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Optimal placement of multi-distributed generation units including different load models using particle swarm optimization

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ABSTRACT

This paper proposes a multi-objective index-based approach for optimally determining the size and location of multi-distributed generation (multi-DG) units in distribution systems with different load models. It is shown that the load models can significantly affect the optimal location and sizing of DG resources in distribution systems. The proposed multi-objective function to be optimized includes a short circuit level parameter to represent the protective device requirements. The proposed function also considers a wide range of technical issues such as active and reactive power losses of the system, the voltage profile, the line loading, and the Mega Volt Ampere (MVA) intake by the grid. An optimization technique based on particle swarm optimization (PSO) is introduced. An analysis of the continuation power flow to determine the effect of DG units on the most sensitive buses to voltage collapse is carried out. The proposed algorithm is tested using a 38-bus radial system and an IEEE 30-bus meshed system. The results show the effectiveness of the proposed algorithm.

1. Introduction

The newly introduced distributed or decentralized generation units connected to local distribution systems are not dispatchable by a central operator, but they can have a significant impact on the power flow, voltage profile, stability, continuity, short circuit level, and quality of power supply for customers and electricity suppliers. Optimization techniques should be employed for deregulation of the power industry, allowing for the best allocation of the distributed generation (DG) units [1].

There are many approaches for deciding the optimum sizing and siting of DG units in distribution systems. In [2–4], the optimum locations of DG in the distribution network were determined. These works aimed to study several factors related to the network and the DG unit itself such as the overall system efficiency, system reliability, voltage profile, load variation, network losses, and the DG loss adjustment factors. In [5], the optimal sizing of a small isolated power system that contains renewable and/or conventional energy technologies was determined to minimize the system's energy cost.

In [6–12], the authors succeeded in merging both the DG location and size in one optimization problem. The main factors included in the optimization problem were investment cost, operation cost, network configuration, active and reactive power costs, heat and power requirements, voltage profile, and system losses. Several methods have been adopted to solve such an optimization problem. Some of them rely on conventional optimization methods and others use artificial intelligence-based optimization methods.

In some research, the optimum location and size of a single DG unit is determined [6,13–17], while in others the optimum locations and sizes of multiple DG units are determined [9,18–20].

In [4], a mixed integer linear program was formulated to solve the optimization problem. The objective was to optimally determine the DG plant mix on a network section. However, that required dealing with the power system approximately as a linear system, which is not the real case. In [5], a tabu search (TS)-based method was proposed to find the optimal solution of their problem, but the TS is known to be time-consuming algorithm in addition to its ability to be trapped in a local minimum. In [6–8], a particle swarm optimization (PSO) algorithm was introduced to determine the optimum size and location of a single DG unit to minimize the real power losses of the system. The problem was formulated as one of constrained mixed integer nonlinear programming, with the location being discrete and the size being continuous. However, the real power loss of the system was the only aspect considered in this work, while trying to optimally find the size of only one DG unit to be placed. In [9], different scenarios were suggested for optimum distribution planning. One of these scenarios was to place multiple DG units at certain locations pre-determined by the Electric Utility Distribution Companies (DISCOs) aiming to improve their profiles and minimize the investment risk. In [10], a genetic algorithm (GA)-based technique together with optimal

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power flow (OPF) calculations was used to determine the optimum size and location of DG units installed to the system in order to minimize the cost of active and reactive power generation. Just as the case of using a TS, the GA is a time-consuming method, although it can reach global or near-global solutions. In [11], the primal–dual interior-point optimization procedure was employed to identify the optimal location and size of DG units introduced to the system. The optimization procedure was formulated using only voltage profile indices, and then the effect of introducing DG units on the line losses was studied. In [12], a sensitivity analysis of power losses in terms of DG size, location, and operating point was performed to find the optimal size and location of DG units. In [13], an optimization technique based on a GA was used. The objective was to minimize a multi-objective performance index function. The indices were reflecting the effect of DG insertion on the real and reactive power losses of the system, the voltage profile, and the distribution line loading. Different load models were taken into consideration. In [15], an analytical method to determine the optimum location–size pair of a DG unit was proposed in order to minimize only the line losses of the power system. In [16], an exhaustive search algorithm was used to optimally locate and size a single DG unit in a meshed system, taking into consideration the system losses and short circuit level. In [17], the placement of a single DG unit with certain size was considered. The impact of placing such a unit at each node of the system was studied. The system indices representing the system losses, voltage profile, line loading capacity, and short circuit level were taken into consideration. As for placing multiple DG units, many research papers have been presented. In [18], a GA-based algorithm was used to determine the optimum size and location of multiple DG units to minimize the system losses and the power supplied by the main grid, taking into account the limits of the voltage at each node of the system. Power–voltage (P–V) curves have been traditionally used as graphical tools for studying the voltage stability in electric power systems. The overall impact of a DG unit on voltage stability is positive. This is due to the improved voltage profiles as well as decreased reactive power losses. In [19], DG units were placed at the most sensitive buses to voltage collapse. The units had the same capacity and were placed one by one. In [20,21], a GA-based algorithm was presented to locate multiple DG units to minimize a cost function including the system losses and service interruption costs. In [22], an adaptive-weight PSO (APSO) algorithm was used to place multiple DG units, but the objective was to minimize only the real power loss of the system. In [23], a combination of PSO and genetic algorithms was used to find the optimal location of a fixed number of DG units with specific total capacity such that the real power loss of the system is minimized and the operational constraints of the system are satisfied. In [24], three types of multi-DG unit were optimally placed, also to minimize the real power loss of the system using PSO.

All the mentioned research placed DG units with unity power factor. In [25], PSO was used to place multiple DG units with non-unity power factor, but the objective was to minimize only the real power loss of the system.

In this paper, all factors, indices, and objective functions are gathered to form a multi-objective optimization problem. The objective function is formed by combining indices showing the effect of DG presence on the real and reactive power losses, voltage profile, and MVA capacity of conductors, in addition to the short circuit level of the system. The multiple DG units are assumed to have unspecified power factor. The placement procedure is carried out taking into consideration different load models. The optimization problem is solved using the particle swarm optimization (PSO) technique, which is capable of finding a global or near-global optimum solution in addition to having a very short simulation time, in the range of a few seconds, compared with other artificial intelligence techniques such as the genetic algorithm (GA), tabu search (TS), or simulated annealing (SA), which require longer simulation times, in the range of several minutes. Although the GA, for example, is very efficient in finding a global or near-global optimal solution of the problem, it requires a very long run time, which may be several minutes or even several hours, depending on the size of the system under study [26]. PSO, first introduced by Kennedy and Eberhart, is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and it has been found to be robust in solving continuous nonlinear optimization problems [27,28]. The PSO technique can generate a high-quality solution and stable convergence characteristic within a shorter calculation time than other stochastic methods [29]. PSO has been motivated by the behavior of organisms, such as fish schooling and bird flocking. Generally, PSO is characterized as a simple concept, easy to implement, and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities.

Table 1
Load types and exponent values.

Load type	α	β
Constant	0	0
Industrial load	0.18	6
Residential load	0.92	4.04
Commercial load	1.51	3.4

The proposed algorithm was applied to two test systems, a radial 38-bus system [13] and a mesh IEEE 30-bus system [30]. The algorithm is built using MATLAB script functions. A continuation power flow is carried out to determine the effect of DG units on the voltage stability limits using the Power System Analysis Toolbox (PSAT) [31].

2. Load models and impact indices

The optimal allocation and sizing of DG units under different voltage-dependent load model scenarios are to be investigated. Practical voltage-dependent load models, i.e., residential, industrial, and commercial, have been adopted for investigations. The load models can be mathematically expressed as [13]

$$P_i = P_{oi} V_i^{\alpha} \quad (1)$$

$$Q_i = Q_{oi} V_i^{\beta}, \quad (2)$$

where P_i and Q_i are real and reactive power at bus i, P_{oi} and Q_{oi} are the active and reactive operating points at bus i, V_i is the voltage at bus i, and α and β are real and reactive power exponents. In the constant power model conventionally used in power flow studies, $\alpha = \beta = 0$ is assumed. The values of the real and reactive exponents used in the present work for industrial, residential, and commercial loads are given in Table 1 [13,14].

In practical situations, loads are mixtures of different load types, depending on the nature of the area being supplied. Therefore, a load class mix of residential, industrial, and commercial loads is to be investigated too, in which every bus of the system has a different type of load connected to it.

There are various technical issues that need to be addressed when considering the presence of distributed generators in distribution systems. Ochoa et al. [17] computed several indices in order to describe the impacts on a distribution system due to the presence of distributed generation during maximum power generation. The studies are presented for each of these load models. MVA_{sys} is the total MVA intake by the DISCO, and it is defined as

$$MVA_{sys} = [(P_{intake} + P_{DG})^2 + (Q_{intake})^2]^{1/2}, \quad (3)$$

where P_{intake} and Q_{intake} are the real and reactive power intakes from the grid and P_{DG} is the power generated by the DG units.

In this work, several indices will be computed in order to describe the effect of load models due to the presence of DG. These indices are defined as follows.

(1) *Real and reactive power loss indices (ILP and ILQ)*: The real and reactive power loss indices are defined as

$$\text{ILP} = [P_{\text{LDG}}]/[P_L] \tag{4}$$

$$\text{ILQ} = [Q_{\text{LDG}}]/[Q_L], \tag{5}$$

where P_{LDG} and Q_{LDG} are the real and reactive power losses of the distribution system after the inclusion of DG. P_L and Q_L are the real and reactive system losses without DG in the distribution system.

(2) *Voltage profile index (IVD)*: One of the advantages of proper location and size of the DG is the improvement in voltage profile. This index penalizes a size–location pair which gives higher voltage deviations from the nominal value (V_{nom}). In this way, the closer the index is to zero better is the network performance. The IVD can be defined as

$$\text{IVD} = \max_{i=2}^{n} \left(\frac{|\overline{V}_{\text{nom}}| - |\overline{V}_i|}{|\overline{V}_{\text{nom}}|} \right), \tag{6}$$

where n is the number of buses.
Normally, the voltage limit ($V_{\min} \le V_i \le V_{\max}$) at a particular bus is taken as a technical constraint, and thus the value of the IVD is normally small and within the permissible limits.

(3) *MVA capacity index (IC)*: As a consequence of supplying power near to loads, the MVA flows may diminish in some sections of the network, thus releasing more capacity, but in other sections they may also increase to levels beyond the distribution line limits (if the line limits are not taken as constraints). The index (IC) gives important information about the level of MVA flow/currents through the network regarding the maximum capacity of conductors. This gives information about the need for system line upgrades. Values higher than unity (calculated MVA flow values higher than the MVA capacity) of the index given the amount of capacity violation in term of line flow, whereas lower values indicate the capacity available.

$$\text{IC} = \max_{i=1}^{\text{NOL}} \left(\frac{|\overline{S_i}|}{|\overline{CS_i}|} \right), \tag{7}$$

where NOL is the number of lines, S_i is the MVA flow in line i, and CS_i is the MVA capacity of line i.
The benefit of placing DG in a system in the context of line capacity released is measured by finding the difference in IC between the system with and without DG. The avoidance of flow near to the flow limits is an important criterion, as it indicates that how earlier the system needs to be upgraded and thus adding to the cost. Normally, the constraint ($S_i \le S_{i,\max}$) at a particular line is taken as a strict constraint.

(4) *Short circuit level index (ISC)*: This index is related to protection and sensitivity issues, since it evaluates the short circuit current at each bus with and without DG [16,17].

$$\text{ISC} = \frac{I_{\text{SC}}^{\text{without DG}} - I_{\text{SC}}^{\text{with DG}}}{I_{\text{SC}}^{\text{without DG}}}, \tag{8}$$

where $I_{\text{SC}}^{\text{without DG}}$ is the short circuit current before installing the DG and $I_{\text{SC}}^{\text{with DG}}$ is the short circuit current after installing the DG.

3. Particle swarm optimization

In this paper, a PSO technique is used to find the best solution of the multi-objective problem of placing and sizing of multiple DG units.

PSO is an optimization technique, and it is an evolutionary computation technique [32–34]. The method has been developed through a simulation of simplified social models. The features of the method are as follows.

(1) The method is based on research on swarms such as fish schooling and bird flocking.
(2) It is based on a simple concept. It works in two steps, which are calculating the particle velocity and updating its position. Therefore, the computation time is short, and it requires little memory.

According to the research results for bird flocking, birds find food by flocking (not individually). This led to the assumption that information is owned jointly in flocking. According to observations of the behavior of human groups, the behavior pattern of each individual is based on several behavior patterns authorized by the groups, such as customs and the experiences by each individual (agent). The assumptions are basic concepts of PSO.

PSO is basically developed through simulation of bird flocking in two-dimensional space. The position of each individual (agent) is represented by the *XY* axis position and the velocity is expressed by vx (the velocity along the X axis) and vy (the velocity along the Y axis). Modification of the agent position is realized by the position and velocity information.

An optimization technique based on the above concept can be described as follows: bird flocking optimizes a certain objective function. Each agent i knows its best value so far (pbest_i) and its *XY* position (S_i). Moreover, each agent knows the best value so far in the group (gbest) among pbests. Each agent tries to modify its position using the following information:

- the current position vector $S_i = [Sx_i, Sy_i]$,
- the current velocity vector $v_i = [vx_i, vy_i]$,
- the distance between the current position and pbest, introduced as ($\text{pbest}_i - S_i$), and
- the distance between the current position and gbest, introduced as ($\text{gbest} - S_i$).

This modification can be represented by the concept of velocity. The velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = w v_i^k + c_1 \text{rand} \times (\text{pbest}_i - s_i^k) + c_2 \text{rand} \times (\text{gbest} - s_i^k), \tag{9}$$

where

v_i^k is the velocity of agent i at iteration k,
w is the adaptive inertia weight linearly adapted to decrease from $w_{\max} = 0.9$ to $w_{\min} = 0.04$, such that
$w = w_{\max} - [(w_{\max} - w_{\min})/\text{number of iterations}]^*$ current iteration number,
c_j are the accelerating coefficients within the range [0,4], which are conventionally set to a fixed value of 2,
rand is random number between 0 and 1,
s_i^k is the current position of agent i at iteration k,
pbest_i is the pbest of agent i, and
gbest is the gbest of the group.

Using the above equation, a certain velocity, which gradually gets close to pbest and gbest, can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1}. \tag{10}$$

Fig. 1 shows a concept of modification of a searching point by PSO and Fig. 2 shows a searching concept with agents in a two-dimensional solution space. This concept can be then extended to an N-dimensional solution space.

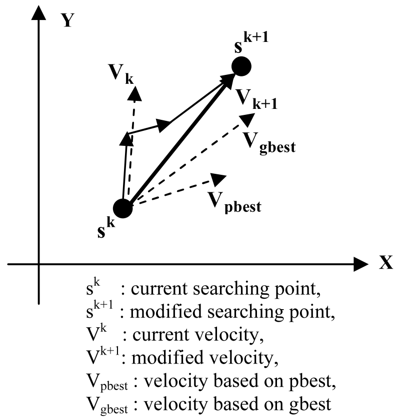


Fig. 1. Concept of modification of a searching point by PSO.

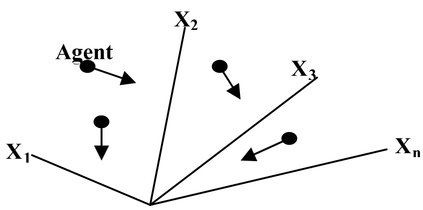


Fig. 2. Searching concept with agents in a solution space by PSO.

PSO in its simplest form has been applied in many fields concerning optimization, and many research studies have attempted to improve the simple PSO performance by improving its variants. In [35–37], adaptive control strategies were developed for the inertia weight and acceleration coefficients for faster convergence speed. In [38], a comprehensive learning particle swarm optimizer (CLPSO), which applied a learning strategy using all other particles' historical best information, was used to update a particle's velocity. The CLPSO showed an improved performance compared to many other PSO variants. In [39–41], a dynamic multi-swarm particle swarm optimizer (DMS-PSO) was introduced. In DMS-PSO, small neighborhoods were used to enable the particles to have more diverse exemplars to learn from to achieve better results on multi-modal problems. In [42,43], the fully informed particle swarm optimization algorithm (FIPS) was proposed. The velocity update rule used in FIPS considered all the neighbors of a particle to update its velocity instead of just the best one. In general, all the improvements to PSO aimed to achieve faster convergence speed while solving the problem of premature convergence especially in a multi-peak, high-dimensional function.

4. Multi-objective-based problem formulation

The multi-objective index for the performance calculation of distribution systems for DG size and location planning with load models considers all previous mentioned indices by giving a weight to each index.

The PSO-based multi-objective function (MOF) is given by

$$\begin{aligned}\mathrm{MOF} = {} & (\sigma_1.\mathrm{ILP} + \sigma_2.\mathrm{ILQ} + \sigma_3.\mathrm{IC} + \sigma_4.\mathrm{IVD} + \sigma_5.\mathrm{ISC}) \\ & + \mathrm{MVA}_{\mathrm{sys(pu)}},\end{aligned} \tag{11}$$

where $\mathrm{MVA}_{\mathrm{sys(pu)}}$ is the total intake from the grid expressed per unit, and

$$\sum_{p=1}^{5} \sigma_p = 1 \quad \wedge \sigma_p \in [0, 1].$$

Table 2
Index weights.

Indices	σ_p
ILP	0.3
ILQ	0.2
IC	0.25
IVD	0.1
ISC	0.15

These weights are indicated to give the corresponding importance to each impact index for the penetration of DG with load models, and they depend on the required analysis (e.g., planning, operation, etc.).

The weighted normalized indices used as the components of the objective function are due to the fact that the indices get their weights by translating their impacts in terms of cost. It is desirable if the total cost is decreased. Table 2 shows the values for the weights used in present work, considering normal operation analysis, and they are selected guided by the weights in [13,17]. However, these values may vary according to engineer concerns. For this analysis, active losses have the higher weight (0.3) since they are important in many applications of DG. The current capacity index (IC) has the second highest weight (0.25) since it gives important information about the level of currents through the network regarding the maximum capacity of conductors in distribution systems. Protection and selectivity impact (ISC) received a weighting of 0.15 since it evaluates important reliability problems that DG presents in distribution networks. The behavior of the voltage profile (IVD) received a weight of 0.1 due to its power quality impact.

The multi-objective function (11) is minimized subject to various operational constraints to satisfy the electrical requirements for a distribution network. These constraints are the following.

(1) *Power-conservation limits*: The algebraic sum of all incoming and outgoing power including line losses over the whole distribution network and power generated from the DG unit should be equal to zero.

$$P_{SS}(i, V) = \sum_{i=2}^{n} P_D(i, V) + \sum_{j=1}^{\mathrm{NOL}} P_{\mathrm{loss}}(j, V) - P_{\mathrm{DG}}, \tag{12}$$

where NOL = number of lines and P_D = power demand (MW).

(2) *Distribution line capacity limits*: The power flow through any distribution line must not exceed the thermal capacity of the line:

$$S_i \le S_{i,\max}. \tag{13}$$

(3) *Voltage limits*: The voltage limits depend on the voltage regulation limits provided by the DISCO:

$$V_{\min} \le V_i \le V_{\max}. \tag{14}$$

The implementation of PSO starts by random generation of an initial population of possible solutions. For each solution, size–location pairs of the DG units introduced to the system are chosen within technical limits of locations and sizes of the DG units. Each solution must satisfy the operational constraints represented by Eqs. (12)–(14). If one of these constraints is violated, such a solution is rejected. After generating a population of solutions satisfying the pre-specified constraints, the objective function of each solution (individual) is evaluated.

Once the population cycle is initialized, the position of each individual in the solution space is modified using the PSO parameters, e.g., pbest, gbest, and the agent velocity, to generate the new population. If the DG size and/or location exceed the limit, they are adjusted back within the specified limits (the

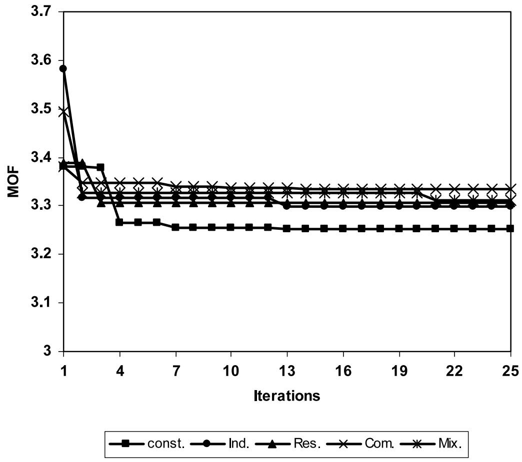


Fig. 3. The multi-objective function optimally minimized under different load models.

boundaries). The operational constraints are then checked. If any of them is violated the new solution is rejected and another one is generated and checked until a solution that satisfies the specified limits is found. The algorithm stops when the maximum number of generations is reached. According to PSO theory, the optimal solution is the best solution ever found throughout the generations (gbest).

To validate the proposed method, it is applied to the 38-bus system of [13] under the same load conditions and using the same objective function (IMO) and same values of index weights used in [13] to optimally place one DG unit in the system.

The results of applying the proposed PSO to the system under different load conditions and the results given in [13] through applying the GA are given in Table 3. It must be noted that the run time of the PSO algorithm ranged from 10 to 20 s, which is relatively a very short time.

As shown in Table 3, for all load models, all the indices are much reduced when using PSO for the problem solution compared with their values when using the GA in [13], except the IC index. From the values of the IC index, it can be concluded that the line loading with the resulting size–location pairs was higher than that of [13] but still within rated limits. However, the overall objective function (IMO) was reduced as well.

From the previous results, it can be concluded that the proposed PSO method is an efficient method to deal with the problem introduced in this work.

5. Simulation results and analysis

The proposed algorithm is tested using both a 38-bus radial test system [13] and an IEEE 30-bus mesh test system [30]. The base values used are 100 MVA and 23 kV. A DG size is considered in a range of 0–0.63 pu. In this study, it is considered that the DG is operated at an unspecified power factor, unlike the situation that has commonly been used in literature.

The first bus is considered as the feeder of electric power from the generation/transmission network. The remaining buses of the distribution system except the voltage-controlled buses are considered for the placement of a DG of given size from the range

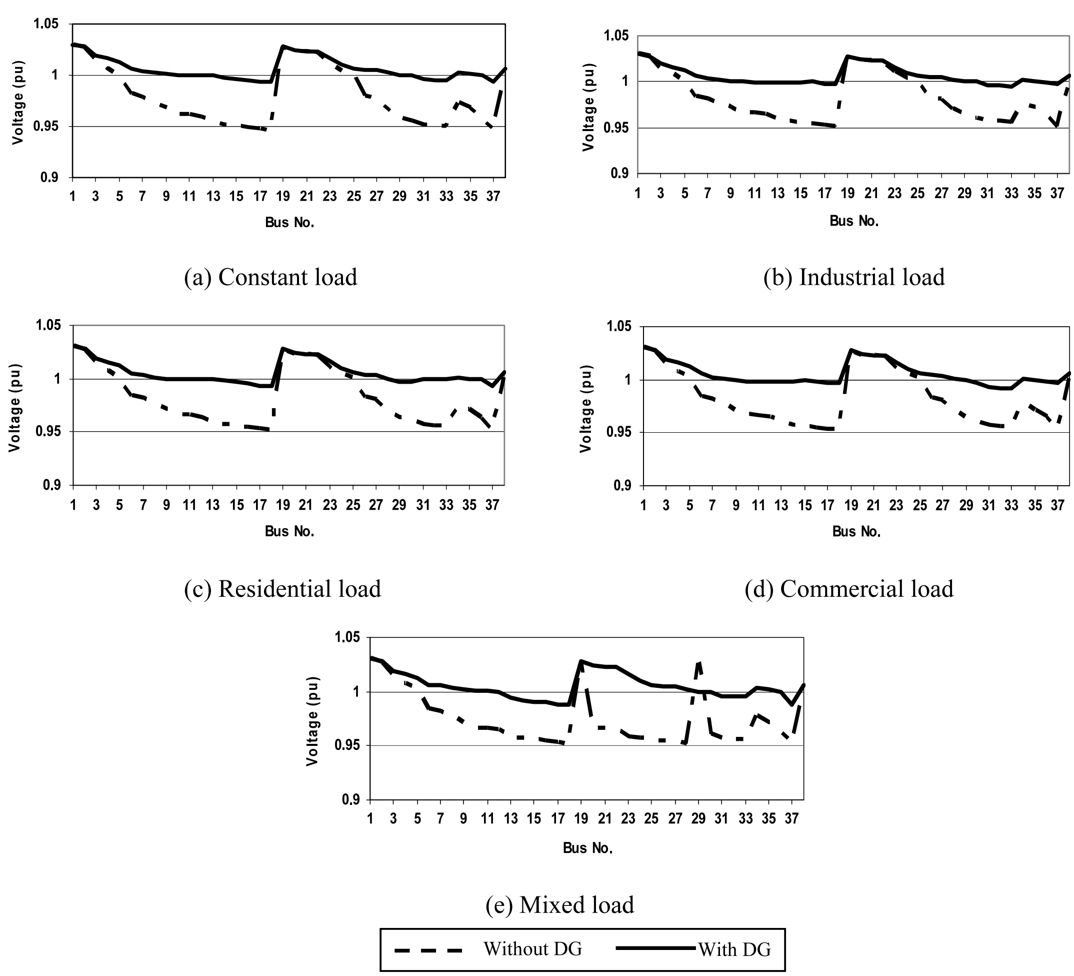
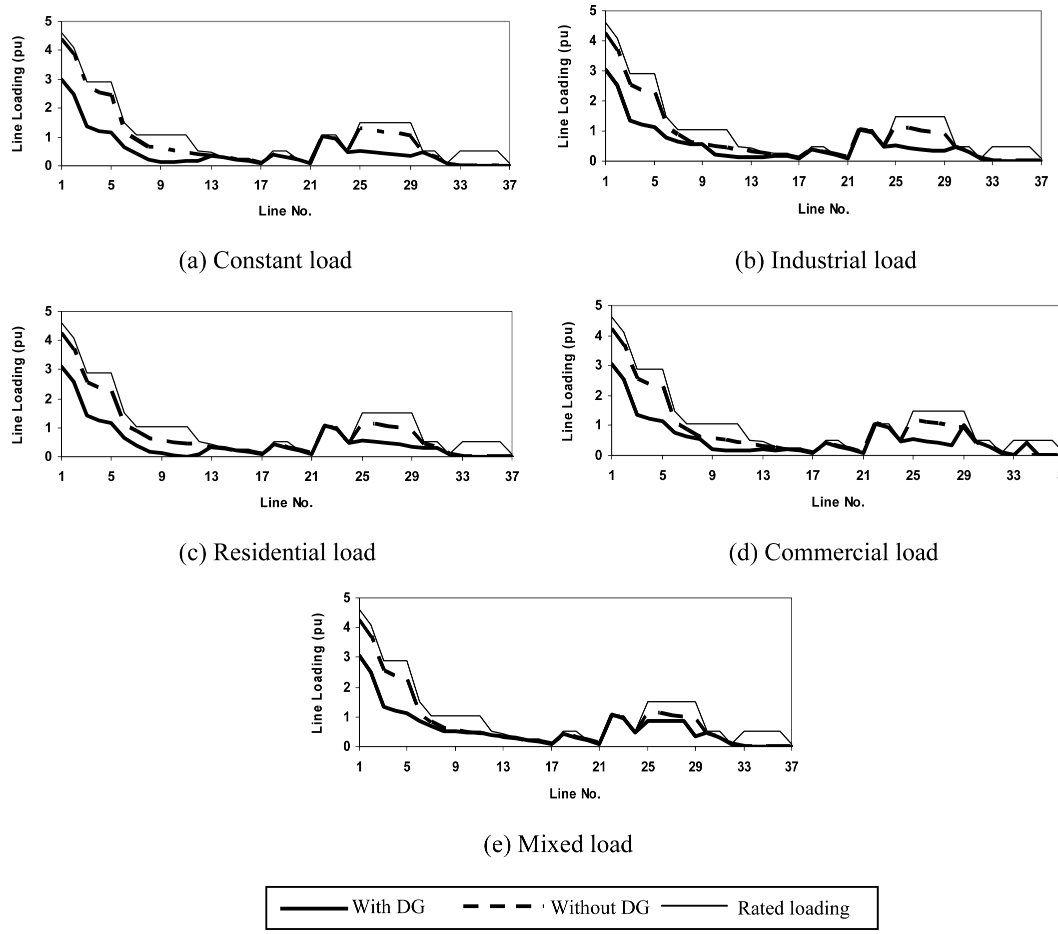


Fig. 4. The voltage profile under different load models.



(a) Constant load (b) Industrial load

(c) Residential load (d) Commercial load

(e) Mixed load

Fig. 5. The line loading under different load models.

Table 3
Impact indices for penetration of a DG unit in the 38-bus system with load models using PSO and GA.

Impact index	Const. load		Ind. load		Res. load		Com. load		Mixed load	
	PSO	GA	PSO	GA	PSO	GA	PSO	GA	PSO	GA
ILP	0.45	0.7104	0.5025	0.8819	0.4852	0.8822	0.4783	0.8846	0.4824	0.8839
ILQ	0.4572	0.7048	0.511	0.8958	0.4928	0.8941	0.4853	0.8957	0.4898	0.8977
IC	0.9944	0.8739	0.765	0.8795	0.9856	0.8812	0.9931	0.8825	0.9745	0.8821
IVD	0.059	0.0689	0.0594	0.0739	0.0575	0.0738	0.0574	0.0732	0.0575	0.0737
Min IMO	0.5289	0.6539	0.5281	0.7629	0.5278	0.7631	0.5277	0.7645	0.5285	0.7647
Optimal size–location pair	0.63–30	0.62–14	0.63–30	0.63–25	0.63–30	0.63–25	0.63–30	0.63–25	0.63–30	0.63–25

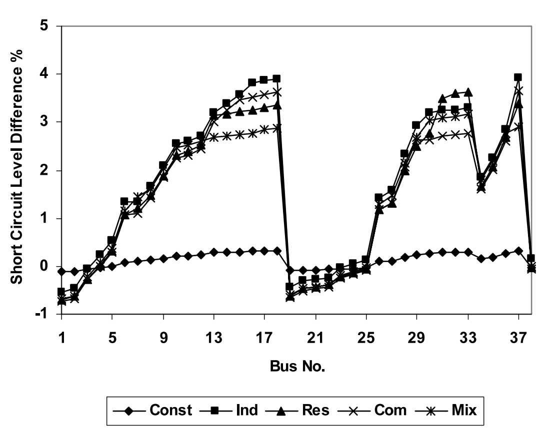


Fig. 6. The short circuit level difference of the system under different load models.

considered. The real and reactive loads were modeled as being voltage dependent.

5.1. Case 1: 38-bus radial system

The proposed PSO-based algorithm was applied to the 38-bus test system to determine the optimal size and location of DG units such that the multi-objective function given in (11) is minimized. The system line data and load data are given in [13]. For this test system, three DG units were optimally sized and placed. The proposed system was applied to different load models. The size and location of each DG unit under different load models are given in Table 4.

The multi-objective function optimally minimized under different load models is shown in Fig. 3. After many trials it was found that, for this optimization problem and this system, the best parameters to be used for PSO in all cases were a population size of 15 and a maximum iteration number of 25. As shown in Fig. 3, the objective function reached a near-global minimum and stayed there till the end of the iterations. The minimum objective function was attained with a computation time of about

Table 4
Size and location of DG units in the 38-bus radial system.

Load type	DG1			DG2			DG3		
	Size		Location	Size		Location	Size		Location
	P (pu)	Q (pu)		P (pu)	Q (pu)		P (pu)	Q (pu)	
Constant	0.6299	0.6289	30	0.2585	0.507	13	0.1957	−0.1853	11
Industrial	0.3038	1.0659	30	0.3802	−0.2334	10	0.3845	0.1522	16
Residential	0.0647	0.6281	31	0.5107	−0.0663	32	0.4076	0.4022	13
Commercial	0.2892	−0.2916	35	0.2862	1.0677	29	0.4575	0.2103	15
Mixed	0.4758	−0.8928	29	0.1307	0.7862	12	0.4582	1.1254	30

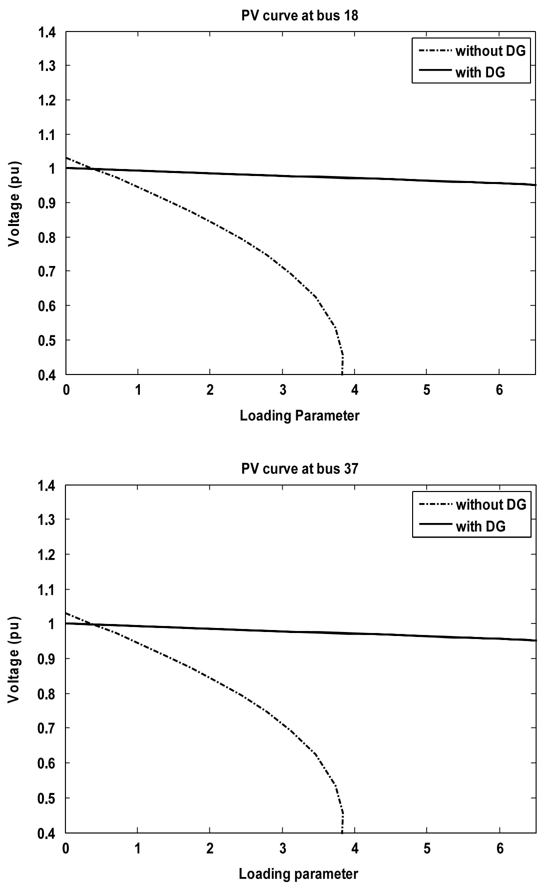


Fig. 7. The P–V curves at the weakest buses of the system.

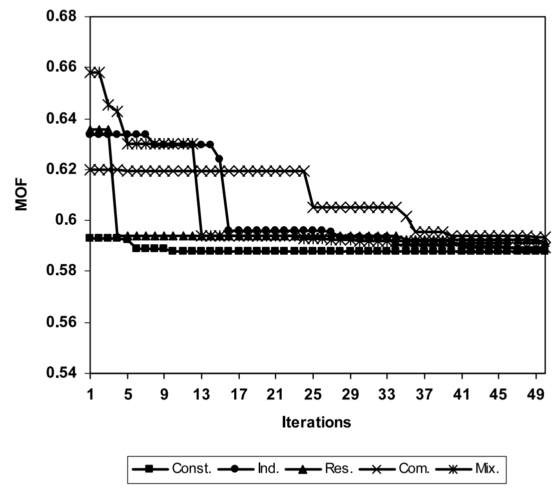


Fig. 8. The multi-objective function optimally minimized under different load models.

20 s on an INTEL Core 2 Duo CPU, 2.1 GHz with 1.97 GB RAM. All the evaluations were carried out with self-developed codes in MATLAB.

The value of the MOF and the impact of optimal placement and sizing of DG units on the active and reactive power losses of the system and the total MVA intake from the grid are given in Table 5.

It is shown that the optimal placement of DG units in the system caused a reduction in both power losses and MVA intake from the grid. The reduction in real power loss was in the range 54–67%. The reduction in reactive power loss was in the range 58–67%. The reduction in the total MVA intake was about 30%.

The effect of inserting DG units in the system on the voltage profile, line flow, and the short circuit level is shown in Figs. 4–6, respectively.

Fig. 4 shows the improvement in voltage profile under different load models. As shown in Fig. 4, the voltage at all buses before inserting DG units in the system is higher than 0.95 pu, except at buses 18 and 37, in the case of the constant load model. Due to the insertion of DG units, the voltage profile significantly improved for all load models studied. As shown in Fig. 4(a), the voltage at bus 18 during the constant load was raised to 0.99 pu.

Fig. 5 shows the line loading of the system with and without DG. It is clear that for most of the lines the loading decreased, while for some lines it remained the same or increased, but still within line loading limits.

As a result of the placement of DG units in the system, the short circuit level at most of the system buses was increased. Fig. 6 shows the difference between the short circuit level at each bus of the system with and without DG as a percentage of the value of the short circuit level before the placement of DG units in the system. As shown in Fig. 6, the maximum increase is very low: a maximum difference of 3.92% occurred in the case of the industrial load model and it happened at bus 37.

Running the continuation power flow using the PSAT for the system with and without DG units and recording the P–V curve at the weakest buses of the system, bus 18 and bus 37, showed a great improvement in the maximum loading and hence in the voltage stability margin for both buses. Fig. 7 shows how the maximum loading and in consequence the voltage stability margin at buses 18 and 37 in the case of the constant load model have been improved by moving the breakdown point far to the right (higher loading parameter λ).

5.2. Case 2: IEEE 30-bus mesh system

The proposed PSO-based algorithm was applied to the IEEE 30-bus test system to determine the optimal size and location of distributed generation units such that the multi-objective function given in (11) is minimized. The system line data and bus data are given in [30]. For this test system, two DG units were optimally sized and placed. The proposed system was applied to different load models. The size and location of each DG unit under different load models are given in Table 6.

The multi-objective function optimally minimized under different load models is shown in Fig. 8. After many trials it was

Table 5
System power losses and MVA intake for different load models in the 38-bus radial system, and the value of the MOF.

Load model	P_L	P_{LDG}	Q_L	Q_{LDG}	MVA_{SYS}	$MVA_{SYS\text{-}DG}$	Value of MOF
Const.	16.516	5.3986	11.006	3.5976	438.57	300.2462	3.252718
Ind.	14.627	5.8781	9.713	3.9236	425.35	304.4423	3.297935
Res.	15.113	5.6135	10.046	3.6998	428.67	311.0265	3.305198
Com.	15.294	6.3262	10.169	4.2428	429.93	308.0879	3.335645
Mixed	15.207	6.9399	10.109	4.7914	429.47	305.5652	3.310678

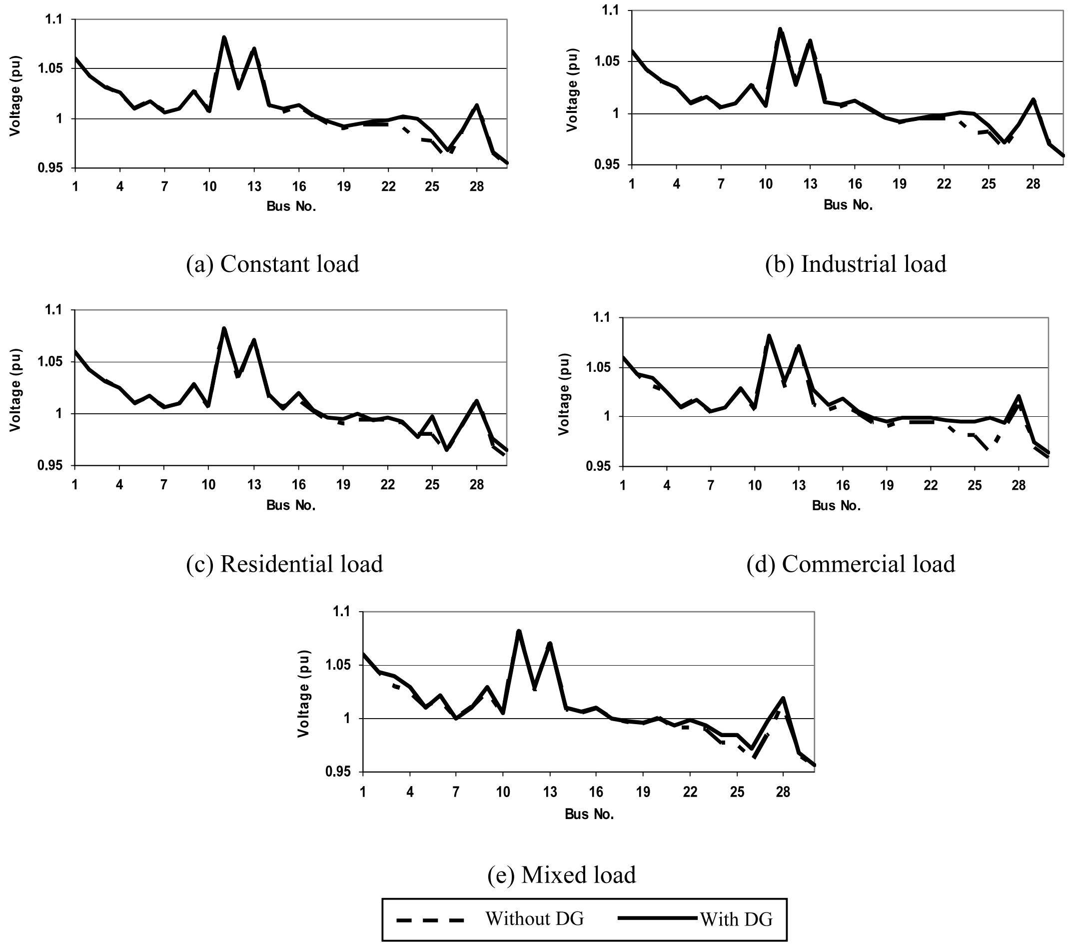


Fig. 9. The voltage profile under different load models.

Table 6
Size and location of DG units in the 30-bus meshed system.

Load type	DG1			DG2		
	Size		Location	Size		Location
	P (pu)	Q (pu)		P (pu)	Q (pu)	
Constant	0.3121	0.0796	24	0.6300	−0.3239	7
Industrial	0.3229	0.0433	24	0.6290	−0.3018	7
Residential	0.3007	0.0498	20	0.6300	−0.3261	7
Commercial	0.3188	−0.0314	17	0.6238	−0.2925	7
Mixed	0.3360	0.03931	20	0.6295	−0.2997	7

found that, for this optimization problem and this system, the best parameters to be used for PSO in all cases were a population size of 25 and a maximum iteration number of 50. As shown in Fig. 8, the objective function reached a global minimum and stayed there till the end of iterations. The minimum objective function was attained with a computation time of about 50 s on an INTEL Core 2 Duo CPU, 2.1 GHz with 1.97 GB RAM. All the evaluations were carried out with self-developed codes in MATLAB.

The value of the MOF and the impact of optimal placement and sizing of DG units on the active and reactive power losses of the system and the total MVA intake from the grid are given in Table 7.

It is shown that the optimal placement of DG units in the system caused a reduction in both power losses and MVA intake from the grid. The reduction in real power loss was in the range 30–37%. The reduction in reactive power loss was in the range 26–31%. The reduction in the total MVA intake was about 62%.

Table 7
System power losses and MVA intake for different load models in the 30-bus meshed system, and the value of the MOF.

Load model	P_L	P_{LDG}	Q_L	Q_{LDG}	MVA_{SYS}	$MVA_{SYS\text{-}DG}$	Value of MOF
Const.	4.951	3.0591	30.5343	20.930	108.79	39.8475	0.587907
Ind.	4.913	3.0673	30.4856	21.017	109.25	39.9897	0.588452
Res.	4.975	3.2501	29.4368	20.815	110.78	40.3807	0.591623
Com.	5.021	3.3728	28.9620	20.659	112.09	40.4207	0.593594
Mixed	4.911	3.3730	29.2556	21.018	109.42	40.1011	0.589224

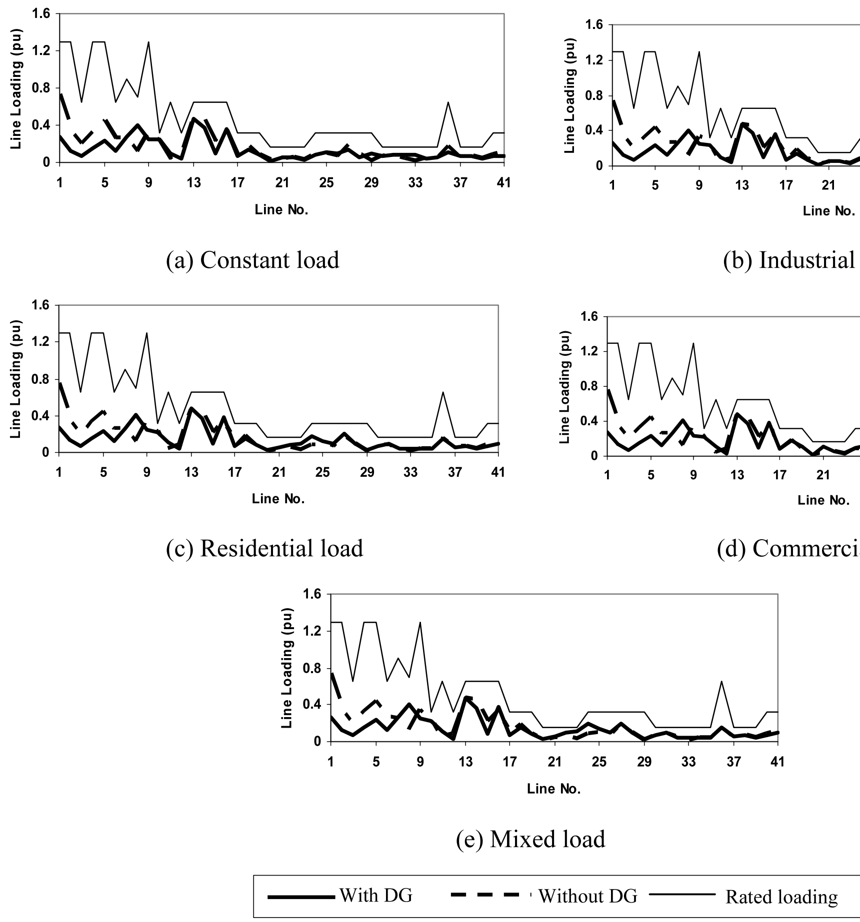


Fig. 10. The line loading under different load models.

The effect of inserting DG units in the system on the voltage profile, line flow, and short circuit level is shown in Figs. 9–11.

Fig. 9 shows the improvement in voltage profile under different load models. As shown in Fig. 9, the voltage at all buses before inserting DG units in the system is higher than 0.95 pu, and the lowest voltage is at bus 30. Due to the insertion of DG units, the voltage profile significantly improved for all load models studied at most of the system buses.

Fig. 10 shows the line loading of the system with and without DG. It is clear that for most of the lines the loading decreased, while for some lines it remained the same or increased, but still within line loading limits.

As a result of the placement of DG units in the system, the short circuit level at most of the system buses was increased. Fig. 11 shows the difference between the short circuit level at each bus of the system with and without DG as a percentage of the value of the short circuit level before the placement of DG units in the system. As shown in Fig. 11, the maximum increase is very low: a maximum difference of 2.3% occurred in the case of the industrial load model, and it happened at bus 23.

Running the continuation power flow using the PSAT for the system with and without DG units and recording the P–V curve at the weakest bus of the system, bus 30, showed an improvement in the maximum loading and hence in the voltage stability margin. Fig. 12 shows how the maximum loading and in consequence the voltage stability margin at bus 30 in the case of the constant load model have been improved by moving the breakdown point more to the right (higher loading parameter λ).

6. Conclusion

Multi-objective optimization analysis, including load models, for size–location planning of distributed generation in distribution systems has been presented. The proposed optimization algorithm was applied to a 38-bus radial test system and an IEEE 30-bus mesh test system. The results showed that the proposed algorithm is capable of optimal and fast placement of DG units. The results clarified the efficiency of this algorithm for improvement of the voltage profile, reduction of power losses, reduction of MVA flows and MVA intake from the grid, and also for increasing the voltage stability margin and maximum loading.

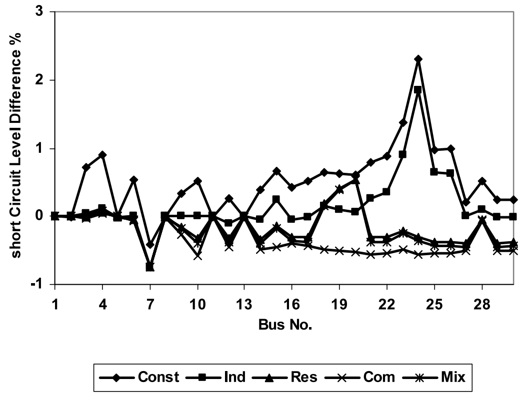


Fig. 11. The short circuit level difference of the system under different load models.

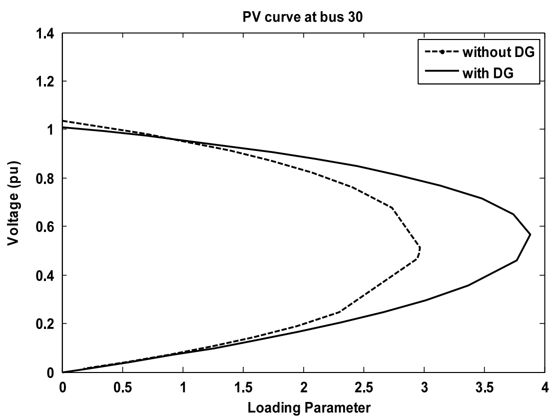


Fig. 12. The P–V curves at bus 30.

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