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MULTI-OBJECTIVE PLANNING MODEL FOR INTEGRATION OF DISTRIBUTED GENERATIONS IN DEREGULATED POWER SYSTEMS*

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Abstract– This paper presents a long-term dynamic multi-objective model for distributed generation investment. The proposed model optimizes three objectives, namely active losses, costs and environmental emissions and determines the optimal schemes of sizing, sitting of DG units and specially the dynamics of investment over the planning period. The Pareto optimal solutions of the problem are found using a GA algorithm and finally a fuzzy satisfying method is applied to select the optimal solution considering the desires of the planner. The solutions of Pareto optimal front are analyzed to extract general useful information for planners about the appropriate DG technologies and placement schemes. The effectiveness of the proposed model is demonstrated by applying it on a test distribution system and the results are presented, discussed and compared to other methods.

Keywords– Distributed generation, genetic algorithm, dynamic planning, multi-objective optimization, active loss reduction

1. 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 the 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. The Natural Gas Foundation has 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 in distribution systems. In liberalized electricity markets distribution companies (DISCOs) are responsible for supplying the customers in their territory. Since only a fixed percent of their losses are compensated, the loss reduction increases their profits [5]–[7]. Another important factor which has become more important in the liberalized electricity industry is the quality of the service which DISCO provides to its customers like voltage control [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

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costs would be beneficial [10]. Additionally, other costs should be taken into account like the cost of purchased energy, cost of energy losses and cost of energy not supplied [11], and the different costs associated with the incorporation of DG units into the distribution systems like installation, operation and maintenance costs. Some restrictions on environmental pollution may force the DISCOs to use green power or less pollutant technologies. On the other hand, there will 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 [12]) gains.

The reported models for DG planning can be divided into two major categories: static and dynamic models. In static models, investment decisions are implemented in the first year of the planning horizon [5]–[7], [11], [13]–[22]. In this category, the models are single or multi-objectives. The single-objective models are either originally single-objective [5]-[6], [13]–[16], [18], or multi-objective which are converted into a single-objective (using a benefit to cost ratio index [17] or an additive utility function [7], [11], [20], [22]); multi-objective models of this category are solved using Pareto optimality concept [19], [21].

This paper proposes a multi-objective model for integration of DG units in a deregulated environment. The proposed model aims to cover all three aspects of the DG planning problem, i.e., sitting, sizing and timing of investment simultaneously when active losses, costs and emissions of the proposed plans and a variety of DG technologies are considered. A genetic algorithm is proposed for finding the Pareto optimal front and then a fuzzy satisfying method is used for selecting the final solution. The rest of this paper is organized as follows: The principles of multi-objective optimization are discussed in section 2. A brief introduction to Genetic Algorithm is given in section 3. In section 4, problem formulation is introduced and discussed. The proposed algorithm is presented in section 5. Section 6 introduces the fuzzy satisfying method applied in this paper. Simulation results and conclusions are given in section 7, 8 respectively.

2. PRINCIPLES OF MULTIOBJECTIVE OPTIMIZATION

In most realistic optimization problems, particularly those applicable in power systems, there exists more than one objective function which should be optimized simultaneously. Generally, every multi-objective optimization problem consists of a number of objectives and several equality and inequality constraints which can be formulated as follows:

$$\begin{aligned} & Min\ F(x) = [f_1(x) \ldots f_{N_o}(x)] \\ & Subject\ to: \{G(x) = \bar{0},\ H(x) \le \bar{0}\} \\ & X = [x_1, \ldots, x_n] \end{aligned} \tag{1}$$

The notion of optimum has been redefined in this context and instead of aiming to find a single solution, we attempt 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. Each solution in Pareto optimal set has two basic characteristics: 1) For every two solutions belonging to the same Pareto front (2) holds:

$$\begin{aligned} & \forall i \mid \exists j, n : f_n(\bar{x}_i) > f_n(\bar{x}_j) \\ & \bar{x}_i, \bar{x}_j \in S \end{aligned} \tag{2}$$

This means for every solution belonging to Pareto front S, at least one solution exists as which is better than 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:

$$\forall k \in \{1,...,N_O\} f_k(\bar{x}_1) \le f_k(\bar{x}_2) \tag{3}$$

$$\begin{aligned} &\exists k' \in \{1,...,N_O\} f_{k'}(\bar{x}_1) < f_{k'}(\bar{x}_2) \\ &\bar{x}_1 \in S, \bar{x}_2 \in S^* \\ &S < S^* \end{aligned} \tag{4}$$

The classical approach for finding the Pareto optimal set is a preference-based method in which a relative preference vector is used to weight the objectives and change them into a scalar value [23]. By converting a multi-objective optimization problem into a single objective one, only one optimum solution can be achieved that 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 the 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 [24], PSO [25] and Tabu search [26]. In all of these algorithms an initial population is created and then guided toward the Pareto front. 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 6.

3. 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 [27]. GA has been used in many power system applications such as power system planning [28] and unit commitment [29]. Each population is a vector containing zeros and ones named genes. They specify the behavior of the population. After creation of individuals, they will enter into an evolution process. The key point of this stage is that the survival of each individual is dependent on its strength. The algorithm involves three operators named:

a) Selection

The 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 children of weak parents for living. It means that the children of a weak couple might be strong people in the future. Actually, it prevents the algorithm of being trapped into a local minima or maxima.

4. PROBLEM FORMULATION

Distributed generation planning consists of various linear and nonlinear sub-problems. The main problem is proposing a plan which maintains the technical constraints and minimizes the total associated costs, emissions and active losses with such a plan. The DISCO, as the planner, has two alternatives to supply its customers, the first one is purchasing energy from the main grid and the second option is using DG in its territory or an optimum combination of them. The aim of the distribution system planner is to seek the best configuration among some available DG categories, and place them on suitable buses 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 multi-objective DG planning problem is formulated in this section. The decision variable is the number of DG units from each specific technology to be installed in each bus in each year, i.e., $\xi_{i,t}^{dg}$, and the generation schedule of installed DGs during different load levels.

b) Constraints

1) Modeling the DG connection: Connection of a DG unit to a bus is modeled as a negative PQ load as shown in Fig. 1.

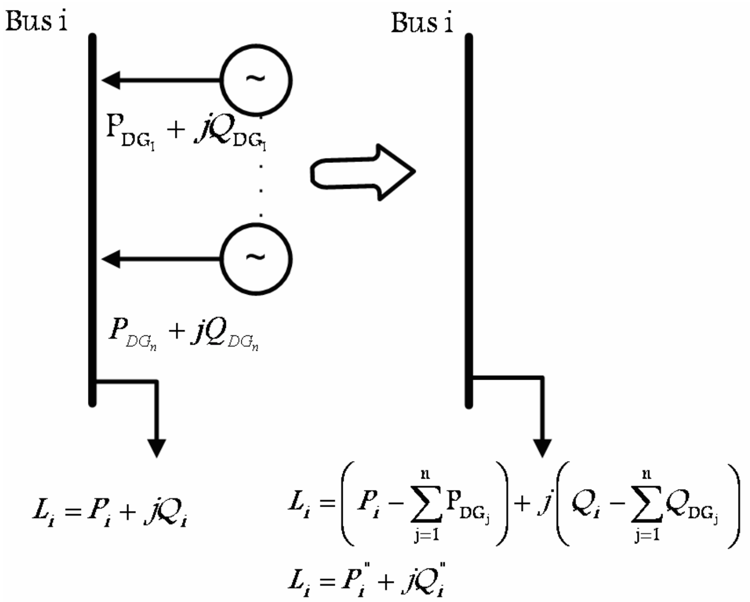

Fig. 1. Model of the DG unit connected to the ith bus

2) Demand level factors and their durations: For getting closer to reality, it is assumed that each day can be divided into different demand levels. Without loss of generality, in this paper three different demand levels namely, Low, Medium and High have been considered which have different demand level factors, i.e. DLF_{dl}. The duration of each load level will be equal to DU_{dl}. The variation of demand level factor in different demand levels in a 24 hour period is depicted in Fig. 2.

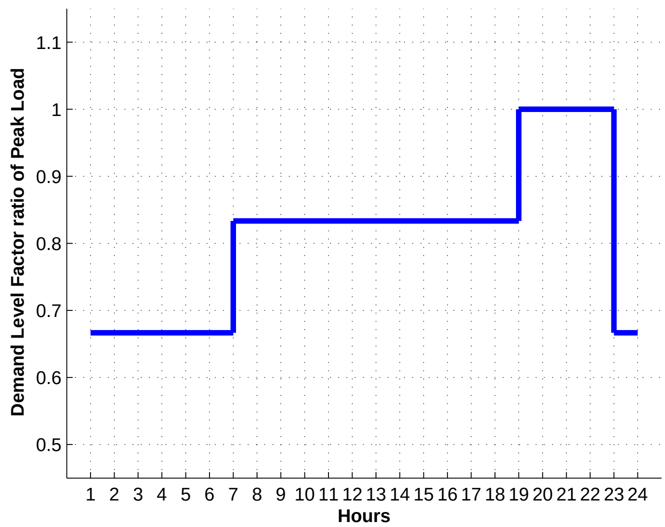

Fig. 2. Demand level factors in 24 hours

3) Demand growth: The demand of a system is not constant during the planning horizon and it increases with a rate called yearly demand growth, i.e. α. The demand at each bus, in each load level and each year can be calculated using (5).

$$
\begin{aligned}
P_{i,t,dl}^{D} &= P_{i,base}^{D} \times (1+\alpha)^{t} \times DLF_{dl} \\
Q_{i,t,dl}^{D} &= Q_{i,base}^{D} \times (1+\alpha)^{t} \times DLF_{dl}
\end{aligned}
\tag{5}
$$

4) Variations of energy price: Obviously the price of purchased energy from a 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 level factor, i.e. PLF_{dl}. Without loss of generality, it is assumed that an electricity price at each demand level can be calculated as $\rho \times PLF_{dl}$, where the base price (i.e. ρ) and PLF_{dl} are known; The variation of grid price demand factor in different load levels during a 24 hour day is depicted in Fig. 3.

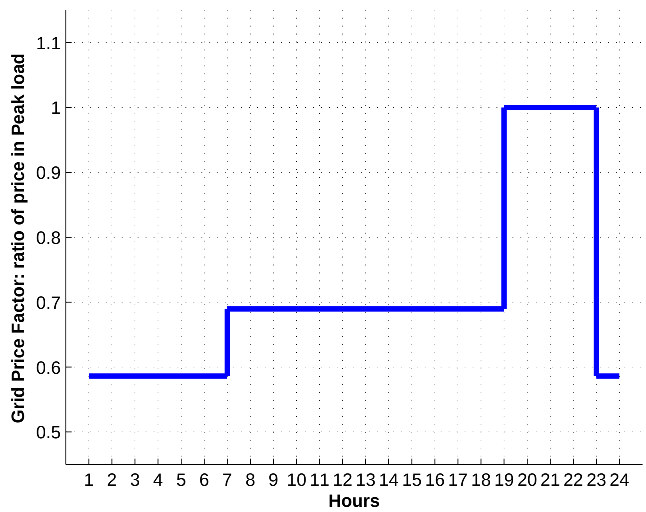

Fig. 3. Price level factors over 24 hours

5) Operating limits of DG units: Each DG should be operated considering its operating limits, i.e.:

$$P_{i,t,dl}^{dg} \le \overline{P}_{lim}^{dg} \tag{6}$$

6) Voltage profile: The voltage magnitude of each bus should be kept between the safe operation limits, as indicated in (7).

$$V_{\min} \le V_{i,t,dl} \le V_{\max} \tag{7}$$

7) Thermal limit of feeders and substation: To maintain the security of the feeders and the substation, the flow of current/energy passing through them should be kept below the feeders/substation capacity limit, as follows:

$$\begin{aligned} I_{t,dl}^{\ell} &\le I_{\max}^{\ell} \\ S_{t,dl}^{grid} &\le S_{\max}^{grid} \end{aligned} \tag{8}$$

8) Power flow constraints: Besides the economic assumptions and calculations made up to now, it is necessary that the technical constraints 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).

$$\begin{aligned} P_{i,t,dl}^{net} &= -P_{i,t,dl}^{D} + \sum_{t'=1}^{t} \xi_{i,t'}^{dg} \times P_{i,t,dl}^{dg} \\ Q_{i,t,dl}^{net} &= -Q_{i,t,dl}^{D} + \sum_{t'=1}^{t} \xi_{i,t'}^{dg} \times Q_{i,t,dl}^{dg} \\ P_{i,t,dl}^{net} &= V_{i,t,dl} \sum_{j=1}^{n} Y_{ij} V_{j,t,dl} \cos\left(\delta_{i,t,dl} - \delta_{j,t,dl} - \theta_{ij}\right) \\ Q_{i,t,dl}^{net} &= V_{i,t,dl} \sum_{j=1}^{n} Y_{ij} V_{j,t,dl} sin\left(\delta_{i,t,dl} - \delta_{j,t,dl} - \theta_{ij}\right) \end{aligned} \tag{9}$$

C. Objective functions

The proposed model minimizes three objective functions, namely, active losses, total costs and total emissions, as follows:

$$\begin{aligned} &Min \quad \{OF_1, OF_2, OF_3\} \\ &Subjec \quad to \\ &(5) \rightarrow (9) \end{aligned}$$

The objective functions are formulated next.

1) Active Losses: Distribution systems are usually designed with just one supply source and this may cause significant active 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 demand level. The total active energy dissipated during the planning horizon is calculated as follows:

$$OF_1 = TAL = \sum_{t=1}^{T} \sum_{dl=1}^{N_{dl}} AL_{t,dl} \times DU_{dl} \tag{10}$$

2) Total Costs: The second objective function, i.e., OF_2, to be minimized is the total costs which include the cost of electricity purchased from the grid, the installation costs and the operating costs of the DG units. The cost of purchasing electricity from the grid can be determined as:

$$GC = \sum_{t=1}^{T}\sum_{dl=1}^{N_{dl}} P_{t,dl}^{grid} \times DU_{dl} \times \rho \times PLF_{dl} \times \frac{1}{(1+d)^{t}} \tag{11}$$

Installation costs of the DG units can be calculated as:

$$DGIC = \sum_{t=1}^{T}\sum_{i=1}^{N_b} \xi_{i,t}^{dg} \times IC_{dg} \times \frac{1}{(1+d)^{t}} \tag{12}$$

The variable costs of the DG units can be calculated as:

$$DGVC = \sum_{t=1}^{T}\sum_{i=1}^{N_b}\sum_{dl=1}^{N_{dl}} DU_{dl} \times (FC_{dg} + OMC_{dg}) \times \left(\sum_{t'=1}^{t} \xi_{i,t'}^{dg}\right) \times P_{t,dl}^{dg} \times \frac{1}{(1+d)^{t}} \tag{13}$$

Thus, OF_2 is defined as:

$$OF_2 = DGIC + DGVC + TGC \tag{14}$$

3) Total Emissions: The third objective function, i.e., OF3, is the total CO2 produced by the DG units and the main grid. OF3 can be formulated as:

$$OF_3 = \sum_{t=1}^{T}\sum_{dl=1}^{N_{dl}} DU_{dl} \times \left(EF_{Grid} \times P_{t,dl}^{dg} + \sum_{i=1}^{N_b} EF_{dg} \times P_{i,t,dl}^{dg} \right) \tag{15}$$

5. PROPOSED ALGORITHM]

a) Parameterization of problem for GA

To solve the 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 matrix containing binary values. Each row is related to one DG. The first column determines whether this DG should be installed or not. The next column determines the year of installation. The third column demonstrates the location of the DG unit in the distribution network. The rest of the columns specify the operating schedule of the DG unit in different demand levels. A sample solution vector is shown in Fig. 4.

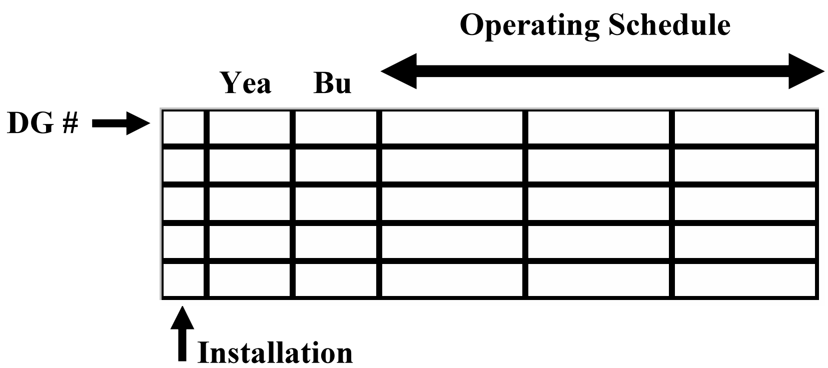

Fig. 4. Proposed vector for modeling the Problem Parameters $\overline{X}_i$

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

$$\text{Population} = [\overline{X}_1\ \overline{X}_2\ \ldots\ \overline{X}_p\ \ldots\ \overline{X}_{N_S}]$$

a) 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).

$$Pseudo_i = FN_i^{-1} + GD_i \tag{16}$$

The first term in (16) guides the population toward the Pareto optimal front since the solutions that 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 the distance between the maximum and minimum is calculated using (17)

$$MD_k = \max_{i=1:N_S} f_k(\bar{x}_i) - \min_{i=1:N_S} f_k(\bar{x}_i) \tag{17}$$

As the solutions are sorted, the first and the last one are their max and min. The diversity of every other solution is its average distance to its neighbors as shown in (18).

$$LD_k^i = \frac{|f_k(\bar{x}_i) - f_k(\bar{x}_{i+1})| + |f_k(\bar{x}_i) - f_k(\bar{x}_{i-1})|}{2MD_k} \tag{18}$$
$$\mathrm{i{=}2{:}N_S},\ k = 1 : N_O$$

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

$$LD_k^{N_S} = LD_k^1 = \max_{i=2:N_S-1} LD_k^i \tag{19}$$

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

$$GD_i = \sum_{k=1}^{N_O} \frac{LD_k^i}{N_O} \tag{20}$$

c) Steps of the algorithm

After analyzing the problem and selecting 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 a decimal number. Evaluate each individual of the population by performing load flow calculations to compute energy loss, total emission and total 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 the pseudo fitness value. Keep the population length limited to N_S .
7) If the stopping criterion is met go to step 16, if not, 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 the elite set based on the roulette wheel method.
10) Perform crossover and generate two children.
11) Mutate these two children based on mutation probability.
12) If still more children are needed, go to 9, if not, continue.
13) Combine the old population and new population to create a single population containing the bests of both.
14) Set iteration = iteration +1.
15) Return to Step 3.
16) End

The flowchart of the proposed algorithm is depicted in Fig.5.

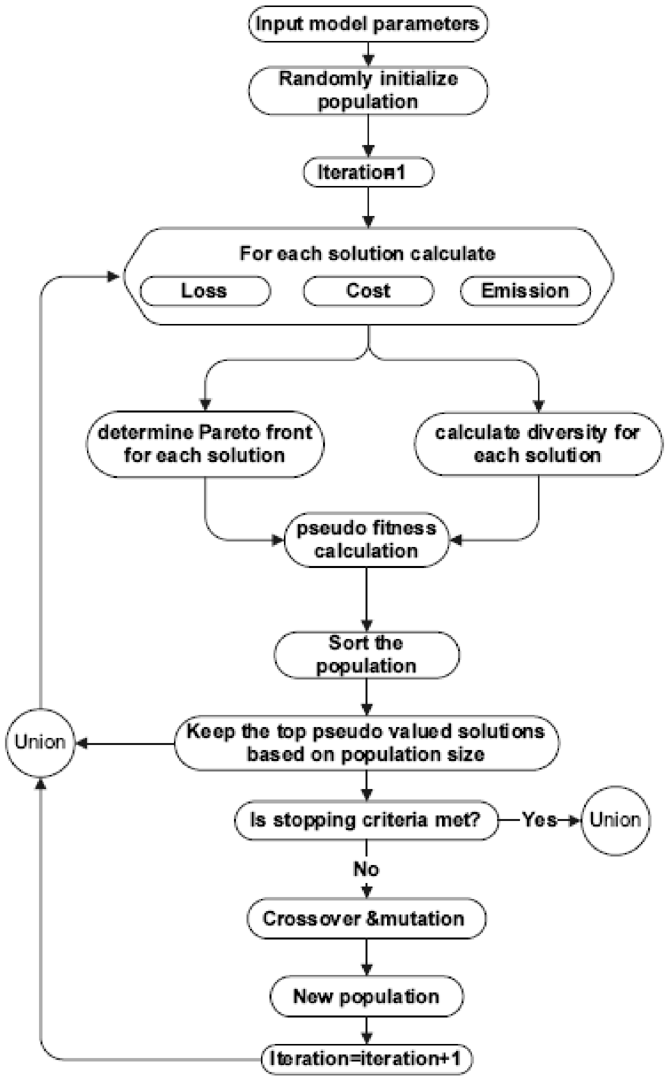

Fig. 5. Flowchart of genetic algorithm

6. 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 $\overline{X}_i$, a membership function is defined as $\mu_{f_k}(\overline{X}_i)$. This value shows the level in which $\overline{X}_i$ belongs to the set that minimizes the k[th] objective function. The value of $\mu_{f_k}(\overline{X}_i)$ varies between zero to one. The membership value of"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 $\overline{x}i$ if $\mu_{f_k}(\overline{X}_i) = 1$ and dissatisfied when $\mu_{f_k}(\overline{X}_i) = 0$ [30]. Different types of membership functions have been suggested like linear or exponential ones. The question is how the planner can select a suitable type of membership function. It should be noted that in this paper the decision making is posteriori not a priory one. This means that no preference should be given to optimizing any objective function before finding the Pareto optimal front. If an exponential membership function is chosen for one of the objectives functions, then it is given priority for minimizing that objective relative to the other objective because this function will assign a smaller membership function in the vicinity of the maximum value of that objective compared to linear type [28]. Here, a linear type of membership function has been used for all objective functions as shown in (21).

$$\mu_{f_i}(\overline{X}) = \begin{cases} 0 & f_i(\overline{X}) > f_i^{Max} \\ \dfrac{f_i^{Max} - f_i(\overline{X})}{f_i^{Max} - f_i^{Min}} & f_i^{Min} \le f_i(\overline{X}) \le f_i^{Max} \\ 1 & f_i(\overline{X}) < f_i^{Min} \end{cases} \quad (21)$$

Figure 6 shows the selected membership function

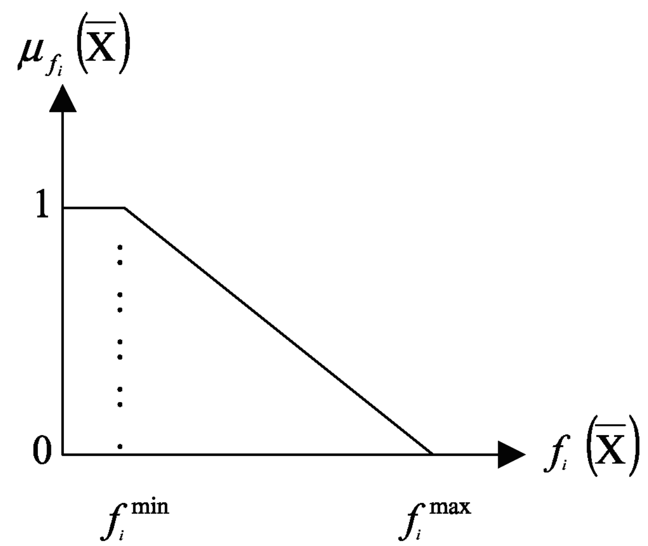

Fig. 6. Linear type membership function

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 of which its Minimum satisfaction is maximum over all objective functions. Using the Max-Min formulation, the final solution can be found by solving (22).

$$\max_{i=1:N_S}\left(\min_{k=1:N_O} \mu_{f_k}(X_n)\right) \tag{22}$$

7. SIMULATION RESULTS

The proposed algorithm is applied to a 33 bus test feeder [33] with slight modifications, which is shown in Fig.7. In the performed simulations, it is assumed that all buses are candidates 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.

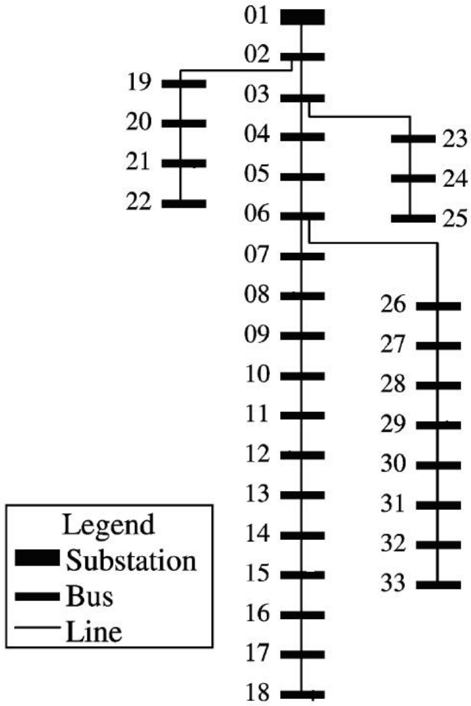

Fig. 7. Single line diagram of the distribution system under study

Here, without loss of generality, the assumptions used in this work are listed:

1) The planning horizon (T) is 10 years.
2) The discount rate (d) is assumed to be 12.5%
3) Transmission system limitation for energy delivery is $S_{\max}^{grid}$ = 200MV A.
4) The demand growth in each year of planning horizon can be different; it is assumed that it is similar in each year and α = 3%.
5) The characteristics of different DG technologies [31], [32] used in this paper are available in Table 1.
6) The duration of low, medium and high demand 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 2.
7) Variations of demand and Grid price are given in Table 2.
8) Emission factor of main grid E_{grid} is assumed to be 672 Kg/MWh.
9) Cost of active power, i.e. ρ in medium demand level is assumed to be 60$/MWh.
10) Maximum and minimum voltage for each bus is assumed to be $V_{\max}$ = 1.05pu, $V_{\min}$ = 0.9pu.

11) Cross over probability =70%
12) Mutation probability =5%
13) Number of population = 100.
14) Stopping criteria: Max iteration =1000.

Table 1. Characteristics of the dg units [31], [32]

DG Technology	Size (MVA)	$E_{dg}\ \frac{kgCO_2}{MWh}$	$IC_{dg}\ \frac{k\$}{MVA}$	$OMC_{dg}\ \frac{\$}{MWh}$	$FC_{dg}\ \frac{\$}{MWh}$	$\cos\varphi$	DG#
Micro Turbine	0.03	801	1485	75	15	0.9	1
	0.07	719	1485	75	15	0.9	2
	0.1	696	1485	75	15	0.9	3
Fuel Cell	0.075	531	3674	29	10	1	4
	0.02	531	3674	29	10	1	5
	0.1	531	3674	29	10	1	6
Combustion Turbine	1	774	715	67	6	0.9	7-8

Table 2. Data used in the study

Demand Levels	$DU_{dl}(hour)$	DLF_{dl}	PLF_{dl}
Low	2920	0.8	0.85
Medium	4380	1	1
High	1460	1.3	1.45

The formulated problem was solved and 97 Pareto optimal solutions were found by the algorithm. The Pareto optimal front is depicted in Fig. 8.

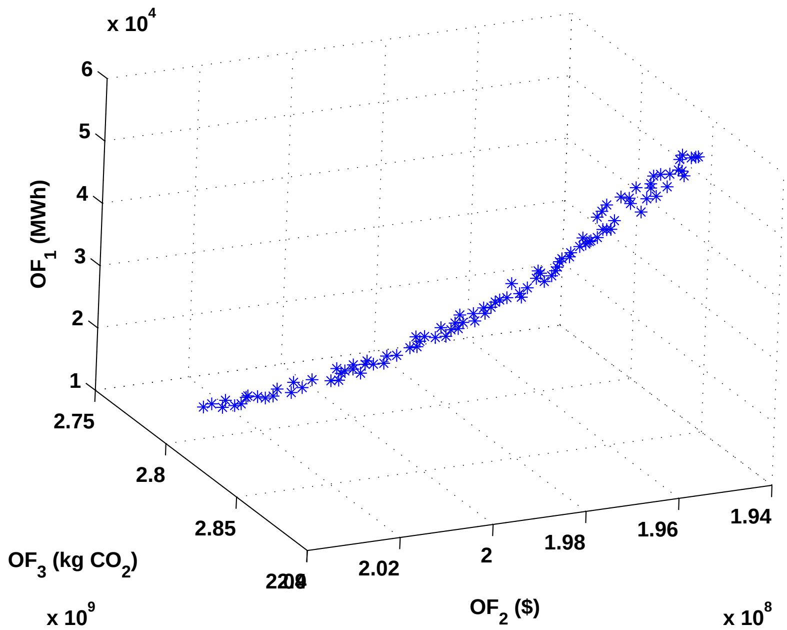

Fig. 8. Pareto Optimal front for three objectives

a) Finding pareto front and selecting final solution

Now the planner has a range of solutions instead of just only one solution. He can decide what to choose based on his requirements. In order to make the comparison more sensible, a Do Nothing Case (DNC) is also added in which no DG option is available for the planner. The variation range of each objective function in the Pareto optimal front is calculated and given in Table. 3. Some of the obtained solutions are given in Table 4. These solutions can be categorized and each category has some special features and the planner can choose the best solution based on its preferences over different objective functions. For example, if the planner is interested in minimizing all objective functions simultaneously, then solution # 55 is the best option. The details of this solution are given in Table 5. Two Micro turbines are installed in bus 18 and 33 in year 4 and 5, simultaneously. Two combustion turbines are installed in bus 13 and 33, both in the first year. Four Fuel cells should be installed in the network. Three of them are installed in the first year and one of them in year 8. If the planner is just interested in only two of the objective functions then solution B, C and D are the best ones. For example, if the planner is only interested in minimizing the OF2 and OF3, then solution D is the best option for the planner.

Table 3. Variation range of objective function for all solutions in Pareto optimal front

	$OF_3(kg\ CO_2)$	$OF_2(\$)$	$OF_1(MWh)$
$f_k^{\min}$	2.796×10^9	1.950×10^8	1.446×10^4
$f_k^{\max}$	2.875×10^9	2.031×10^9	5.965×10^4
DNC	2.900×10^9	2.123×10^9	7.568×10^4

Table 4. Some of the solutions of the Pareto optimal front

Case	Method	Solution #	OF_1 (MWh)	OF_2 $(k\$)$	OF_3 $(Ton\ CO_2)$	μ_{f_2}	μ_{f_3}	μ_{f_1}
A	$\max(\min_{k=1,2,3}(\mu_{f_k}))$	55	29597	197990	2824000	0.6651	0.6403	0.6524
B	$\max(\min_{k=1,2}(\mu_{f_k}))$	43	29846	197880	2825400	0.6569	0.6550	0.6345
C	$\max(\min_{k=1,3}(\mu_{f_k}))$	5	14652	202930	2796400	0.9958	0.0282	1
D	$\max(\min_{k=2,3}(\mu_{f_k}))$	66	30484	197780	2824900	0.6454	0.6674	0.6403

Table 5. The investment plan obtained for case a

DG Technology	Number of Installed DG	Size (MVA)	Year	Bus
Micro Turbine	1	0.07	4	18
	1	0.1	5	33
Combustion Turbine	1	1	1	33
	1	1	1	13
Fuel Cell	2	0.02	1	11
	1	0.075	8	28
	1	0.02	1	33

b) Comparing to other heuristic methods and discussing the results

In order to verify the ability of the proposed algorithm it is compared to two other heuristic methods. The comparison is made between the Particle Swarm Optimization (PSO) [34], Tabu search [26] and the proposed method. Two factors have been monitored, the first one is the number of Pareto optimal solutions found by the algorithm, and also the running time in a number of specified iterations. The Windows-based PC used for the test is equipped with an Intel Core 2 Duo CPU, 2.4GHz, 1 GB RAM. The results of the comparison are given in Table 6. As it is given in Table. 6, the speed of PSO is higher than the Tabu search method, but it will find fewer Pareto optimal solutions. On the other hand, the proposed method finds more Pareto optimal solutions and rusts faster. In this paper, the Newton Raphson method is used for solving load flow equations and that is why the running time might seem too long but, since the calculation process is offline, it will not cause a problem for larger distribution networks or more demand levels. Additionally, using techniques developed for radial load flow [35], calculations can reduce the running time.

Table 6. Comparing the proposed method with other heuristic methods

Method	Running time (min)	# of Pareto Optimal solutions
Tabu Search [26]	394	82
PSO [34]	262	75
Proposed method	186	97

c) Analyzing the Pareto front

The proposed model can be directly used in the power market model in which the DISCO is responsible for DG integration in the network. However, in power market models where the DG investment is done by independent investors instead of DISCO, the provided information would also be useful as an economical and environmental signal for regulators. It can be used for regulating the incentives to encourage the private sector to invest in a particular DG technology, and understanding where it would be more beneficial. The frequency of appearance of each DG technology in the Pareto optimal front can somehow show the appropriateness of each technology for a given distribution system as shown in Fig. 9.

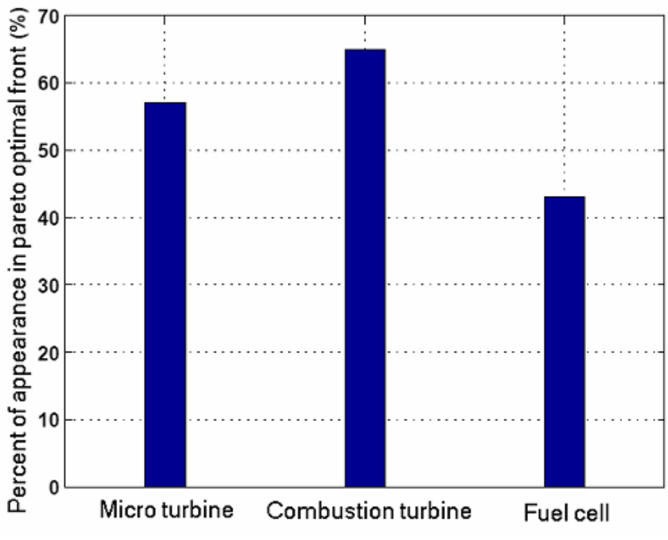

Fig. 9. Percent of appearance of each DG technology in solutions of Pareto optimal front

The more a DG technology appears in the solutions of Pareto optimal front the more suitable that technology is. In the studied network the combustion turbine, micro turbine and finally the fuel cells, are the best options for investment. The frequency of appearance of each bus in the solutions of Pareto optimal front shows the appropriate locations for DG placement, as shown in Fig. 10.

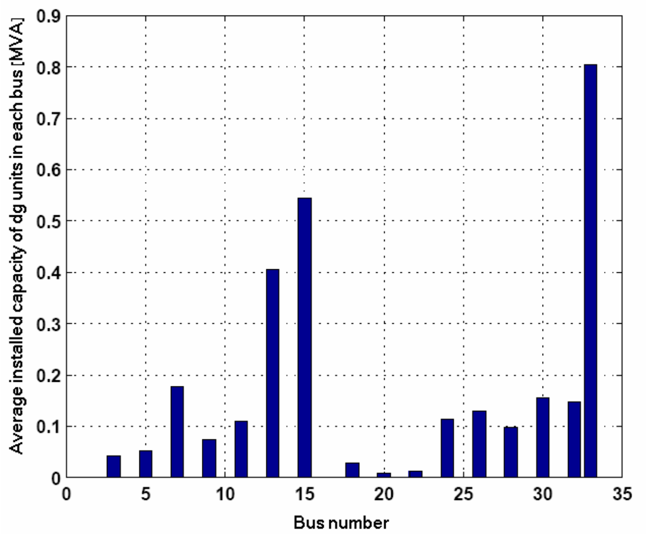

Fig. 10. Percent of appearance of each bus in solutions of Pareto optimal front

The most frequent bus in the Pareto optimal front is bus # 33 and after that the bus # 15 is the next appropriate bus for DG investment and so on.

8. CONCLUSION

This paper presents a dynamic multi-objective model for DG planning problem and a GA based method to solve the formulated problem. The proposed two-step algorithm finds the non-dominated solutions by simultaneous minimization of active losses, costs and emissions in the first stage and uses a fuzzy satisfying method to select the best solution from the candidate set in the second stage. The new planning model is applied to a test system and its flexibility is demonstrated through different case studies. The solution set provides the planner with an insight into the problem and enables him to choose the best solution according to planning preferences.

NOMENCLATURE

Indices

i,j	Bus
dg	DG technology
dl	Demand level
ℓ	Feeder
k, k'	Objective function
n	Solution
t, t'	Year

Constants

DLF_{dl}	Demand level factor in demand level dl
m	Dimension of solutions
d	Discount rate
DU_{dl}	Duration of demand level dl
E_{grid}	Emission factor of the grid
E_{dg}	Emission factor of a dg
IC_{dg}	Installation cost of a dg
OMC_{dg}	Operation and maintenance cost of a dg

FC_{dg}	Fuel cost of a dg
PLF_{dl}	Price level factor in demand level dl
T	Planning horizon
α	Rate of demand growth

Variables

$P_{i,t,dl}^{D}$	Active power demand in bus i, in year t in demand level dl
$P_{i,t,dl}^{grid}$	Active power purchased from grid in year t and demand level dl
$P_{i,t,dl}^{dg}$	Active power injected by a dg in bus i, in year t and demand level dl
$S_{t,dl}^{grid}$	Apparent power imported from grid in year t and demand level dl
$S_{i,t,dl}^{dg}$	Apparent power of dg installed in bus i, in year t and demand level dl
$AL_{t,dl}$	Active power losss in year t, in demand level dl
$P_{,base}^{D}$	Base active power demand in bus i in first year
$Q_{,base}^{D}$	Base reactive power demand in bus i in first year
ρ	Base price of active power purchased from the grid
$I_{t,dl}^{\ell}$	Current magnitude of ℓth feeder in year t and demand level dl
FN_{n}	Front number to which nth solution belongs
GD_{n}	Global Diversity of nth solution
LD_{n}	Local diversity of nth solution in kth objective function
MD_{k}	Maximum difference between the values of kth objective function, regarding all solutions
$\overline{P}_{\lim}$	Maximum operating limit of a dg
$P_{,t,dl}^{net}$	Net active power injected to bus i, in year t and demand level dl
$Q_{i,t,dl}^{net}$	Net reactive power injected to bus i, in year t and demand level dl
$\xi_{i,t}^{dg}$	Number of installed units of a dg in bus i in the year t
N_{b}	Number of buses in the network
N_{P}	Number of population
N_{ℓ}	Number of feeders in the network
N_{O}	Number of objective functions
N_{dl}	Number of considered demand levels
$Pseudo_{i}$	Pseudo fitness of solution i
$Q_{i,t,d}^{dg}$	Reactive power injected by a dg in bus i, in year t and demand level dl
$Q_{i,t,d}^{D}$	Reactive power demand in bus i, in year t in demand level dl
GC	Total cost paid to grid
DGIC	Total installation cost of DG units
DGVC	Total variable costs of DG units
$S_{\max}$	Upper safe operation thermal limits of substation feeding the network
$I_{\max}^{\ell}$	Upper operation thermal limits of feeders
$V_{\max}, V_{\min}$	Upper and lower safe operation limits of voltage

$V_{i,t,d}$ Voltage magnitude in bus i, in year t and demand level dl

$\delta_{i,t,d}$ Voltage angle in bus i, in year t and demand level dl

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