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Optimal Siting And Sizing Of Distributed Generation For Radial Distribution System Using Genetic Algorithm

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Abstract*: Distributed generation (DG) is an emerging concept in the electricity sector, which represents good alternatives for electricity supply instead of the traditional centralized power generation concept.This paper presents a multi-objective performance index –based size and site determination of distributed generations in distribution system with various load models. The Optimal size and site of distributed generation is evaluated with multi-objective optimized values.The Multi-objective index is converted into Single objective performance index with the help of significant weights. It can evaluated the optimal siting and sizing with Genetic Algorithm (GA) and resluts were tested with 37-bus radial distribution system*

Keywords – Distributed Generation (DG), Genetic Algorithm (GA), load model, Multi-Objective Index.

I. INTRODUCTION

The distributed generation [1] is used to refer to generation units that are connected to the distribution network rather than to the high voltage transmission grid. The renewed popularity of Disribution Generator (DG) after a period of hiatus is creating new opportunities for increasing the diversity and efficiency of our electricity supply and It is also challenging the established architecture of the networks.

Since the past years the generation at large scale took place at near fuel center which is far away for the load centers in case of nuclear also.These made intiation of DG is encouraged as part of the government's lowcarbon energy policy aimed at reducing the emissions linked to climate change.

The distributed real power sources can be classified into two categories [4] as Type-1-DG and Type-2-DG.Where Type-1-DG are supply the real power, depending on the availability or demand, to the network without demanding any reactive power. The best examples of Type-1-DG are photovoltaic cell, fuel cell, battery storage. Which are modeled as negative real power loads in the load flow analysis and Type-2-DG are supply the real power to the network only when adequate reactive power support is provided by the network or any local reactive power sources.DG can be installed at load or near the load.In this paper the DG considered at load point only. By using this DG in distribution System,the following economic and technical benefits are being implicated .

The major technical benefits are:

- Reduced line losses
- Voltage profile improvement
- Reduced emissions of pollutants
- Increased overall energy efficiency
- Enhanced system reliability and security

1.2. Load Model:

Normally loads are assumed to b real power and reactive power and is called constant power .In this paper not only the constant loads but industrial load, residential load, commercial load and mixed load are conisdered.The studies of dynamic performance, load representation becomes more important.The Load characteristics affect the dynamic behavior of a power system.The exact composition of the load is often very difficult to estimate. Load composition changes continually reflecting the customers' pattern of using various appliances and devices. It depends on the customers' lifestyle, the weather, the state of economy, and many other factors. It is important to estimate the load composition at time of critical interest such as under a heavy or light load condition. As load demand is increasing day to day life still it is necessary for a reliable estimation of load composition. Even if the load composition is known exactly, it would be impractical to represent each individual load component, as there are usually many thousands of components. Generally the model of the composite load will be impractically complex and will require considerable mathematical processing to obtain a reasonably manageable overall system model. Thus, in one's deal to obtain the optimum and most elegant form of a component model, one may aggravate the difficulties of the aggregation problem. There is, in fact, a problem even in combining models of the same type in the case of dynamic loads such as induction motors. Moreover, the load components are usually operating at different voltages with the same rating of the component. Steadily, though slowly, the available information on load is increasing. The utility industry, including utilities, regulatory agencies, manufacturers and customers, is accumulating data that can be effectively used to estimate the load composition.

The effect of selected voltage dependent on load models which is investigated in different planning scenarios. The load models can be mathematically expressed as:

$$P_i = P_{0i} \times {V_i}^{\alpha} \quad \text{.........................} (1)$$

$$Q_i = Q_{0i} \times {V_i}^{\beta} \quad \text{.......................} (2)$$

Where: P_i and Q_i are real and reactive power at bus i; P_{0i} and Q_{0i} are active and reactive operating point at bus i;

V_i is the voltage at bus i. α and β are real and reactive power exponents.

During investigations the comparison of constant power load model assumption with the practical load models are emphasized. In this paper the 37-bus system has taken to test the varous loads and it will be run with matlab environment using genetic algorithm technique.

By Incorporating the DG at any node, the load at that point can be consider as

$$P_{eff} = P_i - P_{dg} \quad \text{...............................} (3)$$

$$Q_{eff} = Q_i - Q_{dg} \quad \text{...............................} (4)$$

Where :P_{eff} and Q_{eff} are the real and reactive power of load at i_{th} node after installing the DG.

P_i and Q_i are the real and rective power of the load at i_{th} bus before installing of DG.

P_{dg} and Q_{dg} are the real and reactive power of distributed generation.

From the above equqtions The following loads are cosidered for evaluation of optimal siting nad sizing .The loads areshown in Table:1.

Table 1: Load type and exponent values

Load type	**α**	**β**
Constant	0.00	0.00
Industrial	0.18	6.00
Residential	0.92	4.04
Commercial	1.51	3.40
Mixed	0.65	3.36

1.3. Impact Indices

The following indices are used to evaluate the optimal siting and sizing in distribution system for 37-bus system.

a. Real and Reactive power loss Indicies

The real and reactive power loss indices are defined as:

$$\text{ILP} = \frac{[P_{LDG}]}{[P_L]} \quad \text{...} (5)$$

$$\text{ILQ} = \frac{[Q_{LDG}]}{[Q_L]} \quad \text{..} (6)$$

Where :

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

b. Voltage Profile Index (IVD)

The voltage indices is also called as index voltage deviation . one of the advantage of proper location and size of the DG is the improvement in voltage profile. This index penalizes the size-location pair which gives higher voltage deviations from the nominal (V1=1.0 p.u.) In this way, closer the index to zero better is the network performance .The IVD can be defined as follows:

$$\text{IVD} = \max_{2 \le i \le n} \left(\frac{|\overline{V_1}| - |\overline{V_i}|}{|\overline{V_1}|} \right) \quad \ldots\ldots\ldots (7)$$

c. MVA Capacity Index (IC) and Voltage deviation (VD)

As a consequence of supplying power near to loads, 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 distribution line limits i.e if line limits are not taken as constraints. The IC gives important information about the level of MVA flow /currents through the network regarding the maximum capacity of conductors. This gives the information about need of system line upgrades. Values higher than unity (calculated MVA flow values higher than the MVA capacity) of the index give the amount of capacity violation in term of line flows, whereas the lower values indicate the capacity available and propotionatlely the voltage diviations are obtaioned by using the following formulas:

$$\text{IC} = \max_{2 \le i \le n} \left(\frac{|\overline{S_{ij}}|}{|\overline{CS_{ij}}|} \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

$$\text{VD} = \frac{\sum_{i=1}^{N_{nodes}} \big| |V_i| - V_n \big|}{N_{nodes}} \quad \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

The benefit of incorporating DG in a system in context of line capacity released is measured by finding the difference in IC between system with and without DG. The avoidance of flow near to the flow limit is an important criterion as it indicates that how earlier the system needs to be upgraded and thus adding to the cost. The use of IC index may not be applicable in the context available transmission capacity improvement in transmission systems.

II. GENETIC ALGORITHM

The GA is inspired by the evolutionary theory explaining the origin of species. In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection.

In GA terminology, a solution vector $x \in X$ is called an individual or a chromosome. Chromosomes are made of discrete units called genes. Each gene controls one or more features of the chromosome. In the original implementation of GA operates with a collection of chromosomes, called a population. The population is normally randomly initialized, As the search evolves, the population includes fitter and fitter solutions, and eventually it converges, means that it is dominated by a single solution. For convergence to the global optimum where chromosomes are binary vectors GA use two operators to generate new solutions from existing ones crossover and mutation,which are discussed in the susiquent of this paper.

a) Crossover

The crossover operator is the most important operator of GA. In crossover, generally two chromosomes, called parents, are combined together to form new chromosomes, called offspring. The parents are selected among existing chromosomes in the population with reference towards fitness so that offspring is expected to inherit good genes which make the parents fitter. By iteratively applying the crossover operator, genes of good chromosomes are expected to appear more frequently in the population, eventually leading to convergence to an overall good solution. Crossover probability is taken 0.9.

b) Mutation

The mutation operator introduces random changes into characteristics of chromosomes.Mutation is generally applied at the gene level. In typical GA implementations, the mutation rate is very small, typically less than 10%. However the mutation plays a criticalrole in GA. As discussed earlier, crossover leads the population to converge by making the chromosomes in the population alike. Mutation reintroduces genetic diversity backinto the population and assists the search escape from local optima. Mutation probability has taken 0.1.

c) Reproduction

Reproduction involves selection of chromosomes for the next generation. In the most general case, the fitness of an individual determines the probability of its survival for the next generation. There are different selection procedures in GA depending on how the fitness values are used. After initialization the value of objective function is calculated. Corresponding to the value of objective function the next operation selection is done. The following selection process is used in the system.Those are

1. Deterministic selection.
2. Roulette wheel selection.
3. Stochastic selection without replacement
4. Remainder stochastic sampling with replacement
5. Stochastic sampling with replacement

Out of these selection process the Roulette Selection process is considered in this paper since it gives fitness values for each individual values ,that is the most important advantage ,with that the optimal evauation in distribution system is done.

III. ROULETTE WHEEL SELECTION

Roulette Selection process is considered in this paper since it gives fitness values for each individual values ,that is the most important advantage.Those are

1. The objective function is evaluated for each individual, providing fitness values, which are normalized. Normalization means multiplying the each fitness value of each individual by a fixed number, so that the sum of all fitness values equals 1.
2. The population is sorted by descending fitness value.
3. Accumulated normalized fitness are computed (the accumulated fitness value of an individual is the sum of its own fitness value plus the fitness value of all previous individuals). The accumulated fitness of the last individual should be 1.
4. A random number R between 0 and 1 is chosen.
5. The selected individual is the first one whose accumulated normalized value is greater R.

With the above analysis the procedure developed Genetic Algorithm .

Step 1: Initialization: Randomly generate the initial population of size N and set i = 0.

Step 2: Fitness Assignment: Evaluate the fitness value for each population based on its Objective function value.

Step 3: If the stopping criterion is satisfied, terminate the search and display the result Else, go to Step 4.

Step 4: Crossover: To generate the offspring using crossover, randomly select two parents solution from the initial population and then generate the two off-springs using crossover operator.

Step 5: Mutation: This operator randomly **s**elects one parent solution from the initial population and applies the mutation operator to generate a single offspring.

Step 6: Selection: Select *N* solutions from generated population and the old population, sed on their fitness. Set generation i = i+1. Go to step 2. This steps are shown in flow charts of fig:1

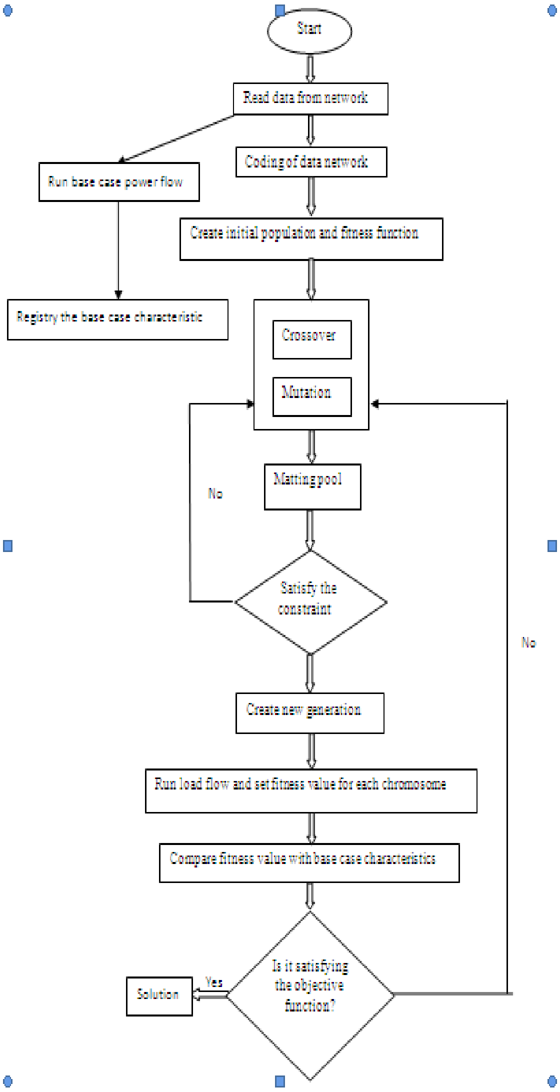

Fig. 1 Flow chart for Genetic Algorithm

IV. TEST OF 37-BUS SYSTEM USING GENETIC ALGORITHM (GA)

The 37-bus test system are taken from[7] the base values used are 100 MVAand 23 kV. The exhaustive power flow solution for the37-bus distribution system is obtained in the following fashion.With this the system is tested at different power factors such as upf,0.8laging and 0.8 leading by considering single DG optimization,two DG,three DG,four DG and five DG optimization are tested with MATLAB environment using Genetic Algorithm Technique and corressponding test results for optimization of objective function is discussed elabrately in the following cases

Case 1.

a. Single DG Optimization for UPF:

The population size is 20. The chromosome length is 15. The first five bit of chromosome contains only 0 or 1. The bit 0 represents that there is no DG and the bit 1 represents there is a DG at the corresponding place. The next five bit represents the number of node and the last five bit represents the size of the DG. After initialization of the population and calculating the fitness function the selection, crossover and mutation is done. And the obtained optimal site and size is as following for all the five type of loads.

b. Single DG Optimization for 0.8 lag:

The population size is 20. The chromosome length is 20. The first five bit of chromosome contains only 0 or 1. The bit 0 represents that there is no DG and the bit 1 represents there is a DG at the corresponding place. The next five bit represents the number of node and the third five bit represents the size of the active DG and the last five bit represents reactive size of DG. After initialization of the population and calculating the fitness function the selection, crossover and mutation is done. And the obtained optimal site and size is as following for all the five type of loads.

c. Single DG Optimization for 0.8 lag:

The population size is 20. The chromosome length is 20. The first five bit of chromosome contains only 0 or 1. The bit 0 represents that there is no DG and the bit 1 represents there is a DG at the corresponding place. The next five bit represents the number of node and the third five bit represents the size of the active DG and the last five bit represents reactive size of DG. After initialization of the population and calculating the fitness function the selection, crossover and mutation is done. And the obtained optimal site and size is as following for all the five type of loads.

Case 2. Multi-DG Optimization

a.Optimization for two DGs:

The population size is 20. The chromosome length is 6. The first two bit of chromosome contains only 0 or 1. The bit 0 represents that there is no DG and the bit 1 represents there is a DG at the corresponding place. The next two bit represents the number of node and the last two bit represents the size of the DG. After initialization of the population and calculating the fitness function the selection, crossover and mutation is done. And the obtained optimal sites and sizes are as following for all the five type of loads.

b.Optimization for three DGs:

Result for optimization of objective function (IMO) for three DG.The population size is 20. The chromosome length is 9. The first three bit of chromosome contains only 0 or 1. The bit 0 represents that there is no DG and the bit 1 represents there is a DG at the corresponding place. The next three bit represents the number of node and the last three bit represents the size of the DG. After initialization of the population and calculating the fitness function the selection, crossover and mutation is done and the optimal sites and sizes are obtained as following for all the five type of loads. Which is shown in table 2.

LOAD	NODE	SIZE	NODE	SIZE	NODE	SIZE	ILP	ILQ	IC	IVD	IMO
CONSTANT	7	0.4813	14	0.5580	24	0.6033	0.7279	0.7220	0.7609	0.0744	0.6368
INDUSTRIAL	15	0.6189	24	0.5697	35	0.1902	0.7134	0.7086	0.7423	0.0736	0.6237
RESIDENTIAL	16	0.5005	24	0.5722	35	0.3006	0.7606	0.7543	0.7947	0.0758	0.6658
COMMERCIAL	10	0.3536	11	0.2678	15	0.6208	0.7318	0.7261	0.7655	0.0746	0.6405
MIXED	14	0.6151	32	0.4157	35	0.6193	0.7202	0.7148	0.7518	0.0740	0.6301

Table 2. Optimal site and size for 37-bus system

c.Optimization for Four DGs:

Result for optimization of objective function (IMO) for four DGs of random sizes.The population size is 20. The chromosome length is 12. The first four bit of chromosome contains only 0 or 1. The bit 0 represents that there is no DG and the bit 1 represents there is a DG at the corresponding place. The next four bit represents the number of node and the last four bit represents the size of the DG. After initialization of the population and calculating the fitness function the selection, crossover and mutation is done and the optimal sites and sizes are obtained as following for all the five type of loads. Which is shown in table 3.

LOAD	NODE	SIZE	NODE	SIZE	NODE	SIZE	NODE	SIZE	IC	IVD	IMO	IVD	IMO
CONSTANT	19	0.2571	27	0.4349	33	0.4274	35	0.4762	0.7955	0.7972	0.8215	0.0803	0.6951
INDUSTRIAL	9	0.3678	13	0.4246	17	0.6233	20	0.5607	0.7303	0.7327	0.7512	0.0740	0.6376
RESIDENTIAL	10	0.6181	15	0.5701	20	0.3364	26	0.2783	0.7340	0.7282	0.7680	0.0747	0.6424
COMMERCIAL	7	0.6050	14	0.5279	16	0.4578	33	0.6109	0.7352	0.7425	0.7554	0.0776	0.6431
MIXED	11	0.6197	17	0.2361	26	0.6158	36	0.3287	0.7348	0.7316	0.7508	0.0740	0.6390

Table 3. Optimal site and size for 37 bus system

From the above analysisl, a DG size is considered in a practical range (0–0.63 p.u.). The DG of 0.0 p.u. corresponds to system without DG whereas 0.63 p.u. corresponds to a case of maximum possible value of DG planned. First it is considered that the DG is operated at unity p.f. and then 0.8 power factor lagging and leading. And for two DGs, three DGs,and four DGs has been evaluated and from table2 ,table3 the optimal site and size are inversely propotional ,it means if more than one DG the cost will become more and the aytem is also more complex i.e.it is better to install the single DG of single DG of lagging power factor (p.f=0.8) is better but in the case of leading power factor DG (p.f=0.8) the value of IMO increases. Finally the comparison between single and multi objective optimizations are

(1) In general, multi-objective optimization requires more computational effort than single-objective optimization. Unless preferences are irrelevant or completely understood, solution of several single-objective problems may be necessary to obtain an acceptable final solution.

(2) The advantage of the weighted sum approach is a straightforward implementation. Since a single objective is used in fitness assignment, a single objective GA can be used with minimum modifications.Amulti-objective GA based set of solutions have difficulty in finding the single solution.

(3) Solutions obtained with no articulation of preferences are arbitrary relative to the Pareto optimal set. In this class of methods, the objective sum method is one of the most computationally efficient, easy-to-use, and common approaches. Consequently, it provides a benchmark approach to multiobjective optimization.

4) Solution obtained by single objective optimization is unique which is globally optimized and user is bound to go for that solution only but in case of multi-objective optimization user is free to choose the solution as per his requirement.

V. CONCLUSION

The exhaustive analysis, including load models, for size-location planning of distributed generation in multiobjective optimization in distribution systems is presented. The multiobjective criteria based on system performance indices of ILP and ILQ, related to real and reactive power losses, and IC and IVD, related to system MVA capacity enhancement and voltage profile improvement, is utilized in the present work. The overall value of multiobjective index (IMO) is found to be significantly different with different load models. The effect of load models on individual performance indices is also shown and it is established that the load models play a decisive role in deciding the size-location pair of DG in any practical distribution system. The application of GA for DG size-location planning has been tested by comparing the results with exhaustive enumeration. It was observed that when GA was run multiple numbers of times at some cases the suboptimal solutions were also obtained. It is worth noting that, no cases is cosidered the suboptimal solution compared to second best solution of suboptimal values.Finally the solution for the small could be obtained in the exhaustive fashion but it becomes prohibitive for large system and therefore GA is useful for such system even with suboptimal solutions.

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List of symbols:

ILP- Real power loss index
ILQ-Reactive power loss index
IC-MVA Capacity index
IVD- Voltage profile index
IMO- Index of multi-objective
VD-Voltage deviation
σ_1-Weight given to ILP

σ_2-Weight given to ILQ

σ_3-Weight given to IC

σ_4-Weight given to IVD