Decision Making: Applications in Management and Engineering
Vol. 3, Issue 1, 2020, pp. 30-42.
ISSN: 2560-6018
eISSN: 2620-0104
DOI: https://doi.org/10.31181/dmame2003065g

MULTI-OBJECTIVE DISTRIBUTED GENERATION PENETRATION PLANNING WITH LOAD MODEL USING PARTICLE SWARM OPTIMIZATION

Sanjib Ganguly [1]

[1] Department of Electronics and Electrical Engineering, Indian Institute of Technology Guwahati, India

Received: 5 January 2019;
Accepted: 6 August 2019;
Available online: 13 August 2019.

Original scientific paper

***Abstract**: The paper presents an approach for simultaneous optimization of Distributed Generation (DG) penetration level and network performance index to obtain the optimal numbers, sites, and sizes of DG units. Two objective functions are formulated. These are: (II) DG penetration level, (II) network performance index. The minimization of the first objective reduces the capital investment cost of a distribution network owner (DNO) to integrate DG. The minimization of the second objective helps in reduction of network losses and improvement in node voltage profile and line loading. The solution approach provides a set of non-dominated solutions with different values of DG penetration level and network performance index. Thus, it offers more flexibility to a DNO to choose a final solution from the set of solutions according to its strategic decisions, regulatory directives, and budget restrictions. The solution approach used is multi-objective particle swarm optimization. The approach is validated on a 38-node distribution system. The results are compared with some existing approaches.*

Keywords: *Distributed generation, multi-objective optimization, Pareto-dominance, particle swarm optimization.*

Nomenclature

S_{DG} - Total DG penetration level;

PI - Network performance index;

y_i - Binary decision variable (=1 if there is a DG unit in i^{th} node, otherwise=0);

s_i - Size of the DG unit;

ILP (ILQ) - Real (reactive) power loss index;

ILO (IVD) - Line loading (voltage deviation) index;

* Corresponding author.
E-mail addresses: sganguly@iitg.ac.in (S. Ganguly)

σ_i - Weights for i^{th} objective function;

LO_{ij} (CL_{ij}) - Line loading (capacity) at line *i-j*;

$N_l(n)$ - Total number of lines (nodes);

V_i - Voltage at node *i*;

iter - Iteration number;

$PV_{i\theta}^{iter}$ ($X_{i\theta}^{iter}$) - Velocity value (position value) for the θ-th dimension of the *i*-th particle in iteration *iter* ;

$\phi_1(\phi_2)$ - Learning coefficients/factors of PSO;

$r_1(r_2)$ - Random number lies within [0,1];

$pbest_{i\theta}^{iter}$ - The best position value for the θ-th dimension of *i*-th particle;

$guide_{i\theta}^{iter}$ - The position of the guide particle for θ-th dimension of the *i*-th particle;

d_i ($\bar{d}$) - Distance (mean) between two neighboring solutions of Pareto approximation fronts in objective space.

1. Introduction

The presence of distributed generation (DG) changes the conventional passive power distribution systems to active systems. The DG has a significant impact on the quality of the power supply provided by distribution systems. It can reduce active and reactive power losses, improve node voltage profile, reduce line loading etc (Pecas Lopes et al., 2007; Chiradeja & Ramakumar, 2004). Also, DG may lessen the impact of future load growth and it can utilize the non-conventional local resources. This becomes a driving force to many power system researchers to investigate its impact on distribution systems (Ochoa et al., 2006; Singh et al., 2007). Simultaneously, a lot of research is going on around the globe to determine a suitable optimization approach for the best allocation of DG units on distribution systems. A suitable optimization approach relies on a realistic problem formulation and an appropriate solution strategy.

The existing approaches are basically focused on the determination of optimal site(s) and size(s) of DG unit(s). This is usually done by formulating suitable objective function(s) aiming at the optimization of several features to improve performance of a distribution network, for example real and reactive power losses (Singh et al., 2009), voltage profile (Singh et al., 2009; Mantway & Al-Muhaini, 2008), line loading (Singh et al., 2009; Mantway & Al-Muhaini, 2008), and short circuit capacity (El-Zonkoly, 2011) etc. The objective functions formulated in different approaches are minimization of DG installation and operational cost (De-Souza & De-Albuquerque, 2006; Celli et al., 2005), the cost of energy purchase from the grid (Celli et al., 2005), and the cost of energy loss (Celli et al., 2005; Carpinelli et al., 2005) etc. In general, there can be multiple objective functions to be optimized in the optimal DG allocation problem. In some approaches (Singh et al., 2009; El-Zonkoly, 2011; Celli et al., 2005), the multiple objective functions are aggregated with different weights to form a single objective function so as to optimize them. However, if the objective functions conflict with each other there exist a set of trade-off solutions of different objectives, known as non-dominated solutions (Deb, 2004). The set of non-dominated solutions is also known as Pareto-approximation set. The set of solutions can be determined using different approaches, for example weighted aggregation of objectives with varying weights (Mantway & Al-Muhaini, 2008), ε-constrained method (Celli et al., 2005; Carpinelli et al., 2005), Pareto-dominance method (Deb, 2004) etc. The most of the approaches are based on the constant load model, except in (Singh et al., 2007; Singh et al., 2009), in which it is shown that voltage dependent load model has significant impact on the solutions.

Practically, the DG penetration level and network performance index conflict with each other up to a certain value of DG penetration level (Bollen & Hassan, 2011). The network performance in terms of losses, node voltage level etc., improves with increasing DG penetration level. But, it may deteriorate beyond a certain value of DG penetration level. For example, network real and reactive power losses reduce with increasing DG penetration level. However, they may increase after a certain value of DG penetration level. The node voltage and line loading can also be improved with increasing DG penetration level. Thus, there is a requirement to have an investigative study so as to determine the optimal value of DG penetration level as well as the optimal network performance index. In this work, the Pareto-dominance-based approach is used to simultaneously minimize these two objectives.

In general, there are two ways of integrating DG in distribution systems: (I) the distribution network owner (DNO) is directly given license to own its generation, and (II) a distributed generation owner (DGO) is only given license to set up DG units and the DNO has to purchase energy from the DGO. In the first case, one of the objectives of the DNO would be minimization of the capital investment cost for DG installation and the operational cost of DG as well. In the second case, one of the objectives of the DNO would be minimization of the quantity of the energy purchased from the DGO, since the energy provided by DG is comparatively expensive than the energy provided by large central generators (De-Souza & De-Albuquerque, 2006). In this work, it is assumed that a DNO needs to integrate DG into distribution networks. Thus, one of the objectives of a DNO would be minimization of the DG penetration level into the network. On the other hand, another objective of the DNO would definitely be improvement of the performance of its network for the sake of customer satisfaction, which is a key issue in the current competitive power market. Thus, the two objective functions formulated in this work are: (i) DG penetration level, (ii) network performance index. The minimization of the first objective reduces the capital investment cost of the DNO to integrate DG. The minimization of the second objective helps in minimization of network losses and improvement in node voltage profile and line loading. Hence, lower value of the index implies to better performance of a network. The formulation of the second objective function is similar to Singh et al. (2009). However, in Singh et al. (2009) only this objective is optimized to determine the site and size of single DG unit. On the contrary, in this work, both the objective functions are simultaneously minimized using the Pareto-dominance principle so as to obtain the sites and sizes of multiple DG units. This approach yields a set of non-dominated solutions representing different values of DG penetration level and network performance index. The voltage-dependent load model as reported in (Singh et al., 2009) is also used in this work.

The solution strategy used in this work is multi-objective particle swarm optimization (MOPSO). Particle swarm optimization (PSO) (Mantway & Al-Muhaini, 2008; El-Zonkoly, 2011) is a population-based meta-heuristic algorithm, such as genetic algorithm (GA) (Singh et al., 2009; Celli et al., 2005; Carpinelli et al., 2005), evolutionary programming (De-Souza & De-Albuquerque, 2006) etc. MOPSO is the multi-objective version of PSO. These types of population-based meta-heuristic algorithms can provide a set of non-dominated solutions in a single run. They do not suffer from the curse-of-dimensionality. In this work, the MOPSO variant, named as heuristics based selection of guides for MOPSO (HSG-MOPSO), proposed by the author in Sahoo et al. (2011), is used as the solution strategy and its performance is compared with another two MOPSO variants (Li, 2003; Zitzler et al., 2001), i.e., non-dominated sorting MOPSO (NS-MOPSO) (Li, 2003) and strength Pareto evolutionary algorithm-II based MOPSO (SPEA2-MOPSO) (Ganguly et al., 2011). These two MOPSO variants are based on the philosophies of two well known multi-objective optimization algorithms of this kind, i.e., NSGA-II and SPEA2, respectively (Deb, 2004). The proposed approach is validated on the 38-node distribution system reported in Singh et al. (2009).

The paper is organized as: The multi-objective DG penetration planning formulation and the proposed planning algorithm using HSG-MOPSO are discussed in Sections 2 and 3, respectively. In Section 4, the results obtained with the simulation study are presented. Section 5 concludes the paper.

2. Multi-Objective DG Penetration Planning Problem

The multi-objective planning problem formulated in this work is aimed at facilitation the decision making of a DNO in integrating DG units in distribution networks. Thus, the simultaneous optimization of DG penetration level and network performance index is the main focus of the proposed planning approach. The DG penetration level of a network is sum of size of all DG units. Network performance index formulation is similar to that of (Singh et al., 2009). It is to be noted that these two objectives conflict with each other up to a certain value of DG penetration level. The aim of this planning approach is to determine this value of DG penetration level and to obtain the Pareto-approximation set below to this DG penetration level. Since each solution in the Pareto-approximation set is equally good (Deb, 2004), this planning offers more flexibility to the DNO to chose a final solution for implementation according to its requirement. The mathematical expressions of these two planning objectives are:

$$S_{DG} = \sum_{i=1}^{n} y_i s_i \tag{1}$$

$$PI = \sigma_1 ILP + \sigma_2 ILQ + \sigma_3 ILO + \sigma_4 IVD \tag{2}$$

The first objective function is a discrete function with discrete decision variable (y_i) to be determined to obtain the sites of DG units and continuous variable s_i to be determined to obtain the sizes of DG units. The second objective function is a performance index which is a sum of weighted objective functions comprising of network real power loss, reactive power loss, line loading, and voltage deviation. The real power loss index is the ratio of total real power loss with DG (PL_{DG}) to the network real power loss without DG (*PL*). This index shows the improvement in real power loss due to DG penetration. Thus, the lower value of this index indicates better performance. Its mathematical expression is:

$$ILP = \frac{PL_{DG}}{PL} \tag{3}$$

The reactive power loss index is the ratio of total reactive power loss with DG (QL_{DG}) to the network reactive power loss without DG (QL). This index shows the improvement in reactive power loss due to DG integration. The lower value of this index also refers to better performance. It is mathematically expressed as:

$$ILQ = \frac{QL_{DG}}{QL} \tag{4}$$

The network line loading index is the maximum value of the ratio of line loading to the capacity of each line. This index should be less than one to satisfy thermal limit of each line. The lower value of this index indicates more line capacity available in the network. It can be expressed as:

$$ILO = \max_{ij=1}^{N_l}\left\{\frac{LO_{ij}}{CL_{ij}}\right\} \tag{5}$$

The voltage deviation index is the maximum ratio of the voltage deviation of each node to the substation voltage. The node 1 is considered to be the substation node. The numerator represents the voltage deviation of each node with respect to the substation node. The lower value of this index means less voltage deviation, which is desirable. Its mathematical expression is:

$$IVD = \max_{i=2}^{n}\left(\frac{|V_1|-|V_i|}{|V_1|}\right) \tag{6}$$

All these indices are added with suitable weights to obtain the network performance index, which is the second objective function in this planning problem, as shown in equation (2). All indices are to be ranked according to the preference of the DNO to set their respective weights. The highest weight is to be given to the most preferable index, which the DNO wants to optimize.

This optimization is subjected to the following constraints:

Power balance constraint: The demand and supply balance needs to be met in each node.

Line capacity constraint: The loading should be less than the respective capacity in each line, i.e.,

$$LO_{ij} \le CL_{ij} \tag{7}$$

Voltage deviation constraint: The voltage deviation in each node should be less than an allowable limit.

$$|V_1 - V_j| \le \Delta V_{\lim} \tag{8}$$

The proposed planning approach is done with different voltage dependent load models as described in (Singh et al., 2009). The Pareto-dominance principle used in simultaneous optimization of these two objective functions is briefly described below.

2.1. Pareto-dominance Principle

In an optimization problem (say, minimization) with M objective functions, a solution x is said to dominate a solution y if the following criteria are satisfied.

$$\forall i \;\; f_i(x) \le f_i(y) \text{ ,and } \exists j \text{ uchthat } f_j(x) < f_j(y) \text{ , } [\, i=1,\ldots,M \,] \tag{9}$$

The aim is to determine a set of non-dominated solutions, in which no solution is inferior to others. The set of optimal non-dominated solutions is called the Pareto-optimal set.

3. The Multi-Objective Planning Algorithm Using HSG-MOPSO

The multi-objective planning approach using HSG-MOPSO is described in this section. The particle decoding/ encoding scheme, a support subroutine used in this planning algorithm, is also provided.

3.1. Multi-Objective Particle Swarm Optimization (MOPSO): An Overview

In MOPSO, each particle representing the sites and sizes of DG units in this optimization problem is encoded by a continuous position vector (X) which consists of multi-dimensional information. The position vector is randomly chosen in initial iteration. Then, it is iteratively updated with particle's velocity. The choice of initial velocity for a particle is also random. The velocity vector (PV) for a particle is also iteratively updated with the help of the respective previous best position (pbest) and the position of a guide. The choice of guides depends upon the MOPSO variants to be used. The particle velocity and position updating equations are given below. The updating equations for the θ^{th}-dimension of the i^{th}-particle are taken from Sahoo et al. (2011).

$$PV_{i\theta}^{iter+1} = PV_{i\theta}^{iter} + \phi_1 r_1 (pbest_{i\theta}^{iter} - X_{i\theta}^{iter}) + \phi_2 r_2 (guide_{i\theta}^{iter} - X_{i\theta}^{iter}) \quad (10)$$

$$X_{i\theta}^{iter+1} = X_{i\theta}^{iter} + PV_{i\theta}^{iter+1} \quad (11)$$

The guide selection is the most important task for such kind of multi-objective evolutionary algorithms (Sahoo et al., 2011). The heuristics-based guide selection technique, HSG-MOPSO, is followed in this work. In HSG-MOPSO, a set of potential guides is selected from an iteration and then, the set is iteratively updated using the set of non-dominated solutions and some dominated solutions from some specific regions of the feasible objective space. The dominated solutions are heuristically chosen from such region in the objective space where no non-dominated solutions are obtained. Each member of the population either follow the nearest non-dominated guide or the nearest dominated guide. The objective is to balance between the exploration and exploitation.

3.2. Particle Encoding/Decoding Scheme

The position vector of a particle is directly encoded with the information on the decision on DG location at each node and the size of DG units. Thus, a particle in the proposed encoding scheme consists of two segments as shown in Fig. 1. In the first segment, the binary decision on integrating DG units in each node of a network is encoded. The other segment contains the sizes of DG units. All nodes of a network, except the substation node (i.e., Node 1), is considered to be the potential locations for integrating DG units. Since a particle is encoded with direct information, its decoding is straight-forward. In the decoding process, if yi at node i is found to be 1 a DG unit with size si is to be integrated in the network. Some infeasible solutions are to be heuristically filtered out. For example, if y_i is zero and s_i at node *i* is found to be non-zero it is forcefully made zero. The size of a DG unit is kept between specified minimum and maximum values.

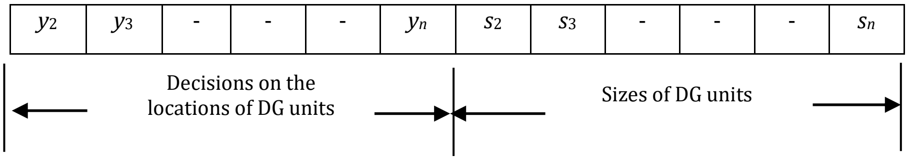

Figure 1. Particle encoding scheme

3.3. Constraint Handling Technique

The constraints of this planning problem are handled as given below.

The demand and supply balance constraint is met using the forward-backward sweep power flow subroutine which in embedded into the HSH-MOPSO.

If line capacity constraint is violated the solution is to be penalized by adding a suitable penalty factor to the both objective functions. The value of the penalty factor is computed as the product of the maximum ratio of line loading to capacity and a very high integer number.

If the voltage limit constraint is seen to be violated in any node, the solution is to be penalized with a suitable penalty factor in a similar way mentioned in Sahoo et al. (2015).

3.4. Complete Planning Algorithm

The pseudo codes of the complete planning algorithm are given in Fig. 2. The non-dominated solutions are preserved in an elite archive with a fixed archive size (η_A). The decision on DG location is updated using the concept of binary PSO (BPSO) (Mantway & Al-Muhaini, 2008). The velocity updating equation in BPSO is same as that of continuous version of MOPSO given in equation (10). The position updating equation follows a sigmoid transformation to restrict the value of position to binary value as shown below.

$$sig(PV_{i\theta}^{iter+1}) = \frac{1}{1+\exp(-PV_{i\theta}^{iter+1})} \tag{12}$$

$$X_{i\theta}^{iter+1} = \begin{cases} 1, & \text{rand}(0,1) < sig(PV_{i\theta}^{iter+1}) \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

```
Begin
    // η_pop = Population size of HSG-MOPSO
    // max_iter = Number of maximum iterations
    Randomly generate the set of initial population of position and velocity
    vectors for HSG-MOPSO using the particle encoding scheme;
    Decode the particles and calculate the fitness functions;
    Find the set of non-dominated solutions and store them in an elite
    archive;
    Determine the set of particles to be chosen as guides;
    itern=1;
    While itern<= max_iter
       For i=1,...,η_pop
          Find a guide for the ith particle from the set of guides;
          Update the particle's velocity and position vectors;
          Decode the particle to obtain the sites and sizes of DG units;
          Perform the forward-backward sweep load flow;
          Calculate the fitness functions using equations (1-2);
       Endfor
          Determine the set of non-dominated solutions
          Update the set of guides;
          itern=itern+1;
    Endwhile
     The Elite archive consists of the optimal solutions with different
     number, sizes and sites of DG units;
End
```

Figure 2. Pseudo codes of the complete planning algorithm using HSG-MOPSO

4. Simulation Results

The proposed multi-objective distribution system planning approach is evaluated via computer simulation studies on a 38-node distribution system. The system data are available in Singh et al. (2009). The MOPSO parameters are optimized sequentially as done in Sahoo et al. (2011). These are shown in Table 1. The plot of Pareto-approximation solutions in objective space is called Pareto-approximation front. One sample Pareto-approximation front obtained with the HSG-MOPSO for mixed load model is shown in Fig. 3. The comparison of the Pareto-approximation fronts obtained with HSG-MOPSO, SPEA2-MOPSO, and NS-MOPSO is shown in Fig. 4. The HSG-MOPSO is a MOPSO variant proposed in Sahoo et al. (2011). The SPEA2 is a GA-based multi-objective optimization approach which is originally proposed in Zitzler et al. (2001). The idea is borrowed to devise SPEA2-MOPSO in Ganguly et al. (2011). The NS-MOPSO is reported in Li (2003). The results show that the performances of HSG-MOPSO and NS-MOPSO are competitive and better than SPEA2-MOPSO. A comparison of the Pareto-approximation fronts obtained with different load models as shown in Fig. 5. This illustrates that there is distinct difference in performance between the practical load models and constant load models. The best solutions in view of the network performance index obtained with the different load models with those given in Singh et al. (2009) are compared in Table 2. The results show that much better solutions in terms of network performance index are obtained in the proposed approach. However, the DG penetration level for those solutions is higher than those obtained in Singh et al. (2009). In fact, the maximum DG penetration level which is set to 0.63 p.u. in Singh et al. (2009), results into sub-optimal solutions. Thus, all reported optimal solutions in Singh et al. (2009) have DG penetration level of 0.62-0.63 p.u. The overall investigation shows that there are certain ranges of DG penetration level and network performance index in which these two objectives conflict with each other. For this 38-node system, these are found to be 0-3.5 p.u. and 0.4-0.8, respectively. These may vary in different systems. The investigation also shows that the planning algorithm should determine these ranges so as to provide many equally good alternative solutions to a DNO.

Table 1. The parameters of different MOPSO variants studied here

Parameters	HSG-MOPSO	SPEA2-MOPSO	NS-MOPSO
Population size	50	50	50
Maximum iteration	200	200	200
Learning factors	ϕ_1=2, ϕ_2=1.5	ϕ_1=2, ϕ_2=1.5	ϕ_1=2, ϕ_2=1.5
Size of Elite Archive	40	40	40

Table 2. Comparison among the best solutions in view of the network performance index obtained with the different load models in proposed approach and the GA-based approach reported in Singh et al. (2009)

Algorithms	Constant load model	Industrial load model	Residential load model	Commercial load model	Mixed load model
GA-based approach	0.6539	0.7629	0.7631	0.7645	0.7647
Proposed approach	0.4363	0.4322	0.4662	0.4778	0.4594

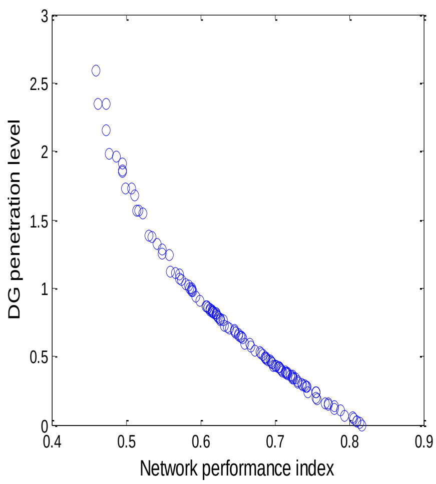

Figure 3. The Pareto-approximation front obtained with HSG-MOPSO for mixed load

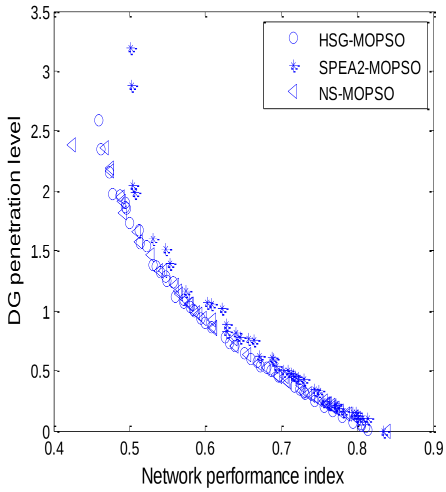

Figure 4. Comparison among the Pareto-approximation fronts obtained with HSG-MOPSO, SPEA2-MOPSO, and NS-MOPSO

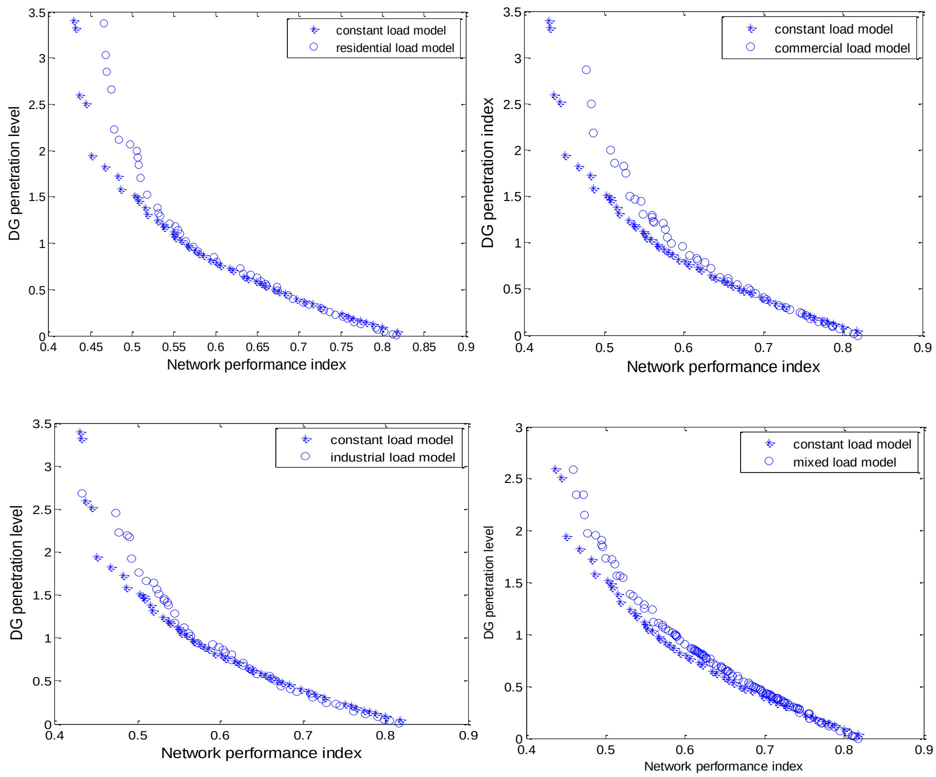

Figure 5. Comparison between the Pareto-approximation fronts

The performances of the SPEA2-MOPSO are assessed with statistical tests and compared with NS-MOPSO and SPEA2-MOPSO. For this purpose, 30 runs are taken separately for those MOPSO variants. Two performance assessment indicators, i.e., hypervolume and diversity indicators (Deb, 2004) are used for this comparison.

I Hypervolume Indicator: This is an indicator used to determine the area/volume of objective space being dominated by the Pareto-approximation set of solutions. The higher value of hypervolume indicator implies to the larger area (for bi-objective problem) or volume (for a problem with more than 2 objective functions) being dominated by the approximation set of solutions. This indicates comparatively better solutions close to the Pareto-optimal set. In this work, the Pareto approximation solutions in objective space are normalized with respect to a reference point, i.e., (4,1). The reference point is judiciously chosen in view of the maximum values of the two objective functions obtained in multiple simulation run. The means and variances of the hypervolume indicator for different test systems are given in Table 3. The higher hypervolume indicator is preferable because it signifies the solutions close to the Pareto-optimal set.

II *Diversity Indicator*: The mathematical expression for the diversity indicator (⊗) is shown in equation (14). It is used to measure the diversity among the solutions in a set of Pareto-approximation solutions.

$$\Delta = \left(\sum_{j=1}^{N_{ndf}} | d_i - \bar{d} | \right) / \left(N_{ndf} \bar{d} \right) \tag{14}$$

The ideal value for diversity indicator is to be zero or close to zero to show that there is good diversity among the Pareto solutions. Hence, the lower diversity indicator implies to better diversity among the solutions. The results illustrate that the better convergence is obtained with NS-MOPSO and HSG-MOPSO. However, the diversity among the solutions obtained with HSG-MOPSO is reasonably better than NS-MOPSO and SPEA2-MOPSO. The mean execution time of HSG-MOPSO is found to be reasonably higher as compared to NS-MOPSO and SPEA2-MOPSO. Since this is a type of investment planning to decide the DG integration capacity, it needs offline optimization. Hence, the execution time may not be a bottleneck to implement the HSG-MOPSO algorithm.

Table 3. The results of statistical tests

MOPSO variants	Hypervolume indicator		Diversity indicator		Mean execution time (sec)
	Mean value	Variance	Mean value	Variance	
HSG-MOPSO	0.4571	**2.32×10^{-5}**	**0.6215**	**0.0102**	59.2348
SPEA2-MOPSO	0.4431	4.56×10^{-5}	0.7656	0.0134	17.5322
NS-MOPSO	**0.4583**	5.93×10^{-5}	0.8141	0.0155	**16.2845**

5. Conclusion

In the paper, an approach for the simultaneous optimization of DG penetration level and the network performance index has been provided to determine the optimal numbers, sites, and sizes of DG units. This planning yields a set of non-dominated solutions with different values of DG penetration level and network performance index. The contributions of this approach are:

The proposed approach offers more flexibility to the DNO to choose a final solution from the set of solutions according to its strategic business decisions, regulatory directives regarding the electric service, and budget restrictions. For example, a DNO may prefer to reduce the DG penetration level instead of improving network performance or vice-versa.

The proposed planning can determine the ranges of DG penetration level and network performance index on which they conflict with each other. The energy provided by DG is relatively expensive than that provided by large central generators. Hence, the allocation of the DG units would be worthy for a DNO if it leads to a significant reduction on power losses, improvement in voltage levels etc.

A comparison between the Pareto-approximation sets obtained with different types of load models is carried out so as to bring out the impact of load models on the multi-objective type of problem formulation. The performance comparison between the three MOPSO variants is also reported in this work.

Author Contributions: Each author has participated and contributed sufficiently to take public responsibility for appropriate portions of the content.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflicts of interest.

References

Bollen, M., & Hassan F. (2011). Integration of distributed generation in the power system. (1. ed.). New York, USA: Wiley- Institute of electrical and electronics engineers press Publishing.

Carpinelli, G., Celli, G., Mocci, S., Pilo, F., & Russo, A. (2005). Optimisation of embedded generation sizing and siting by using a double trade-off method. IEE Proceeding -Generation, Transmission and Distribution, 152(4), 503–513.

Celli, G., Ghiani E., Mocci, S., & Pilo, F. (2005). A multiobjective evolutionary algorithm for the sizing and siting of distributed generation. Institute of electrical and electronics engineers Transmission Power Systems, 20(2), 750–757.

Chiradeja, P., Ramakumar, R. (2004). An approach to quantify the technical benefits of distributed generation. Institute of electrical and electronics engineers Transcations on Energy Conversion, 19(4), 764–773.

Deb, K. (2001). Multi-objective optimization using evolutionary algorithms. In Deb, K. Wiley Interscience Series in Systems and Optimization (pp. 501-525). New York, USA: John Wiley Publishing.

De-Souza, B.A., & De-Albuquerque, J. M. C. (2006). Optimal placement of distributed generators networks using evolutionary programming. 2006 Institute of electrical and electronics engineers /PES Transmission and Distribution Conference and Exposition, 1-6.

El-Zonkoly, A. M. (2011). Optimal placement of multi-distributed generation units including different load models using particle swarm optimization. IET Generation Transmission Distribution, 5(7), 760–771.

Ganguly, S., Sahoo, N. C., & Das, D. (2011). Mono and multi-objective planning of electrical distribution networks using particle swarm optimization. Applied Soft Computing, 11, 2391–2405.

Li. X. (2003). A nondominated sorting particle swarm optimizer for multiobjective optimization. In Tandish, R., Kendall, G., Wilson, S. (Eds.), Genetic and Evolutionary Computation — GECCO 2003: Genetic and Evolutionary Computation Conference Chicago, IL, USA, Part I (37–48). Berlin: Springer.

Mantway A. H., & Al-Muhaini, M. M. (2008). Multi-objective BPSO algorithm for distribution system expansion planning including distributed generation. 2008 Institute of electrical and electronics engineers /PES Transmission and Distribution Conference and Exposition, 1–8.

Ochoa, L.F., Feltrin, A. P., & Harrison, G. P. (2006). Evaluating distributed generation impacts with a multiobjective index. Institute of electrical and electronics engineers Transcations on Power Delivery, 21(3), 1452–1458.

Pecas Lopes, J. A., Hatziargyriou, N., Mutale, J., Djapic, P., & Jenkins, N. (2007). Integrating distributed generation into electric power systems: a review of drivers, challenges and opportunities. Electric Power Systems Research, 77, 1189–1203.

Sahoo, N. C., Ganguly, S., & Das, D. (2011). Simple heuristics-based selection of guides for multi-objective PSO with an application to electrical distribution system planning. Engineering Applications of Artificial Intelligence, 24(4), 567–585.

Singh D., Singh D., & Verma K. S. (2009). Multiobjective optimization for DG planning with load models. Institute of electrical and electronics engineers Transcations on Power Systems, 24(1), 427–436.

Singh, D., Misra, R. K., & Singh, D. (2007). Effect of load models in distributed generation planning. Institute of electrical and electronics engineers Transcations on Power Systems, 22(4), 2204–2212.

Zitzler, E., Laumanns, M., & Thiele, L. (2001). SPEA2: Improving the strength Pareto evolutionary algorithm. Technical Report 103, Computer Engineering and Communication Networks Lab (TIK), Swiss Federal Institute of Technology (ETH) Zurich, 4-18.