scenarios. By comparing the results of the simulation before and after installation of the PV system, it was shown that voltage deviation index has improved and significant reduction in annual energy losses has happened and this reduction could be increased by increasing the number of PVs in different scenarios.

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