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<th><strong>Title</strong></th>
<th>Multi-objective planning model for integration of distributed generations in deregulated power systems</th>
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Abstract—With the introduction of restructuring concepts to traditional power systems, a great deal of attention is given to the utilization of distributed generation. Since the integration of DG units has been known as an alternative for main grid as a resource for energy supply, the determination of optimal sizing and siting is an important issue in the planning procedure of DG. This work presents a comprehensive multi-objective model for integration of distributed generations into a distribution network, regarding various technical, economical and environmental issues such as reduction of active power losses, carbon dioxide emissions, and investment & running costs while the bus voltages shall be kept within acceptable limits. A genetic algorithm and a fuzzy decision making method has been proposed to solve this problem. The method is applied on IEEE-34 feeder test system and the results are presented and discussed.

Index Terms— Distributed Generation, Multi Objective Optimization, Active loss reduction, Voltage Profile, Environmental pollutions.

I. INTRODUCTION

WITH the introduction of restructuring concepts to traditional power systems, a great deal of attention has been given to utilization of distributed generations. DG is defined as all small generators, typically ranging from 15 to 10000 KW, scattered throughout a power system, to provide the electric power needed by customers [1]. In most power systems, a large portion of electricity demand is supplied by large-scale generators; this is because of economic advantages of these units over small ones. However, in the last decades, technological innovations and a changing economic and regulatory environment have resulted in a renewed interest for DG units [2]. A study by the Electric Power Research Institute (EPRI) indicates that by 2010, 25% of the new generation will be distributed. Natural Gas Foundation concluded that this figure
could be as high as 30% [3]. There are five major factors behind this trend [4]: electricity market liberalization, development in DG technology, constraints on the construction of new transmission lines, reliability enhancement and concerns about environmental aspects. In addition to those indicated before, there are other important benefits in using DG units into distribution systems. In liberalized electricity markets the distribution companies (DISCOs) are responsible for supplying the customers in their territory. Since only a fix percent of their losses are compensated, the loss reduction increases their profits [5-7]. Another important factor which has become more important in liberalized electricity industry is the quality of the service which DISCO provides to its customers like voltage profile [8] or reliability [9]. With the increasing demand and potential congestion problems, it is necessary to upgrade the distribution network facilities to meet the current and future needs. Any deferral to these unavoidable costs would be beneficial [10]. Additionally other costs should be taken into account like cost of purchased energy, cost of energy losses and cost of energy not supplied [11] and the different costs associated with incorporation of DG units into the distribution systems like installation, operation and maintenance costs. Some restrictions on environmental pollutions may force the DISCOs to use green power or less pollutant technologies. There are also other benefits mentioned in the literature like voltage stability improvement [12]. On the other hand, there shall be a trade off between the costs associated with utilization of DG units and the mentioned technical and economical (like purchasing the power of DG to main grid [13]) gains.

Priority based methods are often used to find the appealing solutions which satisfy these criterions. In these methods the planner specifies the priorities of objective functions or criteria before solving the problem. Applying these methods change the multi objective function into a benefit to cost ratio index [8, 14] or an additive utility function [15-17] then it is tried to maximize (minimize) the constructed single objective problem. The weighted sum approaches cannot guarantee to find all pareto optimal solutions in the case of non-convex objective spaces [18, 19]. Since it is, in general, difficult to know whether objective space is convex or not, the weighted sum approach should be applied with caution. On the other hand objective functions are usually incommensurable and can not be added together. Moreover, the obtained solution is very sensitive to the given priorities and if the circumstances in which these are determined changes the problem should be solved again.

This paper proposes a multi objective model for integration of DG units in a deregulated environment. This novel heuristic genetic algorithm and incorporated fuzzy satisfying method will help the planner to choose the plans which satisfy the technical, environmental and economical criterions. The rest of this paper is organized as follows: The principles of multi objective optimization are discussed in section II. A brief introduction to Genetic Algorithm is given in section III. in section IV, problem formulation is introduced and discussed. The proposed algorithm is presented in section V. Section VI, introduces the
fuzzy satisfying method applied in this paper. Simulation results and conclusions are given in section VII, VIII respectively.

II. PRINCIPLES OF MULTIOBJECTIVE OPTIMIZATION

In most realistic optimization problems, particularly those applicable in power system, there exists more than one objective function which should be optimized simultaneously. These objectives functions might be in conflict, interdependent or independent of each other so it is impossible to satisfy them all at once.

The main difference between the multi objective optimization and traditional single optimization techniques can be categorized in two areas:

1) Several objective functions are to be optimized at the same time.
2) There exists a set of optimal solutions which are mathematically equally good solutions (it means one of them can not be preferred against others and a trade off shall be made to select one) Instead of a unique optimal solution

Generally, every multi-objective optimization problem consists of a number of objectives and several equality and inequality constraints which can be formulated as (1).

\[
\begin{align*}
\text{Min } & F(\mathbf{x}) = [f_1(\mathbf{x}) \ldots f_{\text{Objective}}(\mathbf{x})] \\
\text{Subject to: } & \begin{cases} 
G(\mathbf{x}) = 0 \\
H(\mathbf{x}) \leq 0
\end{cases}
\end{align*}
\]

The notion of optimum has been redefined in this context and instead of aiming to find a single solution, it is tried to produce a set of good compromises or trade-offs from which the decision maker will select one. The set of all optimal solutions which are non-dominated by any other solution, is known as Pareto-optimal set. Suppose a minimizing problem with two objectives in conflict, the different solutions for this problem and the pareto optimal fronts are shown in fig 1.

![Classification of a population to k non-dominated fronts](image)

Fig. 1. Classification of a population to k non-dominated fronts.
For every two solution in each Pareto front (like A, B) none of them is better than other when all objective functions are considered. Here objective 1 is better minimized in solution A than in B and objective 2 is better minimized in solution B than in A. This also applies for solutions in other fronts. For every solution in the \((i+1)_{th}\) front (for example D in the 2\(^{nd}\) front) there exist at least one solution in \(i_{th}\) front (here A in the 1\(^{st}\) front) that dominates it (is better than it considering all objective functions). Since A and B belong to the first front, there is no solution better than them in respect to all objectives. Each solution in Pareto optimal set has two basic characteristics:

1) For every two solutions belonging to the same pareto front (2) holds:

\[
\forall i | \exists j, n : f_n(\overline{x}_i) > f_n(\overline{x}_j) \quad (2)
\]

This means for every solution \(\overline{x}_i\) belonging to Pareto front \(\{S\}\), at least one solution exists as \(\overline{x}_j\) which is better than \(\overline{x}_i\) at least in one objective function (named n here). In other words there is no solution in Pareto optimal front which is the best among all members of this set considering all objectives.

2) For every solution belonging to an upper Pareto front and the ones in the lower fronts, (3) holds:

\[
\forall i, n | \exists x^* : f_n(x^*) \leq f_n(\overline{x}_i) \quad (3)
\]

\[
\exists m : f_m(\overline{x}^*) < f_m(\overline{x}_i)
\]

\[
\overline{x}_i \in S, \overline{x}^* \in S^* < S
\]

\[
n, m \in \{1, \ldots, N_{Objectives}\}
\]

This means for every solution \(\overline{x}_i\) belonging to an upper Pareto front, there exists at least one solution in a lower Pareto front named \(\overline{x}^*\) which is not worse than \(\overline{x}_i\) in any objective function and is better than it in at least one objective function (named m here).

The classical approach for finding the Pareto optimal set is preference-based method in which a relative preference vector is used to weight the objectives and change them into a scalar value [18]. By converting a multi objective optimization problem into a single objective one, only one optimum solution can be achieved which is very sensitive to the given weights. Evolutionary algorithms seem particularly suitable to solve multi-objective optimization problems, because they deal simultaneously with a set of possible solutions (the so-called population). This allows decision maker to find several optimal solutions (Pareto optimal set) in a single run, instead of having to perform a series of separate runs as in the case of the traditional mathematical methods. To do this, many heuristic algorithms have been proposed like NSGAII [20], PSO [21]. In all of these algorithms an initial population is created and then it is guided toward the Pareto front. The solutions with smaller distance to Pareto optimal front and more diversity are more preferred. This is repeated through several iteration until the stopping criteria is met. The ultimate goal is
to seek the most preferred solution among the Pareto optimal set, in this paper this is done by using a fuzzy satisfying method which will be discussed in section V.

III. OVERVIEW OF GENETIC ALGORITHM

The Genetic Algorithm (GA) is a computational model which is designed to simulate processes in natural systems necessary for evolution. It follows the principles which were first introduced by Holland [22]. Each population is a vector containing zeros & ones named genes. They specify the behaviors of the population. After creation of individuals, they will enter into evolution process. The fundamentals of evolution stage are as follows:

- Survival of each individual is dependent on his/her strength.
- Strongest individuals will have more children than those weaks.

The algorithm involves three operators named as:

A. Selection

Better individuals are more preferred, so they are allowed to pass on their characteristics to the next generation. It must be noted that the criteria to distinguish between strong and weak generations is their performance.

B. Crossover

Two individuals are chosen from the population using the selection operator. A Number of bits (genes) are randomly chosen from each parent. The values of the selected bits are exchanged. Two newborn children will enter to the next generation of the population.

C. Mutation

A portion of the new individuals must be selected with some low probability and then they will change some of their bits in random. Mutation is a chance given to the childes of weak parents for living. It means that the children of a weak couple might be a strong person in the future. Actually, it prevents the algorithm of being trapped into a local minima or maxima. GA has been used in many power system applications such as power plant control system design [23], Economic dispatch [24], and Unit commitment [25].

IV. PROBLEM FORMULATION

Distributed generation planning consists of various linear and nonlinear sub problems. The concerned problem is proposing a plan which maintains the technical and environmental constraints in an optimum level and minimizing the total associated costs with such a plan.

The DISCO, as the planner, has two alternatives to supply its customers, the first one is purchasing
energy from main grid and the second option is using DG in its territory or an optimum combination of them. The aim of distribution system planner is seeking the best configuration among some available DG categories and placing them on suitable buses with considering various factors such as active power losses, investment and operation costs and environmental emissions. The following assumptions are employed in problem formulation:

A. Decision variables

The number of installed DG from a specific technology, in each bus $IDG_{(BUS,DGtech)}$, generation schedule of installed DGs during different load levels $[P_{(BUS,DGtech,Loadlevel)} , Q_{(BUS,DGtech,Loadlevel)}]$ and also the amount of electric energy purchased from main grid including its active and reactive part $[P_{Grid(Loadlevel)} , Q_{Grid(Loadlevel)}]$ constitute the set of decision variables of the planning problem.

B. Constraints

1) Dynamics of investment

The timing of investment is not concerned in this work, the best plan which satisfies the technical constraints and also minimizes the proposed objective functions at the end of the planning horizon, is being sought.

2) Modeling of DG connection

Connection of a DG unit to a bus is modeled as a negative PQ load with a variable but bounded power factor as shown in fig.2.

![Fig.2. Model of the DG Unit Connected To the ith Bus](image)

$$L_i = P_i + jQ_i$$

$$L_i = \left( P_i - \sum_{j=1}^{n} P_{DGj} \right) + j \left( Q_i - \sum_{j=1}^{n} Q_{DGj} \right)$$

$$L_i = P_i + jQ_i$$

3) Planning horizon

The planning horizon is the amount of time (T) that the DISCO will look into the future when preparing a strategic plan for integration of DG units.
4) **Limitation on Transmission system**

It shall be noted that the DISCO has a physical limitation for the amount of purchased energy from the main grid. This means that the total energy purchased from the main grid cannot exceed the transformer and substation capacity. This constraint is addressed in (4).

\[
\sqrt{P_{\text{Grid}}(\text{Load level})^2 + Q_{\text{Grid}}(\text{Load level})^2} \leq \text{GridCap}
\]  

(4)

5) **Demand level factors and their durations**

For getting closer to reality it is assumed that each day has three different load levels Low, Medium, and High with different demand level factors $DLF_{\text{Load level}}$. The duration of each load level will be equal to $DU_{\text{Load level}}$. The variation of demand level factor in different load levels in 24 hours is depicted in fig. 3.

6) **Demand growth**

The demand of a system is not constant during the planning horizon and it increases with a rate called Yearly demand growth. At the end of the planning horizon the demand has increased with a factor equal to \(\prod_{\text{year}=1}^{T} (1 + \text{Growth}_{\text{year}})\). The demand at each bus in each load level can be calculated using (5).

\[
D_{(\text{Bus}, \text{Load level})} = \text{Load}_{\text{Base}} \times DLF_{\text{Load level}} \times \prod_{\text{year}=1}^{T} (1 + \text{Growth}_{\text{year}})
\]  

(5)

7) **Variations of energy price**

Obviously the price of purchased energy from the grid is competitively determined and is not constant during different load levels. Forecasting the variation of this parameter would not be an easy job but it is assumed that the variation pattern of this parameter can be modeled by a factor named grid price factor $GPF_{\text{Load level}}$. The variation of grid price demand factor in different load levels during the 24 hours of a day is depicted in fig. 4.
8) Limitation on the number of available DGs

It is assumed that the planner can choose between discrete capacity choices up to a maximum capacity from each DG technology. The number of available DG units in each technology is constrained by resource availability or regulation. This is illustrated in (6).

\[ \sum_{Bus} IDG_{(Bus,DGtech)} \leq N_{DGtech} \quad (6) \]

9) Operating limits of DG units

a) Active power

The total active power generated by each installed distributed generator can not violate its maximum and minimum allowed operating ranges as shown in (7).

\[ P_{(Bus,DGtech,Loadlevel)} \leq IDG_{(Bus,DGtech)} \times P_{MaxDGtech} \]
\[ P_{(Bus,DGtech,Loadlevel)} \geq IDG_{(Bus,DGtech)} \times P_{MinDGtech} \quad (7) \]

b) Reactive power

The capabilities of different DG technologies in reactive power production are not the same as each other. This limitation is modeled using (8).

\[ Q_{(Bus,DGtech,Loadlevel)} = \text{tg}(arccos(\varphi)) \times P_{(Bus,DGtech,Loadlevel)} \]
\[ MinPF_{DGtech} \leq \cos\varphi \leq MaxPF_{DGtech} \quad (8) \]

10) Power flow constraints

Besides the economic assumptions and calculations made till now, it is necessary that the technical constraint are also satisfied. The most viable constraints are well known power flow equations that shall be satisfied for each configuration and load level as indicated in (9).

\[ P'_i = V_i \sum_{j=1}^{n} Y_{ij} V_j \cos(\delta_i - \delta_j - \theta_j) \]
\[ Q'_i = V_i \sum_{j=1}^{n} Y_{ij} V_j \sin(\delta_i - \delta_j - \theta_j) \]
\[ V_{\text{min}} \leq V_i \leq V_{\text{max}} \quad (9) \]

C. Objective functions

1) Active Losses

Distribution systems are usually designed with just one supply source and this may cause significant active and reactive losses. The active losses mainly depend on the line resistance and currents and are usually referred to as thermal losses. While the line resistances are fixed, the currents are a complex function of the system topology and the location of DG units and system load level.

\[ OF_1 = TAL = \sum_{Loadlevel} AL_{Loadlevel} \times DU_{Loadlevel} \quad (10) \]
2) Total Costs

The total cost which DISCO has to pay, consists of three components including Total Grid Costs, Installation & Operating costs of DG units. Each component is defined and calculated as follows:

As stated before, the DISCO has the DG as an alternative in his plans and the main grid (which is called grid here) is its main source of energy. By purchasing energy from grid, DISCO has to pay for it. Total grid payment can be calculated by summation of the cost of both active and reactive energy purchased from grid as stated in (11).

\[
TGC = \sum_{\text{Loadlevel}} \left( P_{\text{Grid(\text{Loadlevel})}} \times PC_{\text{Grid}} + Q_{\text{Grid(\text{Loadlevel})}} \times QC_{\text{Grid}} \right) \times DU_{\text{Loadlevel}} \times GPF_{\text{Loadlevel}}
\]

Installation cost of DG units is calculated as the sum of costs associated to all installed DGs over all DG technologies and buses.

\[
DGIC = \sum_{\text{Bus}} \sum_{\text{DGtech}} IDG_{(\text{bus,\text{DGtech})}} \times IC_{\text{DGtech}}
\]

The operating costs of DG units can be calculated by summation of cost of active energy generated by each installed DG technology multiplied by its associated operating cost as stated in (13).

\[
DGOC = \sum_{\text{Bus}} \sum_{\text{DGtech}} \sum_{\text{Loadlevel}} DU_{\text{Loadlevel}} \times OC_{\text{DGtech}} \times P_{(\text{Bus,\text{DGtech,Loadlevel})}}
\]

The final objective function is obtained by adding all the introduced cost components. This is done in (14).

\[
OF_2 = DGIC + DGOC + TGC
\]

3) Emissions

The total produced emission has two parts:

1. The emission caused by the main grid
2. The emission produced by installed DGs which are being used.

The total emission cost is obtained by summation of these two parts as calculated in (15).

\[
OF_3 = TE = \sum_{\text{Loadlevel}} DU_{\text{Loadlevel}} \times \left( EF_{\text{Grid}} \times P_{\text{Grid(\text{Loadlevel})}} + \sum_{\text{Bus}} \sum_{\text{DGtech}} EF_{\text{DGtech}} \times P_{(\text{Bus,\text{DGtech,Loadlevel})}} \right)
\]

V. PROPOSED ALGORITHM

A. Parameterization of problem for GA

To solve DG planning problem through genetic algorithm, problem parameters must be modeled in terms of genetic parameters:

1) In the proposed problem each solution is a vector containing the situation of installation (whether it is installed or not), active and reactive power generated by DG unit and the bus on which this DG is to be
installed for each available DG unit. A sample solution vector is shown in fig 5.

Fig. 5. Proposed vector for modeling the Problem Parameters $\bar{X}_i$.

2) Population: A population consists of a number of solutions in the search space.

Population = $[\bar{X}_1 \ \bar{X}_2 \ldots \bar{X}_p \ldots \bar{X}_{N_{Solutions}}]^T$

Where $N$ is the number of population used in GA method.

B. Determination of Pareto front

As stated before to direct the population toward the Pareto optimal front two things shall be noted:

1) Getting closer to Pareto optimal front
2) Maintaining the diversity among the solutions

In single objective optimization it is easily done because there is no need to diversify the solutions and also just one objective function shall be considered for guiding the population. To solve this problem a pseudo fitness value is assigned to each solution as (16)

$$Pseudo_i = Pareto_{front}^i + GDiversity^i$$

(16)

The first term in (16) guides the population toward the pareto optimal front since the solutions which are members of lower fronts get higher fitness while the second term insures the diversity among the solutions. It is calculated as follows:

A local diversity factor is defined according to each objective function then a global diversity factor is introduced. For every objective function, solutions are sorted and distance between the maximum and minimum is calculated using (17)

$$Maxdistance_k = \text{Max}(f_k(\bar{X}_i)) - \text{Min}(f_k(\bar{X}_i))$$

(17)

As the solutions are sorted, so the first and the last one are the max and min of them. The diversity of every other solution is the average distance of it to its neighbors as shown in (18).
\[
Diversity_k^i = \frac{\left| f_k(x^i) - f_k(x^i_{i+1}) \right| + \left| f_k(x^i) - f_k(x^i_{i-1}) \right|}{2 \times \text{Maxdistance}_i} \quad (18)
\]

For the first and the last solution local diversity can be calculated using (19):

\[
Diversity_1^1 = \max(\text{Diversity}_{1}^i) \quad (19)
\]

\[
Diversity_N^N = \text{Diversity}_1^1
\]

The global diversity factor for each solution is calculated as the average of its local diversities as shown in (20).

\[
GDiversity^i = \frac{\sum_{k=1}^{N_{\text{solution}}} \text{Diversity}_k^i}{N_{\text{objective}}} \quad (20)
\]

C. Steps of the Algorithm

After analyzing the problem and selection of a proper expression of solution the topology of the algorithm is as follows:

1. Generate an initial random solution.
2. Set iteration = 1.
3. Evaluate the fitness for each member of the population as follows:
   - Convert the binary solution into decimal number.
   - Evaluate each individual of the population by performing load flow calculations to compute energy loss and voltage magnitudes at each node, total emission and total costs (including installation and operation costs).
4. Determine the pareto front and the global diversity factor for each solution.
5. Compute pseudo fitness for each solution.
6. Sort the population based on pseudo fitness value. Keep the population length limited to \( N_{\text{solution}} \).
7. If the stopping criterion is met go to step 16, else continue.
8. Consider a predefined top percent of the population as the potential parents (elite set) based on their pseudo fitness.
9. Select two parents from elite set based on roulette wheel method.
10. Perform crossover and generate two children.
11. Mutate these two children based on mutation probability.
12. If there still more children are needed, go to 9, else continue.
13. Combine the old population and new population to create a single population containing the bests of both.
15. Return to Step 3.
16. End

The flowchart of the proposed algorithm is depicted in fig.6.

Figure 6: Flowchart of genetic algorithm
VI. FUZZY SATISFYING METHOD

The next step after obtaining the Pareto front is to select the solution among the candidates. A fuzzy satisfying method has been used to obtain the satisfactory solution for the decision maker from the Pareto optimal set. For each solution in the Pareto optimal front, like $\overline{x}$, a membership function is defined as $\mu_{f_i}(\overline{x})$. This value shows the level of which $\overline{x}$ belongs to the set that minimizes the objective function $f_i$. $\mu_{f_i}(\overline{x})$ varies between 0 to 1. The membership value “0” indicates incompatibility with the set, while “1” means full compatibility. In other words, the membership function gives a numerical description of how the decision maker is satisfied by which level of achievement of solution with respect to a specific objective function. The decision maker is fully satisfied with $\overline{x}$ if $\mu_{f_i}(\overline{x}) = 1$ and dissatisfied when $\mu_{f_i}(\overline{x}) = 0$ [26].

Different types of membership functions have been suggested like linear or exponential ones. Note that by selecting the shape of membership function other than linear type can be used by the decision maker to give more priority to a specific objective function. Here a linear type of membership function has been used for all objective functions as shown in (21).

$$\mu_{f_i}(x) = \begin{cases} 0 & \text{if } f_i(\overline{x}) > f_i^{\text{Max}} \\ \frac{f_i^{\text{Max}} - f_i(\overline{x})}{f_i^{\text{Max}} - f_i^{\text{Min}}} & \text{if } f_i^{\text{Min}} \leq f_i(\overline{x}) \leq f_i^{\text{Max}} \\ 1 & \text{if } f_i(\overline{x}) < f_i^{\text{Min}} \end{cases}$$

Fig. 7 shows the selected membership function

![Linear type membership function](image)

After defining the membership functions, there are several ways to choose the final solution. Each method considers a different philosophy. The method used in this paper is introduced as follows:

As the planners will live with their plans, a conservative decision can be achieved by trying to find the
solution which its Minimum satisfaction is Maximum over all objective functions. Using the MaxMin formulation, the final solution can be found by solving (22).

\[
\text{Max} \left( \text{Min}_{i \in N_{\text{Objective}}} \left( \mu_{i} \left( \bar{x} \right) \right) \right)_{k \in N_{\text{Solution}}}
\]

(22)

VII. SIMULATION RESULTS

The proposed algorithm is applied to IEEE 34 bus test feeder [27] with slight modifications which is shown in fig.8.

In the performed simulations, it is assumed that all buses are candidate for DG installation and more than one DG can be installed in a specific bus.

The proposed framework can be used for different technologies and operation and planning philosophies. Here, without loss of generality, the assumptions used in this work are listed:

1. The planning horizon (T) is 10 years.
2. Transmission system limitation for energy delivery is GridCap=200MVA.
3. The demand growth in each year of planning horizon can be different, it is assumed that it is similar in each year and Growth_{year}=5%. With this assumption, demand growth at the end of the 10th year will be equal to (1+0.05)^{10}=1.551.
4. The duration of low, medium and high load level in each day, are assumed to be 8,12,4 hours respectively. So the duration of these load levels in a year will be multiplied by 365. These are given in table II.
5. Variations of demand and Grid price are given in table II.
6. Emission factor of main grid (EF_{Grid}) is assumed to be 672 Kg/MWh
7. Cost of active (PC_{Grid}) and reactive energy (QC_{Grid}) purchased from main grid are 60$/MWh, 30$/MVRh respectively.
8. Maximum and minimum voltage for each bus is assumed to be V_{Max}=1.05Pu, V_{Min}=0.9Pu.
9. Cross over probability =70%.
10. Mutation probability = 5%.
11. Number of population = 500.
12. Stopping criteria: Max iteration = 1000.
13. The characteristics of different DG technologies [28, 29] used in this paper are available in table I.

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<tr>
<th>DG #</th>
<th>DG Technology</th>
<th>IC $/kW</th>
<th>OC $/(MWh)</th>
<th>$P_{MIN}$ (MW)</th>
<th>$P_{MAX}$ (MW)</th>
<th>$EF$ (kg/MWh)</th>
<th>$PF$</th>
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<td>90</td>
<td>0.003</td>
<td>0.03</td>
<td>801</td>
<td>0.9 lag</td>
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TABLE II
ASSUMPTIONS

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<th>$DU_{LoadLevel}$</th>
<th>$DLF_{LoadLevel}$</th>
<th>$GPF_{LoadLevel}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>2920</td>
<td>0.8</td>
<td>0.85</td>
</tr>
<tr>
<td>Medium</td>
<td>4380</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>High</td>
<td>1460</td>
<td>1.3</td>
<td>1.45</td>
</tr>
</tbody>
</table>

The pareto optimal front is depicted in fig.9.
Some of the obtained solutions are given in Table III, these solutions can be categorized and each category have some special features and the planner can choose the best solution based on its preferences over different objective functions. It should be noted that the total emission is given in Tons and Total cost is in *1000 scale. For example if the planner is more interested in just one of the objective functions the B, C, D categories can be good options. Suppose we are interested in the first one, the solutions belonging to B have the least OF1. If the planner decides to choose the #1 solution, although it has the greatest satisfaction value over the OF1, but by choosing solution #284 he can obtain almost the same loss with a less cost and of course this solution has a worse environmental emission over the #1.

The C and D category contain the solutions with better OF2, OF3 respectively. The same strategy for obtaining the satisfactory solution among these solutions can be taken.

Some times the planner has to choose the solutions which require satisfying more than one criterion. In these cases, E, F, G categories can help him to choose the best alternative. In E category, OF1, and OF2 have their best values while in F, the OF1, OF3 and finally in G the OF2, OF3 have the appealing values.

For obtaining the final solutions the previously described method has been used and the solution is chosen in a manner which the least satisfaction over all objective functions is maximum. Here the solution #495 has this property and given in more detail in Table IV.
### TABLE III
**CATEGORIZED SOLUTIONS**

<table>
<thead>
<tr>
<th>Solution #</th>
<th>OF1</th>
<th>OF2</th>
<th>OF3</th>
<th>$\mu_{f_1}$</th>
<th>$\mu_{f_2}$</th>
<th>$\mu_{f_3}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>495</td>
<td>30.6585</td>
<td>3725.152</td>
<td>161318.53</td>
<td>0.610082</td>
<td>0.603108</td>
</tr>
<tr>
<td>1</td>
<td>13.38474</td>
<td>4351.207</td>
<td>16744.59</td>
<td>1</td>
<td>0.010081</td>
<td>0.23391</td>
</tr>
<tr>
<td>101</td>
<td>13.4266</td>
<td>4284.034</td>
<td>16754.5</td>
<td>0.999055</td>
<td>0.073652</td>
<td>0.225319</td>
</tr>
<tr>
<td>134</td>
<td>13.59475</td>
<td>4353.928</td>
<td>16738.99</td>
<td>0.99526</td>
<td>0.007505</td>
<td>0.238756</td>
</tr>
<tr>
<td>284</td>
<td>13.73758</td>
<td>4034.705</td>
<td>16775.54</td>
<td>0.992035</td>
<td>0.309615</td>
<td>0.207087</td>
</tr>
<tr>
<td>295</td>
<td>13.68167</td>
<td>4346.338</td>
<td>16696.43</td>
<td>0.993297</td>
<td>0.014688</td>
<td>0.275643</td>
</tr>
<tr>
<td>303</td>
<td>13.80089</td>
<td>4348.343</td>
<td>16684.55</td>
<td>0.990606</td>
<td>0.01279</td>
<td>0.285934</td>
</tr>
</tbody>
</table>

| B          | 8       | 38.62785    | 3305.211    | 16402.74    | 0.430191    | 0.530136    |
| 41         | 48.02708| 3309.612    | 16251.12    | 0.218023    | 0.995836    | 0.661525    |
| 198        | 47.64264| 3306.904    | 16258       | 0.226701    | 0.998398    | 0.655563    |
| 315        | 46.54598| 3314.466    | 16255.24    | 0.251456    | 0.991241    | 0.657957    |
| 430        | 37.18939| 3312.332    | 16400.97    | 0.462661    | 0.993262    | 0.531669    |

| C          | 4       | 45.54593    | 4156.607    | 15860.52    | 0.27403     | 0.194248    |
| 37         | 45.76728| 4156.492    | 15860.8     | 0.269033    | 0.194356    | 0.999759    |
| 79         | 44.0688 | 4158.793    | 15866.89    | 0.307373    | 0.192178    | 0.994483    |
| 380        | 43.97763| 4264.803    | 15870.65    | 0.309431    | 0.091852    | 0.991222    |

| D          | 6       | 15.42629    | 3352.961    | 16987.53    | 0.953916    | 0.95481     |
| 19         | 15.58022| 3349.181    | 16965.2     | 0.950442    | 0.958387    | 0.04274     |
| 74         | 15.50675| 3349.805    | 16951.86    | 0.9521      | 0.957797    | 0.054296    |
| 269        | 15.48034| 3353.102    | 16983.1     | 0.952696    | 0.954677    | 0.027224    |

| E          | 350     | 26.63872    | 4275.364    | 16160.78    | 0.70082     | 0.739807    |
| 407        | 26.40465| 4279.71     | 16216.09    | 0.706103    | 0.077745    | 0.691881    |

| F          | 81      | 53.82195    | 3384.262    | 16216       | 0.087216    | 0.691958    |
| 110        | 54.88573| 3380.145    | 16206.96    | 0.063204    | 0.929083    | 0.699793    |
| 202        | 49.06957| 3470.397    | 16210.17    | 0.194491    | 0.84367     | 0.697007    |

### TABLE IVV
**FINAL SOLUTION**

<table>
<thead>
<tr>
<th>Load level L</th>
<th>Load level M</th>
<th>Load level H</th>
</tr>
</thead>
<tbody>
<tr>
<td>DG#</td>
<td>Bus</td>
<td>P</td>
</tr>
<tr>
<td>6</td>
<td>19</td>
<td>0.096221</td>
</tr>
<tr>
<td>1</td>
<td>22</td>
<td>0.007008</td>
</tr>
<tr>
<td>7</td>
<td>28</td>
<td>0.278418</td>
</tr>
<tr>
<td>8</td>
<td>31</td>
<td>0.470898</td>
</tr>
</tbody>
</table>
VIII. CONCLUSIONS

In this paper, a multi objective optimization model for integration of DG units into a distribution network in a deregulated power system has been proposed. The main contributions of this study can be summarized as follows:

1) Consideration of different load levels and their duration instead of assuming the load as a constant parameter during the planning period.

2) As the planning procedure is performed in a liberalized power market, the variations of energy price during different load levels are considered in the calculations.

3) The ability of providing ancillary services like reactive power for DG units is considered in this work.

4) Different DG technologies with their different technical, economical and environmental characteristics are considered as available alternatives for DG planner.

5) The operation schedule of installed DG units has been incorporated in the optimization process.

The advantages of this model have been demonstrated by applying it on a standard test system. Results presented in this paper indicate that the proposed algorithm can be used to find the optimal sitting and sizing of DG units in a distribution system to reduce the active power losses, operation, investment costs and environmental pollutions simultaneously. Since the proposed method is a posterior one there is no need to resolve the problem if the importance of objective functions change for the planner. Instead, it gives a broad range of solution to the planning problem, which makes the planner enable to decide what to choose according to the condition he has considered about different objective functions. Future research will be consecrated on defining a more comprehensive objective functions, which considers other potential benefits like reliability enhancements.

NOMENCLATURE

GridCap: Grid capacity for energy supply.

\( P_{\text{Grid}(\text{LoadLevel})} \): Active power purchased from grid in a specific load level in MWh.

\( Q_{\text{Grid}(\text{LoadLevel})} \): Reactive power purchased from grid in a specific load level in MVARh.

\( D_\text{Load} \): Demand in a specific bus and load level in MW.

\( DLF_{\text{LoadLevel}} \): The demand level factor in a load level.

\( Load_{\text{Base}} \): The base load of each bus.

\( Growth_{\text{Year}} \): Yearly load growth.

\( DGIC \): DG installation costs in $.

\( IDG_{(\text{Bus},\text{DGtech})} \): Number of installed DG in a specific bus.

\( IC_{\text{DGtech}} \): Installation cost of a DG technology in $.

\( P_{(\text{Bus},\text{DGtech},\text{LoadLevel})} \): Active power generated by a DGtech in a specific bus and load level in MWh.

\( Q_{(\text{Bus},\text{DGtech},\text{LoadLevel})} \): Reactive power generated by a DGtech in a specific bus and load level in MVARh.
\( N_{\text{DGtech}} \) Number of available units of a DG technology.

\( \text{MinPF}_{\text{DGtech}} \) The minimum power factor for a DG technology in producing reactive power.

\( \text{MaxPF}_{\text{DGtech}} \) The maximum power factor for a DG technology in producing reactive power.

\( P_{\text{MaxDGtech}} \) Maximum limit for active power generation of a specific DG technology in MW.

\( P_{\text{MinDGtech}} \) Minimum limit for active power generation of a specific DG technology in MW.

\( \text{OC}_{\text{DGtech}} \) Operating cost of a DG technology in $/MWh.

\( \text{DGOC} \) Total operating cost of all installed DG technology in $.

\( \text{EF}_{\text{Grid}} \) Grid emission factor in kg/MW.

\( \text{DGtechEF} \) DG technology emission factor in kg/MW.

\( \text{EF}_{\text{DGtech}} \) Total emission in Ton.

\( \text{TGC} \) Total grid cost paid for purchasing active, reactive energy from grid in $.

\( \text{DU}_{\text{Loadlevel}} \) Duration of load level in hours.

\( \text{GPF}_{\text{Loadlevel}} \) Grid price factor in a specific load level.

\( \text{PC}_{\text{Grid}} \) Cost of active power purchased from grid in $/MWh.

\( \text{QC}_{\text{Grid}} \) Cost of reactive power purchased from grid in $/MVARh.

\( \text{TAL} \) Total active losses in MWh.

\( \text{AL}_{\text{Loadlevel}} \) Active losses in a specific load level in MWh.

\( \text{V}_{\text{in}} \) The amplitude of voltage in the \( i_{th} \) bus in pu.

\( \delta_{i} \) The angle of voltage in the \( i_{th} \) bus in radian.

\( \theta_{ij} \) The angle of \( i_{th} \) row and the \( j_{th} \) column element of admittance matrix in radian.

\( \text{V}_{\text{min}} \) Minimum allowed voltage in the \( i_{th} \) bus.

\( \text{V}_{\text{max}} \) Maximum allowed voltage in the \( i_{th} \) bus.

\( \text{P}^{i} \) Total active power injected to \( i_{th} \) bus in MW.

\( \text{Q}^{i} \) Total reactive power injected to \( i_{th} \) bus in MVAR.

\( \text{iV} \) The amplitude of voltage in the \( i_{th} \) bus in pu.

\( \delta \) The angle of voltage in the \( i_{th} \) bus in radian.

\( \theta \) The angle of \( i_{th} \) row and the \( j_{th} \) column element of admittance matrix in radian.

\( \text{iP}^{i} \) Total active power injected to \( i_{th} \) bus in MW.

\( \text{iQ}^{i} \) Total reactive power injected to \( i_{th} \) bus in MVAR.

\( \text{iPseudo} \) Pseudo fitness for the \( i_{th} \) solution.

\( \text{Diversity}_{i} \) Diversity of \( i_{th} \) solution in the \( k_{th} \) objective function.

\( \text{GDiversity}_{i} \) Global diversity of \( i_{th} \) solution among all objective functions.

\( \text{Paretofront}_{i} \) The pareto optimal front which \( i_{th} \) solution belongs to.

\( \mu_{i} \) Membership function of the \( k_{th} \) objective function.

\( \text{Maxdistance}_{i} \) Maximum distance between solutions respecting \( k_{th} \) objective function.

\( N_{\text{Solution}} \) Number of solutions

\( N_{\text{Objective}} \) Number of objective functions

**IX. REFERENCES**


Biographies

A. Soroudi was born in Iran and received his B. Sc and M. Sc degrees in electrical engineering in 2002 and 2003 respectively (both with honors) from Sharif University of Technology, Tehran-Iran. Presently, he is a Ph.D candidate in Sharif University of Technology. His research interests are power system deregulation, Distributed generation, power system Planning.

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