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AN INTERACTIVE FUZZY MULTI-OBJECTIVE APPROACH FOR SHORT TERM DG PLANNING

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Abstract. *This paper presents a short term multi-objective planning model for Distributed Generators (DGs) deployment in an electrical network. "Total Cost" and "Emission Cost" are two objective functions which have been going to be minimized in this model by finding the optimal schemes of sizing, placement and DG technologies over a short planning period (static planning). The proposed model can be used for a long term planning period (dynamic planning) in order to consider the timing concept. An interactive fuzzy satisfying method based on Chaotic Local Search and Modified Honey Bee Mating Optimization (CLS-MHBMO) is used to choose the final solution. The effectiveness of the proposed model and search method are assessed and demonstrated by various studies on an actual distribution network.*

Keywords: Multi-objective optimization, Distribution network, Short term DG planning, Interactive fuzzy set, Chaotic local search, Modified HBMO algorithm

1. **Introduction.** In recent years Distributed Generators (DGs) have been defined as small generation resources which can be located close to load points in distribution level. It is expected that the use of DG capacity would be over 40% in the near future all over the world [1,2]. Distribution networks are configured radially and DGs deployment is the integrated use of small generation units connected to the distribution system or inside the facilities of the great customers. Microgrid is a concept used in distribution level and with its decentralized electricity generation could provide reliable and high quality power to its customers at an economical cost. DGs, especially the ones based on the renewable energy technologies, are becoming more popular as they address climate change and energy security issues. Apart from climate change, current trend of deregulation in

electric supply industry and market and some technical benefits are driving forces for penetration increase of dispatch-able DGs in the distribution system [3].

In some market models, the Distribution Network Operator (DNO) is authorized to install DG units in his territory along with network reinforcements and in some cases the DNOs are unbundled from DG ownership while it is done by non-DNO entities [9].

For the integration use of DG units in distribution networks different models have been proposed in the literature addressing which consider different objectives, including technical (voltage profile and its stability), economical (network investment deferral and active loss reduction) and environmental (emission reduction) issues. For example, Basu et al. [4] conducted the CHP based DERs deployment in distribution system by the definition of loss sensitivity index and PSO technique. Teng et al. [5] proposed a method for DG planning based on Genetic Algorithm (GA) and it takes power losses reduction and customer interruption cost into account as the benefit of DGs' placement. Asano et al. [6] studied the long-term optimization with the objective function of minimum running cost for DG capacity sizing of P.V. and G.T. DERs in a Microgrid. Maurhoff et al. [7] reported some successful studies and experiences of DG deployment in Central Virginia Electric corporative. Abdelaziz et al. [8] used the evolutionary algorithm (E.A.) to find the optimal DG placement in a meshed Microgrid. Mitra et al. [21] presented an analysis on the six-bus meshed network based on dynamic programming to find the optimal size and site to meet the electrical and thermal loads.

One way of treating with multi-objective problems is converting them into a single objective model which may deprive the DNO to have a set of solutions to do trade off analysis. With high penetration of DGs, the planners require new planning paradigms and procedures to face complex scenarios with multi-objective functions. In this paper an interactive fuzzy satisfying method based on Chaotic Local Search and Modified Honey Bee Mating Optimization (CLS-MHBMO) is proposed. These methods are considered due to their population-based search capability as well as simplicity, convergence, speed and robustness [16,19].

There are some shortcomings associated with the reported multi-objective models of DG-owned DNOs. It is because of having non optimum plan in a short term period. Since in the planning procedure all investments are designed to be done at the beginning of the planning horizon to meet the load at the end of the planning time, the planning horizon must be divided into some planning intervals. In each interval a short time optimized planning must be done in order to have an optimized plan for a long term period.

So this paper proposes a planning model in a short term period which is multi-objective and static (static planning). "Total Cost" and "Emission Cost" are two objective functions which have been going to be minimized in this regard. Load flow analysis is used to simulate different DG planning paradigms. Also different applicable DG technologies will be determined during the planning procedure. So with the nonlinearity nature of load flow formulations and the integer nature of DG technologies, in this paper the multi-objective DG planning problem is modeled as a mixed integer nonlinear programming. The proposed model aims to provide a comprehensive multi-objective model which covers all aspects of placement, sizing and technology of DG and network investments simultaneously.

Numerical results on a large scale radial 11kV, 69-bus distribution test system by consideration of a load growth model have been presented to illustrate the performance and applicability of the proposed method for a short term planning period.

The contributions of the paper are as the following:

- Present a multi-objective DG planning model for a short term planning period

- Propose a new evolutionary optimization algorithm approach

2. **DG Planning Model Formulation.** The proposed planning model is formulated and presented in this section. In the DG planning programming the main system analysis is load flow analysis. So because of the nonlinearity nature of load flow formulations and the integer nature of DG technologies, multi-objective DG planning programming is a mixed integer nonlinear programming problem. The decision variables are defined as the number of DG units from each specific technology, to be installed in bus i in short planning period, reinforcement decision in feeder l which can be 0 or 1, the 1 means that the feeder cannot tolerate the thermal constraint so the feeder capacity must be increased. "Total Cost" and "Emission Cost" are two objective functions which have been going to be minimized in this model. In the following parts the objective functions and related constraints will be presented.

2.1. **Objective functions.** In this paper, two objective functions are considered and they have been defined in the following subsections.

2.1.1. *Total costs.* The first objective function to be minimized is the total cost which includes the cost of electricity purchased from the grid, the installation and the operating costs of DGs and finally the reinforcement costs of the distribution network [9]. Generally, the cost of each kilowatt-hour of electric energy generated by each DG is composed of the following components [19]:

- *Investment (equipment purchasing, establishment)*
- *Operation, maintenance and fuel cost*

The cost of purchasing electricity from the grid (GC) can be determined as:

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

Installation cost of the DG units ($DGIC$) can be defined as:

$$DGIC = \sum_{t=1}^{T} \sum_{i=1}^{N_b} \sum_{dg} \xi_{i,t}^{dg} \times IC_{dg} \times \frac{1}{(1+d)^t} \tag{2}$$

The operating cost of the DG units ($DGOC$) can be calculated as:

$$DGOC = \sum_{t=1}^{T} \sum_{i=1}^{N_b} \sum_{dg} \sum_{dl=1}^{N_{dl}} \tau_{dl} \times OC_{dg} \times P_{i,t,dl}^{dg} \times \frac{1}{(1+d)^t} \tag{3}$$

The reinforcement cost of the distribution network is the sum of all costs paid for installation and operation of new feeders and transformers. The feeder reinforcement costs (LC) and substation reinforcement costs (SC) can be calculated as the following:

$$LC = \sum_{t=1}^{T} \sum_{l=1}^{N_l} C_l \times d_l \times \gamma_t^l \times \frac{1}{(1+d)^t} \tag{4}$$

$$SC = \sum_{t=1}^{T} C_{tr} \times \psi_t^{tr} \times \frac{1}{(1+d)^t} \tag{5}$$

In the above equations:

N_{dl}: number of demand levels
PLF_{dl}: price level factor in demand level dl
ρ: base price for grid

$P^{grid}_{t,dl}$: power purchased from the grid in year t, in demand level dl
$P^{dg}_{i,t,dl}$: power generated by the i^{th} DG unit in year t, in demand level dl
τ_{dl}: duration of demand level dl
d: discount rate
N_b: number of bus
$\xi^{dg}_{i,t}$: number of DG units from each specific technology to be installed
IC_{dg}: investment cost of DG units
OC_{dg}: operating cost of DG units
C_l: feeder investment cost
d_l: feeder length
γ^l_t: reinforcement decision (0 or 1) in feeder l
C_{tr}: transformer investment cost
ψ_{tr}: number of new transformers installed in year t
So the total cost can be defined as follows:

$$\text{Total Cost} = f_1 = GC + DGIC + DGOC + LC + SC$$

f_1: Total cost in (\$/year)

Table 1. Important factors of DG technologies

DG	TPYE	GAS I.C. (Power Only) 1	GAS I.C. (CHP) 2	M.T. (Power Only) 3	M.T. (CHP) 4	F.C. (CHP) 5
Capacity	kW	100	100	100	100	200
Capital Cost	\$/kW	1030	1491	1485	1765	3674
Fuel Cost	\$/kWh	0.067	0.027	0.075	0.035	0.029
O.&M.Cost	\$/kWh	0.018	0.018	0.015	0.015	0.01
Service Life	Year	12.5	12.5	12.5	12.5	12.5
Heat Rate	Btu/kWh	11780	4717	13127	6166	5106

2.1.2. *Emission cost (externality cost).* This objective function considers emission during power generation such as NO_x, CO_2 and SO_2. Externality costs and emission factors for different DG technologies have been stated in [6-9]. In this paper simple model has been considered for emission cost. Total discounted cost of environmental externalities has been considered with the following equation.

$$\begin{aligned}\text{Emission Cost} = f_2 = &\sum_{t=1}^{T}\sum_{dl=1}^{N_{dl}}\left\{\sum_{k=1}^{M}(EX_k \times EF_k \times P^{grid}_{t,dl}) \times \tau_{dl}\right\} \\ &+\sum_{t=1}^{T}\sum_{dl=1}^{N_{dl}}\left\{\sum_{i=1}^{N_b}\sum_{k=1}^{M}(EX_k \times EF_{ik} \times P^{dg}_{i,t,dl}) \times \tau_{dl}\right\} \quad (6)\end{aligned}$$

EX_k: Externality cost of emission type k in (\$/lb)
EF_{ik}: Emission factor of DG unit i and emission type k in (\$/MWh)
M: Emission type (NO_x, CO_2, SO_2)
f_2: Total emission cost in (\$/year)
Table 2 shows different values of externality cost and emission factors for different DG technologies and pollution.

TABLE 2. Externality cost and emission factors for different DG technologies

Emission Type	Externality Costs ($/lb)	Emission Factors (lb/MWh) GAS I.C. (Power Only)	GAS I.C. (CHP)	M.T. (Power Only)	M.T. (CHP)	F.C. (Power Only)	Grid
NO_x	4.2	4.7	4.7	0.44	0.44	0.03	5.06
CO_2	0.014	1432	1432	1596	1596	1078	2031
SO_2	0.99	0.454	0.454	0.008	0.008	0.006	7.9

2.2. **Constraints.** Related constraints with the above objective functions can be defined as the following:

- *Active power constraints of DGs*:

$$P_{gi\min} \leq P_{gi} \leq P_{gi\max} \tag{7}$$

- *Distribution line limits*:

$$\left|P_{ij}^{Line}\right| < P_{ij,\max}^{Line} \tag{8}$$

- *Three-phase power flow equations*

$$\begin{aligned} -P_{i,t,dl}^{D} + \sum_{dg} P_{i,t,dl}^{dg} &= V_{i,t,dl} \sum_{j=1}^{N_b} Y_{ij}^{t} V_{j,t,dl} \cos(\delta_{i,t,dl} - \delta_{j,t,dl} - \theta_{ij}^{t}) \\ -Q_{i,t,dl}^{D} + \sum_{dg} Q_{i,t,dl}^{dg} &= V_{i,t,dl} \sum_{j=1}^{N_b} Y_{ij}^{t} V_{j,t,dl} \sin(\delta_{i,t,dl} - \delta_{j,t,dl} - \theta_{ij}^{t}) \end{aligned} \tag{9}$$

- *Bus voltage magnitude*

$$V_{\min} \leq V_i \leq V_{\max} \tag{10}$$

- *Constant power factor*

DGs are capable to support reactive power requirements of distribution networks; however, reactive power generation may restrict DGs for more active power generation. It should be noted that this situation causes generators to make less revenue in energy market. Constant power factor has been considered in this research.

$$\cos\phi^{dg} = \frac{P_{i,t,dl}^{dg}}{\sqrt{(P_{i,t,dl}^{dg})^2 + (Q_{i,t,dl}^{dg})^2}} = const. \tag{11}$$

2.3. **Assumptions.** Following assumptions have been considered in DG planning model formulations:

- *Load growth model*

The daily load variation is modeled using a load variation curve which is divided into N_{dl} discrete demand levels. The model will be defined by a base load at the beginning of the planning horizon ($S_{i,base}^{D}$), a demand level factor (DLF_{dl}) and a demand growth rate (α). So the demand in bus i, in year t and in demand level dl can be described as [9]:

$$S_{i,t,dl}^{D} = S_{i,base}^{D} \times DLF_{dl} \times (1+\alpha)^t \tag{12}$$

- *Grid electricity price model*

The DNO have the authorization to purchase the energy from the main grid and/or produce it using DG units to supply its customers. The variation of grid electricity price in each demand level is modeled by multiplication of base price (ρ) and price level factor in each demand level (PLF_{dl}) [24].

• *Investment authorization*

The DNO is authorized to invest in DG units and/or network components in an integrated framework.

3. **Interactive Fuzzy Satisfying Model.** As the existing conflict between objective functions, in this paper a fuzzy satisfying approach is used to solve the multi objective problem. A fuzzy set is generally shown by a membership function $\mu_{f_i}(X)$. The higher value of the membership function implies a greater satisfaction level with the solution. The fuzzy sets are defined as functions that map a member of the set to a number between 0.0 and 1.0 indicating its actual degree of satisfaction as means to model the uncertainty of natural language. Figure 1 shows the graph of the possible shape of the mentioned membership function [14,16].

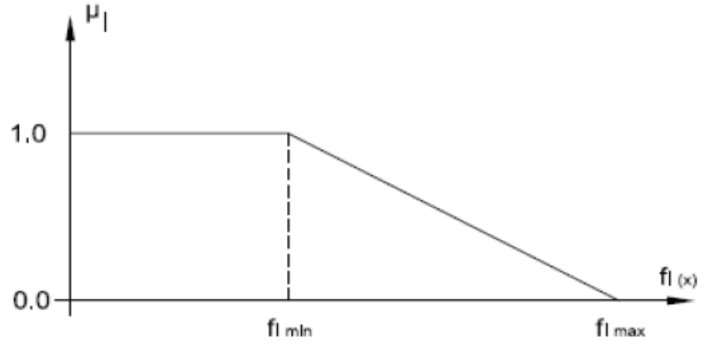

FIGURE 1. Membership function for each objective function

The lower and upper limits of each objective function ($f_i^{\min}$, $f_i^{\max}$) under given constraints are established to extract a membership function $\mu_{fi}(X)$ for each objective function $f_i(X)$. $f_i^{\min}$ is calculated by single objective optimization separately. So the i^{th} membership function is defined as the following:

$$\mu_{fi}(X) = \begin{cases} 1 & \text{for } f_i(X) \le f_i^{\min} \\ 0 & \text{for } f_i(X) \ \ge f_i^{\max} \\ \dfrac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}} & f_i^{\min} \le f_i(X) \ \le f_i^{\max} \end{cases} \qquad i = 1, \ldots, k \tag{13}$$

In this paper a new interactive fuzzy satisfying model is presented to solve the multi-objective DG planning problem. In this method by the definition of membership functions, the DNO can specify his/her desirable levels of satisfaction for each membership functions which is called the expected membership values $\mu_{\exp i}$, $i = 1 \ldots k$, where k is the number of objective functions. The expected value is a real number ranges between 0 and 1. It represents the expected satisfaction level of each objective functions. By the definition of $\mu_{f_i}(X)$ as the i^{th} membership function and $\mu_{\exp i}$ as the i^{th} expected membership value, the following formula must be solved to get the desired solution. It can be considered as the most satisfactory solution, which is close to the requirements of the DNO's expected values.

$$Object(X) = \min \left[\max_{i=1\ldots p} \left| \mu_{\exp i} - \mu_{f_i}(X) \right| \right] \tag{14}$$

The expected value of an objective is estimated from the DNO's experience or by trial and error according to the current values of the membership and objective functions. Thus the DNO can determine the most satisfactory solution for the minimax problem using the interactive fuzzy satisfying model.

4. **DG Modelling and Technologies.**

PV or *PQ* models can be selected for DG modeling in the distribution system planning. Since the distribution networks can be used in unbalance three-phase state, DGs can be controlled in the following two forms [23]:

- *Simultaneous three phase control*
- *Independent three phase or single phase control*

Therefore, regarding the control modes and DG models, following states can be adopted for simulation of DGs [23]:

- *PQ model with simultaneous three-phase control*
- *PV model with simultaneous three-phase control*
- *PQ model with independent three-phase control*
- *PV model with independent three-phase control*

With PV models, DGs must be able to generate reactive power to maintain their voltage magnitudes in desirable level. Since in DG planning process, the power of units, locations and technologies are undetermined, so they cannot be modeled as PV buses during planning procedure. With this regard PQ model with simultaneous three-phase control and constant power factor is selected for DG modeling. Determination of DG technologies for each bus is one of the decision variables in the planning process.

5. **HBMO Approach and Modifications.**

5.1. **Original HBMO.**

Honey Bee Mating Optimization (HBMO) is inspired by social behavior of bees and wasps. These insects have following features in common: "cooperative work among adults in brood care and nest construction", "overlapping of at least two generations" and "division of labor". The honey bee community consists of a queen (or queens), drones, workers and broods. These castes are associated with different functions in the colony [14].

The HBMO algorithm simulates the mating process of honey bees [16]. The drones are the fathers of colony. They are haploid and act as amplify their mother's genomes without altering their genetic composition, expect through the mutation. The drones practically considered as agents that pass one of their mother's gametes and function to enable females to act genetically as males. Worker bees specialized in brood care and sometimes lay eggs. Broods arise from fertilized (represents queen or worker) and unfertilized (represents drones) eggs [17].

Before the process of mating begins, the user has to define a number that corresponds to the queen's size of spermatheca. This number corresponds to the maximum number of queen's mating in a single mating flight. Each time the queen successfully mates with a drone the genotype of the drone is stored and a variable is increased by one until the size of spermatheca is reached. Another two parameters have to be defined, the number of queens and the number of broods that will be born by all queens. In this implementation of Honey Bees Mating Optimization (HBMO) algorithm, the number of queens is set equal to one as in the real life only one queen will survive in a hive, and the number of broods is set equal to the number corresponding to the size of queen's spermatheca. Then, the mating flight of the queen begins. At the start of the flight, the queen is initialized with some energy content (initially, the speed and the energy of the queen are generated at random) and returns to her nest when the energy is less than a threshold value and spermatheca is not full [18].

In order to develop the algorithm, the capability of workers is restrained in brood care and thus each worker may be regarded as a heuristic that acts to improve and/or take care of a set of broods. An annealing function is used to describe the probability of a drone (D) that successfully mates with the queen (Q) shown in the following equation:

$$\Pr ob(Q, D) = e^{\left(\frac{-\Delta f}{S(t)}\right)} \tag{15}$$

where Δf is the absolute difference of the fitness of D and the fitness of Q, and the $S(t)$ is the speed of queen at time "t". After each transition of mating, the queen's speed and energy are decayed according to the following equation [17]:

$$S(t+1) = \beta \times S(t) \tag{16}$$

where β is the decreasing factor ($\beta = [0, 1]$).

Initially the speed of the queen is generated at random. At the start of a mating flight drones are generated randomly and the queen selects a drone using the probabilistic rule. If the mating is successful, the drone's sperm is stored in the queen's spermatheca. Workers adopt some heuristic mechanisms such as crossover or mutation to improve the brood's genotype. The fitness of the resulting genotype is determined by evaluating the value of the objective function of the brood genotype. Following stages are the principles of HBMO algorithm [17]:

- *The algorithm starts with the mating flight, where a queen (best solution) selects drones probabilistically to form the spermatheca (list of drones). Then a drone will be selected randomly for the creation of broods*;
- *Creation of new broods by crossover the drone's genotypes with the queens*;
- *Use of workers to conduct local search on broods (trial solutions)*;
- *Adaptation of worker's fitness, based on the amount of improvement achieved on broods*;
- *Replacement of weaker queen by fitter broods.*

5.2. **Modified HBMO (MHBMO).** In the original form of HBMO, a population of broods is generated based on mating between the queen and the drones stored in the queen's spermatheca. For the generation of i^{th} brood, the i^{th} individual of the queen's spermatheca is randomly selected; then the j^{th} brood will be generated with the following equations.

$$\begin{aligned} &X_{Queen} = X_{best} = \left[\begin{array}{cccc} X_{best}^1 & X_{best}^1 & \ldots & X_{best}^n \end{array}\right] \\ &SP_i = \left[\begin{array}{ccc} SP_i^1 & SP_i^1 \ldots & SP_i^n \end{array}\right] \\ &X_{Brood\,j} = X_{best} + rand(.) \times (X_{best} - SP_i); \quad j = 1, 2, \ldots, N_{brood} \end{aligned} \tag{17}$$

The proposed algorithm of brood generation in the original HBMO often converges to local optima and this is a disadvantage of this method. In order to avoid this happening in this paper a modified method has been proposed to improve the brood generation. This method improves the mating process in original HBMO and the Modified HBMO (MHBMO) will be concluded and used in simulations. In the proposed modification three sperms (SP_{k1}; SP_{k2}; SP_{k3}) are randomly selected from the queen's spermatheca so that $k1 \neq k2 \neq k3$. Then, two improved new drones will be calculated with the following equations.

$$\begin{aligned} &X_{improved1} = SP_{k1} + rand(.) \times (SP_{k2} - SP_{k3}) = \left[\begin{array}{cccc} x_{im1}^1 & x_{im1}^2 & \ldots & x_{im1}^n \end{array}\right] \\ &X_{Brood1} = \left[\begin{array}{cccc} x_{Br1}^1 & x_{Br1}^2 & \ldots & x_{Br1}^n \end{array}\right] \\ &x_{Br1}^j = \begin{cases} x_{im1}^j, & \text{if} \quad \gamma_1 \leq \gamma_2 \\ x_{SPk1}^j, & \text{otherwise} \end{cases} ; \quad j = 1, \ldots, n \\ &X_{improved2} = X_{best} + rand(.) \times (SP_{k2} - SP_{k3}) = \left[\begin{array}{cccc} x_{im2}^1 & x_{im2}^2 & \ldots & x_{im2}^n \end{array}\right] \end{aligned}$$

$$X_{Brood2} = \left[\begin{array}{cccc} x^1_{Br2} & x^2_{Br2} & \ldots & x^n_{Br2} \end{array} \right]$$
$$x^j_{Br2} = \left\{ \begin{array}{ll} x^j_{im2}, & \text{if} \quad \gamma_3 \le \gamma_2 \\ x^j_{best}, & \text{otherwise} \end{array} \right. ; \quad j = 1, \ldots, n \tag{18}$$

In the above equations γ_1, γ_2 and γ_3 are random numbers in range 0 and 1. The best individual between X_{Brood1}, X_{Brood2} and that concluded in original HBMO is considered as a new brood.

5.3. **CLSMHBMO.** The chaotic local search (CLS) is applied to the modified HBMO in order to enrich the searching behavior, in which the mating process has been improved. Since chaos queues experience all the states in a specific area without repetition, chaotic search becomes a new tool used as an optimizer [16]. Tent equation is a well known chaos system. It has been applied in the chaotic local search with the following equations in which N_{chaos} is the number of individuals for CLS and cx^j_i is the j^{th} chaotic variable.

$$Cx_i = \left[\begin{array}{cccc} cx^1_i & cx^2_i & \ldots & cx^n_i \end{array} \right], \quad i = 0, 1, 2, \ldots, N_{chaos}$$
$$cx^j_{i+1} = \left\{ \begin{array}{ll} 2cx^j_i, & 0 < cx^j_i \le 0.5 \\ 2(1 - cx^j_i), & 0.5 < cx^j_i \le 1 \end{array} \right. ; \quad j = 1, 2, \ldots, n$$
$$cx^j_i \in [0, 1], \quad cx^j_0 \notin \{0.25, 0.5, 0.75\}; \quad cx^j_0 = rand(.) \tag{19}$$

In the proposed algorithm, the initial population (X^0_{cls}) must be defined and scaled into the interval $[0, 1]$. With this regard the best solution (Queen's place) is considered as the initial population in this research. $x^j_{\min}$ and $x^j_{\max}$ are the minimum and maximum values of state variables vector.

$$X^0_{cls} = X_{best} = \left[\begin{array}{cccc} x^1_{cls,0} & x^2_{cls,0} & \cdots & x^n_{cls,0} \end{array} \right]$$
$$Cx_0 = \left[\begin{array}{cccc} cx^1_0 & cx^2_0 & \ldots & cx^n_0 \end{array} \right]$$
$$cx^j_0 = \frac{x^j_{cls,0} - x^j_{\min}}{x^j_{\max} - x^j_{\min}}; \quad j = 1, 2, \ldots, n$$
$$X^i_{cls} = \left[\begin{array}{cccc} x^1_{cls,i} & x^2_{cls,i} & \cdots & x^n_{cls,i} \end{array} \right]; \quad i = 1, 2, \ldots, N_{chaos}$$
$$x^j_{cls,j} = cx^j_{i-1} \times (x^j_{\max} - x^j_{\min}) + x^j_{\min}; \quad j = 1, 2, \ldots, n \tag{20}$$

Finally, the objective function is evaluated for all individuals of CLS. The best solution among them must be replaced with a drone which is selected randomly.

6. **Application the Method in Short Term DG Planning Algorithm.**

This section presents the application of Chaotic Local Search with Modified HBMO (CLSMHBMO) to propose the DG planning model for short term planning period. It should be noted that the decision variables are sizing, placement and technology of DGs and network reinforcements. Due to the different nature of the objective functions, in the proposed model they will be considered as fuzzy sets. In this paper an interactive fuzzy satisfying methodology will be used. Figure 2 shows a schematic representation of the proposed model for DG planning in short term period. To apply the proposed algorithm for short term DG planning, the following steps must be taken into consideration.

Step 1. Input data definition. In this step the following data must be defined. It includes the network configuration, line characteristics, objective functions and their objective functions minimum and maximum values ($f_{i\text{-min}}$, $f_{i\text{-max}}$), the speed of queen at the start of the mating flight ($S_{\max}$), the speed of queen at the end of the mating flight ($S_{\min}$), the speed reduction factor (β), the number of iterations, the number of workers

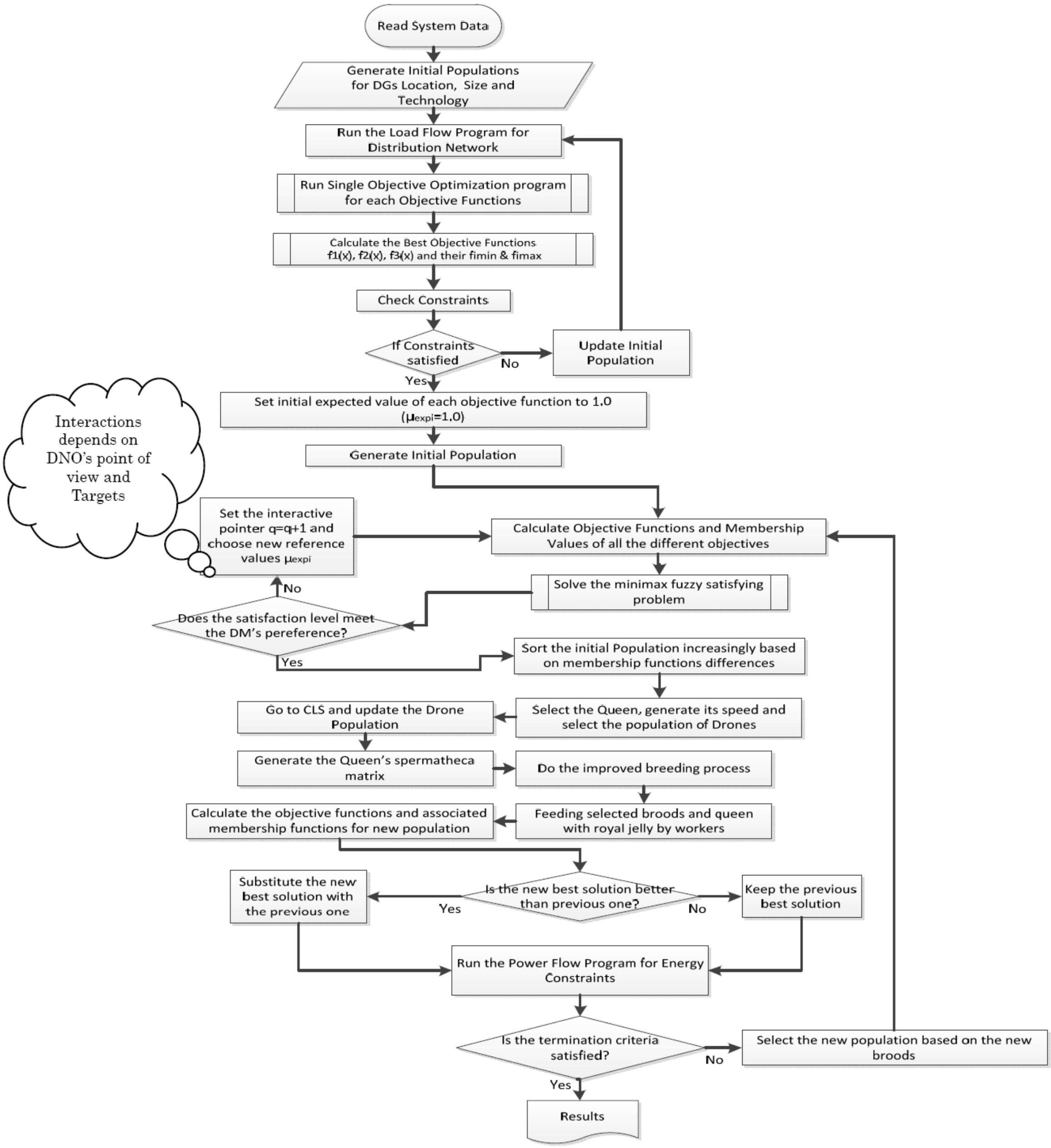

FIGURE 2. Flowchart of the proposed algorithm

(N_{Worker}), the number of drones (N_{Drone}), the size of the queen's spermatheca (N_{Sperm}) and the number of broods (N_{Brood}).

Step 2. Initial population generation. In this step an initial population will be generated randomly based on state variables constraints.

$$\text{Initial Population} = \begin{bmatrix} X_1 \\ X_2 \\ \dots \\ X_{Nipop} \end{bmatrix}$$

$$X_i = [x_j]_{1\times n} = \left[\overline{P_g}, \overline{Type_g} \right], \quad i = 1, 2, \dots, N_{ipop}$$

$$x_j = rand(.) \times (x_j^{\max} - x_j^{\min}) + x_j^{\min}; \quad j = 1, 2, \dots, n \tag{21}$$

In the above equations rand(.) is the random function generator.

Step 3. Objective functions calculation. In this step objective functions are calculated for each member X_i by using the results of the distribution load flow. Also the associated fuzzy membership values of each individual X_i for all different objectives are evaluated. A fuzzy decision for overall satisfaction may be defined as the choice that satisfies all of the objectives according to the DNO point of view. In this paper the interactive fuzzy satisfying intersection as described in Section 3 (Equation (14)) is used. By this method the DNO can specify his/her expected membership values for each of the objective functions and the corresponding best compromising solution is obtained by solving the minimax proposed problem.

Step 4. Chaotic Local Search (CLS). The Chaotic Local Search (CLS) as described in Section 5.3 (Equations (19) and (20)) is used in this step. In this research the best solution is considered as the initial population for CLS.

Step 5. Sorting. The initial population must be sorted increasingly based on the values obtained from minimax procedure in order to separate different castes of the colony.

Step 6. Queen selection. The Individual which has the maximum membership value (X_{best}) can be considered as the queen.

Step 7. Queen speed generation. The queen speed is generated randomly with the following equation:

$$S_{Queen} = rand(.) \times (S_{\max} - S_{\min}) + S_{\min} \tag{22}$$

Step 8. Drones population selection. The population of drones (N_{Drone} member) will be selected from the sorted initial population.

$$\text{Drone Population} = \begin{bmatrix} D_1 \\ D_2 \\ \cdots \\ D_{N_{Drone}} \end{bmatrix}$$

$$D_i = \left[\overline{P_g}, \overline{Type_g}\right]_{1\times n}, \quad i = 1, 2, \ldots, N_{Drone} \tag{23}$$

Step 9. Queen's spermatheca matrix generation (mating flight). At the start of the mating flight, the queen flies with her maximum speed. A drone is randomly selected from the population of drones. The mating probability is calculated based on the objective function values of the queen and the selected drone. A number between 0 and 1 is randomly generated and compared with the calculated probability. If it is less than the calculated probability, the drone's sperm is stored in the queen's spermatheca and the queen speed is decreased. Otherwise, the queen speed is decreased and another drone from the population of drones is selected until the queen reaches to her minimum speed or the queen's spermatheca is full. If SP_i is the i^{th} sperm in the queen's spermatheca, then its matrix will be generated as follows:

$$\text{Spermatheca Matrix} = \begin{bmatrix} SP_1 \\ SP_2 \\ \cdots \\ SP_{N_{Sperm}} \end{bmatrix}$$

$$SP_i = \left[\overline{P_g}, \overline{Type_g}\right]_{1\times n}, \quad i = 1, 2, \ldots, N_{sperm} \tag{24}$$

Step 10. Broods population generation. In this paper as described in Section 5.2 the breeding process in original HBMO is improved. So in the proposed MHBMO model the mating process has been changed in order not to trap in local optima. This process is performed according to Equation (18).

Step 11. Improvement the selected broods with the royal jelly by workers. By implementing the heuristic functions and mutation operators the brood population can be improved. For this reason a number (equal to or less than N_{worker}) of individuals are randomly generated around the i^{th} brood. Then the values of the objective function and its associated membership functions are evaluated for each individual. The best individual among these generated broods will be replaced with the i^{th} brood.

Step 12. Objective function calculation and sorting. In this step objective functions are calculated for the new population as mentioned in Step 3.

Step 13. Termination and criteria checking. The termination criteria will be checked in this step. If all criteria are satisfied, the algorithm will be finished; else N_{best} individuals must be selected among broods. They will be considered as the new population and the algorithm must be started again until all the convergence criteria are met.

7. **Simulation Results.** The proposed multi-objective DG planning model is applied to an actual 11kV, 69 bus distribution network which is shown in Figure 3. This system has 4 main feeders and 68 load points. The related system information is given in [3]. This network is fed through an 11kV substation with 5MVA capacities. The options for reinforcement the network are as follows: transformers with 5MVA capacities and a cost of $C_{tr} = 0.1$ Million \$ for each and feeder replacement at a cost of $C_l = 0.15$ Million \$/km [9]. Four demand levels, i.e., minimum, medium, base and high are considered for simulations with four demand level factors (DLF_{dl}) which are 0.75, 0.87, 1.0 and 1.25 respectively; the price level factors for each demand level (PLF_{dl}) are 0.65, 0.82, 1.0 and 1.65 respectively; the duration of each demand level (τ_{dl}) is 2920, 2920, 2874 and 73h respectively and the stopping criterion is reaching to a maximum number of iterations. Other simulation assumptions and characteristics of the DG units and network are presented in Tables 1-3.

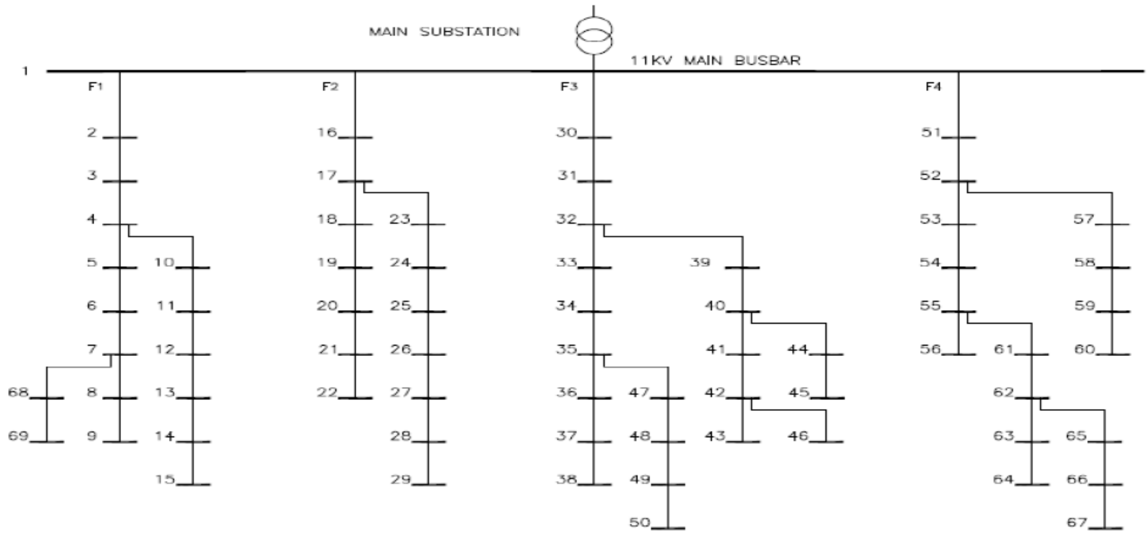

FIGURE 3. 69 bus distribution test systems

TABLE 3. Other data used in simulation

Parameter	Unit	Value	Remarks
T	Year	1	Planning Horizon
ρ	\$/kWh	0.07	Grid electricity base price
α	%	3.5	Load groth base rate
d	%	12	Discount rate
Maximum Iteration	–	500	–

For optimal planning, it is needed to consider each probable plan in the network to evaluate its effectiveness and associated costs in short planning period. It is assumed that each bus is capable of handling distributed generators with minimum capacity of 50kW. At the beginning of the planning year the total power loss of the system is "264.3kW", the total power supplied by substation is "4732.3kW" and the minimum voltage of the system is in bus number "68" with the value of "9.9785kV". By considering the load growth model, the system must be able to respond the excess load by using DGs and/or network reinforcements. By considering all objective functions, the algorithm considers DG expansion plan in some buses in order to respond the load growth in short planning period and then the algorithm starts to optimize the locations, sizes and DG technologies.

7.1. **Robustness and effectiveness of the proposed method.** For the checking of model robustness the total cost and emission cost are separately considered for single objective optimization. The best results are obtained by optimizing each objective function separately by implementing different calculation methods. The results are shown in Tables 4 and 5 and represent the Genetic Algorithm (GA), original HBMO, MHBMO and CLS-MHBMO optimization methodologies for 20 random executions for short term planning period. In these tables the best and the worst values of the objective functions have been shown. Comparison between the best and the worst solutions in the proposed optimization algorithm with the other methods show the robustness and the effectiveness of the proposed model. Since these tables provide the standard deviation, and average values of the objective functions, it can be seen that the best results are associated with the proposed CLS-MHBMO model.

Table 4. Comparison of average and standard deviation for 20 execution (total cost)

Optimization Method	Average	Standard Deviation ($/year)	Worst Solution	Best Solution
Genetic	2,004,790	42,908	2,144,000	1,983,900
Original HBMO	3,389,490	130,568	3,685,000	3,193,000
MHBMO	3,351,610	241,143	3,711,800	2,897,600
CLS-MHBMO	1,983,900	0	1,983,900	1,983,900

Table 5. Comparison of average and standard deviation for 20 execution (emission)

Optimization Method	Average	Standard Deviation ($/year)	Worst Solution	Best Solution
Genetic	1,046,736	15,290	1,134,400	1,071,400
Original HBMO	956,744	25,173	998,760	911,030
MHBMO	959,900	24,787	988,990	886,790
CLS-MHBMO	874,882	15,372	897,650	828,810

Single and multi-objective results of the proposed DG planning model for short term planning period are compared in Table 7. Simulations show that total cost does not change a lot when the total energy is supplied by the network or by sharing with DG deployment. It means that the total electrical energy cost will not change considerably in distribution system with and without DG existence. This situation happens because with DG deployment the energy demand level supplied by the network will be reduced and it will be replaced with energy supplied by the DGs locally. In the mentioned state, the optimization program tends to reduce the total electrical energy cost which relates to DG technologies, fuel cost, operation and maintenance cost and finally finds the best situation in conjunction with the network. This is because of the expensiveness of new technologies in the different types of DGs which limits to exploit DG deployment. But with the emission reduction base, more DGs must be exploited in order to have considerably the emission reduction. Simulations show that the emission reduction and loss reduction act in the same system reaction.

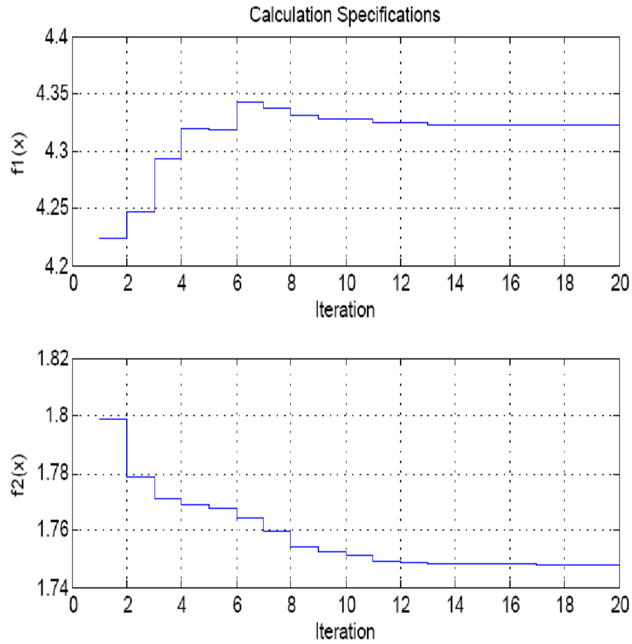

Figure 4. Convergence characteristic of the CLSMHBMO DG planning model (20 iterations)

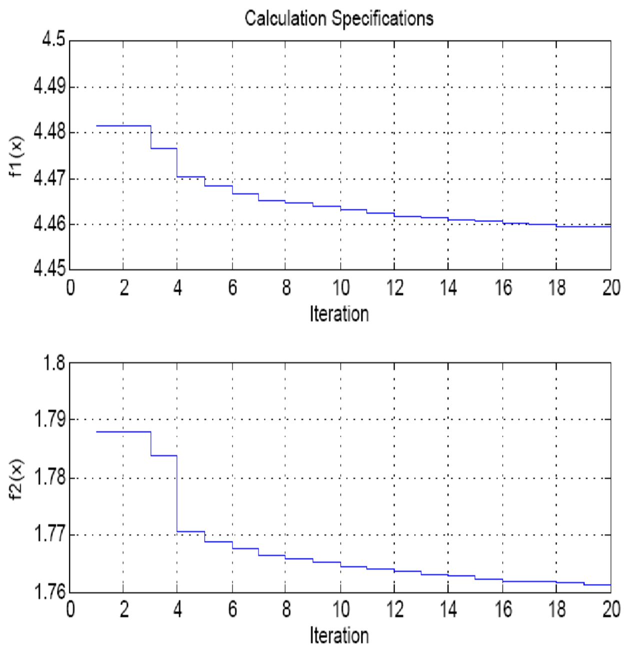

Figure 5. Convergence characteristic of the MHBMO DG planning model (20 iterations)

7.2. **Non-Interactive fuzzy multi-objective optimization model.** In multi-objective planning problem the DNO tends to consider all objective functions together in order to reach the optimized solution according to his/her targets. In the non-interactive fuzzy model all objective functions have the same importance. Figures 4 and 5 show the convergence characteristics of the CLS-MHBMO and HBMO models for the best solution when the expected membership values are equal to one ($\mu_{\exp 1} = \mu_{\exp 2} = 1$). These figures show the better convergence characteristics of the CLSMHBMO optimization method in comparison with the HBMO method.

The optimized solution may not be converged to each single optimized result; but in general it considers some parts of all optimal solutions together. By implementing the proposed Fuzzy-CLSMHBMO optimization model, the best solution has been determined.

Table 6. Fuzzy-CLSMHBMO multi-objective response for DG planning (location, size and technology)

Bus No.	DG No. & Cap.(kW)	DG Type	DG Occupied Cap.(kW)	Bus No.	DG No. & Cap.(kW)	DG Type	DG Occupied Cap.(kW)	Bus No.	DG No. & Cap.(kW)	DG Type	DG Occupied Cap.(kW)	Bus No.	DG No. & Cap.(kW)	DG Type	DG Occupied Cap.(kW)
1	–	–	0	17	–	–	0	31	–	–	0	52	–	–	0
2	–	–	0	18	–	–	0	32	–	–	0	53	–	–	0
3	1 * 100	4	80.981	19	–	–	0	33	–	–	0	54	–	–	0
4	–	–	0	20	–	–	0	34	–	–	0	55	–	–	0
5	2 * 100	4	116.35	21	–	–	0	35	–	–	0	56	–	–	0
6	–	–	0	22	–	–	0	36	–	–	0	57	–	–	0
7	–	–	0	23	–	–	0	37	–	–	0	58	–	–	0
8	–	–	0	24	–	–	0	38	–	–	0	59	3 * 100	3	248.4
9	–	–	0	25	–	–	0	39	–	–	0	60	2 * 100	3	117.94
10	–	–	0	26	1 * 100	3	82.8	40	–	–	0	61	–	–	0
11	–	–	0	27	1 * 100	4	97.795	41	–	–	0	62	–	–	0
12	–	–	0	28	1 * 100	4	94.433	42	1 * 100	3	80.303	63	–	–	0
13	–	–	0	29	–	–	0	43	–	–	0	64	–	–	0
14	1 * 100	3	83.886	30	–	–	0	44	–	–	0	65	–	–	0
15	–	–	0					45	–	–	0	66	1 * 100	1	79.695
16	–	–	0					46	–	–	0	67	–	–	0
DG Different Types:								47	1 * 100	3	53907	68	–	–	0
1: Internal Combastion Engine, ICE (Power)								48	1 * 100	3	90.513	69	1 * 100	3	88.348
2: Internal Combastion Engine, ICE (CHP)								49	1 * 100	1	68.247				
3: Micro Turbine, MT (Power)								50	–	–	0				
4: Micro Turbine, MT (CHP)								51	1 * 100	4	83.729				
5: Fuel Cell, FC															

The DG planning non interactive fuzzy model proposes the location, size and DG technologies in the network. The results have been shown in Table 6. The values of the objective functions associated with the non interactive Fuzzy-CLSMHBMO model has been proposed in Table 7.

The results illustrate that in short planning period the total cost increases and the emission decreases with DG existence based on the proposed model. The system characteristics and has been improved by implementing Fuzzy-CLSMHBMO planning procedure in comparison with HBMO plan. For example by consideration the optimal solution, 15 DG sets are localized in CLSMHBMO model and in this case in comparison with HBMO

Table 7. Fuzzy comparison of objective function results in multi-objective optimization (in 20 iterations)

Objective Function		Base Solution Single/Multi-Objective	Total Electrical Energy Cost (Million $/Year)	Emission Cost (Million $/Year)	No. of Buses with bad Voltage Loss ΔU < 10%	No. of Bus with DG Installed –
Dist. Network Without DG Planning		–	1.9839	2.1492	9	0
DG Planning MODEL		CLSMHBMO – Single Objective-1	1.9839	2.1492	9	0
		CLSMHBMO – Single Objective-2	25.683	0.90827	0	33
		HBMO Multi-Objective	4.4155	1.7959	0	16
		CLSMHBMO Multi-Objective	4.3876	1.7379	0	15

Table 8. Fuzzy important factors with (CLSMHBMO) and without DG exploitation

Item	No. of DG	Sub. Power (kW)	System Min Voltage (kV)	No. of Buses With ΔU < 10%	Min $[f_1(x)]$ (Million $/Year)	Min $[f_2(x)]$ (Million $/Year)
Dist. System Without DG	0	6243.9	9.6392	9	1.9839	2.1492
Dist. System With DG (Multi-Objective-CLSMHBMO)	15	3298.3	9.915	0	4.3876	1.7379

which localizes 16 DG sets the values of total cost decreases from 4.4155 to 4.3876 Million $ and the emission cost decreases from 1.7959 to 1.7379 Million $.

It can be seen that the Fuzzy-CLSMHBMO multi-objective model conducts the planner to the more optimized results. The first objective function is not better than the single objective one and it is because of the expensiveness of the distributed generators new technologies.

Table 8 shows the variation of important system operating characteristics by considering the system with and without DG exploitation. For example the grid purchased power decreases from 6243.9kW to 3298.3kW, the emission cost reduces from 2.1492 Million $ to 1.7379 Million $ and the total cost increases from 1.9839 Million $ to 4.3876 Million $ in short planning period.

7.3. **The interactive fuzzy multi-objective optimization method.** In the interactive fuzzy model, the definition of DNO's planning targets is very important and directly affects the final planning decision. So the DNO expected membership values must be defined and if it is needed it must be improved in DNO's control pattern. The control pattern is defined according to the DNO's experience or with the optimization algorithm by the DNO's control in conjunction with the system expansion constraints.

In this paper the minimax problem is solved to derive a global solution in the first interaction for the initial expected membership values $\mu_{\exp i} = 1$. If the solution satisfies the DNO's targets, the DNO terminates the interactive steps and if not, he/she selects and inputs a set of new reference memberships for the following interactive steps.

As the results obtained in single objective optimization represented in the previous subsection, the cost objective function conflicts with other objectives because the population that minimize the total cost can not minimize the others as originates from the expensiveness of new DG technologies. The proposed tradeoff method can be used to resolve the conflicts among multiple objectives so that the DNO can select a compromise or the most satisfactory plan. The interactive steps will be executed until the algorithm generates the desired solution. In the interactive fuzzy satisfying model the DNO checks the values of the membership and objective functions. The procedure continues till the DNO's targets are satisfied. Table 9 shows some reference membership values and associated results which the DNO uses for satisfying his/her goals. It can be seen from the table that the DNO with the consideration of his/her experience can change the expected membership values in order to reach the desired solutions.

For example, if the DNO wants to minimize the emission cost (f_2), first he/she reduces $\mu_{\exp 1}$ from 1.0 to 0.8 (interaction 1) then in this case f_1 is increased 150.73% and f_2 is decreased 20.62%. The minimum value of the emission cost obtained in single objective optimization is 0.90827, and it has some difference with the value obtained in this interaction (1.3796).

If the DNO wants to minimize the total cost (f_1), first he/she reduces $\mu_{\exp 2}$ from 1.0 to 0.85 (interaction 2) then in this case f_2 is increased 20.54% and f_1 is decreased 35.10%. But as shown in single objective optimization state, the minimum value of the total cost is 1.9839 which has considerable difference with the value obtained in this interaction (2.8477).

Table 9. Results of interactive fuzzy satisfying procedure

Interaction	Reference membership Value	Memebership function	Objective Functions f_1 (Million \$/Year), f_2 (Million \$/Year)	Increment Percent (%)	Decrement Percent (%)
0	$\mu_{\exp 1} = 1$	$\mu_{f_1} = 0.93623$	$f_1 = 4.3876$	0.00%	0.00%
	$\mu_{\exp 2} = 1$	$\mu_{f_2} = 0.9383$	$f_2 = 1.7379$	0.00%	0.00%
1	$\mu_{\exp 1} = 0.8$	$\mu_{f_1} = 0.76079$	$f_1 = 11.001$	150.73%	–
	$\mu_{\exp 2} = 1$	$\mu_{f_2} = 0.96186$	$f_2 = 1.3796$	–	−20.62%
2	$\mu_{\exp 1} = 1$	$\mu_{f_1} = 0.97708$	$f_1 = 2.8477$	–	−35.10%
	$\mu_{\exp 2} = 0.85$	$\mu_{f_2} = 0.91481$	$f_2 = 2.0948$	20.54%	–

8. **Conclusion.** This paper presents a multi-objective model for distribution network expansion planning based on the interactive fuzzy satisfying CLSMHBMO method to solve the short term period planning problem. For the selection of optimal location, size and DG technologies, total cost and emission cost are considered as two objective functions to be minimized. The multi-objective optimization problem has been solved by the CLSMHBMO method to derive a good optimal solution because it can search many paths to solve a problem with nonlinear mixed integer equations. By the interactive process the DNO updates the expected membership values by considering their current values as well as the objective function values associated with them until the satisfactory solution is obtained. The proposed model was implemented on an actual 69 bus distribution network and following results were concluded:

- The CLSMHBMO interactive fuzzy satisfying model can lead to the optimal planning paradigm according to DNO's point of view for short term period.
- The proposed model by the selection of proper membership expected values enables the DNO to choose the most satisfactory solution from the multiple objectives.
- By consideration of the total cost, there is not considerably difference between system planning with and without DG. It is because of energy law. In the proposed model, the energy will generate in weak system positions and locally injects to load; so main grid does not tend to inject active and reactive energy to remote loads. In this state a little increase can be seen by exploiting DGs which relates to expensiveness of new DG technologies. But these new technologies have the advantage of lower fuel consumption which conducts to lower fuel cost.

- In Emission Cost point of view a considerably reduction in emission cost is seen in system planning. This is because of new technologies of distributed resources and it is very important factor to have a green world.
- As the future work, since in the system DG plan, the power level and main DG technologies will be determined in short term planning period, the system planner would be able to conduct system generation to lower emission generation. This can be achieved by implementing new green energy resources and Microgrid concept.

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