Optimal Access Point and Capacity of Distributed Generators in Radial Distribution Systems for Loss Minimization Including Load Models

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ABSTRACT

Distributed generation (DG) sources are predicated to play major role in distribution systems due to the demand growth for electrical energy. Location and sizing of DG sources found to be important on the system losses and voltage stability in a distribution network. This article proposes, an approach to determine the optimal sizing of multiple distributed generators in radial distribution system at unspecified power factor considering different load models. It is shown that load models can significantly affect the optimal sizing of DG units in radial distribution systems. The prior objective is to minimize network power losses hence to improve the voltage profile. Various optimization techniques are applied on the objective function. A detailed performance analysis is carried out on 38-bus radial distribution systems to demonstrate the effectiveness of the proposed techniques. Performing multiple power flow analysis on 38-bus system, the effect of DG sources on the most sensitive buses to voltage collapse is also carried out.

Keywords: distributed generation, load models, meta heuristic algorithms, optimal sizing, optimization techniques, radial distribution system.

INTRODUCTION

Distributed Generators are becoming increasingly attractive to utilities and consumers because these units produce energy close to the load, and are more efficient (less losses), easier to site and have less environmental impact. DGs are primarily installed on the distribution and sub transmission level networks. Their main technical benefits include [1]:

- Reduced line losses
- Voltage profile improvement
- Improved reliability and security

Several optimization studies have been performed to quantify these benefits and identify DG penetration threshold limits by optimally locating and sizing DGs to improve a particular objective, or a combination of objectives. Authors in [2], has been addressed a novel technique for placement of DG in power system. A Genetic Algorithm (GA) based approach for sizing and placement of DG keeping in view of system power loss minimization in different loading conditions is explained. In [3], authors suggested a multi-objective performance index based size and location of DG in distribution system with different load models. In [4], a method for placement of DG units in distribution networks has been presented. The effect of load models on DG planning in distribution system is investigated in this article. A comparative study of real and reactive power loss, real and reactive power intake at the main substation and MVA support provided by installing DG sources for different type of load models has been presented in [5]. In [6], particle swam optimization has been used as optimization technique in order to minimize performance index based multi-objective function as in [3]. The indices were reflecting the effect of multi DG insertion on real and reactive power losses of the system, the voltage profile and the distribution line loading. Different load models were taken into consideration. Authors used third party software called power system analysis toolbox (PSAT) for conducting continuation power flow to determine the effect of DG units on voltage stability limits. In this article optimal placement of multiple distributed generators under different voltage dependent load model scenarios in radial distribution systems has been presented using different Meta-Heuristic algorithms. A detailed analysis on 38-bus radial distribution system [3] for the planning of multiple DGs is made on the basis of power loss minimization and extent up to which load models can affect the location and size of the DGs. Later, a multiple power flow analysis is carried out to determine the effect of DGs on the voltage stability. The entire technique is built in through a MATLAB platform.

LOAD MODELS

Distribution system loads are characterized by voltage sensitivity, and most distribution load flow programs offer the following standard models:

- Constant Power – The real and reactive power stays constant as the voltage changes.
- Constant Current- The current stays constant as the voltage changes.
- Constant Impedance- The impedance is constant as the voltage changes.

In short feeders' power loss is of great concern and for large feeders voltage stability is great importance. Modeling all loads as constant current is a good approximation for many circuits while modeling all loads as constant power is conservative for voltage profile analysis [8, 9]. Practical voltage dependent load models, that is residential, commercial and industrial have been adopted for investigation purpose. Static load models are used to represent customer classes, specifically, constant, industrial, residential and commercial using the following relations:

$$P_i = P_0(V_i)^{np} \tag{1}$$

$$Q_i = Q_0(V_i)^{nq} \tag{2}$$

Where P_0 and Q_0 are the nominal real and reactive powers at operating point, P_i and Q_i are real and reactive power at bus *I*, V_i is the bus voltage and *np, nq* are load exponents vary with the type of load shown in Table 1 and are obtained from a reference given in [6].

Table 1. Load Type and Exponent Values

Load Type	np	nq
Constant power	0.0	0.0
Constant current	1.0	1.0
Constant impedance	2.0	2.0
Industrial	0.18	6.00
Residential	0.92	4.04
Commercial	1.51	3.40

In the practical situations, loads are mixture of different load types depending on the nature of area being supplied. Therefore a load class mix of residential, commercial and industrial load is to be investigated too where every bus of the system has different types of load connected to it. It is assumed that all loads are spot loads.

Problem Formulation

The objective is to determine combination of optimal location and size of distributed generators that minimize the total real power loss under system constraints. The operating constraints are voltage profile of the system, thermal capacity of the feeder and radial structure of the distribution system. The objective function for the minimization of real power loss is described as follows:

$$F = \text{Min}\ (P_{T,\ Loss}) \ \ldots\ldots \text{with DGs} \tag{3}$$

Subjected to:

Active Power balance constraint:

$$P_{\mathrm{DGi}} \le P_{Di} + P_{Loss} \tag{4}$$

Voltage constraints:

$$V_{imin} \le V_i \le V_{imax} \tag{5}$$

$$P_{DGimin} \le P_{DGi} \le P_{DGimax} \tag{6}$$

Reactive power generation constraints

$$Q_{DGimin} \le Q_{DGi} \le Q_{DGimax} \tag{7}$$

Where V_i is the voltage magnitude of bus *i*, V_{min} and V_{max} are bus minimum and maximum voltage limits, respectively.

Particle Swarm Optimization (PSO)

The PSO was first introduced by Kennedy and Eberhart [10]. It is an evolutionary computational model and a stochastic search technique based on swarm intelligence. PSO is developed through simulation of bird flocking in multidimensional space. Each particle's present position is realized by the previous position and present velocity information. Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pBest). This information corresponds to personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gBest) among pBests. Namely, each agent tries to modify its position using the following information:

- The current position.
- The current velocity.
- The distance between the current position and pBest.
- The distance between the current position and gBest.

Mathematically, velocities of the particles are modified according to the following Velocity updating equation:

$$V_m^{k+1} = V_m^k + C_1\, rand(pbest_m^k - X_m^k) + C_2\, rand(gbest^k - X_m^k) \tag{8}$$

Where, v_m^k is the velocity of agent i at iteration k, r1 and r2 are the random numbers between 0 and 1. X_i^k is the current position of agent i at iteration k, $pBest_i$ is the pBest of agent i, gBest is the smallest of the group. Position updating equation:

$$X_j^{k+1} = X_j^k + V_j^{k+1} \tag{9}$$

Particle swarm optimization with inertia weight approach

Search procedure by PSO deeply depends on pbests and gbest, the searching area is limited by pBest's and gBest. Using pBest's and gBest, PSO changes the current searching points successively. On the contrary, IPSO can from jump the current searching points into effective area directly by the selection me chanism. Agent positions with low evaluation values are replaced by those with high evaluation values using the selection. The replaced rate is called selection ratio (sr).

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min})}{iter_{max}} * iter \tag{10}$$

Where, w_{max} is the initial weight; w_{min} is the final weight; $iter_{max}$ is the maximum iteration number; and iter is the current iteration number.

The use of linearly decreasing inertia weight factor w has provided improved performance in all the applications. Its value is decreased linearly from about 0.9 to 0.4 during iteration cycles. Suitable selection of the inertia weight provides a balance between global exploration, local exploration, and exploitation, which results in less iteration on average to find a sufficiently optimal solution. A large inertia weight facilitates a global search while a small inertia weight facilitates a local search. By linearly decreasing the inertia weight from a relatively large value to a small value through the course of the PSO run, the PSO tends to have more global search ability at the beginning of the run while having more local search ability near the end of the run.

The velocity and position will be updated using (11) and (12).

$$V_m^{k+1} = \omega V_m^k + C_1\, rand(pbest_m^k - X_m^k) + C_2\, rand(gbest^k - X_m^k) \tag{11}$$

$$X_j^{k+1} = X_j^k + V_j^{k+1} \tag{12}$$

Harmony Search Algorithm

Harmony Search (HS) [11] is one of the evolutionary algorithms, imitating the improvisation process of musicians was proposed and has been successfully applied to many optimization problems. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques. The HS algorithm uses a stochastic random search that is based on the harmony memory considering rate and the pitch adjustment rate so that derivative information is not necessary. In the HS algorithm, musical performances seek a perfect state of harmony determined by aesthetic estimation, as the optimization algorithm seek a best state (global optimum) determined by the objective function value.

Improved Harmony Search Algorithm

HS is good at identifying the high performance regions of the solution space at a reasonable time, but gets into trouble in performing local search for numerical applications. In order to improve the performance of the HS algorithm and eliminate the drawbacks lie with fixed values of HMCR and PAR. An improved harmony search algorithm uses variable PAR and BW and an improvisation step [11]. The proposed HIS algorithm has exactly same as classical HS algorithm but with little exception at the improvisation step, where the HIS dynamically updates PAR. In this case, PAR is updated as follows:

$$PAR = PAR_{min} + \frac{PAR_{max} - PAR_{min}}{SI} * itr \quad (13)$$

Where, *PAR* is the pitch adjustment rate for generation. PAR_{min} is the minimum adjustment rate PAR_{max} is the maximum adjustment rate and *itr* is the generation number. In addition, BW is dynamically updated as follows:

$$BW = BW_{max} exp^{\left[\frac{ln\left[\frac{BW_{min}}{BW_{max}}\right]}{SI} * itr\right]} \quad (14)$$

Where, BW is the band width for generation, BW_{min}, BW_{max} is minimum, maximum bandwidth.

Global Harmony Search Algorithm

A major drawback of the IHS is that the user needs to specify the values for BW_{min} and BW_{max} which are difficult to guess and problem dependent. Inspired by the concept of swam intelligence as proposed in particle swam optimization (PSO), a new variation of HS is proposed. In a global best PSO system, a swam of individuals fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of each particle is influenced by the best position visited by itself and the position of the best particle in swam. The new approach, called global-best harmony search (GHS), modifies the pitch adjustment step of the HS such that the new harmony can mimic the best harmony in the HM. Thus, replacing the BW parameter altogether and adding a social dimension to the HS. Intuitively, this modification allows the GHS to work efficiently on both continuous and discrete problems. The GHS has exactly the same steps as the IHS with the exception that the pitch adjustments step.

Implementation of GHS, IPSO and LSFSA approaches for optimal placement of DGs in 38-bus radial distribution system including load models

In this section, methods described in previous sections i.e., IPSO, GHS and also LSFSA [9, 12] has been implemented to evaluate the optimal placement of multiple DGs in a 38-bus radial distribution system including different load models with an objective of minimizing real power loss and hence improvement in voltage profile and line loading capacity. If the system structure and topology is fixed, all the branches between the buses are known, and the evaluations of objective function depend only on location and size of the DG. The implementation of GHS and IPSO algorithms is same. Both algorithms optimize the location and size of multiple DGs with an objective of minimizing real power loss.

Implementation of LSFSA

The implementation of LSFSA starts by selecting optimal locations using loss sensitivity factors (LSF), procedure for calculation of loss sensitive factors has been already explained in previous chapter. It should be noted that, the values of loss sensitivity factors varied according to their load models but, this variation is too small so that it can be negligible. Hence, load models have least effect on loss sensitivity factors. Treating that, the locations determined by LSF method are constant for all load models. Later, the implemented SA starts by random generation of an initial solution based on size of the population. For each solution a size of DGs with respect to their pre determined locations is generated by the planner with technical justifications. A number of size pairs are randomly chosen until the total power loss of the system is near optimal for DGs penetration level. At this point objective function is evaluated for verifying all technical constraints. If one of them is violating such solution is rejected. According to SA theory, the new is population is formed comparing old and new solutions and choosing the best solution among them. This process is repeated until it leads to near optimal solution and algorithm stops according to stopping criteria. The main advantage in SA is ability to not being trapped at local minima unlike GA and PSO [12].

Computational procedure for DG placement using GHS and IPSO algorithms

Step 1: Read the system data and run the base case load flow and find total P_L. where total P_L is the total active power loss of the system.

Sep 2: Generate the locations randomly out of all buses except the source node bus.

Step 3: Place DG at generated node and vary DG capacity from minimum to maximum through optimization technique and find total P_L.

Step 4: Evaluate the objective function for different combination of locations and DG sizes.

Step 5: Store the size of DGs and locations that gives the minimum losses.

Sep 6: Start evolution procedure for new combination and evaluate the objective function and compare the solution with previous solution.

Step 7: Repeat the step 6 for optimum solution until stopping criterion reached.

Step 8: Print the final results.

Assumptions made for DG placement

a) DG is considered as negative load.

b) DG injects active and reactive power.

c) The size of the DG should be less than (or) equal to total load demand plus loss of the system (70%).

d) The node at which load is connected considered as the location for DG.

e) The source node is not considered as the location for DG placement.

f) The real and reactive power loads were modeled as being voltage dependent.

Description of parameters of IPSO and GHS algorithms

The parameter selection is simple for IPSO and GHS algorithms, the main parameters of these algorithms are population size, number of particles, cognitive parameters i.e. c_1 and c_2, inertia weight factors and maximum number of iterations for stopping criterion. An appropriate value of population size and number of iterations is related to the complexity of the problem.

And for GHS algorithm; the main parameters of these algorithms are population size, *HCMR*, *PAR* and *SI*. The values for these parameters are selected by the number of trails on the performance on the proposed method. In general these values are tuned by conducting number of trials on the performance of the proposed method. The parameter description and assigned values are furnished in Table 2 and Table 3.

Simulation results and discussions

Proposed method is tested on 38-bus radial test systems [3]. In this study, it is considered that the DG is of Type-3, unlike the situation has

Table 2. Parameter description and assigned values of IPSO

Parameter	Description	Assigned value
m	Population size	100
ω_{max}	Maximum inertia weight factor	0.9
ω_{min}	Minimum inertia weight factor	0.4
C_1, C_2	Cognitive parameters	2, 2
$Iter_{max}$	Maximum no if iterations	150
$Iter_{min}$	Maximum no if iterations	150

Table 3. Parameter description and assigned values of GHS

Parameter	Description	Value
P (HMS)	Population Size	100
HMCR	Harmony memory consideration rate	0.9
PAR_{min}	Minimum pitch adjustment rate	0.35
PAR_{max}	Maximum pitch adjustment rate	0.8
SI	Maximum number of improvisation steps	200

commonly been used in the literature. The maximum number of DGs is restricted to three in this study, but the developed technique can handle any number of DGs. In fact, the number of DGs is purely dependent on size of the test system, because inserting as many DGs in the system sometimes may result higher power loss. The system is radial distribution system having 37 branches and 38 buses with connected real and reactive power load are 3.607 p.u 1.523 p.u and the real and reactive power losses in the system is about 8% of the total load. System data is given in [3]. The proposed method was applied to the system to determine the optimal placement of multiple DGs such that the objective function is minimized. Maximum penetration of DG is considered in a range of (0-0.63) p.u. for this test system. The objective function optimally minimized under different load models for the test system for GHS, IPSO and LSFSA algorithms is shown in Figure 1, Figure 2 and Figure 3 respectively. As shown in Figure 1, Figure 2 and Figure 3, the objective function converges to global optimum solution within a reasonable computing time on an INTEL Core 2 Duo processor; 2.93GHz with 1.96 GB of RAM. From Table 4, the computational time required by LSFSA is less than GHS and IPSO algorithms because the reason is relieving SA from finding optimal locations so that reducing the lot of search space.

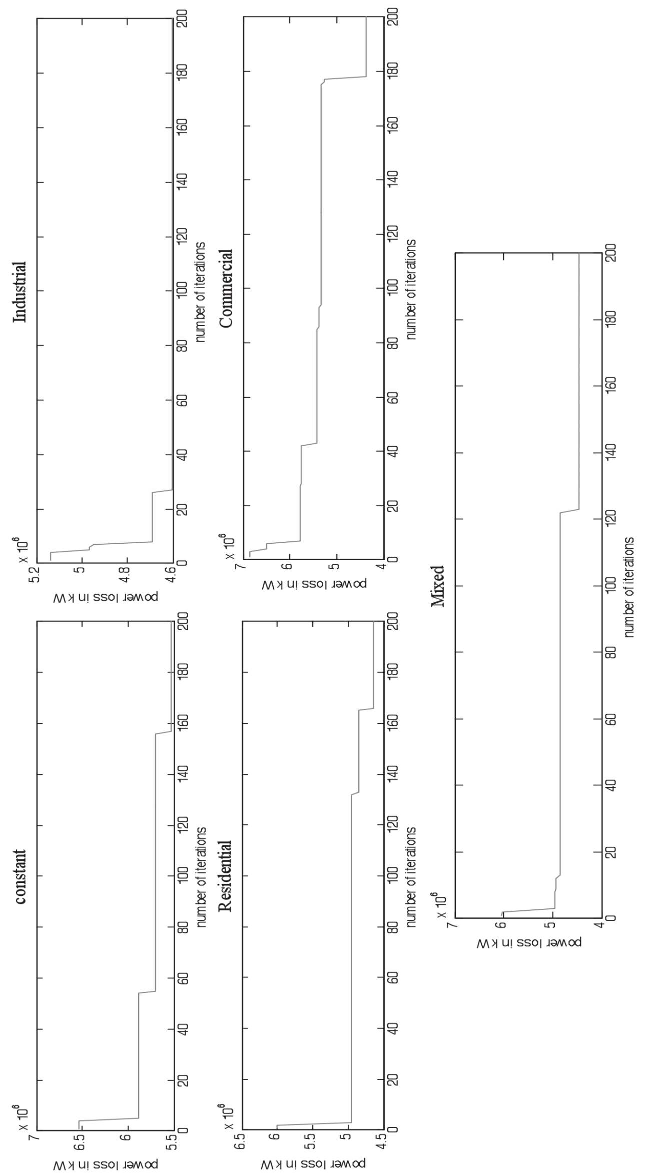

Figure 1. Convergence characteristics of GHS algorithm with different load models

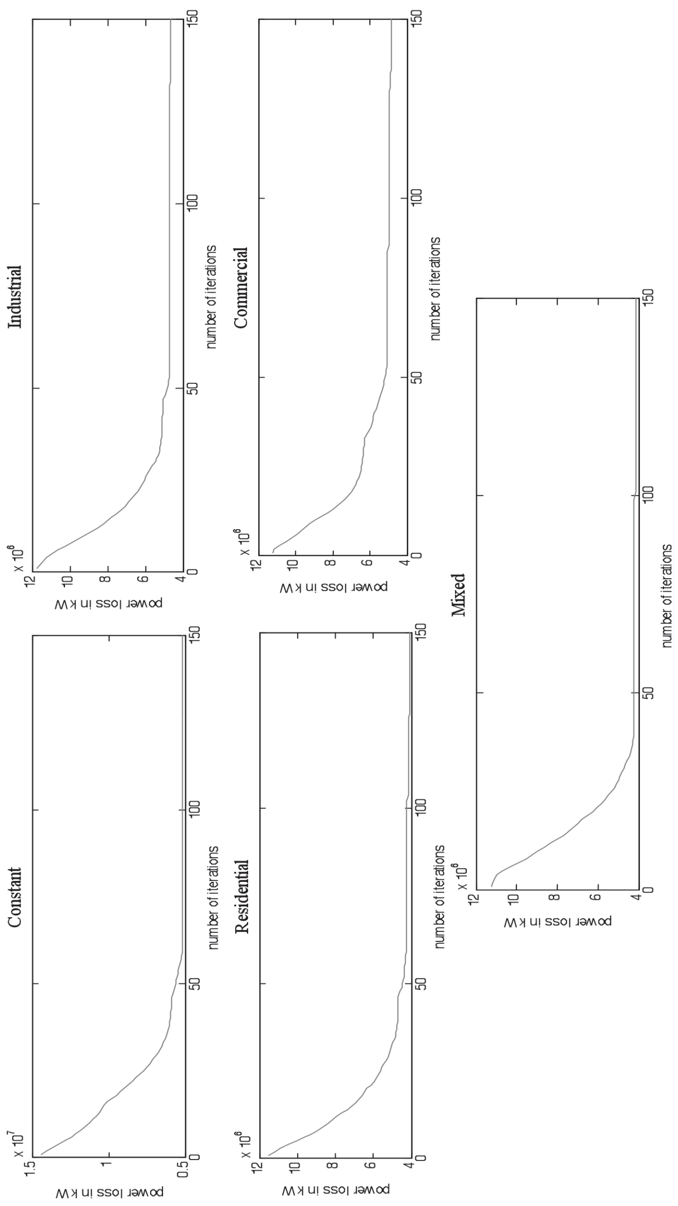

Figure 2. Convergence characteristics of IPSO algorithm with different load models

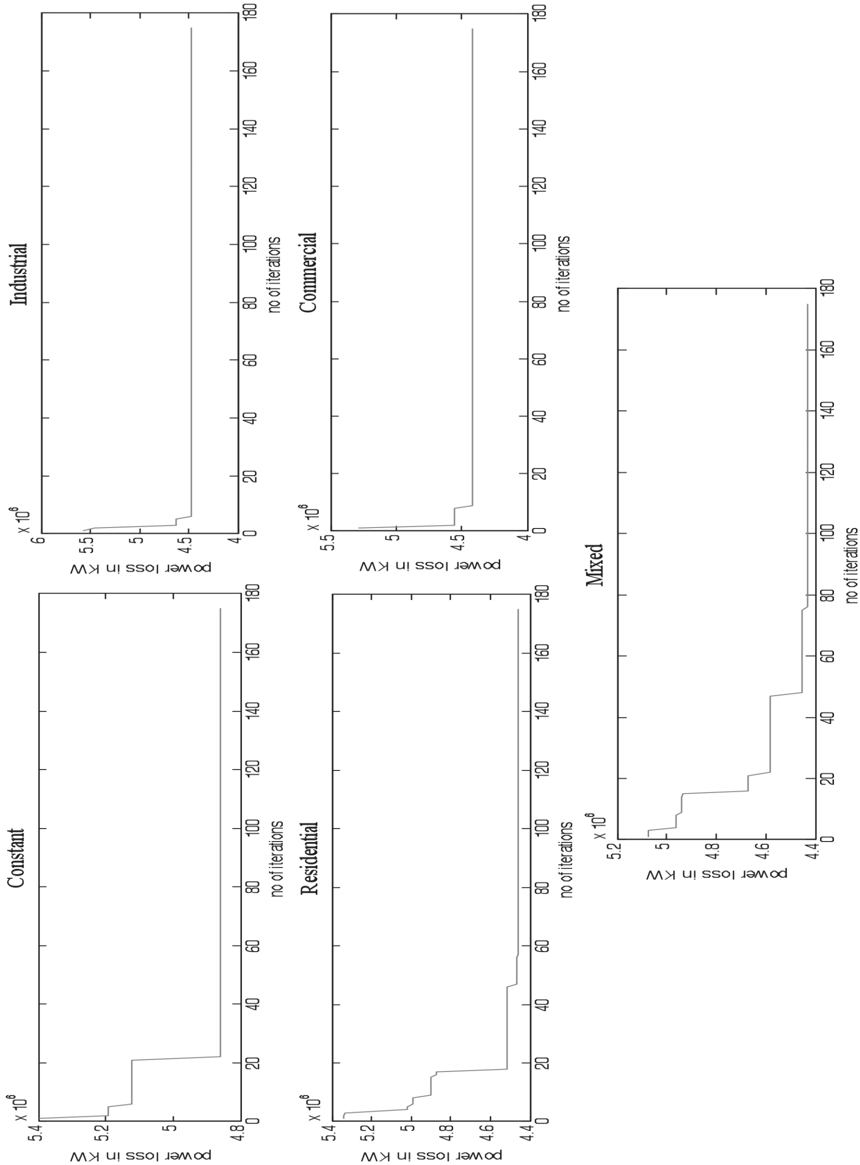

Figure 3. Convergence characteristics of LSFSA algorithm with different load models

It is observed that in case of constant and industrial load models LSFSA has given good results, in case of residential and mixed load models IPSO has given better results and in case of commercial load model GHS algorithm has given best results than other methods. The time taken for IPSO algorithm is relatively large for all load models. All evaluations were carried out with self developed MATLAB codes. The developed code has an ability to find optimal sizing of any number of DGs of different types. The size of each DG unit with respect to their location under different load models is given in Table 4. Table 4 shows that the optimal sizing and placement of DG units in the system caused significant reduction in real power loss was in the range of 66% up to 76%. The effect of inserting DG units in the system on the voltage profile is shown in Figure 4, Figure 5 and Figure 6 for GHS, IPSO and LSFSA algorithms respectively for all load models.

Summary of voltage profile analysis results for GHS, IPSO and LSFSA algorithms has been provided in Table 5, which shows significant improvement in the voltage profile for all load models.

Voltage stability analyses for 38-bus RDS considering load models

In this section, impact of optimal location and optimal size of DGs on voltage stability of the 38-bus radial distribution systems including different load models with type-3 DGs only has been analyzed with the help of voltage stability indicator developed in [13] and continuous power plow, each node or bus stability index (S.I) values are calculated, and the bus which has minimum stability index value is recorded as the critical bus, which is most sensitive to voltage collapse. Continuous power flow program for the test system with and without DGs has been developed, in which each node or bus power is multiplied by a load factor (λ) as $P = \lambda P_b$ and then P-V curves has been recorded. Critical bus analysis has been carried out and the results were presented in Table 6.In Table 6 summary of sensitive bus analysis for 38-bus systems with type 3 DG has been provided. Figure 7, 8, 9, 10 and Figure 11 shows the variation of critical bus stability index value and voltage magnitude with the increase of the system load for 38-bus system. Form Figure 7 to 11, it is observed that the critical bus index value decreases with increase of the system load, and its value is close to zero when system's total power closes to the critical loading point. And it is worth noting point that the integration of DG in to the system would increases the level of stability index and magnitude of voltage for all load models.

Table 4. Results summary of GHS, IPSO and LSFSA algorithms

Load Type	Method	Location	P_{DG} (p.u)	Q_{DG} (p.u)	P_{LOSS} (WODG) kW	P_{LOSS} (WDG) kW	% Reduction in loss	Comp. time in (s)
Constant	GHS	31	0.4817	0.2781	20135.01	5529.7	72.54	12.8
		15	0.3926	0.2267				
		28	0.3952	0.2282				
	IPSO	14	0.4411	0.2547		5174.6	74.36	14.3
		7	0.4248	0.2453				
		32	0.5288	0.3053				
	LSFSA	28	0.4927	0.2844		4895.5	75.68	9.3
		12	0.4859	0.2805				
		30	0.4997	0.2885				
Industrial	GHS	14	0.4334	0.2503	16069.08	4604.2	71.34	15.0
		33	0.4748	0.2742				
		11	0.5320	0.3072				
	IPSO	33	0.5018	0.2897		4650.6	71.05	16.6
		9	0.4882	0.2819				
		17	0.3959	0.2286				
	LSFSA	28	0.4981	0.2876		4419.9	72.49	10.1
		12	0.4953	0.2860				
		30	0.4884	0.2820				
Residential	GHS	14	0.4783	0.2762	15893.55	4639.4	70.81	13.6
		26	0.5098	0.2944				
		31	0.4311	0.2489				
	IPSO	31	0.6212	0.3587		4063.5	74.43	16.4
		13	0.4176	0.2411				
		8	0.4792	0.2767				
	LSFSA	28	0.4865	0.2809		4475.0	71.84	9.7
		12	0.4858	0.2805				
		30	0.5019	0.2898				
Commercial	GHS	31	0.4961	0.2865	15498.95	4303.9	72.23	13.3
		6	0.4711	0.2720				
		15	0.5297	0.3059				
	IPSO	30	0.4211	0.2431		4814.2	68.90	15.0
		14	0.4985	0.2879				
		29	0.3811	0.2200				
	LSFSA	28	0.4993	0.2883		4415.2	71.51	9.8
		12	0.4896	0.2827				
		30	0.4982	0.2877				
Mixed	GHS	14	0.4879	0.2817	15818.11	4462.0	71.79	13.4
		28	0.5245	0.3028				
		32	0.3836	0.2215				
	IPSO	15	0.4778	0.2759		4133.5	73.86	14.8
		30	0.4218	0.2435				
		31	0.5371	0.3101				
	LSFSA	28	0.5014	0.2895		4424.9	72.03	9.7
		12	0.4912	0.2836				
		30	0.4951	0.2858				

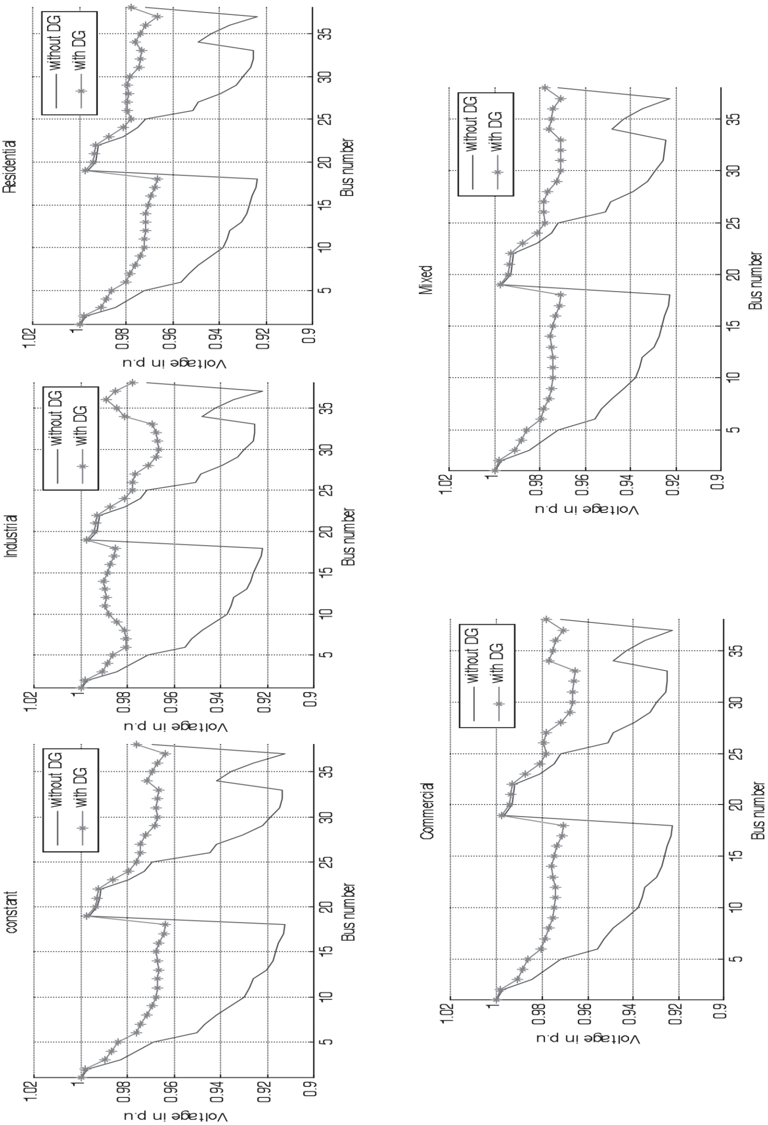

Figure 4. Voltage profile correction with GHS under different load models

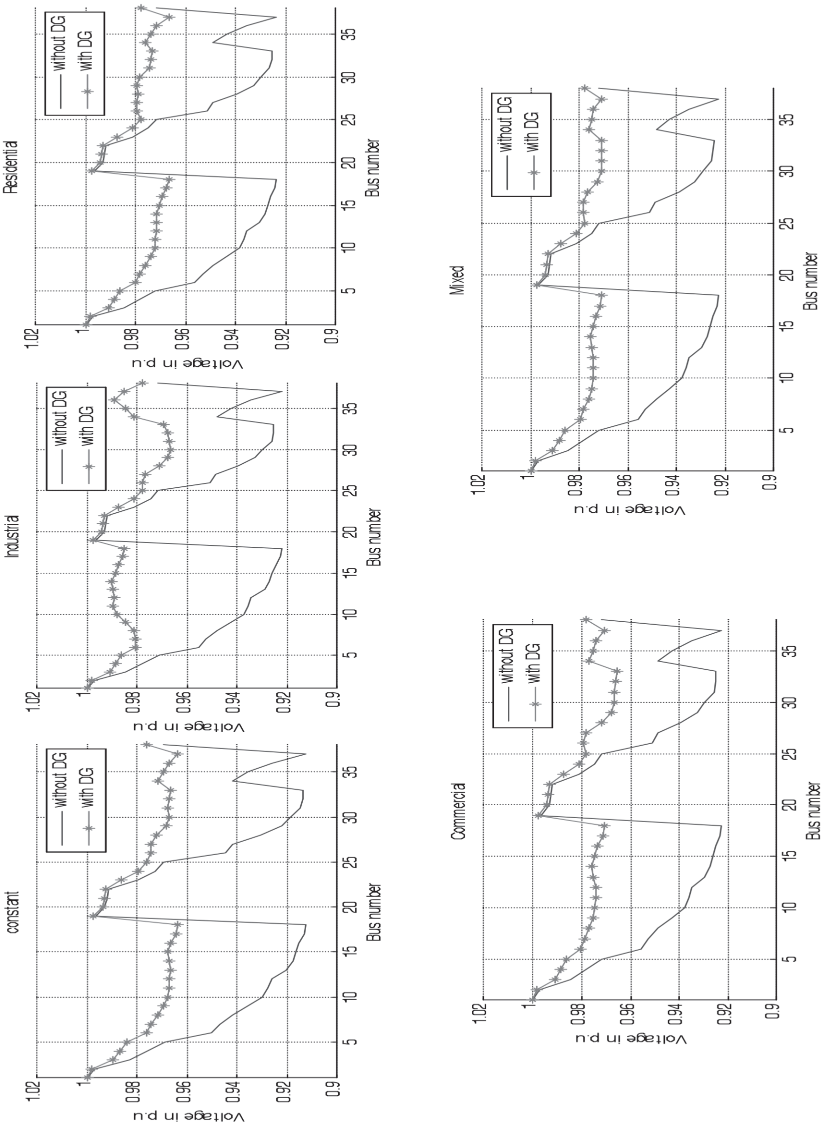

Figure 5. Voltage profile correction with IPSO under different load models

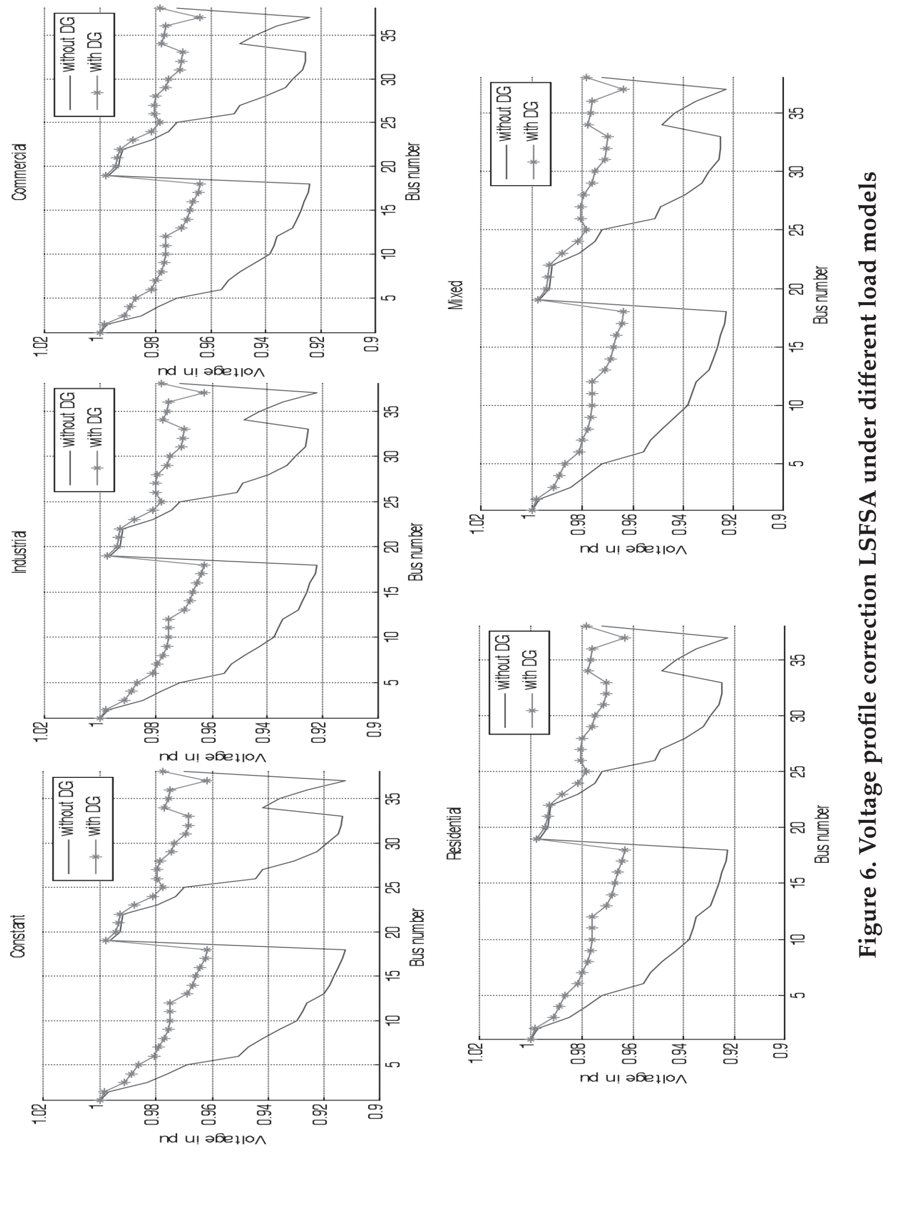

Figure 6. Voltage profile correction LSFSA under different load models

Table 5. Summary of voltage profile analysis

Load Type	Method	V_{min} (p.u) WODG	Bus Number	V_{min} (p.u) WDG
Constant	GHS	0.9125	17	0.9641
	IPSO		29	0.9643
	LSFSA		18	0.9617
Industrial	GHS	0.9224	30	0.9667
	IPSO		18	0.9663
	LSFSA		18	0.9631
Residential	GHS	0.9228	18	0.9658
	IPSO		18	0.9711
	LSFSA		18	0.9633
Commercial	GHS	0.9239	33	0.9670
	IPSO		33	0.9661
	LSFSA		18	0.9638
Mixed	GHS	0.9230	30	0.9708
	IPSO		32	0.9735
	LSFSA		18	0.9639

CONCLUSIONS

In this article, optimal placement of distributed generators in radial distribution systems including load models has been presented. The proposed algorithms were applied to 38-bus radial distribution systems. Obtained results of all algorithms were compared. As summarized in Table 6, all algorithms have been shown an improved performance and gave better results. The results showed that the proposed algorithms were simple in nature and capable of solving optimal placement of multiple DGs very quickly (less computation time). The results clarified the efficiency of those methods for the improvement of voltage profile, loss reduction. Proposed methods can efficiently handle the optimal DG placement problem in distribution system including load models. Distributed Generator affects the system voltage level through the integration point due to their power injection. They improve the system voltage profile and support the voltage stability. This allows the distribution system to withstand higher loading condition and defers the construction or up gradation of new transmission and distribution infrastructures. Since the location of DG has a major impact on the ability to support voltage stability. Results shown that optimal placement of DG would definitely improve the level of voltage stability.

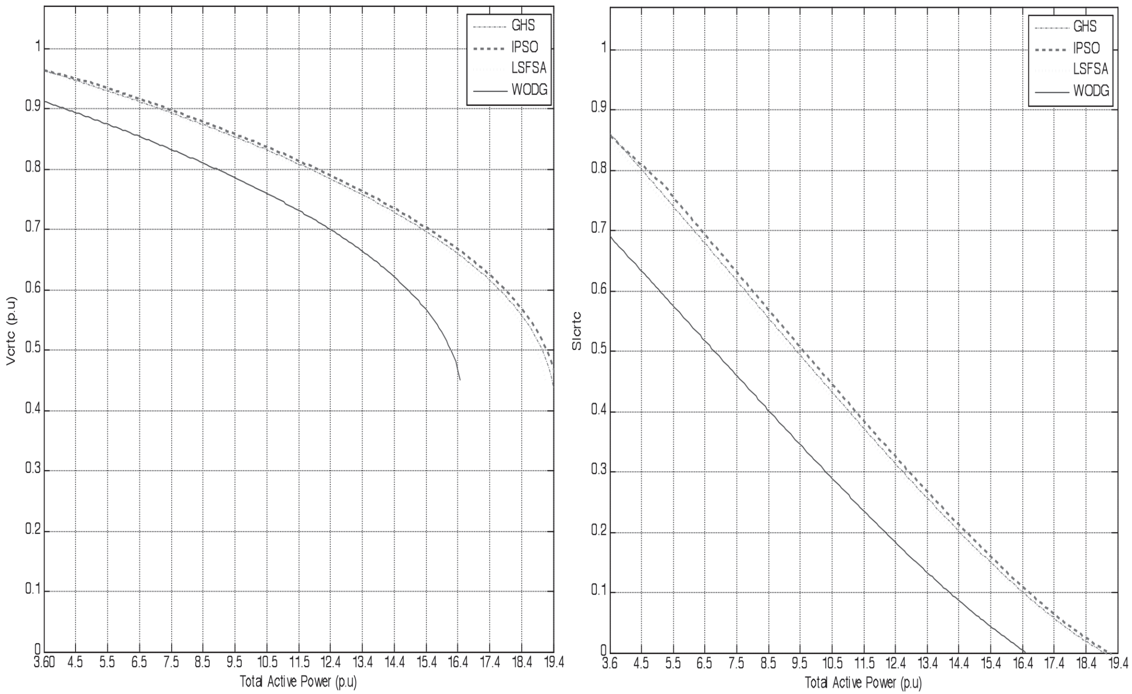

Figure 7. Variation of stability index and critical bus voltage magnitude with increasing load power with type3 DG for 38-bus RDS of constant load model

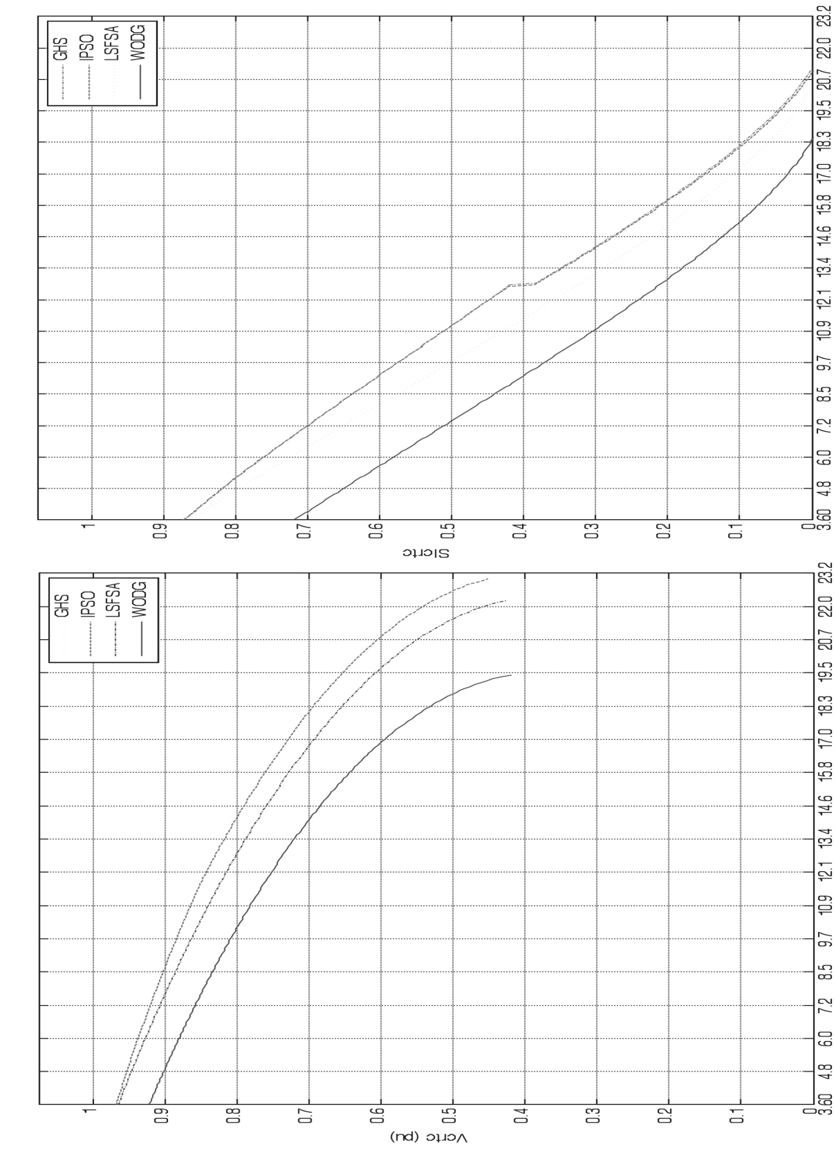

Figure 8. Variation of stability index and critical bus voltage magnitude with increasing load power with type3 DG for 38-bus RDS of industrial load model

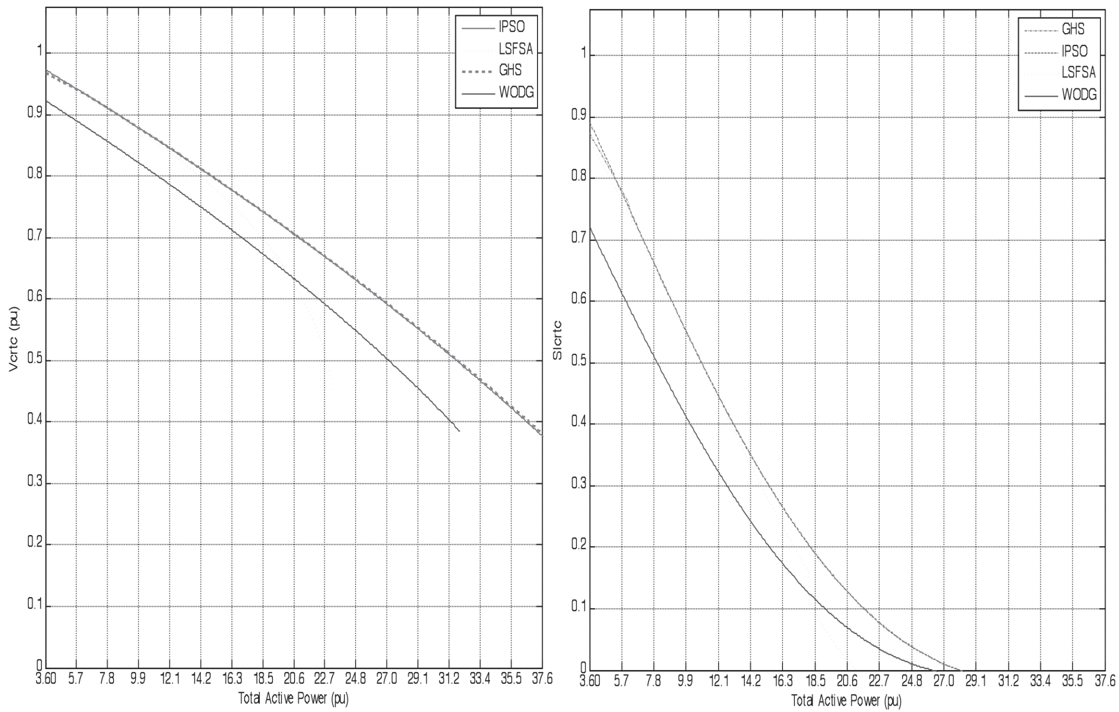

Figure 9. Variation of stability index and critical bus voltage magnitude with increasing load power with type3 DG for 38-bus RDS of residential load model

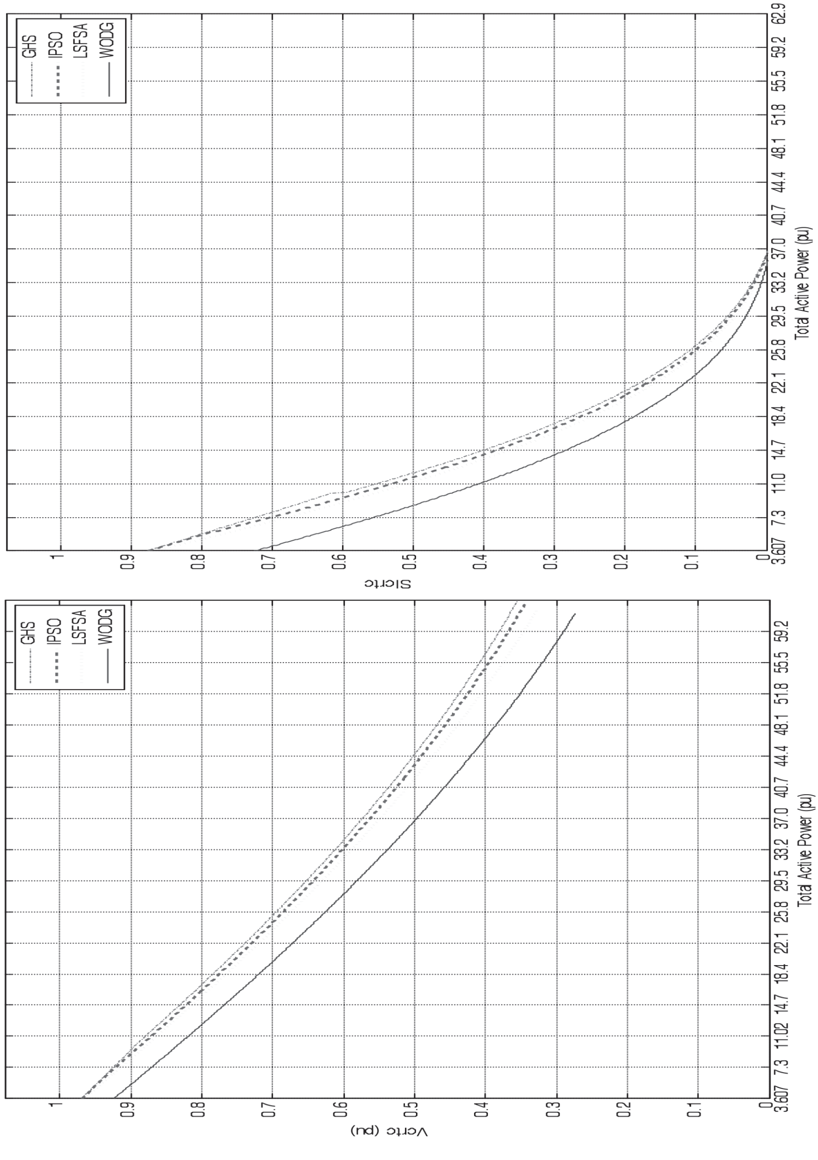

Figure 10. Variation of stability index and critical bus voltage magnitude with increasing load power with type3 DG for 38-bus RDS of commercial load model

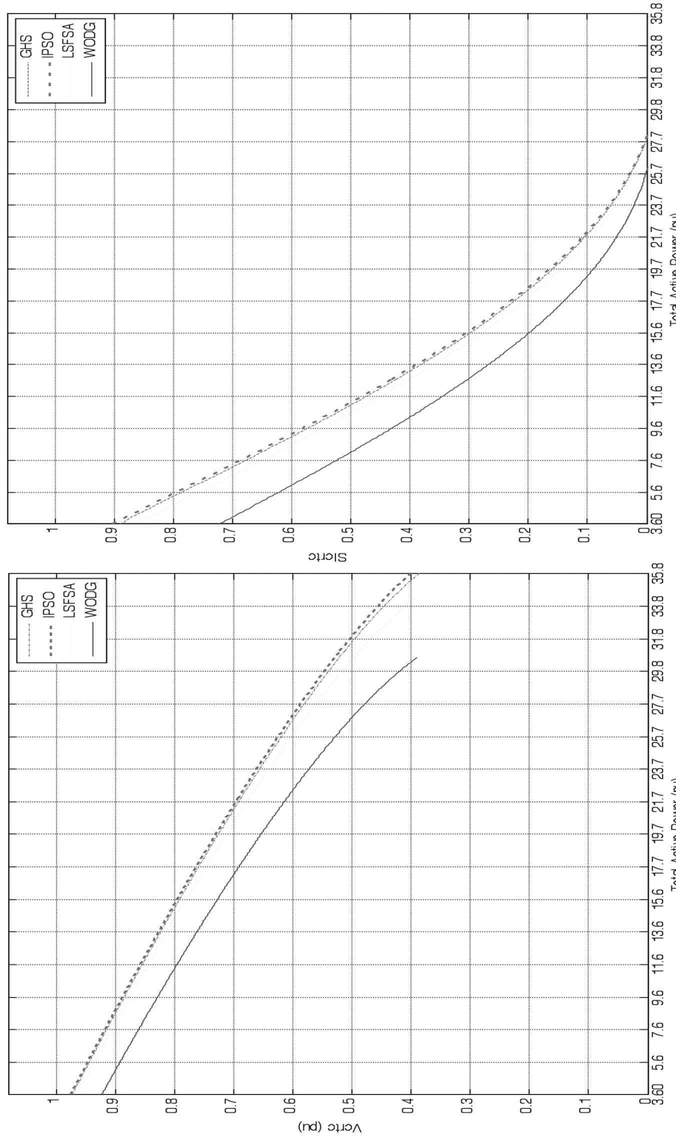

Figure 11. Variation of stability index and critical bus voltage magnitude with increasing load power with type3 DG for 38-bus RDS of mixed load model

Table 6. Summary of critical bus analysis for 38-bus RDS with Type-3 DGs

Constant			
Method	Bus No.	Voltage (p.u)	Stability Index (SI)
Without DG	18	0.9125	0.6950
GHS	18	0.9640	0.8614
LSFSA	18	0.9610	0.8505
IPSO	18	0.9642	0.8614
Industrial			
Method	Bus No.	Voltage (p.u)	Stability Index (SI)
Without DG	18	0.9223	0.7189
GHS	18	0.9681	0.8719
LSFSA	18	0.9652	0.8650
IPSO	18	0.9680	0.8719
Residential			
Method	Bus No.	Voltage (p.u)	Stability Index (SI)
Without DG	18	0.9227	0.7213
GHS	18	0.9730	0.8901
LSFSA	18	0.9645	0.8638
IPSO	18	0.9730	0.8901
Commercial			
Method	Bus No.	Voltage (p.u)	Stability Index (SI)
Without DG	18	0.9239	0.7254
GHS	18	0.9695	0.8770
LSFSA	18	0.9655	0.8665
IPSO	18	0.9683	0.8771
Mixed			
Method	Bus No.	Voltage (p.u)	Stability Index (SI)
Without DG	18	0.9230	0.7222
GHS	18	0.9728	0.9040
LSFSA	18	0.9653	0.8656
IPSO	18	0.9728	0.9040

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