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A Practical Eco-Environmental Distribution Network Planning Model Including Fuel Cells and Non-renewable Distributed Energy Resources

Alireza Soroudi ^{*a,1}, Mehdi Ehsan^{a,b}, Hamidreza Zareipour^c

^aDepartment of Electrical Engineering, Sharif University of Technology, Tehran, Iran

^bCenter of Excellence in Power System Management and Control, Sharif University of Technology

^cDepartment of Electrical and Computer Engineering, University of Calgary, Alberta, Canada

Abstract

This paper presents a long-term dynamic multi-objective planning model for distribution network expansion along with distributed energy options. The proposed model optimizes two objectives, namely costs and emissions and determines the optimal schemes of sizing, placement and specially the dynamics (i.e., timing) of investments on distributed generation units and network reinforcements over the planning period. An efficient two-stage heuristic method is proposed to solve the formulated planning problem. The effectiveness of the proposed model is demonstrated by applying it to a distribution network and comparing the simulation results with other methods and models.

Keywords: Distributed generation, Immune algorithm, NSGA-II, Dynamic planning, Multi-objective optimization.

1. Introduction

Distributed Generation (DG) is an electric power source connected directly to the distribution network. Different factors like electricity market liberalization, system reliability enhancement[1] and efforts to lower the global warming [2] have made them more interesting for electricity sector. DG units are owned either by distribution network operators (DNOs) [3] or by non-DNO entities [4]. In either case, DG may offer DNOs more diverse, flexible, and secure options for managing their electricity systems to meet the load growth as an alternative to traditional network reinforcement. In recent years, many approaches have been proposed addressing DG planning and integration of them into distribution systems. The literature suggests a wide range of objectives, such as investment deferral in network capacity [5] and active loss reduction [6], reactive loss reduction [7, 8], reliability improvement [9], reducing the cost of energy required for serving the customers [9], increasing the incentives received by distribution network owners for using DGs [7], reducing the cost of energy not supplied and emission reduction [10, 6]. These studies have considered a variety of technical issues including voltage profile [5, 8], capacity limits of

^{1*}Corresponding Author: Azadi Ave., P. O. Box 11365-9363, Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran, Tel : (Office) +98(21) 66164324, Fax : +98(21) 66023261, Email: Alireza.soroudi@gmail.com

conductors [5, 8], substation capacity[5, 11], three phase and single phase to ground short circuit, and load modeling [8]. The reported models for DG planning can generally 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[9]. In this category, the models are single or multi-objectives. The DG planning can be formulated as a single or multi-objective optimisation problem. If only a single-objective is of interest for the planner, then it is formulated as a single objective problem. When many objectives are of interest, the problem is either translated to a single-objective problem (usually adding objectives into a single measure of performance [5]), or formulated as “true” multi-objective problem using Pareto optimality concept [11, 10]. In static models, [12] and [13] consider network reinforcement along with DG investment. The value of multi-objective problem formulation of DG planning is that the objectives are usually in conflict or they can not be easily converted into a single-objective problem[14]. It should also be noted that using the multi-objective methods can provide a decision making support tool for the planner that is able to justify its choices clearly and consistently [15]. In this paper, a planning model for DG-planning problem is formulated which is not only multi-objective but also it is dynamic and a two-stage algorithm is proposed to solve the problem. In the first stage, the set of Pareto optimal solutions is found using a new hybrid Immune-GA method, and in the second stage, the best solution is chosen using a fuzzy satisfying technique. The model aims at all three aspects of placement, sizing and timing of DG investment simultaneously, while also considering distribution feeder and transformer reinforcements. The main contributions of this paper are:

1. A multi-objective dynamic DG planning model with the consideration of network reinforcements is proposed.
2. The proposed model is solved using a new efficient heuristic method which dominates the other heuristic methods.

This paper is set out as follows: section 2 presents problem formulation, section 3 sets out the proposed solution method for solving the problem. The application of the proposed model and the simulation results are presented in section 4 and finally, section 5 summarizes the findings of this work.

2. Problem Formulation

The multi-objective DG planning formulation is presented in this section. The decision variables are the number of DG units from each specific technology, to be installed in each bus in each year, i.e., $\xi_{i,t}^{dg}$; binary investment decision in feeder ℓ in the year t , i.e. γ_t^ℓ which can be 0 or 1, and finally the number of new installed transformers in the year t , i.e. ψ_t^{tr} . The assumptions used in problem formulation, constraints and the objective functions are explained next.

2.1. Assumptions

The following assumptions are employed in problem formulation:

- Connection of a DG unit to a bus is modeled as a negative PQ load [12]. It should be noted that this assumption is not valid for some DG technologies like wind turbines which have stochastic behaviors.
- All of the investments are done at the beginning of each year.
- The daily load variations over the long-term is modeled as a load duration curve with N_{dl} demand levels. Assuming a base load of $P_{i,base}^D$, a Demand Level Factor of DLF_{dl} and a demand growth rate of α , the demand in bus i , in year t and in demand level dl can be calculated as:

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

- The price of energy purchased from the grid is competitively determined in a liberalized market environment and thus, it is not constant during different demand levels. Estimating the variations of electricity market prices in the long-term is beyond the scope of this paper- see [16] for some insights. Without losing generality, it is assumed that the electricity price at each demand level can be determined as $\rho \times PLF_{dl}$, where the base price (i.e. ρ), and the Price Level Factors (i.e. PLF_{dl}), are known; the potential economic risks of this assumption are not analyzed in this paper.
- The DNO is assumed to own and operate the network and thus having access to all network information. Also, network reinforcement in the form of adding new feeders or transformers is considered by the DNO along with adding DG units as an integrated framework.

A nomenclature of symbols and abbreviations is defined at the end of the paper.

2.2. Constraints

2.2.1. Power Flow Constraints

The power flow equations that should be satisfied for each configuration and demand level are:

$$\begin{aligned} P_{i,t,dl}^{net} &= -P_{i,t,dl}^D + \sum_{dg} P_{i,t,dl}^{dg} \\ Q_{i,t,dl}^{net} &= -Q_{i,t,dl}^D + \sum_{dg} Q_{i,t,dl}^{dg} \\ P_{i,t,dl}^{net} &= V_{i,t,dl} \sum_{j=1}^{N_b} Y_{ij}^t V_{j,t,dl} \cos(\delta_{i,t,dl} - \delta_{j,t,dl} - \theta_{ij}^t) \\ Q_{i,t,dl}^{net} &= V_{i,t,dl} \sum_{j=1}^{N_b} Y_{ij}^t V_{j,t,dl} \sin(\delta_{i,t,dl} - \delta_{j,t,dl} - \theta_{ij}^t) \end{aligned} \quad (2)$$

2.2.2. Operating limits of DG units

The DG units should be operated considering the limits of their primary resources, i.e.:

$$P_{i,t,dl}^{dg} \leq \sum_{t=1}^t \xi_{i,t}^{dg} \times \bar{P}_{lim}^{dg} \quad (3)$$

The power factor of DG unit is kept constant [7] in all demand levels as follows:

$$\cos\varphi^{dg} = \frac{P_{i,t,dl}^{dg}}{\sqrt{(P_{i,t,dl}^{dg})^2 + (Q_{i,t,dl}^{dg})^2}} = \text{const.} \quad (4)$$

2.2.3. Voltage profile

The voltage magnitude of each bus should be kept between the operation limits, as follows:

$$V^{min} \leq V_{j,t,dl} \leq V^{max} \quad (5)$$

2.2.4. Capacity 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:

$$I_{\ell,t,dl} \leq \bar{I}_{\ell} + Cap_{\ell} \times \sum_{i=1}^t \gamma_i^{\ell} \quad (6)$$

where, $Cap_{\ell} \times \sum_{i=1}^t \gamma_i^{\ell}$ represents the added capacity of feeder due to the investments made until year t.

For substation capacity constraint, also, the same philosophy holds, as follows:

$$S_{t,dl}^{grid} \leq \bar{S}_{tr} + Cap_{tr} \times \sum_{i=1}^t \psi_i^{tr} \quad (7)$$

Where, $Cap_{tr} \times \sum_{i=1}^t \psi_i^{tr}$ represents the added capacity of substation resulting from adding new transformers until year t.

2.3. Objective Functions

The proposed model minimizes two objective functions, namely, total costs and total emissions of the DG investment problem, as follows:

$$\min \{OF_1, OF_2\}$$

subject to:

$$(1) \rightarrow (7)$$

The objective functions are formulated next.

2.3.1. Total Costs

The first objective function, i.e., OF_1 , to be minimized is the total costs which includes the cost of electricity purchased from the grid, the installation and the operating costs of the DG units and finally the reinforcement costs of the distribution network. The cost of purchasing electricity from the grid can be determined as:

$$GC = \sum_{t=1}^T \sum_{dl=1}^{N_{dl}} PLF_{dl} \times \rho \times P_{t,dl}^{grid} \times \tau_{dl} \times \frac{1}{(1+d)^t} \quad (8)$$

Installation costs of the DG units can be calculated as:

$$DGIC = \sum_{t=1}^T \sum_{i=1}^{N_b} \sum_{dg} \xi_{i,t}^{dg} \times IC_{dg} \times \frac{1}{(1+d)^t} \quad (9)$$

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

$$DGOC = \sum_{t=1}^T \sum_{i=1}^{N_b} \sum_{dg} \sum_{dl=1}^{N_{dl}} \tau_{dl} \times OC_{dg} \times P_{i,t,dl}^{dg} \times \frac{1}{(1+d)^t} \quad (10)$$

The reinforcement cost of the distribution network is the sum of all costs paid for installation and operation of new feeders and transformers. The total feeder reinforcement cost, i.e. LC, and substation reinforcement cost, i.e. SC, are calculated as follows:

$$LC = \sum_{t=1}^T \sum_{\ell=1}^{N_{\ell}} C_{\ell} \times d_{\ell} \times \gamma_{\ell}^{\ell} \times \frac{1}{(1+d)^t} \quad (11)$$

$$SC = \sum_{t=1}^T C_{tr} \times \psi_t^{tr} \times \frac{1}{(1+d)^t}$$

Thus, OF_1 is defined as:

$$OF_1 = GC + DGIC + DGOC + LC + SC \quad (12)$$

2.3.2. Total Emissions

The second objective function, i.e., OF_2 , is comprised of the emissions produced by the electricity purchased from main grid and the DG units. The emissions produced by the main grid in year t and demand level dl , is calculated by multiplication of purchased power from grid in each demand level, i.e. $P_{t,dl}^{grid}$, and the emission factor of the grid, i.e. E_{grid} . The total emissions generated by the DG units is calculated by the multiplication of power generated by each DG and its emission factor, i.e. E_{dg} . This value is summarized over all buses in the network to consider all installed DG units. The two introduced terms are multiplied by the duration of each load level, i.e. τ_{dl} , and summed together over planning horizon from $t = 1$ to $t = T$. OF_2 , is formulated as follows:

$$OF_2 = \sum_{t=1}^T \sum_{dl=1}^{N_{dl}} \tau_{dl} \times [E_{grid} \times P_{t,dl}^{grid} + \sum_{i=1}^{N_b} \sum_{dg} E_{dg} \times P_{i,t,dl}^{dg}] \quad (13)$$

3. The proposed solution Method

The DG planning problem formulated in Section 2 is a mixed integer non-linear multi-objective problem. In general, multi-objective optimization problem consists of more than one objective function which are needed to be simultaneously optimized. One available approach for solving such problems is the weighted sum approach in which the multi-objective problem is converted into a single-objective problem using pre-specified weights. Although the weighted sum approach is simple and easy to understand but there are some disadvantages associated with it, such as: it is not applicable on non-convex problems

[17]; if the priorities (weights) of the objective functions are changed, the problem should be re-solved; value of incommensurable objectives can not be added together and at finally, there is only one solution for a given set of weights and the decision maker can not have a good set of trade-off solutions among the objectives [18]. To address the shortcomings of weighted sum methods, alternative heuristic search methods based on the concept of Pareto optimality are proposed which deal with a set of possible solutions simultaneously, and allow the decision maker to find several optimal solutions in a single run. In such methods, the multi-objective optimization problem can be described as finding a set of decision variables which maximizes/minimizes a vector of objective functions, subject to a set of equality and inequality constraints. An overview of the concept of Pareto optimality is provided in Appendix. In this context, the Non-dominated Sorting Genetic Algorithm (NSGA-II) [11] and Immune Algorithm [19] have been applied to multi-objective optimization in power systems planning applications. In the present work, a hybrid Immune-Genetic Algorithm (Immune-GA) is proposed to find the Pareto optimal front. The proposed algorithm strengthens the Immune algorithm by incorporating the crossover operator of Genetic Algorithm (GA), for better exploration of solution space. The proposed Immune-GA algorithm along with a fuzzy satisfaction approach is employed in a two-stage algorithm to find the final optimal solution to the formulated problem.

3.1. The Proposed Immune-GA-Based Technique for Finding Pareto Fronts

Immune Algorithm is a computational tool which imitates the behavior of human body against the external invasions and is a powerful method in pattern recognition [20]. This algorithm has been previously used for solving multi-objective optimization problems in [21]. Immune algorithm considers the objective functions and their associated constraints as antigens, which are to be identified by the antibodies, and the solutions which play the rule of antibodies. Affinity factors are defined which indicates the ability of antibodies in recognizing the antigens, this is further explained later. Antigen recognition means performance of antibodies (i.e. solution) in optimizing the objective function while satisfying the constraints. Similar to other evolutionary algorithms, it is an iterative methodology: an initial set of antibodies is generated and then it is tried to improve their response in identifying the antigens.

There are two important operators in immune algorithm, namely, cloning and mutation. The cloning operator gives the antibodies a chance to reproducing [22]. This chance is proportional to their affinities, i.e. AF_n , the ones with a better response are given a more chance. After selecting the solutions using cloning operator, mutation operator tries to apply some perturbation on them in hope to find better ones. The mutation probability is proportional to the inverse value of the affinity of antibodies. In other words, the better a solution is, the more will be cloned and the less will be mutated.

Since the Immune algorithm deals with each antibody separately, it can not use the memory of the population in finding the best solution. In order to increase the performance capability of the algorithm, crossover operator [23] of GA is proposed in the present work to overcome this shortcoming. By doing this, when the algorithm is in the cloning phase, it will select two solutions (instead of one) and performs

the crossover operation. It then generates two new solutions and passes them to mutation operator. Mutation operator uses the value of affinity factor of the selected parents (i.e. antigens) as a measure for mutating them. In the context of multi-objective optimization, it is needed that the population be directed toward the Pareto optimal front considering two important aspects: getting closer to Pareto optimal front and maintaining the diversity among the solutions [18]. To do so, a pseudo fitness value is assigned to each solution, referred to as affinity factor AF_n , as follows:

$$AF_n = w_1 \times FN_n^{-1} + w_2 \times GD_n \quad (14)$$

The first term in (14) guides the population toward the Pareto optimal front since the solutions which belong to lower fronts get higher affinity (fitness). The second term insures the diversity among the solutions. In order to calculate the global diversity of the n^{th} solution, i.e. GD_n , a local diversity factor, i.e. LD_n^k , is defined for each objective function [18]. For every objective function k , the solutions are sorted and the difference between the maximum and minimum values is calculated as:

$$MD_k = \max(f_k(X_n)) - \min(f_k(X_n)) \quad (15)$$

$$n = 1, \dots, N_p$$

Since the solutions are sorted, the first and the last ones are the maximum and minimum, respectively. The local diversity of each of the other solutions is its average distance to its neighbors, as follows:

$$LD_n^k = \frac{|f_k(X_n) - f_k(X_{n+1})| + |f_k(X_n) - f_k(X_{n-1})|}{2MD_k} \quad (16)$$

$$n = 2 : N_p - 1$$

For the first and the last solutions, local diversity can be calculated as:

$$LD_{N_p}^k = LD_1^k = \max(LD_n^k) \quad (17)$$

The global diversity factor for each solution is then calculated as the average of its local diversities as follows:

$$GD_n = \sum_{k=1}^{N_O} \frac{LD_n^k}{N_O} \quad (18)$$

In initial iterations, a small number of solutions belong to the first Pareto front, so getting closer to Pareto optimal front is more important than maintaining the diversity among them. It is necessary to enable the algorithm in distinguishing between the solutions in different Pareto fronts, w_1 and w_2 in (14) are adaptively selected which guarantees that the solution belonging to a lower Pareto front has a bigger affinity factor than a solution belonging to an upper front level (w_1 is bigger than w_2 in the initial iterations) and when most of the solutions are in the Pareto optimal front, w_2 is chosen bigger than w_1 to maintain the diversity among the solutions.

3.2. The Proposed Two-stage Solution Algorithm for Solving the Multi-objective DG Planning Problem

The solution algorithm proposed here consists of two stages. In the first stage, the solutions which form the Pareto optimal front are found and in the second stage, the best solution is selected considering the planner's preferences. Both stages are described as follows:

3.2.1. Stage I (finding the Pareto optimal front)

The Immune-GA algorithm proposed in section 3.1 is used to find the Pareto optimal front. To do so, each antibody i.e. solution, is a vector containing the installation decision of DG units, the bus on which a DG units is to be installed, the year of installation and their generated power and for all available DG technologies. the steps of the first stage of the solution algorithm are as follows:

- a. Generate an initial random solution.
- b. If the stopping criterion is met, go to step (k), else, continue.
- c. Calculate OF_1, OF_2 for each member of population.
- d. Calculate the affinity factor using (14) for each antibody.
- e. Keep a predefined percent of population as antigens and the rest as antibodies.
- f. Assign a probability to each antigen proportional to its AF_n and by using the *roulette wheel* method [24], select some parents in pair and perform cloning phase. In this phase, use crossover operator to produce new children from selected parents for cloning.
- g. Use the average affinity factor of the parents to mutate the cloned antibodies and generate a new solution as a new antibody.
- h. Construct a new population by combining the new antibodies and old population.
- i. Sort the population based on the affinity factor of its members and keeps the best of them.
- j. Return to step (b).
- k. End.

The flowchart of the first stage of the proposed method is depicted in Fig.1.

3.2.2. Stage II (Selecting 'the best' solution)

The ultimate goal of the planner is to choose the "most preferred" solution among the Pareto optimal front. Because of the uncertainty of priorities of objective functions for planner, a fuzzy satisfying method [25] is used in this paper to find the 'the best' solution [26]. The principles of this method are as follows: for each solution in the Pareto optimal front, X_n , a membership function is defined as $\mu^{f_k(X_n)}$. This value, which varies between 0 to 1, shows the level of which X_n belongs to the set that minimizes the

objective function f_k . A linear membership function [26] is used in the present work for all objective functions, as follows:

$$\mu^{f_k(X_n)} = \begin{cases} 0 & f_k(X_n) > f_k^{max} \\ \frac{f_k^{max} - f_k(X_n)}{f_k^{max} - f_k^{min}} & f_k^{min} \leq f_k(X_n) \leq f_k^{max} \\ 1 & f_k(X_n) < f_k^{min} \end{cases} \quad (19)$$

A conservative decision maker tries to maximize minimum satisfaction among all objectives or minimize the maximum dissatisfaction [25]. The final solution can then be found as:

$$\max(\min(\mu^{f_k(X_n)}))_{k=1:N_O, n=1:N_p} \quad (20)$$

4. Simulation Results

The proposed methodology is applied to a 9-bus test system which is shown in Fig.2. The technical data of this network are shown in Table. 1 [11, 12]. This network consists of a 132/33kV substation with 40 MVA capacity and 8 feeders with eight aggregated loads which their base value, i.e. $S_{i,base}^D$, are given in Table. 1. Total base load of the system in the first year, is 28.12 MVA and at the end of the planning horizon this value reaches to 38.325 MVA. The peak power of the system will be 51.1 MVA in final planning year. The power factor of the system is assumed to be 0.9. Reinforcing distribution transformers is limited to maximum two three-phase transformers with a capacity of $Cap_{tr}=10$ MVA and a cost of $C_{tr}=0.2$ Million \$ for each. The cost of reinforcing each feeder is $C_\ell=0.15$ Million \$ /km [12] and it is assumed that $Cap_\ell = 210A$.

Three DG technology options, namely, Micro Turbine (MT), Gas Turbine (GT) and Fuel Cell (FC) are considered. It is also assumed that all buses are potential DG installation candidates and more than one DG can be installed in a specific bus. Three demand levels, i.e., low, medium and high are considered here with DLF_{dl} are 0.867, 1, 1.334, respectively; the corresponding PLF_{dl} values are 0.7, 1, 1.45, respectively; The value of τ_{dl} for selected demand levels are 2920, 4380, 1460 hours, respectively; the stopping criterion is reaching to a predefined maximum number of iterations. Other simulation assumptions and characteristics of the DG units [27, 28] are presented in Table. 2 and 3 respectively. The formulated problem was implemented in MATLAB [29].

In this section, first, a test case is presented to demonstrate the proposed formulation and solution algorithm. Second, the proposed formulation and solution algorithm are compared with other available models/techniques.

4.1. Proposed Dynamic Integrated Planning

The formulated problem is solved using the proposed two-stage algorithm and 50 non-inferior solutions are found. The planner can choose the best solution based on the planning criteria. The Pareto optimal front of the search space, found in the first stage, is depicted in Fig.3, where the best cost and lowest emission solutions are indicated on the Pareto optimal front. The variation ranges of all objective functions are given in Table 4.

In the second stage, the planner can choose the most preferred solution using the fuzzy satisfaction method introduced in section 3.2 . Three different case results are presented here for discussion:

- Case I: When the planner is not constrained/biased toward any of the objective functions, all objective functions are dealt with without any discriminations. Solution #30 is found as the best solution and its attributes are presented in Table 5. The investment plan is as follows: one transformer is installed in year 7 and one feeder is reinforced in year 4. The DG technologies used in this plan are fuel cell and micro turbine. Five fuel cell units are installed in first year and one in second year. Three micro turbines are installed in years 4, 6 and 8. The placement of DG units is given in Table. 6.

However, there exist situations in which, the decision maker is obliged to choose solutions with special properties, referred to as biased cases II and III here. In these cases, the focus of planner is on a specific objective function. Thus, the planner should choose a plan for which the degree of satisfaction for the specified objective is more than a certain satisfaction level. This level is a number between 0 and 1 and is chosen by the planner. The solutions which satisfy the preferred objective more than the required satisfaction level are kept. Then, for each solution, minimum values of satisfactions for the remaining objectives are calculated and the one with the biggest value will be selected as the best solution.

- Case II: This case considers the limitation on satisfaction of environmental objective function. Total emission is assumed to be limited to 1.65×10^6 ton over the planning horizon. In this case, minimum satisfaction is thus equal to $\frac{1.65 \times 10^6 - f_2^{max}}{f_2^{min} - f_2^{max}} = 0.7138$. All solutions with $\mu^{f_2} \geq 0.7138$ are found, among them, the solution with biggest value of $\min(\mu^{f_1}, \mu^{f_2} - 0.7138)$ is selected. The solution with such characteristics is solution #10. The investment plan is as follows: two transformers are installed in years 2 and 10 and one feeder is reinforced in the first year. The DG technology used in this plan is fuel cell. Two fuel cell units are installed in years 2 and 4 in buses 9 and 7 respectively. The complete investment plan can be found in Table. 6.
- Case III: Here, the focus is on total cost that should be paid. Suppose the total budget of DNO is limited to $\$1.3 \times 10^8$. The planner should take into account this constraint that the total cost of the final solution can not exceed this value. Since f^{max} and f^{min} of all objectives are given in Table II, the minimum satisfaction for μ^{f_1} can be calculated easily $\frac{Budget - f_1^{max}}{f_1^{min} - f_1^{max}} = 0.7473$. Minimum satisfaction in this case is thus equal to 0.7473. When all solutions with $\mu^{f_1} \geq 0.7473$ are found, the solution with the biggest value of $\min(\mu^{f_1} - 0.7473, \mu^{f_2})$ is found. The solution with such characteristics is solution #17. The investment plan is as follows: in this case, network investment is not done and only DG units are used. All DG technologies are used in this plan. One micro turbine is installed in each of years 1, 3 and 5. Two micro turbines units are installed in year 9. Six fuel cell units are installed in first year and one gas turbine unit is installed in year 5. The placement of these units are given in Table.6.

The best solution of each of the above cases are marked on the Pareto optimal front of Fig.3. The solution set can provide the planner with useful information. For example, knowing the number of solutions on the Pareto optimal front which use a specific bus as a location for DG installation may help the planner in identifying the key buses in system planning. The percentages of appearance of each bus in the solution set are shown in Fig. 4. For example, bus 9 appears in all of the solutions. This basically indicates that this bus is a good candidate for DG placement. Note that the next important bus is bus #3. Also, analyzing the solutions of the Pareto optimal front provides some information about the employed DG technologies. The percentages of times that each technology appeared in the Pareto optimal set are shown in Fig. 5. According to the obtained results, fuel cell is the most popular DG technology followed by micro turbine and gas turbine.

It should be noted that in the proposed model, it is assumed that the DNO is the planner and decides about installing DG units and/or reinforcing the network. However, the model can also provide useful investment signals to non-DNO entities and the regulator where investing in DG or environmental regulations are concerned.

4.2. Comparing with other planning models and methods

In this section, a number of comparative analyses are presented verify the effectiveness of both the proposed DG-planning model and the proposed solution algorithm. The dynamic of investments is eliminated from the proposed model and the new static model, referred to here by M1, is solved using the proposed solution algorithm. Such static model is similar to those models presented in [12, 13]. In another alternative static model, referred to by M2, DG panning is eliminated from M1 which basically leaves network reinforcement as the only option to deal with the future load growth. In the third static alternative, referred to by M3 here, network reinforcement is eliminated from M1; this basically leaves DG installations as the only planning option. M3 is similar to the model presented in [3]. The Pareto fronts of the models M1, M2 and M3, along with the one for the proposed dynamic model, are presented Fig. 6. Alternative dynamic models, in which only DG planning is considered, referred to by M4, and where only network reinforcement is considered, referred to by M5 here, are also studied. The Pareto fronts of M4 and M5, along with that of the proposed model, are presented in Fig. 7.

The Pareto fronts presented in Fig.s 6 and 7 demonstrate that the proposed model provides a wider range of options for the planner and for each solution on the Pareto front of other models, there exists at least one solution on the Pareto front found by the proposed model which has lower cost and emission attributes (compare solution D and A in Fig.9 in the appendix for the general idea). In other words, the Pareto optimal front of the proposed model construct the front number one.

In order to examine the strength of the proposed hybrid Immune-GA method, the proposed model is also solved using the Immune algorithm and NSGA-II separately. The Pareto fronts found by each of these two approaches, and the one found by the proposed Immune-GA method are depicted in Fig. 8. These fronts clearly show that the solutions found by the proposed algorithm dominates the ones

found by the two other methods- see appendix for clarifications. These results confirm the fact that using the abilities of both Immune algorithm and GA, guides the solution method to a better exploration of solution space and finding a lower Pareto optimal front.

5. Conclusion

This paper presents a dynamic multi-objective formulation of DG-planning problem and an Immune-GA based method to solve the formulated problem. The proposed two-step algorithm finds the non-dominated solutions by simultaneous minimization of total 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 and effectiveness is demonstrated through different case studies and comparative analyses. The results show the Pareto optimal front found from solving the proposed DG-planning model is more efficient than other studied alternative models, including a variety of dynamic and static models. The presented analyses also show that the solutions found by the proposed Immune-GA dominates the ones found by the Immune or NSGA-II solution techniques. The solution set found for the proposed model provides the planner with an insight into the problem and enables the planner to choose the best solution according to planning preferences. It should be noted that although the proposed model can be directly used in power market model in which the DNO is authorized for DG integration in addition to the network reinforcement. However, in power market models where the DG investment is done by independent investors instead of DNO, 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 what DG technology and where, to be more beneficial.

List of Symbols and Abbreviations

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 |
| τ_{dl} | Duration of demand level dl |
| E_{grid} | Emission factor of the grid |
| E_{dg} | Emission factor of a dg |
| IC_{dg} | Investment cost of a dg |
| C_{ℓ} | Investment cost of feeder ℓ |
| C_{tr} | Investment cost of transformer in substation |
| OC_{dg} | Operation 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 |
| $P_{t,dl}^{grid}$ | 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 |
| Y_{ij}^t | Admittance magnitude between bus i and j , in year t |
| θ_{ij}^t | Admittance angle between bus i and j , in year t |
| $S_{t,dl}^{grid}$ | 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 |
| AF_n | Affinity factor of n^{th} solution |
| $P_{i,base}^D$ | Base active power demand in bus i in first year |
| $Q_{i,base}^D$ | Base reactive power demand in bus i in first year |

List of Symbols and Abbreviations

| | |
|----------------------|--|
| $S_{i,base}^D$ | Base apparent power demand in bus i in first year |
| ρ | Base price of power purchased from the grid |
| \bar{S}_{tr} | Capacity limit of existing substation feeding the network |
| \bar{I}_ℓ | Capacity limit of existing feeder ℓ |
| Cap_ℓ | Capacity limit of potential feeder ℓ |
| Cap_{tr} | Capacity limit of potential transformer |
| $I_{\ell,t,dl}$ | Current magnitude of ℓ^{th} feeder in year t and demand level dl |
| $\mu^{fk}(X_n)$ | Degree of minimization satisfaction of k^{th} objective function by solution X_n |
| FN_n | Front number to which n^{th} solution belongs |
| GD_n | Global diversity of n^{th} solution |
| γ_t^ℓ | Investment decision in feeder ℓ , in the year t |
| d_ℓ | Length of feeder ℓ in km |
| LD_n^k | Local diversity of n^{th} solution in k^{th} objective function |
| V^{min} | Lower operation limit of voltage |
| MD_k | Maximum difference between the values of k^{th} objective function |
| \bar{P}_{lim}^{dg} | Maximum operating limit of a dg |
| $P_{i,t,dl}^{net}$ | 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 |
| ψ_t^{tr} | Number of installed transformers, 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 |
| $\cos\varphi^{dg}$ | Power factor of a dg |
| $Q_{i,t,dl}^{dg}$ | Reactive power injected by a dg in bus i , in year t and demand level dl |
| $Q_{i,t,dl}^D$ | Reactive power demand in bus i , in year t in demand level dl |
| GC | Total cost paid to grid |
| LC | Total cost of feeder reinforcement |
| SC | Total cost of substation reinforcement |
| DGIC | Total installation cost of DG units |
| DGOC | Total operation cost of DG units |
| V^{max} | Upper operation limit of voltage |
| $V_{i,t,dl}$ | Voltage magnitude in bus i , in year t and demand level dl |
| $\delta_{i,t,dl}$ | Voltage angle in bus i , in year t and demand level dl |

Apendix

Pareto Optimality

Assume $F(X)$ is the vector of objective functions, and $H(X)$ and $G(X)$ represent equality and inequality constraints, respectively. A multi-objective optimization problem can be formulated as follows:

$$\min \quad F(X) = [f_1(X), \dots, f_{N_O}(X)] \quad (21)$$

Subject to:

$$\{G(X) = \bar{0}, H(X) \leq \bar{0}\}$$

$$X = [x_1, \dots, x_m]$$

Suppose X_1 and X_2 belong to the solution space. X_1 dominates X_2 if:

$$\forall k \in \{1 \dots N_O\} f_k(X_1) \leq f_k(X_2) \quad (22)$$

$$\exists k' \in \{1 \dots N_O\} f_{k'}(X_1) < f_{k'}(X_2)$$

Any solution which is not dominated by any other is called to belong to a Pareto front which is referred to as the first Pareto front or optimal front or non-dominated front. For finding the second Pareto front, all solutions belonging to the first front are discarded and the conditions of (22) are investigated for the remaining ones. The process is repeated for the remaining fronts. Pareto fronts of a typical minimization problem with two objectives are shown in Fig.9. As can be seen in Fig.9, there is no solution in search space which can dominate the solutions lying on Pareto front 1. For all solutions which do not belong to Pareto front 1, there exists at least one solution which dominates it. In Fig.9, solution B dominates D, because:

$$\forall k \ OF_k(B) \leq OF_k(D)$$

$$\exists k' = 2 \ OF_{k'}(B) < OF_{k'}(D)$$

The solutions of Pareto front 1 can not even dominate themselves. For example solution A is better than B if just OF_1 is considered but solution B is better than A if OF_2 is considered.

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List of Figure Captions :

- Fig.1 : The flowchart of the first stage of the proposed method
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- Fig.3 : Pareto optimal front of planning problem found by proposed model and method
- Fig.4 : Percent of appearance of each bus in solutions of Pareto optimal front
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Table 1: Technical characteristics of conductors and base load data of the distribution network

| ℓ | From bus | To bus | d_ℓ (km) | R (Ω) | X (Ω) | \bar{I}_ℓ (A) | $S_{i,base}^D$ (To bus) MVA |
|--------|----------|--------|---------------|----------------|----------------|--------------------|-----------------------------|
| 1 | 1 | 2 | 8 | 1.390 | 2.255 | 210 | 5.6057 |
| 2 | 2 | 3 | 16 | 2.780 | 4.510 | 210 | 6.3981 |
| 3 | 1 | 4 | 12 | 2.085 | 3.383 | 210 | 5.6057 |
| 4 | 4 | 5 | 16 | 2.780 | 4.510 | 210 | 2.9349 |
| 5 | 1 | 6 | 10 | 1.738 | 2.819 | 210 | 3.3605 |
| 6 | 6 | 7 | 12 | 2.085 | 3.383 | 210 | 5.3342 |
| 7 | 1 | 8 | 13 | 2.259 | 3.664 | 210 | 4.4831 |
| 8 | 8 | 9 | 14 | 2.433 | 3.946 | 210 | 3.7714 |

Table 2: Data used in the study

| Parameter | Unit | Value |
|-------------------|------------------|-------|
| T | year | 10 |
| N_p | | 50 |
| \bar{S}_{tr} | MVA | 40 |
| E_{grid} | kg emissions/MWh | 910 |
| ρ | \$/MWh. | 70 |
| α | % | 3.5 |
| d | % | 12 |
| \bar{V} | Pu | 1.05 |
| \underline{V} | Pu | 0.95 |
| Maximum iteration | | 1000 |

Table 3: Characteristics of the DG units

| DG Technology | Size (MVA) | Emission (kg/MWh) | IC (k\$/MVA) | OC (\$/MWh) | $\cos\varphi^{dg}$ |
|------------------|---------------|----------------------|-----------------|----------------|--------------------|
| Micro Turbine | 0.5 | 502 | 1485 | 90 | 0.9 |
| Gas Turbine | 1 | 773 | 1030 | 85 | 0.9 |
| Fuel Cell | 2 | 340 | 3674 | 39 | 1 |

Table 4: Variation ranges of objective functions in Pareto optimal front

| | OF_1 (\$) | OF_2 (ton of emissions) |
|-------------|----------------------|---------------------------|
| f_k^{min} | 1.1386×10^8 | 1.3847×10^6 |
| f_k^{max} | 1.7772×10^8 | 2.3116×10^6 |

Table 5: Characteristics of solutions in different cases

| Cases | $Solution\#$ | μ^{f_1} | μ^{f_2} |
|--------------|--------------|-------------|-------------|
| I | 30 | 0.5678 | 0.5505 |
| Biased Cases | | | |
| II | 10 | 0.2204 | 0.9136 |
| III | 17 | 0.8889 | 0.1429 |

Table 6: Investment plans in different cases

| Cases | DG | | | Feeder | | | Substation | | |
|-------|----|------------------|---|-----------|-----------------|---|------------|---------------|----|
| | dg | $\xi_{t,i}^{dg}$ | t | Bus i | γ_t^ℓ | t | ℓ | ψ_t^{tr} | t |
| I | FC | 1 | 1 | 7,3,4,9,5 | 1 | 4 | 1 | 1 | 7 |
| | FC | 1 | 2 | 3 | | | | | |
| | MT | 1 | 4 | 8 | | | | | |
| | MT | 1 | 6 | 6 | | | | | |
| | MT | 1 | 8 | 7 | | | | | |
| II | FC | 1 | 2 | 9 | 1 | 1 | 1 | 1 | 2 |
| | FC | 1 | 4 | 7 | | | | 1 | 10 |
| III | MT | 1 | 1 | 7 | | | | | |
| | MT | 2 | 2 | 9 | | | | | |
| | MT | 1 | 3 | 5 | | | | | |
| | MT | 1 | 5 | 8 | | | | | |
| | FC | 3 | 1 | 3 | | | | | |
| | FC | 2 | 1 | 5 | | | | | |
| | FC | 1 | 1 | 6,7,8,9 | | | | | |
| | GT | 1 | 5 | 4 | | | | | |

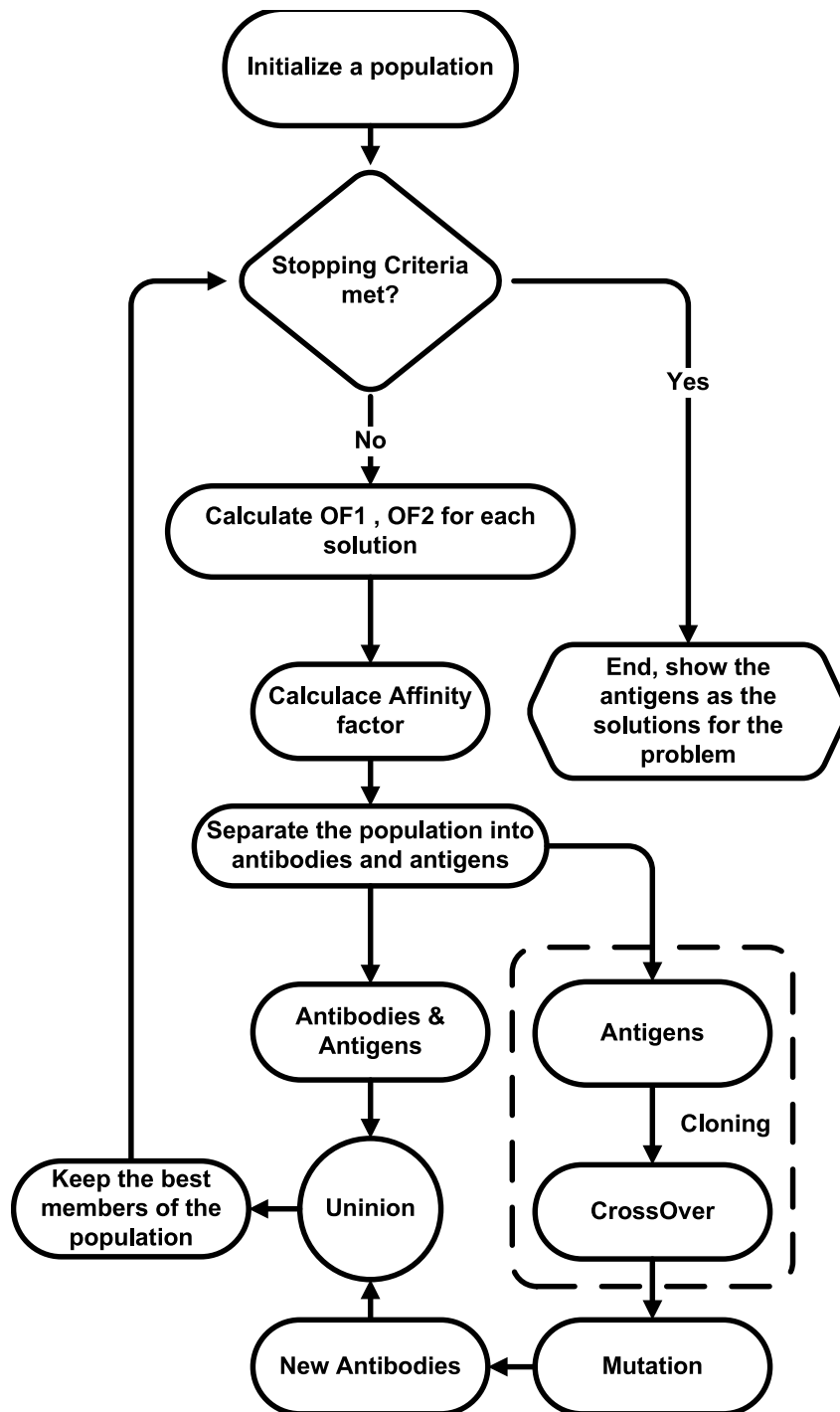


Figure 1: The flowchart of the first stage of the proposed method

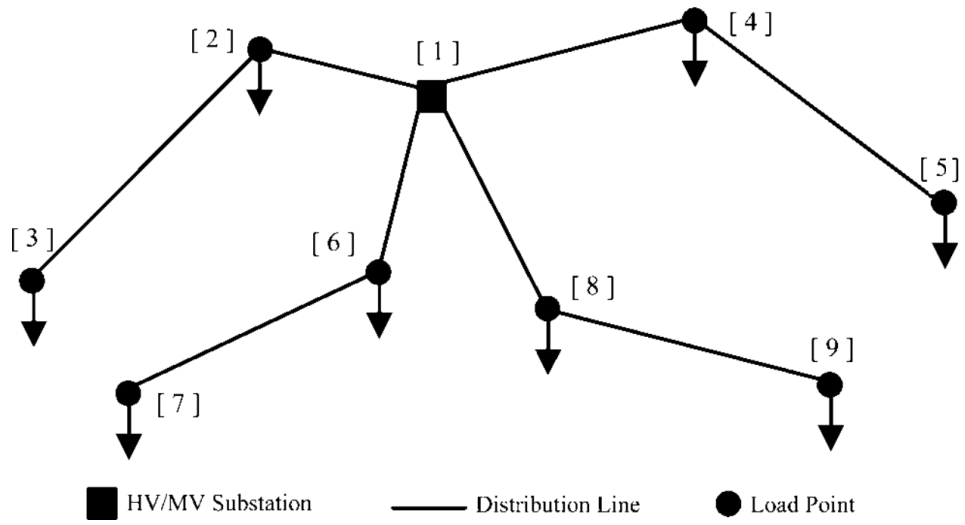


Figure 2: Single-line diagram of the test system

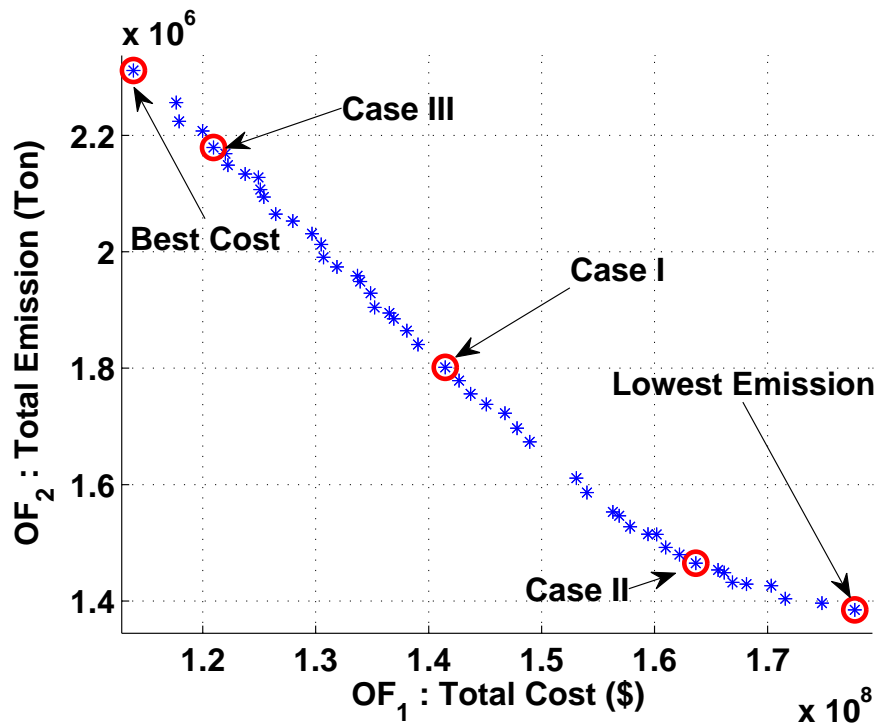


Figure 3: Pareto optimal front of planning problem found by proposed model and method

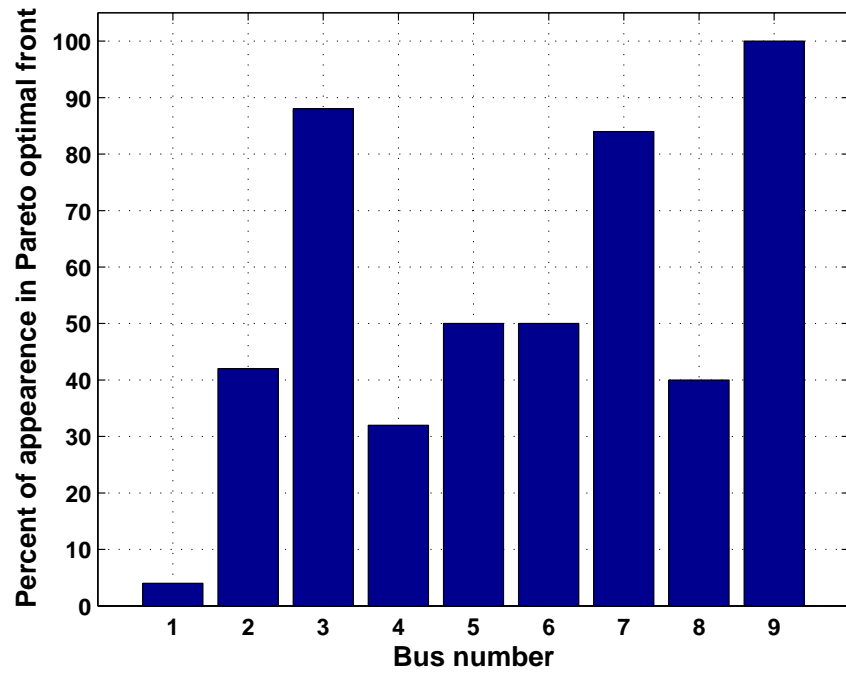


Figure 4: Percent of appearance of each bus in solutions of Pareto optimal front

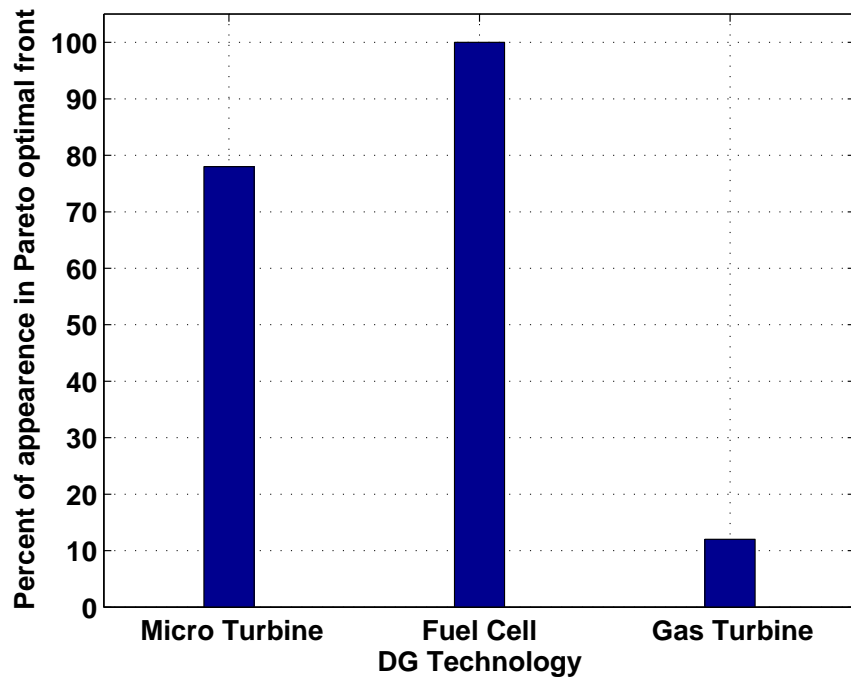


Figure 5: Percent of appearance of each DG technology in solutions of Pareto optimal front

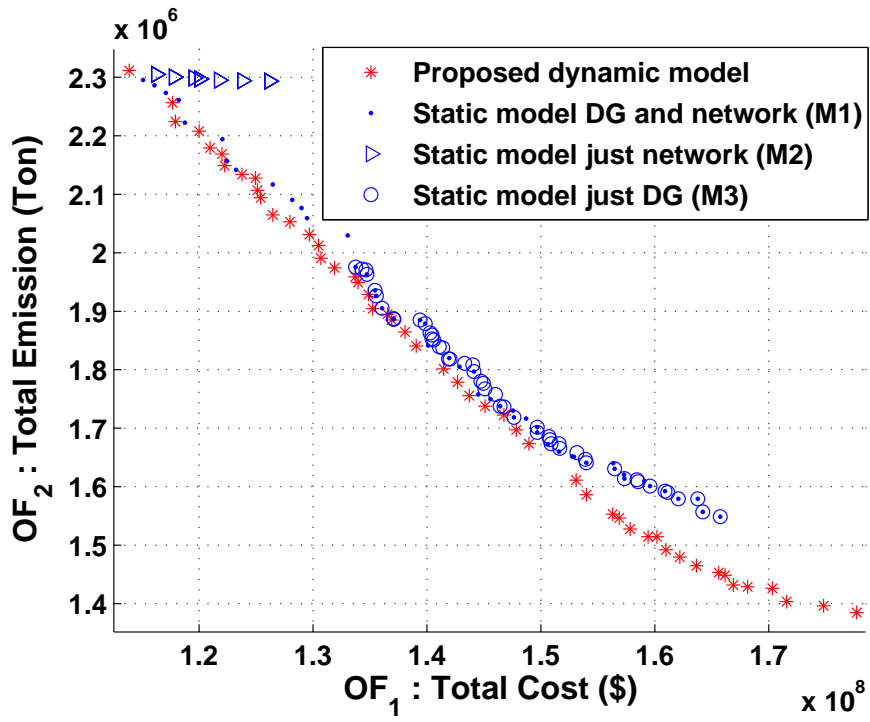


Figure 6: Comparison of Pareto optimal front found by proposed model to other static models

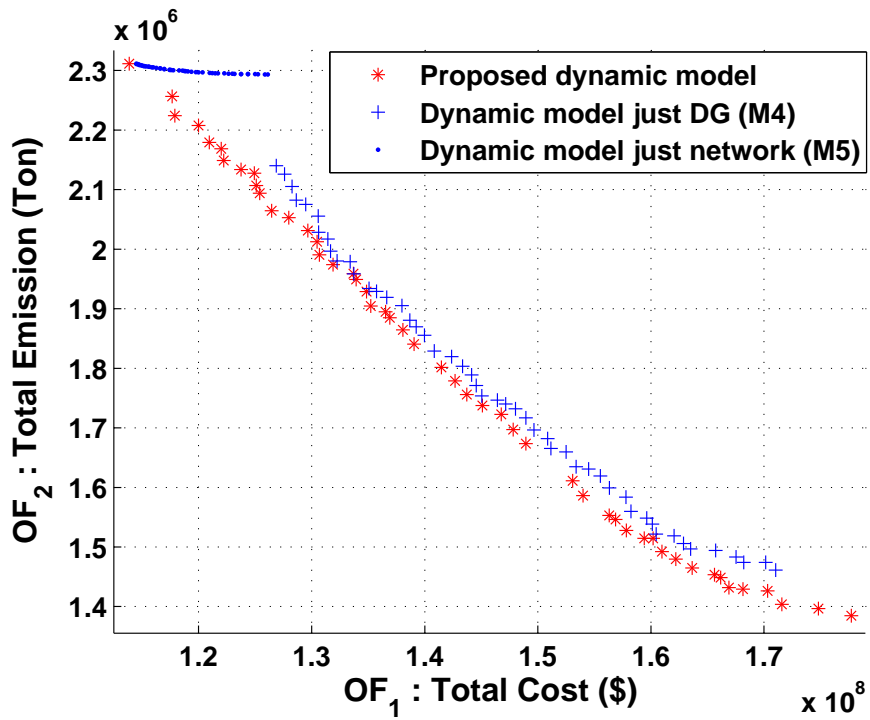


Figure 7: Comparison of Pareto optimal front found by proposed model to other dynamic models

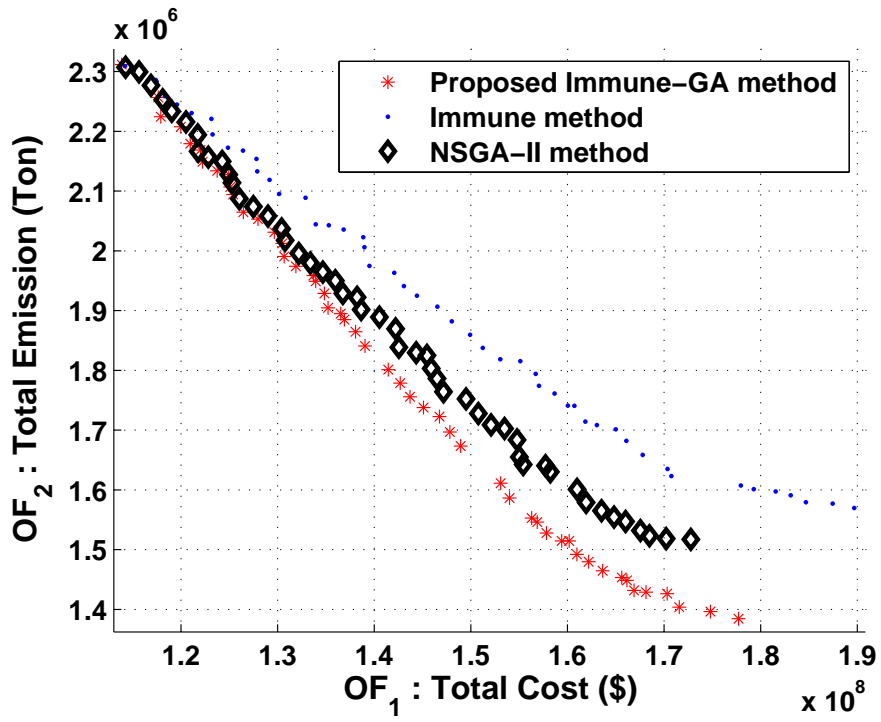


Figure 8: Comparison of Pareto optimal front found by proposed method to other heuristic search methods

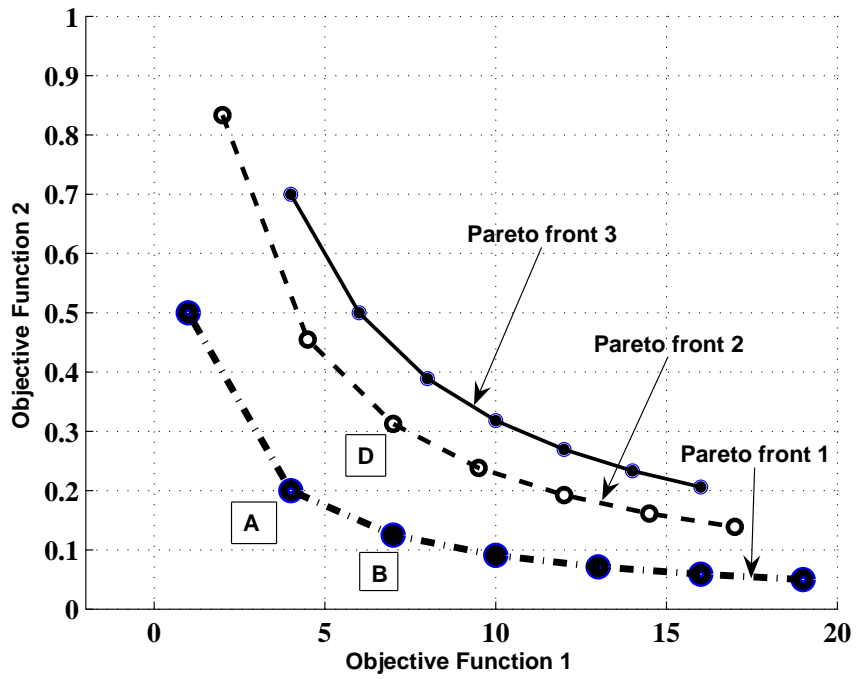


Figure 9: Classifying the population into different Pareto fronts