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Distributed Generation Planning Optimization Using Multiobjective Evolutionary Algorithms

Mahmood Sheidaee, Mohsen Kalantar

Abstract— In this paper, a method to determine the size - location of Distributed Generations (DGs) in distribution systems based on multi objective performance index is provided considering load models. We will see that load models affect the location and the optimized size of Distributed Generations in distributed systems significantly. The simulation studies are also done based on a new multi objective evolutionary algorithm. The proposed method has a mechanism to keep the diversity to overcome the premature convergence and the other problems. A hierarchical clustering algorithm is used to provide a manageable and representative Pareto set for decision maker. In addition, fuzzy set theory is used to extract the best solution. Comparing this method with the other methods shows the superiority of proposed method. Furthermore, this method can easily satisfy other purposes with little development and extension.

Index Terms— Distributed generation, Distribution systems, Load models, Strength Pareto Evolutionary Algorithm.

1 Introduction

Optimization was used to reconstruct electricity industry and looked for the best location for distributed products. Development in technology and client requirements to have cheap electric power and reliable one caused more motivation in distributed generation .Discussion about reliability and maintaining prevent the penetration of DG resources in the distribution systems.

In [1] one approach was described based on genetic algorithm for multistage planning of distribution systems optimizations. In this work, it's expressed as a mathematical model and algorithmic one and also tested with real systems. In [2] – [5], it was studied on load models that are usable for power flow and dynamic studies. This study was done on load models depended on frequency or voltage. During the recent years, studies on evolutionary algorithm have shown that these methods don't have the difficulties of classical methods. In principle, multiple Pareto optimal solutions can be found in one single run.

This paper has discussed on load model effects in location and size planning and distributed generation optimization. We can see that the load models affect on location and size planning of DGs in distribution network. For the purpose of studying on load models, its delivered location and size planning for single DG, its assumed that the regarded DG has enough capacity. The proposed method is general and it can be used for case of multiple DG in the network with increasing some variables.

This paper also suggested a new Strength Pareto Evolutionary Algorithm (SPEA) based approach for solving the problem. The diversity-preserving mechanism embedded in the search algorithm makes it effective in exploring the problem space and capable of finding widely different solutions. A hierarchical clustering technique is implemented to provide a representative and manageable Parto-optimal set. Also, a fuzzy-based mechanism has used the best solution for extraction.

2 Load Models and Impact Indices

To determine different load model effects on distributed generation planning, 37-bus distribution system will be studied (appendix 1)[7]. The effect of load models depends on voltage, means residential, industrial and commercial, will be studied in different planning scenarios. Load model defined as followed.

$$P_i = P_{0i}|V_i|^{\alpha} \, / \, Q_i = Q_{0i}|V_i|^{\beta} \qquad (1)$$

Where P_i and Q_i are active and reactive power at bus i, P_{0i} and Q_{0i} are active and reactive power operating point in bus I, V_i is voltage in bus i and α and β are active and reactive power exponents. In a constant power model conventionally used in power flow studied $\alpha = \beta = 0$ is assumed. The values of the real and reactive exponents used in the present paper for industrial, residential and commercial loads are given in Table 1 [7].

TABLE 1
EXPONENT VALUES

Load Type	α	β
Constant	0	0
Industrial	0.18	6.00
Residential	0.92	4.04
Commercial	1.51	3.40

During studying residential, it's assumed that 38-bus systems just has residential load. It's assumed that for industrial and commercial load, all loads are a kind of industrial and commercial. In real situations, loads aren't exactly residential, commercial and industrial, so the mixture load class should be foreseen for distribution system. There are different ideas for studying DG effects in distribution systems .One of this idea is different indices evaluation on the purpose of effect description on distribution system because of DG during maximum power production. These indices are

1) Active and Reactive Power Loss Indices (ILP and ILQ):

$$ILP = \frac{[P_{\mathrm{LDG}}]}{[P_{\mathrm{L}}]}\times 100 / ILQ = \frac{[Q_{\mathrm{LDG}}]}{[Q_{\mathrm{L}}]}\times 100 \qquad (2)$$

Where P_{LDG} and Q_{LDG} are total loss of active and reactive power distribution system with DG, P_L and Q_L are total loss of active and reactive power of total system without DG in the distribution network.

2) Voltage Profile Index (IVD): One of the advantage of proper location and size of the DG is the improvement in voltage profile.

$$IVD = \max_{\mathrm{i}=2}^{\mathrm{n}}\left(\frac{|V_1| - |V_{\mathrm{i}}|}{|V_1|}\right)\times 100 \qquad (3)$$

3) MVA Capacity Index (IC): This informational index gives information in the field of system necessities for promoting transmission line.

$$IC = \max_{\mathrm{i}=2}^{\mathrm{n}}\left(\frac{|S_{\mathrm{ij}}|}{|CS_{\mathrm{ij}}|}\right) \qquad (4)$$

3 PROPOSED APPROACH

Recently evolutionary algorithm showed that this algorithm can be effective for removing old method problems [8]. The main element method of SPEA is

1) External set: It's a set of Pareto optimal solutions. These solutions were recorded externally and continuously be updated. Finally recorded solutions show Pareto optimal front.

2) Strength of a Pareto optimal solution: It is an assigned real value S∈[0,1) for each individual in the external set. The strength of an individual is proportional to the number of individuals covered by it.

3) Fitness of population individuals: Fitness of each individual in population is the sum of the strengths of all external Pareto optimal solutions by which it is covered. The strength of a Pareto optimal solution is at the same time its fitness.

Algorithm is in the following steps [8].

Step 1) primary amounts: produce population and make empty external Pareto optimal set.

Step 2) updating external set: External Pareto optimal set is updated as following:

a) Search population for the nondominated individuals and copy them in the external pareto set.

b) Search external Pareto set for the nondominated individuals and emit all dominated individuals from the set.

c) If the amount of the individuals externally stored in the Pareto set exceeds a prespecified maximum size, reduce the set by means of clustering.

Step 3) Fitness assignment: Calculate the amount of fitness values of individuals in both external Pareto set and the population as follows.

a) Assign appropriate each individual s strength amount in external set. The strength amount is proportional to the number of individuals covered by that individual.

b) The fitness of each individual in population is equal to the sum of the strengths of all external Pareto solutions which dominate that individual.

Step 4) Selection: combine the population and external set individuals. Choose two individuals randomly and compare their fitness. Choose the best one and copy in a mating pool.

Step 5) Crossover and Mutation: do the crossover and mutation according to new population production probabilities.

Step 6) Ending: check the ending criteria if all things are being done finish the work else substitute the old population with the new one and go to step2.

In this paper, time searching will be stopped if the generation counter exceeds its maximum number.

In some cases, the Pareto optimal set is extremely big or has extra solutions. An average linkage based hierarchical clustering algorithm is used to reduce the Pareto set. We want to change P given set which its size exceeds the maximum allowable size N to P* set with size of N. Algorithm is such as following [8].

Step 1) Give primary amount to set C. each member of P means a distinct cluster.

Step 2) if the number of clusters ≤ N, go to Step 5, else go to Step 3.

Step 3) Calculate all the pairs of clusters distance. The distance d_c of two clusters C_1, $C_2 \in C$ is given as the average distance between pairs of individuals across the two clusters

$$d_{\mathrm{c}} = \frac{1}{n_1 n_2}\sum_{\mathrm{i}_1\in \mathrm{c}_1, \mathrm{i}_2\in \mathrm{c}_2} d(i_1, i_2) \qquad (5)$$

Where n_1 and n_2 are clusters individuals of C1 and C2. Function d shows Euclidian distance between i_1 and i_2.

Step 4) Determine two clusters that have minimum dc distance. Combine these clusters into a larger one. Go to Step 2.

Step 5) find centroid for each cluster and choose the nearest individual to the centroid as agent and emit other individuals from the cluster.

Step 6) Compute the reduced nondominated set P* by uniting the representatives of the clusters.

As soon as having the Pareto optimal set of nondominated solution, the proposed approach presents one solution as the best compromise solution. Each objective function of the i-th solution is represented by a membership function μ_i defined as

$$\mu_i = \begin{cases} 1 & F_i \le F_i^{min} \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} \le F_i \le F_i^{max} \\ 0 & F_i \ge F_i^{max} \end{cases} \qquad (6)$$

For each nondominated solution, the normalized membership function μ^k is

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^k} \qquad (7)$$

where M is the number of nondominated solutions. The best solution is the one that has more μ^k.

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4 IMPLEMENTATION OF THE PROPOSED APPROACH

Because of Binary representation problems when search space has wide dimension, the proposed approach has been implemented using Real Coded Genetic Algorithm (RCGA). Decision variable x_i has real amount within limit of a_i and b_i ($x_i \epsilon [a_i,b_i]$). The RCGA mutation and crossover operators RCGA is like this.

Crossover: A blend crossover operator (BLX-α) has been employed in this paper. This operator will choose one number randomly from the interval $[x_i - \alpha(y_i - x_i)\ ,\ y_i + \alpha(y_i - x_i)]$, where x_i and y_i are the ith parameter values of the parent solutions and $x_i < y_i$. Because of ensure the balance between exploitation and exploration from search space, $\alpha = 0.5$ is chosen.

Mutation: Nonuniform mutation was used here. In this operator, new amount x'_i of parameter x_i produced after mutation in t time.

$$x_i' = \begin{cases} x_i + \Delta(t, b_i - x_i)\, if, \tau = 0 \\ x_i - \Delta(t, b_i - x_i)\, if, \tau = 1 \end{cases} \qquad (8)$$

$$\Delta(t, y) = y\left(1 - r^{\left(1 - t/g_{max}\right)^{\beta}}\right) \qquad (9)$$

Where τ is a binary random number, r is a random number $r \epsilon [0,1]$, g_{max} is maximum number of generations and β is a positive constant that is desirable. $\beta = 5$ is selected. This operator gives a value $x'_i \epsilon [a_i,b_i]$ such that the probability of returning a value close to x_i increases as the algorithm advances. This makes uniform search in the initial stages where t is small and for later stages is so local.

5 MULTIOBJECTIVE BASED FORMULATION

Multiobjective index for evaluating distribution systems operation on purpose of DG location and size planning with load models, considers all previously mentioned indices by strategically giving a weight. The multiobjective index operation on basis of SPEA algorithm is according to (10).

$$IMO = \left(\sigma_1.ILP + \sigma_2.ILQ + \sigma_3.IC + \sigma_4.IVD\right) \qquad (10)$$

These weights are because of giving the corresponding importance to each impact indices. Table 2 identifies used amount for the weights with regarding normal operation analysis [7].

TABLE 2
INDICES WEIGHTS

Indices	σ_p
ILP	0.40
ILQ	0.20
IC	0.25
IVD	0.15

Multiobjective function (10) can be minimized with regarding to various operational constraints to satisfy the electrical requirements for distribution network. These limitations are:

1) Power Conservation Limits: The algebraic sum of all input and output powers, such as distribution network total losses and power generated from DG, which should be equal with zero. (NOL = no of lines)

$$P_{SS}(i,V) = \sum_{i=2}^{n} \left(P_D(i,V)\right) + \sum_{n=1}^{NOL} P_{loss}(V) - P_{DGi} \qquad (11)$$

2) Distribution Line Capacity Limits: Transmission capability in each line should be equal with thermal capacity.

$$S_{(i,j)} \le S_{(i,j)_{max}} \qquad (12)$$

3) Voltage Drop Limits: voltage drop should base on voltage regulation that DISCO gives.

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$$\left|V_1 - V_{\mathrm{j}}\right| \le \Delta V_{\max} \qquad (13)$$

If voltage and MVA limits in system buses for a particular size and location, accept that pair for next generation, else this size and location will be ignored and rejected. Size and location should be had minimum IMO.

6 Simulation Results

The multiobjective index based analysis is carried out on 37-bus test systems as given in the Appendix [7]. A DG size is considered in a practical range (0–0.63 p.u.). It's assumed that DG is operated at unity p.f.. This assumption has two reasons:

1) Usually when the DG has unity power factor, has maximum profit because the cost of active power is higher. Use at unity power factor cause to have maximum capacity.

2) Used models in this paper are simple and more attention is for voltage changes dependence of load models.

The using method hasn't been limited by DG models and it's general. First bus was chose as feeder of electric power from network and the rest buses are regarded as DG location. On all optimization runs, the population size and maximum number of generations were selected as 200 and 500, respectively. The Pareto optimal set maximum size includes 20 solutions. The crossover and mutation probabilities were selected as 0.9 and 0.01, respectively. For 37-bus system, variation of impact indices and IMO have been shown with DG size and location in figure 3-7 for constant, industrial, residential, commercial and mixed load models. The value of IVD for all load models is near zero. It shows that voltage profile improves with present DG.

We can see from Figs. (1) – (5) that the indices ILP, ILQ, IC and IMO achieve values greater than zero and smaller than one, indicating the positive impact of DG placement in the system. Fig. 1 shows that values of IC, ILP and ILQ for buses 2-4 as IC<ILP<ILQ and for buses 6-8 like ILQ<ILP<IC. Figure 2 shows the value of optimum DG size, IMQ and its components for all buses for industrial load model. So load models affect on solutions.

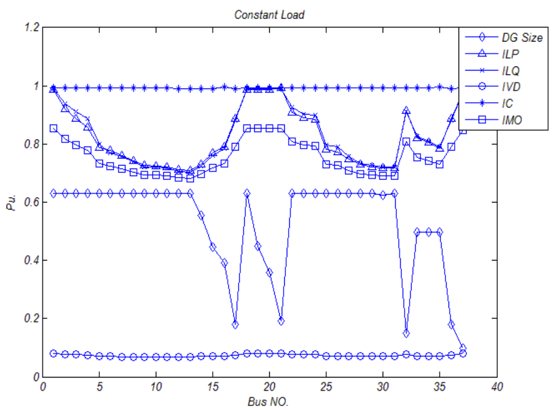

Fig. 1. Impact indices and IMO with DG size-location pair for constant load

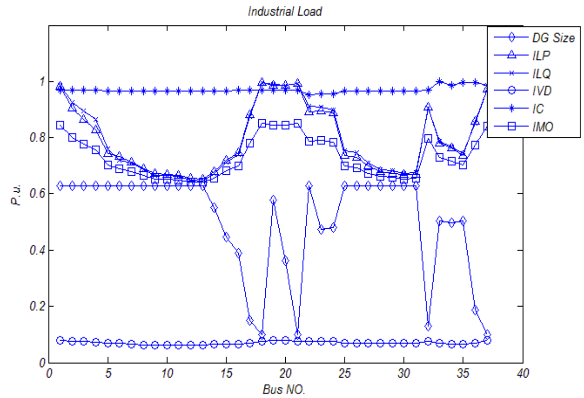

Fig. 2. Impact indices and IMO with DG size-location pair for industrial load

The solution obtained using constant power load models may not be feasible for industrial load. A similar and significant effect of load models can be easily be observed from the Figs. (3) – (5) for residential commercial and mixed load models. The differences in values of DG size, IMO and its components are significant, showing that the load models effects are important for suitable planning of size and location. Table 3 summarizes the optimal DG size-location pairs, IMO along with its components for each kind of load. From Table 3, the optimal size-location for constant load model (0.6299 p.u. – bus 14) is different with industrial load model (0.63 p.u. – bus 14) residential load model (0.4672 p.u. – bus 14) commercial load model (0.4419 p.u. – bus 14) and mixed load (0.5113 p.u. – bus 32). Similarly IMO and other effective indices for optimal DG location-size are different.

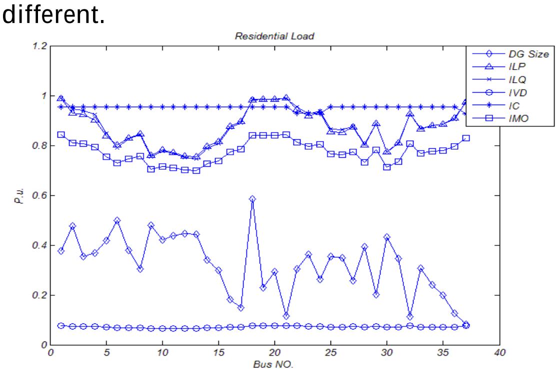

Fig. 3. Impact indices and IMO with DG size-location pair for residential load

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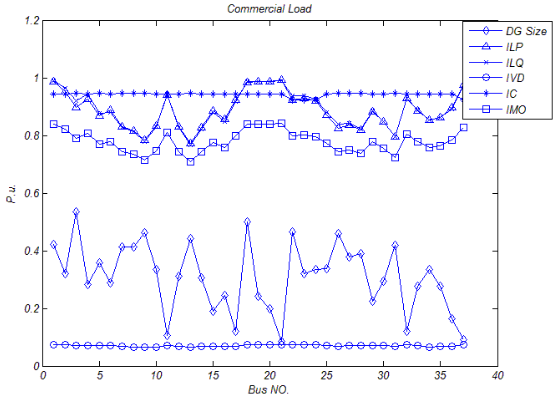

Fig. 4. Impact indices and IMO with DG size-location pair for commercial load

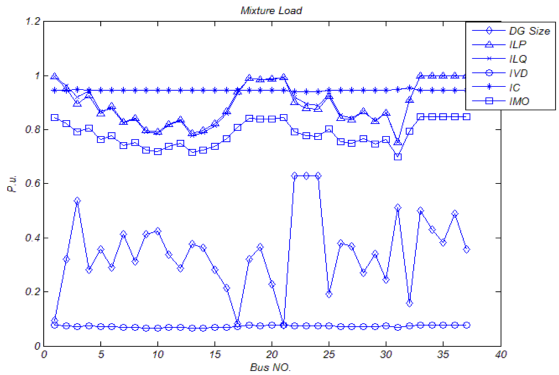

Fig. 5. Impact indices and IMO with DG size-location pair for mixture load

The probable DG location-sizes may be little (because of constraints), but the number of candidate solution are fairly large to suggest the application of SPEA. The differences in values of DG size, IMO and its components are significant for load models, showing that the load models effects are important for suitable planning of size and location. The values of Q_{LDG} and P_{LDG} related to optimal size –location for any kind of load model have been shown in table 4, although the values of Q_{LDG} and P_{LDG} for nonconstant load models (industrial – residential – commercial and mixture) aren't different but their difference is significant when compared to constant load model.

TABLE 3
IMPACT INDICES COMPARISON FOR PENETRATION OF DG WITH LOAD MODELS

Indices	Constant	Industrial	Residential	Commercial	Mixture
ILP	0.7078	0.6517	0.7459	0.7756	0.7526
ILQ	0.7035	0.6449	0.7383	0.7685	0.7551
IC	0.9913	0.9671	0.9570	0.9476	0.9478
IVD	0.0687	0.0634	0.0661	0.0653	0.0696
IMO	0.6823	0.6409	0.6952	0.7106	0.6994
Location	14	14	14	14	32
Size	0.6299	0.63	0.4672	0.4419	0.5113

TABLE 4
COMPARISON OF SYSTEM POWER LOSSES AT OPTIMAL LOCATION OF DG WITH LOAD MODELS

Load model	Optimal location	P_{LDG} × 0.01 p.u.	P_L × 0.01 p.u.	Q_{LDG} × 0.01 p.u.	Q_L × 0.01 p.u.
Constant	14	0.1499	0.2002	0.0991	0.1335
Industrial	14	0.1464	0.1671	0.0968	0.1112
Residential	14	0.1358	0.1604	0.0896	0.1066
Commertial	14	0.1166	0.1548	0.0767	0.1028
Mixture	32	0.1142	0.1588	0.0766	0.1056

6.3 Conclusion

The general analysis includes load models is proposed for location–size of distributed generation planning in multiobjective optimization in distribution systems. The multiobjective criteria depends on system operation indices is used in this work. It was seen that while regarding load models, there will be changed in DG location and size. The overall value of multiobjective index (IMO) changed during charge model changing.

Also in this paper, we suggested a new method based on Pareto evolutionary algorithm and used for DGs location – size planning problem. This problem formulized as a multiobjective optimization problem, A diversity preserving mechanism for finding widely different Pareto optimal solutions was used. A hierarchical clustering technique is implemented to provide a representative and manageable Pareto optimal set without destroying the characteristics of the trade-off front and a fuzzy based mechanism is used for finding the best compromise solution. The result shows that the suggestive method for multiobjective optimization problem is useful, because multiple Pareto optimal solutions are found during simulation. Since the proposed approach does not impose any limitation on the number of objectives, its extension to include more objectives is a straightforward process.

APPENDIX

Fig. 6 shows the 37-bus test system.

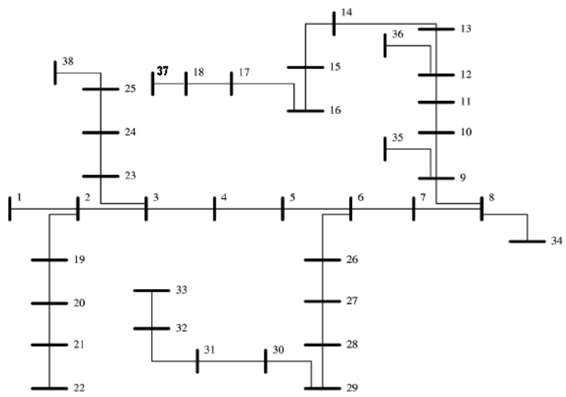

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Fig. 6. 37-bus test system

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