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Hybrid Immune-Genetic Algorithm Method for Benefit Maximization of DNOs and DG Owners in a Deregulated Environment

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Abstract

In deregulated power systems Distribution Network Operators (DNO) are responsible for maintaining the proper operation and efficiency of distribution networks. This is achieved traditionally through specific investments in network components and by using some optimization methods for reducing the active losses. The event of Distributed Generation (DG) has introduced new challenges to these distribution networks both at the planning and operation stages. The role of Distributed Generation (DG) units must be correctly assessed to optimize the overall operating and investment cost for the whole system. However the Distributed Generation Owners (DGOs) have different objective functions which might be contrary to the objectives of DNO. This paper presents a long-term dynamic multi-objective model for planning of distribution networks regarding the benefits of DNO and DGOs. The proposed model simultaneously optimizes two objectives, namely the benefits of DNO and DGO 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. The proposed model also considers the uncertainty of electric load, electricity price and wind turbine power generation using the point estimate method. The effect of benefit sharing is investigated for steering

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the decisions of DGOs. An efficient two-stage heuristic method is proposed to solve the formulated planning problem and tested on a real large scale distribution network.

Key words: Distributed generation, Immune algorithm, Dynamic planning, Multi-objective optimization, Point estimate method.

1. Introduction

1.1. Motivation and problem description

Distributed Generation (DG) is an electric power source connected directly to the distribution network with small size capacity. The DG units have been, in the last decade, in the spotlight of the power industry and scientific community and constitute a new paradigm for on-site electric power generation. There are three key factors driving this change namely, environmental concerns, technological innovation and new government policy [1]. The power injection of DG units into distribution network may change the power flow in distribution feeders so the size (number of DG modules), location, technology and timing of investment have decisive impacts on potential benefits of them. In an open access environment, the decisions related to DG investment/operation are taken by DG Owners/operators (DGOs) and maintaining the reliability and efficiency of the network is the duty of DNOs. The question is that if the DNO has some benefits in proper DG investment, how can he guide/promote the DGOs to act in favor of both DGO and DNO interests? In other words, should DNO pay the DGO a percent of what he gains because of DG power injection into the network and on what basis? If not, would it be still rational for DGO to invest or not beyond the incentives? Although many previous works have attacked the DG planning problem but few of them have focused on the interaction between the conflicting or convergent objectives of DGO and DNO. Thus, there is a clear need to enhance the current DG planning methodologies to include an appropriate treatment of various DG technologies, uncertainty handling and different objectives of DGO and DNOs. A win-win strategy is needed which not only promotes the

DG investment for DGOs but also does not impose additional costs to DNOs (compared to the case when no DG exists in the network). This need motivates the work proposed in this paper.

1.2. Literature review

Much has been done on proposing planning frameworks for DG integration in the distribution networks. To do this, different technical, economical and environmental issues have been taken into account such as voltage stability improvement [2], investment deferral in network capacity [3], active loss reduction [4], reliability improvement, network security [5], emission reduction [6], system restoration [7] and load modeling [8]. The reported models for DG planning can be categorized based on four main attributes as follows:

- Static/Dynamic investment (considering DG units and network reinforcement); The models in this category are even static or dynamic. In static models, investment decisions are implemented in the first year of the planning horizon [9, 4]. The dynamic models are those in which the year of investment over the planning period is also decided by the planner which may not necessarily be the first year of the planning horizon [3, 5, 10, 6].
- Multi/single Objective; In this category, the models are even single [9, 11, 12] or multi-objectives [4].
- Uncertainties of input parameters; The uncertainty modeling in DG planning problem has been treated in three different ways namely, probabilistic [13, 14, 15, 16], possibilistic (fuzzy arithmetic) [4] or mixed probabilistic-possibilistic [17].
- DG ownership; The ownership of DG units is another important issue which essentially affects the decision related to investment/operation of these units. The DG units are owned either by DNOs [18, 4] or by non-DNO entities [3, 19, 20].

Some of these methods are introduced and compared in Table 1. However, substantial work is still needed to provide a win-win strategy which has all four aforementioned attributes altogether to optimize the objective functions of DNO and DGO simultaneously and cooperatively.

1.3. Contributions

The contributions of this paper are four-fold:

- To multi-objectively consider the benefits of DNO and DG owners and provide a win-win strategy for both parties.
- To include the timing of investment for network and DG units in the problem formulation.
- To model the uncertainties of electricity price, electric loads and generation of wind turbines using a two point estimate method (2PEM).
- To propose a hybrid Immune-Genetic Algorithm (IGA) for solving the formulated framework.

1.4. Paper organization

This paper is set out as follows: section 2 presents problem formulation, section 3 sets out the implementation of proposed IGA, a case study is reported in section 4 and finally, section 5 summarizes the findings of this work.

2. Problem Formulation

The assumptions used in problem formulation, decision variables, constraints and the objective functions are explained in this section.

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.
- 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 [6]. Assuming a base load, $P_{i,base}^D + i \times Q_{i,base}^D$, a Demand Level Factor, DLF_{dl} , and a demand growth rate, α , the demand in bus i , in year t and in demand level dl is computed as follows:

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

Where, $P_{i,t,dl}^D, Q_{i,t,dl}^D$ are the actual active and reactive demand in bus i , year t and demand level dl , respectively.

- 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. Without loss of generality, it is assumed that the electricity price at each demand level can be determined as follows:

$$\lambda_{dl} = \rho \times PLF_{dl} \quad (2)$$

where the base price (i.e. ρ), and the Price Level Factors (i.e. PLF_{dl}), are assumed to be known.

2.2. Decision variables

The decision variables are the number of non-renewable DG units and wind turbines, to be installed in each bus in each year, i.e., $\xi_{i,t}^{dg/w}$; 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} .

2.3. Constraints

2.3.1. Power Flow Constraints

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

$$\begin{aligned}
 P_{i,t,dl}^{net} &= -P_{i,t,dl}^D + P_{i,t,dl}^{dg} + P_{i,t,dl}^w & (3) \\
 Q_{i,t,dl}^{net} &= -Q_{i,t,dl}^D + Q_{i,t,dl}^{dg} \\
 P_{i,t,dl}^{net} &= V_{i,t,dl} \sum_{j=1}^{N_b} Y_{ij}^t V_{j,t,dl} \cos(\delta_{i,t,dl} - \delta_{j,t,dl} - \theta_{ij}^t) \\
 Q_{i,t,dl}^{net} &= V_{i,t,dl} \sum_{j=1}^{N_b} Y_{ij}^t V_{j,t,dl} \sin(\delta_{i,t,dl} - \delta_{j,t,dl} - \theta_{ij}^t)
 \end{aligned}$$

Where, $P_{i,t,dl}^{net}, Q_{i,t,dl}^{net}$ are the net injected active and reactive power in bus i , year t and demand level dl , respectively. The $P_{i,t,dl}^{dg}, Q_{i,t,dl}^{dg}$ are the active and reactive power of DG unit in bus i , year t and demand level dl , respectively. The $P_{i,t,dl}^w$ is the active power of wind turbine in bus i , year t and demand level dl , respectively

2.3.2. Active losses

The active losses in year t and demand level dl , i.e. $P_{t,dl}^{loss}$, is computed as follows:

$$P_{t,dl}^{loss} = \sum_{i=1}^{N_b} P_{i,t,dl}^{net} \quad (4)$$

2.3.3. Operating limits of DG units

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

$$P_{i,t,dl}^{dg} \leq \sum_{\acute{t}=1}^t \xi_{i,\acute{t}}^{dg} \times \bar{P}_{lim}^{dg} \quad (5)$$

Where, $\xi_{i,t}^{dg}$ is the number of DG units installed in bus i in year t . \overline{P}_{lim}^{dg} is the operating limit of DG unit.

The power factor of DG unit is kept constant [10] in all demand levels as follows:

$$\cos\varphi^{dg} = \frac{P_{i,t,dl}^{dg}}{\sqrt{(P_{i,t,dl}^{dg})^2 + (Q_{i,t,dl}^{dg})^2}} = const. \quad (6)$$

2.3.4. Voltage profile

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

$$V_{min} \leq V_{j,t,dl} \leq V_{max} \quad (7)$$

2.3.5. Capacity limit of feeders and substation

The flow of current/energy passing through the feeders and the substation should be kept below the feeders/substation capacity limit as follows:

$$I_{\ell,t,dl} \leq \overline{I}_{\ell} + Cap_{\ell} \times \sum_{i=1}^t \gamma_i^{\ell} \quad (8)$$

$$I_{\ell,t,dl} = \frac{V_{i,t,dl} - V_{j,t,dl}}{Z_{\ell}^t}$$

i, j are the sending and receiving ends of feeder ℓ

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 . The $I_{\ell,t,dl}$ is the current magnitude of feeder ℓ in year t and demand level dl . \overline{I}_{ℓ} is the capacity of feeder ℓ at the beginning of the planning horizon.

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

$$S_{i,dl}^{grid} \leq \overline{S}_{tr} + Cap_{tr} \times \sum_{i=1}^t \psi_i^{tr} \quad (9)$$

Where, $Cap_{tr} \times \sum_{i=1}^t \psi_i^{tr}$ represents the added capacity of substation resulting from adding new transformers (or replacing them) until year t . $S_{t,dl}^{grid}$ is the apparent power passing through substation in year t and demand level dl . Cap_{tr} is the capacity of transformer to be added in substation. \bar{S}_{tr} is the capacity of substation at the beginning of the planning horizon.

2.3.6. Emission Limit

The total emission produced in each year should not exceed a certain limit, i.e. E_{lim} . The emission produced by the main grid in year t and demand level dl , is computed by is computed by multiplying the purchased power from grid in each demand level, i.e. $P_{t,dl}^{grid}$, by the emission factor of the grid, i.e. E_{grid} . The total emission generated by the DG units is computed by multiplying the power generated by each DG by its emission factor, i.e. E_{dg} . This value is summed 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 as follows:

$$TE_t = \sum_{dl=1}^{N_{dl}} \tau_{dl} [E_{grid} P_{t,dl}^{grid} + \sum_{i=1}^{N_b} E_{dg} P_{i,t,dl}^{dg}] \quad (10)$$

$$TE_t \leq E_{lim}$$

Where, TE_t is the total emission in year t , E_{grid} , E_{dg} are the emission factor of main grid and DG unit, respectively.

2.4. Uncertainty handling

In this paper, the uncertainty of three parameters are taken into account namely, wind power generation, electric load and electricity price. In this section, the uncertainty modeling of uncertain parameters of this study is described first and then the method used for handling them is given.

2.4.1. Wind Turbine generation uncertainty modeling

The generation schedule of a wind turbine highly depends on the wind speed in the site. There are various methods to model wind behavior like time-series model [21], relative frequency histogram [15] or considering all possible operating conditions of the wind turbines and accommodating the model in a deterministic planning problem [13]. In this paper, the variation of wind speed, i.e. v , is modeled using a Rayleigh Probability Density Function (PDF) [13] and its characteristic function which relates the wind speed and the output of a wind turbine.

$$f_w(v) = \left(\frac{2v}{c^2}\right) \exp\left[-\left(\frac{v}{c}\right)^2\right] \quad (11)$$

where c is the scale factor of the Rayleigh PDF of wind speed in the zone under study. The generated power of the wind turbine in each demand level is approximated using its characteristics as follows:

$$P_{i,t,d}^w(v) = \sum_{t=1}^t \xi_{i,t}^w \times \begin{cases} 0 & \text{if } v \leq v_{in}^c \text{ or } v \geq v_{out}^c \\ \frac{v-v_{in}^c}{v_{rated}^c-v_{in}^c} P_{i,r}^w & \text{if } v_{in}^c \leq v \leq v_{rated} \\ P_{i,r}^w & \text{else} \end{cases} \quad (12)$$

Where, $P_{i,r}^w$ is the rated power of wind turbine installed in bus i , P_i^w is the generated power of wind turbine in bus i , v_{out}^c is the cut out speed, v_{in}^c is the cut in speed and v_{rated} is the rated speed of the wind turbine. The speed-power curve of a typical wind turbine is depicted in Fig. 1 [17]. It is assumed that the wind turbines are operated with unity power factor [22].

2.4.2. Electric demand and market price uncertainty modeling

The variation of electric demand and market price is modeled using (1) and (2), respectively. However, the values of DLF_{dl} and PLF_{dl} are uncertain values. In this paper, it is assumed that an appropriate forecasting tool is available to forecast the price and

demand uncertainty (like [23]) to estimate their associated probability density functions. The uncertainty of these values are assumed to follow a Lognormal PDF as used in [24]. This means for each demand level, (i.e. dl), a mean and standard deviation is specified for PDF_{dl} and DLF_{dl} .

$$f_{\lambda}(PLF_{dl}) = \frac{1}{\sqrt{2\pi(\sigma_{dl}^{\lambda})^2}} \exp\left[-\frac{(PLF_{dl} - \mu_{dl}^{\lambda})^2}{2(\sigma_{dl}^{\lambda})^2}\right] \quad (13)$$

$$f_D(DLF_{dl}) = \frac{1}{\sqrt{2\pi(\sigma_{dl}^D)^2}} \exp\left[-\frac{(DLF_{dl} - \mu_{dl}^D)^2}{2(\sigma_{dl}^D)^2}\right]$$

The method used for handling these uncertainties is the two point estimate method (2PEM)[25] which is described as follows:

2.4.3. Two point estimate method

Suppose we have a function, i.e. $Y = h(x_1, x_2, \dots, x_{N_{uv}})$, knowing the PDF of N_{uv} uncertain variables x_i , the question is how can the PDF of output value, i.e. Y can be estimated. The two point estimate method (2PEM) answers this question in the following steps:

Step.1 Determine the number of uncertain variables, N_{uv} .

Step.2 Set $k = 1$.

Step.3 Determine the locations of concentrations $\epsilon_{k,i}$ and the probabilities of concentrations $P_{k,i}$, as follows:

$$\epsilon_{k,i} = \frac{\lambda_{k,3}}{2} + (-1)^{i+1} \sqrt{N_{uv} + \frac{\lambda_{k,3}^2}{2}} \quad (14)$$

$$P_{k,i} = (-1)^i \frac{\epsilon_{k,3-i}}{2N_{uv} \sqrt{N_{uv} + \frac{\lambda_{k,3}^2}{2}}} \quad (15)$$

$$i = 1, 2$$

where $\lambda_{k,3}$ is the skewness of variable x_k .

Step.4 Determine the concentration points $x_{k,i}$, as follows:

$$x_{k,i} = \mu_{x_k} + \epsilon_{k,i} \times \sigma_{x_i} \quad (16)$$

$$i = 1, 2$$

Where, μ_{x_k} and σ_{x_k} are the mean and the standard deviation of x_k , respectively.

Step.5 Run the deterministic power flow for both $x_{k,i}$, as follows:

$$X = [x_1, x_2, \dots, x_{k,i}, \dots, x_{N_{uv}}] \quad (17)$$

$$i = 1, 2$$

Compute $h(X)$

Step.6 Set $k = k + 1$, if $k \leq N_{uv}$ go to Step. 3; Else continue.

Step.7 Calculate $E(Y)$ and $E(Y^2)$ using:

$$E(Y) \cong \sum_{k=1}^{N_{uv}} \sum_{i=1}^2 P_{k,i} h(x_1, x_2, \dots, x_{k,i}, \dots, x_{N_{uv}}) \quad (18)$$

$$E(Y^2) \cong \sum_{k=1}^{N_{uv}} \sum_{i=1}^2 P_{k,i} h^2(x_1, x_2, \dots, x_{k,i}, \dots, x_{N_{uv}})$$

Step.8 Calculate the mean and the standard deviation as follows:

$$\mu_Y = E(Y) \quad (19)$$

$$\sigma_Y = \sqrt{E(Y^2) - E^2(Y)}$$

Step.9 End.

2.5. Objective functions

The proposed model maximizes two objective functions, namely, total benefits of DNO and DGO benefits, as follows:

$$\begin{aligned} & \max \{OF_1, OF_2\} \\ & \text{subject to: (1) } \rightarrow \text{(19)} \end{aligned}$$

The objective functions are formulated next.

2.5.1. DNO: Costs and Benefits

The first objective function, i.e., OF_1 , to be maximized is the total saving accrued to DNO due to the presence of DG units in distribution network. For calculating these benefits, the cost and benefits of the DNO are introduced and computed. The cost payable by DNO includes the cost of electricity purchased from the grid for compensating the active losses, i.e. LC , reinforcement costs of feeders, i.e. FC and substation, i.e. SC and finally the emission costs due to energy purchased from main grid and DG units, i.e. TEC . Each term is explained as follows: The cost of purchasing electricity from the grid can be determined as:

$$LC = \sum_{t=1}^T \sum_{dl=1}^{N_{dl}} (\lambda_{dl} \times P_{t,dl}^{loss}) \times \tau_{dl} \times \frac{1}{(1+d)^t} \quad (20)$$

Where, LC is the loss cost, ρ is the base electricity price and $P_{t,dl}^{loss}$ is the active power loss in year t and demand level dl . d is the discount rate.

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. FC , and substation reinforcement cost, i.e. SC , are computed as follows:

$$FC = \sum_{t=1}^T \sum_{\ell=1}^{N_{\ell}} C_{\ell} \times L_{\ell} \times \gamma_{\ell}^t \times \frac{1}{(1+d)^t} \quad (21)$$

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

Where, FC and SC are the total feeder and substation reinforcement cost, respectively. C_ℓ, C_{tr} are the cost of each feeder and transformer, respectively.

The last term of DNO cost is total emission cost, i.e., TEC , which is comprised of the emission produced by the electricity purchased from main grid and the DG units over planning horizon from $t = 1$ to $t = T$. TEC , is formulated as follows:

$$TEC = \sum_{t=1}^T TE_t \times E_c \times \frac{1}{(1+d)^t} \quad (22)$$

where E_c is the cost of each Ton of generated CO_2 . The total cost that DNO should pay, DNO_c is computed as follows:

$$DNO_c = LC + FC + SC + TEC \quad (23)$$

To compute the benefits of DNO due to presence of DG units, the value of DNO_c is computed two times, one when no DG unit is present, i.e. DNO_c^{nodg} and one when DG units are participated in the planning problem, i.e. DNO_c^{dg} . The differences of these two values show the benefits of DNO, i.e. DNO_b , thanks to DG units, as follows:

$$DNO_b = DNO_c^{nodg} - DNO_c^{dg} \quad (24)$$

2.5.2. DGO: Costs and Benefits

The cost that DGO should pay is the sum of operating and investment cost of DG units.

The installation cost of the DG units is computed as:

$$IC = \sum_{t=1}^T \sum_{i=1}^{N_b} \sum_{dg/w} \xi_{i,t}^{dg/w} \times IC_{dg/w} \times \frac{1}{(1+d)^t} \quad (25)$$

where IC_{dg} is the investment cost of DG units.

The operating cost of the DG units is computed as:

$$OC = \sum_{t=1}^T \sum_{i=1}^{N_b} \sum_{dl=1}^{N_{dl}} \sum_{dg/w} \tau_{dl} \times OC_{dg/w} \times P_{i,t,dl}^{dg/w} \times \frac{1}{(1+d)^t} \quad (26)$$

where OC_{dg} is the operating cost of DG units.

The total cost that DGO should pay is the sum of operating and investment costs of DG units, as follows:

$$DGO_c = IC + OC \quad (27)$$

The benefits of DGO are coming from selling energy to the distribution network consumers. The price of energy that DG units can sell their energy depends on the way they play in the market. They can have bilateral contracts with consumers at fixed price or they can sell their output power at market price. In this paper, it is assumed that DGO sell their produced power at market price, as follows:

$$DGO_b = \sum_{t=1}^T \sum_{dl=1}^{N_{dl}} \tau_{dl} \times \sum_{i=1}^{N_b} \lambda_{dl} \times P_{i,t,dl}^{dg} \quad (28)$$

2.5.3. Objective functions

As it is observed till now, the DNO and DGO follow different goals of their investment. The question is how to guide the decisions of DGO toward the benefits of DNO while he can just be encouraged to that. In this paper, the effect of DG units in investment deferral of distribution network is precisely modeled and computed by comparing two cases when

DG is present or not, as follows:

$$OF_1 = (1 - \beta) \times DNO_b \quad (29)$$

$$OF_2 = (DGO_b - DGO_c) + \beta \times DNO_b$$

3. Proposed Immune-Genetic Algorithm

The formulated problem of 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. The Pareto front concept answers this need (see appendix for more information). In the present work, a hybrid Immune-Genetic method is proposed to find the Pareto optimal front. The following sections describe the implementation of the proposed algorithm as follows:

In the context of multi-objective optimization, it is needed that the population be directed towards the Pareto optimal front considering two important aspects: getting closer to Pareto optimal front and maintaining the diversity among the solutions [26]. To do so, a pseudo fitness value is assigned to each solution, referred to as $Fitness_n$, as follows [10]:

$$Fitness_n = \frac{w_1}{FN_n} + w_2 \times GD_n \quad (30)$$

where FN_n is the front number to which the n^{th} solution belongs.

The first term in (30) helps the population to get closer to the Pareto optimal front while the second term maintains the diversity among the solutions. In IGA, two diversity factors are defined for each objective function namely, global diversity i.e. GD_n and local diversity i.e. LD_n . For each objective function k , the solutions are sorted and MD_k is defined as the difference between the maximum and minimum values regarding objective function k as follows:

$$MD_k = \max_{n=1}^{N_p}(f_k(X_n)) - \min_{n=1}^{N_p}(f_k(X_n)) \quad (31)$$

$$k = 1 \cdots N_o$$

where N_o, N_p are the number of objectives and population, respectively. The local diversity of each of the other solutions is defined as its average distance to its neighbors, as follows:

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

$$n = 2 : N_p - 1$$

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

$$LD_1^k = LD_{N_p}^k = \max_{n=2:N_p-1} (LD_n^k) \quad (32)$$

The global diversity factor of each solution is thus computed as the average of its local diversities [6], as follows:

$$GD_n = \sum_{k=1}^{N_o} \frac{LD_n^k}{N_o} \quad (33)$$

In initial iterations, a few number of solutions exist in the first Pareto front, so it is important to get closer to the Pareto optimal front instead of maintaining the diversity in the beginning iterations. It is necessary to enable the algorithm in distinguishing between the solutions in different Pareto fronts, w_1 and w_2 in (30) are adaptively selected which guarantees that the solution belonging to a lower Pareto front has a bigger fitness than a solution belonging to an upper Pareto front (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. In this paper, the following formulation is proposed to update the weight values, i.e. $w_{1,2}$):

$$w_1 = 100 \times \left(\max_{n=1}^{N_p} (FN_n) - \min_{n=1}^{N_p} (FN_n) \right) \quad (34)$$

$$w_2 = 50$$

3.1. The Proposed Two-stage Solution Algorithm for Solving the Planning Problem

The proposed solution algorithm 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:

3.1.1. Stage I (finding the Pareto optimal front)

The algorithm proposed in section 3, is used to find the Pareto optimal front in first stage. To do so, each solution is a vector containing the installation decision of DG units, the bus on which a DG unit is to be installed, the year of installation and their generated power and for all available DG technologies. The steps of the proposed Immune Genetic Algorithm (IGA) are as follows:

- Step 1. Generate an initial set of antibodies with a size of N_p
- Step 2. Set Iteration=1
- Step 3. Calculate the objective function for each antibody using (30) and assign it as its affinity factor
- Step 4. If the maximum number of iteration is reached, then end and go to Stage II; else continue
- Step 5. Keep the best N_p antibodies (for controlling the population size)
- Step 6. Set the cloning counter, i.e. m , equal to 1
- Step 7. Select two antibodies (p and q) probabilistically (roulette wheel [27]) as the parents from the best antibodies, using their affinity values
- Step 8. Calculate the number of cloning replica, i.e. k_m , and mutation probabilities based on the average values of parent affinities. The value of k_m is determined as follows:

$$k_m = \text{round}(\Gamma \times \frac{AF_p + AF_q}{2\max(AF_n)} \times N_p) \quad (35)$$

$$p_m = 0.1 \times \left(1 - \frac{AF_p + AF_q}{2\max(AF_n)}\right)$$

Where, Γ is a controlling factor and *round* is the function which gives the nearest integer number. p_m is the mutation probability.

Step 9. Clone the selected parents selected in Step.7, for k_m times, by applying the crossover and mutation operators and produce new antibodies

Step 10. Store the new generated antibodies

Step 11. If the cloning counter is below the population size, then increase cloning counter and go to Step.7 ; else, construct the new antibody set using the union of newly generated antibodies and the preserved antibodies, increase the iteration counter and go to Step.3

3.1.2. Stage II (Selecting ‘the best’ solution)

The ultimate goal of the planner is choosing the “best” solution from the Pareto optimal front. A fuzzy satisfying method [28] is used in this paper to find the ‘the best’ solution [29]. 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 and 1, shows the ability of solution X_n in minimizing the k^{th} objective function, i.e. f_k . A linear membership function [30] is used for all objective functions, as follows:

$$\mu^{f_k(X_n)} = \begin{cases} 0 & f_k(X_n) > f_k^{max} \\ \frac{f_k(X_n) - f_k^{min}}{f_k^{max} - f_k^{min}} & f_k^{min} \leq f_k(X_n) \leq f_k^{max} \\ 1 & f_k(X_n) < f_k^{min} \end{cases} \quad (36)$$

A conservative decision maker tries to maximize the minimum satisfaction among all objectives [28]. The final solution can then be found as:

$$\max_{n=1}^{N_p} \left(\min_{k=1}^{N_o} (\mu^{f_k(X_n)}) \right) \quad (37)$$

The flowchart of the both stages of the described algorithm is depicted in Fig.2.

4. Application Study

The proposed methodology is applied to an actual distribution network which is shown in Fig.3. This system has 574 nodes, 573 sections and 180 load points. The average load and power factor at each load point are 55.5 kW and 0.9285, respectively [31]. This network is fed through a 20kV substation with, $\bar{S}_{tr,s}^{t=0} = 20$ MVA. The options for reinforcing the network are as follows: transformers with a capacity of $Cap_{tr}=10$ MVA and a cost of $C_{tr}=0.2$ Million \$ for each; replacing the feeders at a cost of $C_{\ell}=0.15$ Million \$/km [11]. In this paper, the non-renewable and renewable DG technologies are taken into account. The characteristics of Gas turbine, Diesel and CHP are given in Table 3 and wind turbine power curve and it's rating is described in Table 4. Four demand levels, i.e., minimum, medium, base and high are considered in this paper. The predicted values of demand and price level factors and their duration are given in Table 2. The standard deviations of demand level factors, i.e. σ_{dl}^D , and price level factors, i.e. σ_{dl}^{λ} are assumed to be 2% of their corresponding mean values. The proposed model enables the planner to consider different wind speed parameter during different demand levels but here, for simplicity it is assumed that the changes of wind pattern during the different demand levels can be neglected; the stopping criterion for the search algorithm is reaching to a maximum number of iterations. Other simulation assumptions and characteristics of the DG units [32, 33] are presented in Table 5. The total cost of DNO for investing in distribution network is computed to be 1.15542×10^7 \$ when no DG investment is done. The formulated problem was implemented in MATLAB [34] and solved using the proposed two-stage algorithm.

In order to clarify the purpose of this paper two scenarios are considered namely no benefit sharing and benefit sharing; additionally, the proposed heuristic method is compared to other heuristic methods too, as follows:

4.1. Scenario I: No benefit sharing $\beta = 0$

First of all, no benefit sharing scenario is analyzed. In this scenario, it is assumed that all benefits of DG existence in the network are received by DNO. The formulated problem in Section 2 was solved assuming $\beta = 0\%$. The Pareto optimal front has 20 non-inferior solutions which are depicted in Fig.4. The Pareto optimal front shown in Fig.4 demonstrates that if there is no benefit sharing then the DG investment in 13 solutions can not be beneficial to DGOs. Analysing the Fig.4, shows that only 7 solutions have positive net profit for DGO. The values of objective functions of Pareto optimal solutions are tabulated in Table 6. The planning scheme for solution #1 is described in Table 7. In this case, both DGO and DNO have positive benefit values. Three DG technologies are used namely, Wind turbine, Gas turbine and CHP. The installation bus and also the timing of investment are given in Table 7. In this solution, the network reinforcement is done by feeder reinforcement and no investment is needed in substation.

4.2. Scenario II: Benefit sharing with non-zero β

In this scenario, the share of DGO of DNO's benefit, i.e. β , is determined by the optimization procedure. This means that the share of DGO is not assumed to be zero. The obtained Pareto optimal front contains 20 non-inferior solutions as it is given in Fig.5. All of the solutions have non-negative values for both objective functions. This means that all of the solutions propose positive profit for both DNO and DGO. The difference between different solutions refers to the amount of benefit that each of them may be willing to make. The share of DNO of DG benefits, β varies from 29% to 98.5%. The simulation results of the proposed algorithm are given in Table 8. In Table 8, the values of OF_1, OF_2 and the satisfaction of each solution in maximizing each objective function $\mu^{OF_k(X_n)}$ are given for each value of β . Now the non-inferior solutions are obtained by the IGA method. It just remains to select the final solution. Referring to (37), the solution which has the maximum of minimum satisfaction (for both objective functions) is solution #11. The planning scheme for solution #11 is described in Table 9. In this case, both

DGO and DNO have positive benefit values. Four DG technologies are used namely, Wind turbine, Gas turbine, CHP and Diesel generator. The installation bus and also the timing of investment are also provided in Table 9. In this solution, the network reinforcement is done by feeder and substation reinforcement.

4.3. Comparing with other methods

The proposed algorithm is compared with four other methods namely, Particle Swarm Optimization combined with Simulated Annealing method (PSO-SA) [35], Non-dominated sorting Genetic Algorithm (NSGA-II) [29], Immune Algorithm [10] and Tabu Search (TS) [36]. The Pareto optimal front found by each method is depicted in Fig.6. In table 10, the number of Pareto optimal solutions found by each method, the maximum and minimum values of OF_1 , OF_2 and the computing time of each algorithm are compared. The comparison shows that the solutions found by the proposed IGA can not be dominated by the solutions found by other methods. This means there is no solution in the Pareto optimal fronts found by other methods that can propose higher values in both OF_1 , OF_2 compared to those found by IGA. They may even provide more non-inferior solutions but since they can not dominate the solutions of IGA, it does not give a priority to them. Another aspect is the computational time; it is always appealing to reduce the computational burden of the algorithms but there is always a trade off between the performance and computational burden. The computing time for the proposed IGA is higher when compared with some algorithms like (PSO-SA, IA,TS). This is mainly because of high number of power flow computation in this method. The computation time can be effectively reduced using fast radial power flow solution techniques like those proposed in [37, 38]. It should be noted that the proposed planning method is not going to be used on-line, so the computational burden would not cause serious problem.

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 maximization of benefits of DNO and DGO 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 real distribution network and its flexibility and effectiveness is demonstrated through different case studies. It is not imposing an obligation for DGOs and DNOs on what to do. Instead, it is a win-win proposal in nature for both entities and can provide useful technical, economical and environmental signals for regulators. It can be used for regulating the incentives to encourage the market actors to invest in appropriate DG technology and where to be more beneficial. The proposed methodology can also consider the uncertainties of input parameters and help the planners to make more robust decisions. The Pareto optimal front found from solving the proposed DG-planning model is more efficient than other studied methods. The presented analysis also shows that the solutions found by the proposed Immune-GA present higher performances when compared to the ones found by the other heuristic techniques.

List of Symbols and Abbreviations

Indices

i, j Bus

dl Demand level

ℓ Feeder

k, k' Objective function

n Solution

t, \hat{t} Year

Constants

Γ Controlling factor for determining the number of cloning replica

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

E_c Emission cost

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

T Planning horizon

α Rate of demand growth

c Scale factor of the Rayleigh PDF of wind speed

Variables

$P_{i,t,dl}^D$ Active power demand in bus i , in year t in demand level dl

$P_{t,dl}^{loss}$ Active power demand 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 non-renewable dg in bus i , in year t and demand level dl
- $P_{i,t,dl}^w$ Active power injected by a wind turbine 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
- $S_{i,base}^D$ 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
- v_{in}^c Cut-in wind speed
- v_{out}^c Cut-out wind speed
- $\mu^{f_k(X_n)}$ Degree of minimization satisfaction of k^{th} objective function by solution X_n
- DLF_{dl} Demand level factor in demand level dl

- λ_{dl} Electricity price in demand level dl
- 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
- $\xi_{i,t}^{dg}$ Investment decision for non-renewable DG technology dg in bus i , in the year t
- $\varsigma_{i,t}^w$ Investment decision for wind turbine in bus i , in the year t
- ψ_t^{tr} Investment decision in transformer, in the year t
- Z_ℓ^t Impedance of feeder ℓ , in the year t
- L_ℓ Length of feeder ℓ in km
- LD_n^k Local diversity of n^{th} solution in k^{th} objective function
- μ_{dl}^λ Mean value of PLF_{dl} in demand level dl
- μ_{dl}^D Mean value of DLF_{dl} in demand level dl
- V_{min} Minimum operating voltage limit
- V_{max} Mimum operating voltage limit
- MD_k Maximum difference between the values of k^{th} objective function
- \bar{P}_{lim}^{dg} Maximum operating limit of a dg
- p_m Mutation probability
- $P_{i,t,dl}^{net}$ 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
- 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
- N_{uv} Number of uncertain variables
- $\cos\varphi^{dg}$ Power factor of a dg
- PLF_{dl} Price level factor in demand level dl
- $f_\lambda(\cdot)$ Probability density function of price level factor in demand level dl
- $f_D(\cdot)$ Probability density function of demand level factor in demand level dl
- $f_w(\cdot)$ Probability density function of wind speed
- $P_{i,r}^w$ Rated power power of wind turbine installed in bus i
- $Q_{i,t,dl}^{dg}$ 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
- σ_{dl}^λ Standard deviation of price level factor in demand level dl
- σ_{dl}^D Standard deviation of demand level factor in demand level dl
- $\lambda_{k,3}$ Skewness of uncertain variable x_k
- 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 Wind speed

Appendix: 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 maximization problem can be formulated as follows:

$$\max \quad F(X) = [f_1(X), \dots, f_{N_o}(X)] \quad (38)$$

Subject to:

$$\{G(X) = \bar{0}, H(X) \leq \bar{0}\} \quad (39)$$

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

$$\begin{aligned} \forall k \in \{1 \dots N_o\} \quad f_k(X_1) &\geq f_k(X_2) \\ \exists k' \in \{1 \dots N_o\} \quad f_{k'}(X_1) &> f_{k'}(X_2) \end{aligned} \quad (40)$$

Any solution which is not dominated by any other solution, belongs to the Pareto front.

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References

- [1] ENA, Distributed Generation Connection Guide, Ver. 3, Technical Report, Energy Networks Associations, 2010.

- [2] H. Hedayati, S. Nabaviniaki, A. Akbarimajd, A method for placement of dg units in distribution networks, *IEEE Transactions on Power Delivery* 23 (2008) 1620–1628.
- [3] G. Harrison, A. Piccolo, P. Siano, A. Wallace, Exploring the tradeoffs between incentives for distributed generation developers and dnos, *IEEE Transactions on Power Systems* 22 (2007) 821–828.
- [4] M.-R. Haghifam, H. Falaghi, O. Malik, Risk-based distributed generation placement, *Generation, Transmission and Distribution, IET* 2 (2008) 252–260.
- [5] D. T.-C. Wang, L. F. Ochoa, G. P. Harrison, Dg impact on investment deferral: Network planning and security of supply, *IEEE Transactions on Power Systems*, 25 (2010) 1134 –1141.
- [6] A. Soroudi, M. Ehsan, H. Zareipour, A practical eco-environmental distribution network planning model including fuel cells and non-renewable distributed energy resources, *Renewable Energy* 36 (2011) 179 – 188.
- [7] T. T. H. Pham, Y. Besanger, N. Hadjsaid, New challenges in power system restoration with large scale of dispersed generation insertion, *IEEE Transactions on Power Systems*, 24 (2009) 398 –406.
- [8] D. Singh, K. S. Verma, Multiobjective optimization for dg planning with load models, *IEEE Transactions on Power Systems* 24 (2009) 427–436.
- [9] W. El-Khattam, K. Bhattacharya, Y. Hegazy, M. Salama, Optimal investment planning for distributed generation in a competitive electricity market, *IEEE Transactions on Power Systems* 19 (2004) 1674–1684.
- [10] A. Soroudi, M. Ehsan, A distribution network expansion planning model considering distributed generation options and techno-economical issues, *Energy* 35 (2010) 3364 – 3374.

- [11] W. El-Khattam, Y. Hegazy, M. Salama, An integrated distributed generation optimization model for distribution system planning, *IEEE Transactions on Power Systems* 20 (2005) 1158–1165.
- [12] R. Jabr, B. Pal, Ordinal optimisation approach for locating and sizing of distributed generation, *Generation, Transmission & Distribution, IET* 3 (2009) 713–723.
- [13] Y. Atwa, E. El-Saadany, Probabilistic approach for optimal allocation of wind-based distributed generation in distribution systems, *Renewable Power Generation, IET* 5 (2011) 79 –88.
- [14] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, R. Seethapathy, Optimal renewable resources mix for distribution system energy loss minimization, *IEEE Transactions on Power Systems*, 25 (2010) 360 –370.
- [15] R. Jabr, B. Pal, Intermittent wind generation in optimal power flow dispatching, *Generation, Transmission Distribution, IET* 3 (2009) 66 –74.
- [16] W. El-Khattam, Y. Hegazy, M. Salama, Investigating distributed generation systems performance using monte carlo simulation, *IEEE Transactions on Power Systems*, 21 (2006) 524 – 532.
- [17] A. Soroudi, M. Ehsan, A possibilistic-probabilistic tool for evaluating the impact of stochastic renewable and controllable power generation on energy losses in distribution networks—a case study, *Renewable and Sustainable Energy Reviews* 15 (2011) 794 – 800.
- [18] A. Zangeneh, S. Jadid, A. Rahimi-Kian, Normal boundary intersection and benefit-cost ratio for distributed generation planning, *European Transactions on Electrical Power* (2008) 1430–1440.

- [19] S. Wong, K. Bhattacharya, J. Fuller, Electric power distribution system design and planning in a deregulated environment, *Generation, Transmission Distribution, IET* 3 (2009) 1061 –1078.
- [20] H. Gil, G. Joos, Models for quantifying the economic benefits of distributed generation, *IEEE Transactions on Power Systems*, 23 (2008) 327 –335.
- [21] A. Kusiak, Z. Zhang, Short-horizon prediction of wind power: A data-driven approach, *IEEE Transactions on Energy Conversion* 25 (2010) 1112 –1122.
- [22] D. Jakus, R. Goic, J. Krstulovic, The impact of wind power plants on slow voltage variations in distribution networks, *Electric Power Systems Research* 81 (2011) 589 – 598.
- [23] F. Nogales, J. Contreras, A. Conejo, R. Espinola, Forecasting next-day electricity prices by time series models, *IEEE Transactions on Power Systems*, 17 (2002) 342 –348.
- [24] A. Conejo, F. Nogales, J. Arroyo, Price-taker bidding strategy under price uncertainty, *Power Systems, IEEE Transactions on* 17 (2002) 1081 – 1088.
- [25] J. Morales, L. Baringo, A. Conejo, R. Minguez, Probabilistic power flow with correlated wind sources, *Generation, Transmission Distribution, IET* 4 (2010) 641 –651.
- [26] K. Deb, *Multi Objective Optimization Using Evolutionary Algorithms*, JOHN WILEY & SONS, USA, 2003.
- [27] B. Liu, L. Wang, Y.-H. Jin, An effective pso-based memetic algorithm for flow shop scheduling, *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 37 (2007) 18–27.
- [28] C. Kahraman, *Fuzzy Multi-Criteria Decision Making: Theory and Applications with Recent Developments*, Springer, 2008.

- [29] A. Soroudi, M. Ehsan, Multi-objective planning model for integration of distributed generations in deregulated power systems, *Iranian Journal of Science and Technology, Transaction B: Engineering* 34 (2010) 307–324.
- [30] M. Basu, Dynamic economic emission dispatch using evolutionary programming and fuzzy satisfying method, *International Journal of Emerging Electric Power Systems* 8 (2007) 1–15.
- [31] B. Berseneff, *Reglage de la tension dans les reseaux de distribution du futur/ Volt VAR Control in future distribution networks*, Ph.D. thesis, Grenoble, France, 2010.
- [32] EPRI, *Distributed Energy Resources Emissions Survey and Technology Characterization*, Technical Report, Electric Power Research Institute, 2004.
- [33] CBO, *Prospects for distributed electricity generation*, Technical Report, Congress of the United States congressional budget office, 2003.
- [34] MATLAB, Accessed online on jan, 2011. [Http://www.mathworks.com](http://www.mathworks.com).
- [35] N. Sadati, T. Amraee, A. Ranjbar, A global particle swarm-based-simulated annealing optimization technique for under-voltage load shedding problem, *Applied Soft Computing* 9 (2009) 652 – 657.
- [36] C. Rego, B. Alidaee, *Metaheuristic Optimization via Memory and Evolution: Tabu Search and Scatter Search*, Springer, USA, 2005.
- [37] M. AlHajri, M. El-Hawary, Exploiting the radial distribution structure in developing a fast and flexible radial power flow for unbalanced three-phase networks, *IEEE Transactions on Power Delivery* 25 (2010) 378 –389.
- [38] G. Chang, S. Chu, H. Wang, An improved backward/forward sweep load flow algorithm for radial distribution systems, *IEEE Transactions on Power Systems*, 22 (2007) 882 –884.

- [39] A. Kumar, W. Gao, Optimal distributed generation location using mixed integer non-linear programming in hybrid electricity markets, *Generation, Transmission Distribution, IET* 4 (2010) 281 –298.
- [40] N. Khalesi, N. Rezaei, M.-R. Haghifam, Dg allocation with application of dynamic programming for loss reduction and reliability improvement, *International Journal of Electrical Power and Energy Systems* 33 (2011) 288 – 295.

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Table 1: DG planning methods

Reference	Single/Multi objective	Static/Dynamic	Uncertainty handling	Network reinforcement	DNO	DGO	Method
El-Khattam et al.[11]	S	S	N	Y	Y	N	Classic MINLP
Jabr et al.[12]	S	S	N	Y(not exact)	Y	N	Ordinal optimization
El-Khattam et al.[9]	S	S	N	N	Y	N	Classic MINLP
Wang et al.[5]	S	D	N	Y	Y	N	Greedy heuristic
Kumar et al.[39]	S	S	N	N	Y	N	Classic MINLP
Soroudi et al.[10, 6]	M	D	N	Y	Y	N	Heuristic Immune-GA
Wong et al.[19]	S	D	N	Y	Y	Y	Classic MINLP
Zangeneh et al.[18]	M	S	N	N	Y	N	Normal boundary intersection
Haghifam et al.[4]	M	S	Y	N	Y	N	Heuristic NSGA-II
Atwa et al.[13]	S	S	Y	N	Y	N	Classic MINLP
Khalesi et al.[40]	S	S	N	N	Y	N	Dynamic programming
Atwa et al.[14]	S	S	Y	N	Y	N	Classic MINLP
Harrison et al.[3]	M	S	N	Y(not exact)	Y	Y	ϵ -constrained technique
Proposed model	M	D	Y	Y(exact)	Y	Y	Heuristic Immune-GA

Table 2: The predicted values of demand and price level factors and their duration

Parameter	High	Base	Medium	Minimum
μ_{dl}^D	1.25	1	0.87	0.75
μ_{dl}^λ	1.65	1	0.82	0.65
τ_{dl} (hr)	73	2847	2920	2920

Table 3: Characteristics of the DG units [33, 32]

Technology	Size (MVA)	E_{dg} ($kgCO_2/MWh$)	IC_{dg} ($k\$/MVA$)	OMC_{dg} ($\$/MWh$)
GT	0.35	630	183	75
Diesel	0.4	650	172	90
CHP	0.25	129	650	50
WT	0.5	0	1227	45

Table 4: The technical characteristics of wind turbines

v_{in}^c (m/s)	v_{rated} (m/s)	v_{out}^c (m/s)	$P_{i,r}^w$ (MW)
3	13	25	0.5

Table 5: Data used in the study

Parameter	Unit	Value
T	year	5
N_p		50
N_o		2
c		8.78
E_{lim}	$kgCO_2$	30000 [14]
E_{grid}	$kgCO_2/MWh$	910 [14]
E_c	$\$/TonCO_2$	10 [39]
ρ	$\$/MWh.$	70 [9]
α	%	3.5
d	%	12
V_{max}	Pu	1.05
V_{min}	Pu	0.95
Maximum iteration		1000

Table 6: The Pareto Optimal Front of Scenario I with $\beta = 0$
Profits in $10^6\text{\$}$

Solution #	OF_1	OF_2	β
1	0.0399	1.1399	0
2	6.2215	-0.9267	0
3	0.0974	0.4392	0
4	0.0782	1.0632	0
5	6.0782	-0.5667	0
6	0.7847	0.3596	0
7	2.8510	-0.2142	0
8	1.9387	0.1024	0
9	5.7155	-0.4920	0
10	1.2401	0.2277	0
11	3.5812	-0.2257	0
12	2.0134	-0.0954	0
13	1.3965	0.1541	0
14	4.0098	-0.3078	0
15	4.5975	-0.3233	0
16	2.4960	-0.1722	0
17	5.2794	-0.4500	0
18	2.3015	-0.1471	0
19	5.1275	-0.4007	0
20	4.7250	-0.3967	0

Table 7: The Planning scheme of solution #1 in scenario I

Year	Bus			FC	SC
t	CHP	WT	GT	($10^5\$$)	($10^5\$$)
1	574,226,167,200,366	0		4.7333	0
2		456		10.7390	0
3	574	261		8.9660	0
4				10.2120	0
5			332,19	14.1790	0

Table 8: The Pareto Optimal Front of Scenario II with variable β

Solution#	Profits in $10^6\$$			Satisfaction	
n	OF_1	OF_2	β	$\mu^{OF_1(X_n)}$	$\mu^{OF_2(X_n)}$
1	3.5152	0.0391	0.290	1.000	0.000
2	0.0747	3.9232	0.985	0.000	1.000
3	0.7747	3.8067	0.853	0.203	0.970
4	2.9154	0.9363	0.356	0.826	0.231
5	0.9625	3.4101	0.821	0.258	0.868
6	1.4843	2.4801	0.719	0.410	0.628
7	0.1065	3.8606	0.977	0.009	0.984
8	2.5762	1.5350	0.540	0.727	0.385
9	1.1856	2.9067	0.782	0.323	0.738
10	3.2821	0.8998	0.326	0.932	0.222
11	2.0178	2.3618	0.602	0.565	0.598
12	3.4326	0.4737	0.290	0.976	0.112
13	2.0229	2.1970	0.595	0.566	0.556
14	3.4080	0.5543	0.322	0.969	0.133
15	2.3171	1.6675	0.540	0.652	0.419
16	1.3709	2.7152	0.727	0.377	0.689
17	2.0406	1.8383	0.602	0.571	0.463
18	2.5302	1.5488	0.508	0.714	0.389
19	2.1716	1.6697	0.540	0.609	0.420
20	1.2722	2.8178	0.751	0.348	0.715

Table 9: The Planning scheme of solution #11 in scenario II

Year	Bus				FC	SC
t	CHP	Diesel	WT	GT	($10^5\$$)	($10^5\$$)
1	574			352	5.7639	0
2	504-35		574		7.2362	0
3					8.6461	0
4	420-574				18.8580	2
5	574	574	59	574	25.7470	0

Table 10: Performance comparison between the proposed method and other methods

Method	no of Pareto optimal solutions	$\min(OF_1)$ ($10^6\$$)	$\max(OF_1)$ ($10^6\$$)	$\min(OF_2)$ ($10^6\$$)	$\max(OF_2)$ ($10^6\$$)	running time (s)
IGA	20	0.0747	3.5152	0.0391	3.9232	29746
NSGA-II	24	0.1529	2.4121	0.0147	2.7261	36057
PSO-SA	19	0.1612	2.1611	0.1516	2.4331	26789
IA	22	0.0462	1.9633	0.0113	2.3262	19344
TS	16	0.1688	1.7407	0.1945	1.7275	23482

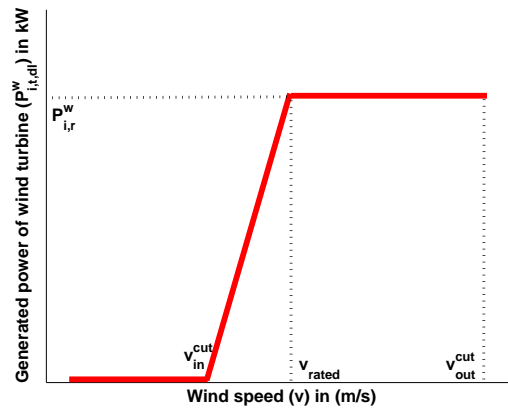


Figure 1: The idealized power curve of a wind turbine

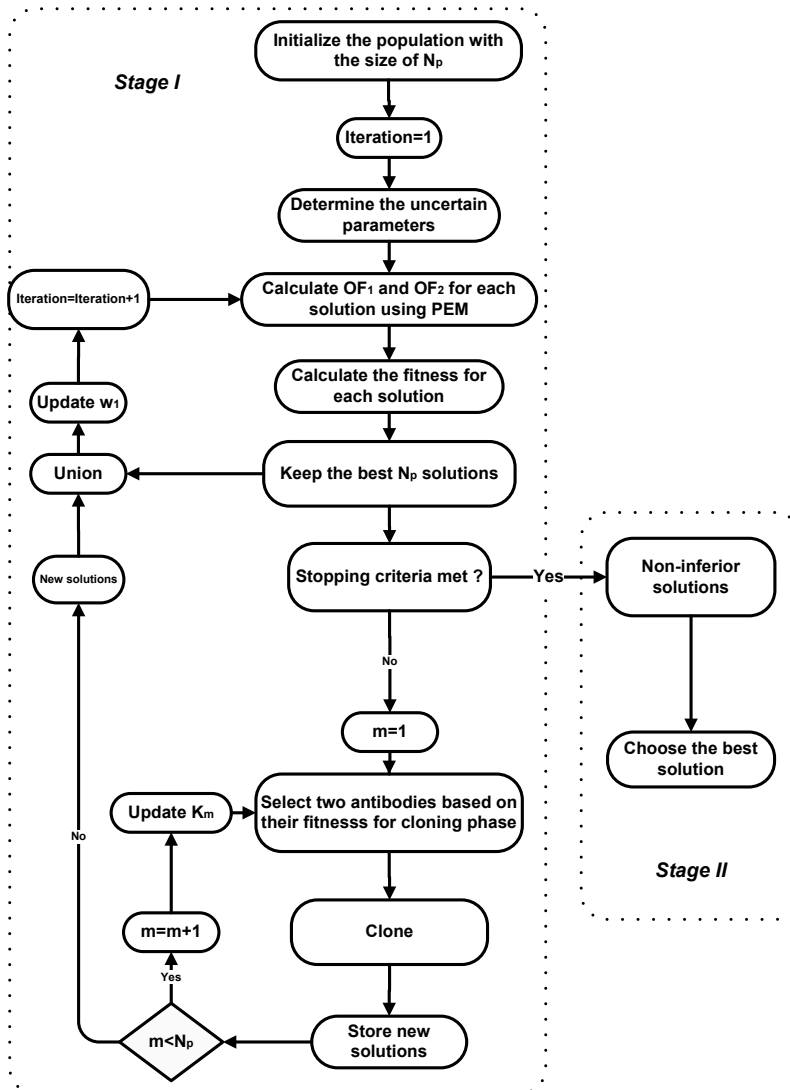


Figure 2: The flowchart of the first stage of the proposed method

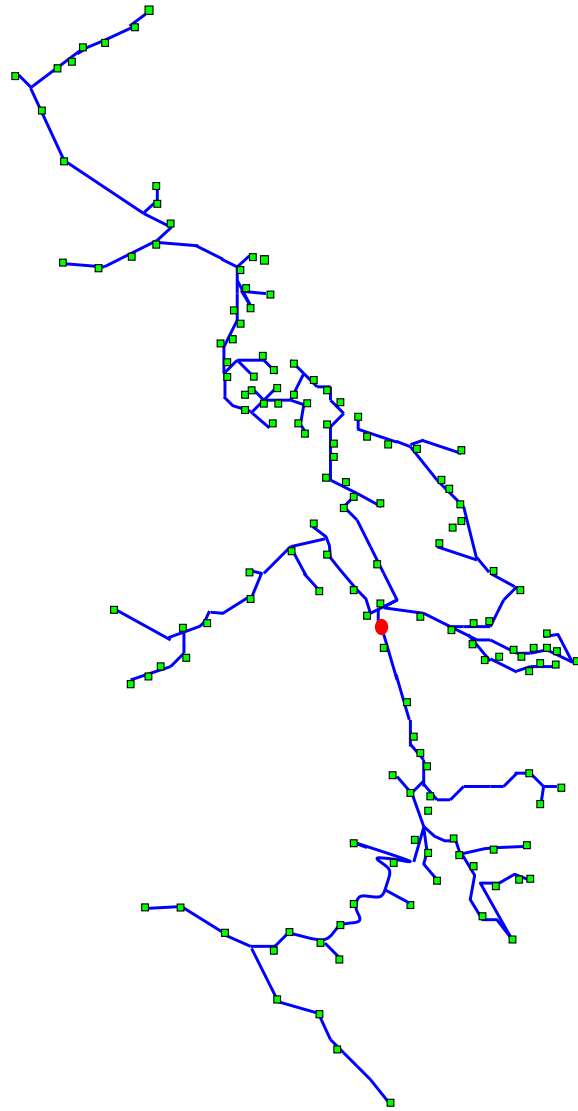


Figure 3: A 574-node distribution network

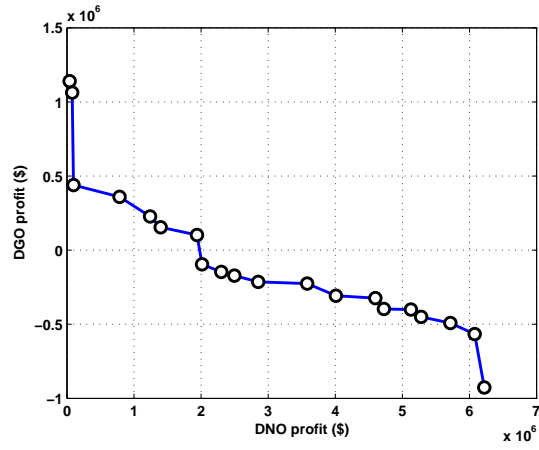


Figure 4: Pareto optimal front with $\beta = 0\%$

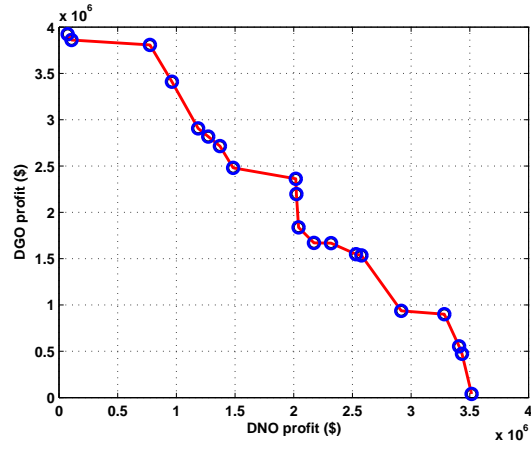


Figure 5: Pareto optimal front with variable β

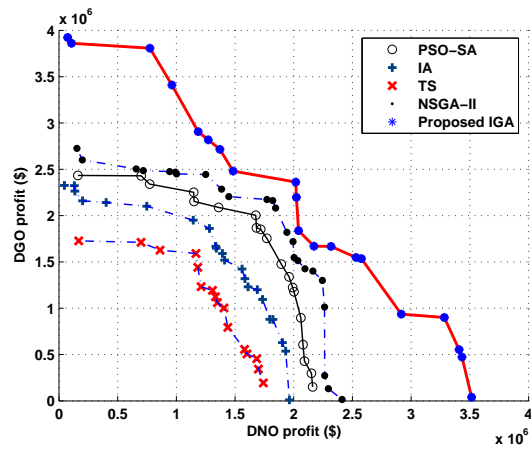


Figure 6: Comparing the proposed model with other methods