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# Stochastic Multi-objective Distribution Network Reconfiguration Considering Wind Turbines

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**ABSTRACT:** Distribution Network Reconfiguration (DNR) is an important challenge in the operation of distribution networks which may be influenced by factors such as Wind Turbine Generators (WTG). In this paper, a novel policy is implemented to solve the DNR problem in presence of WTGs. The objectives of proposed DNR policy are minimization of active power losses, total electrical energy costs, and total emissions of the network. To solve the problem, an improved version of Honey Bee Mating Optimization (IHBMO) algorithm is implemented. Moreover, a stochastic scenario-based model is considered to meet the uncertainty of WTGs and loads. The bases of the proposed stochastic model are generation of stochastic scenarios using the roulette wheel mechanism, and a scenario reduction technique to decrease the computation burden of the problem. For each scenario, a multi-objective mechanism is employed to save non-dominated solutions extracted by IHBMO. A decision-making procedure based on fuzzy clustering technique is used to rank the obtained non-dominated solutions according to the decision-maker preferences. Finally, an 84-bus distribution test network is considered to evaluate the feasibility and effectiveness of the proposed method. Obtained results show that the proposed method can be a very promising potential method for solving the stochastic multi-objective reconfiguration problem in distribution systems.

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## 1- INTRODUCTION

### A. Research motivation

With the entry of WTGs into distribution networks, the management and operation of these networks has become more complex [1]. One of the important issues in the operation of distribution networks is the reconfiguration in radial networks. DNR is the action of closing the tie switches and opening the sectionalizing switches in the network to obtain a new radial configuration. DNR is performed for various purposes such as reducing losses, costs, and etc. [2-5].

The DNR problem, considering WTGs, is a mixed integer nonlinear optimization problem due to the binary variables representing the status of switches, and the nonlinear characteristics of power flow constraints [2].

### B. Literature review

In the recent years, important research has been conducted on the DNR problem and a great number of methods have been proposed in the technical literature. In [6], two domains are simultaneously considered for reconfiguration problem: re-switching strategies and transformer tap-changer adjustments. In [7], optimal network reconfiguration is obtained in large-scale distribution system using harmony search algorithm. In [8], network reconfiguration is implemented using minimum cost maximum flow-based branch exchanges and random walks-based loss estimations. In [9, 10], single-objective DNR problem is solved using hybrid optimization algorithms; in the hybrid algorithms, two algorithms are combined to cover weaknesses of one another. In [11], a new formulation of DNR problem is presented for reducing the voltage volatility induced by distributed generation.

In the new distribution networks, distributed generations (DG) and WTGs play a key role in the network operation [12-14]. The study on the reconfiguration of distributions in presence of DGs and WTGs has been done in several papers. In [12], the contingency assessment and network reconfiguration is studied in the presence of wind power and energy storage. In [13], a stochastic reconFiguration approach is considered for optimal coordination of V2G plug-in electric vehicles considering correlated wind power generation. In [14], an integrated approach is proposed for distribution network reconfiguration incorporating distributed generators.

### C. Necessity of the research

The papers surveyed above did not implicitly incorporate with the WTGs into the DNR problem using an exact multi-objective optimization method. Indeed, DNR is a nonlinear and non-differentiable optimization problem which could not be solved by the conventional approaches. Additionally, existence of uncertain parameters in the network such as loads and wind, may lead to undesired solutions for conFiguration

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of the networks. This paper aims to address these specific problems and presents a novel multi-objective optimization algorithm to solve the DNR problem considering the random nature of loads and wind.

In the proposed approach, DNR is modeled as a multi-objective optimization problem with the objectives of power losses, total costs, and emission of the network. To solve the proposed problem, HBMO algorithm is considered, and to improve the local search procedure of the HBMO, a new formulation is considered. Moreover, to solve the multi-objective aspect of the problem, an external memory is used to storage non-dominated solutions found along the search process, and a fuzzy clustering technique is utilized to evaluate the obtained non-dominated solutions. Finally, the goal attainment optimization (GAO) is implemented as a tool for decision making to select the proper solution based on the network requirement.

To cope the uncertainty of wind and loads, a scenario-based random approach is proposed. The scenarios are generated according to the probability distribution function and using the roulette wheel mechanism. Later, in order to reduce the computational load of the problem, a method of reducing the number of scenarios has been used.

### D. Novelty and main contributions

With considering this explanation, the novelty of the paper compared to the previous articles can be summarized as follows:

1- The DNR problem is modeled for several objectives and the uncertain effects of wind and loads are considered on the DNR problem.

2. The GAO method is used to extract the appropriate solutions to the needs of the network, which provides the ability for the decision maker to select the best response among the non-dominant solutions.

3- A new method has been used to improve the performance of the HBMO optimization algorithm, which improves the local search process of the algorithm and leads to the production of more accurate answers in less amount of time.

### E. Organization and structure of the paper

The rest of the paper includes different sections: Section II includes the mathematical model of the DNR problem. Later, in section III, the original HBMO algorithm and the method of modification of that is implemented. In section IV, the multi-objective problem is illustrated. In section V, the fuzzy clustering technique is illustrated. In section VI, the solution of stochastic problem is described. The proposed multi-objective IHBMO method is presented in section VII. The results of using the proposed method on a practical system are presented and discussed in Section VIII. Finally, the conclusion is made in Section IX.

## 2- DISTRIBUTION NETWORK RECONFIGURATION PROBLEM

In this paper, the multi-objective DNR problem is formulated for three objective functions, as follow:

1) Minimization of the power losses:

$$f_1(X) = p_{loss}(X) = \sum_{i=1}^{N_{br}} R_i \times \left|I_i\right|^2 \tag{1}$$

$$X_i = [\underbrace{Tie_1, Tie_2, ..., Tie_{N_{tie}}}_{Tie\,sweithes}, \underbrace{p_1, p_2, ...., p_{N_{DG}}}_{Power\,of\,DG\,units}, \underbrace{pf_1, pf_2, ..., pf_{g,N_{DG}}}_{Power\,factor\,of\,DG\,units}]_{1\times(N_{tie}+2N_{DG})}$$

where the vector X includes the control variables. The state of the $i^{th}$ tie switch is specified by $Tie_j$, which 0 and 1 correspond to open and close states, respectively.

2) Minimization of the total cost of injected power into the network

$$\begin{aligned} f_2(X) &= Cost(X) = \sum_{i=1}^{N_{DG}} (Cost_{DG}^{i}) + Cost_{Grid} \\ Cost_{DG}^{i} &= (C_{DG}^{i})^{\$/KW} \times p_i \\ Cost_{Grid} &= (C_{Grid})^{\$/KW} \times p_{sub} \end{aligned} \tag{2}$$

3) Minimization of emissions produced by DGs and substation bus:

$$\begin{aligned} f_3(X) &= Emission(X) = \sum_{i=1}^{N_{DG}} (E_{DG}^{i}) + E_{Grid} \\ E_{DG}^{i} &= (NOx^{DG^i} + CO2^{DG^i} + SO2^{DG^i})^{lb/MW} \times p_i \\ E_{Grid} &= (NOx^{Grid} + CO2^{Grid} + SO2^{Grid})^{lb/MW} \times p_{sub} \end{aligned} \tag{3}$$

## 3- IMPROVED HONEY BEE MATING OPTIMIZATION

### A. Primary HBMO

The basis of the primary HBMO algorithm is based on the mating process of honey bees' social life. At the beginning of the algorithm, an initial population of bees is produced, which is divided into three groups: the non-reproductive females or workers, the males or drones, and the reproductive female or queen [15]. Continuing to the process of mating begins with the queen's flight and departure from the nest. The drones follow the queen and mate with her in the air while flying. At the start, the queen starts her flight at a random speed and returns to the nest when her speed reaches near zero, or when her spermatheca is full. The details of the mating process between queen and drones have been presented in [16 and 17].

### B. Improvement of HBMO (IHBMO)

As mentioned, mating between the queen and the drones produces a population of broods. In the primary algorithm, the process of producing broods is modeled with the following formulation:

$$\begin{aligned} &\overline{X}_{best} = [x_{best,1}, x_{best,2}, \ldots, x_{best,(N_{tie}+2N_{DG})}] \\ &Sp_i = [s_{i,1}, s_{i,2}, \ldots, s_{i,(N_{tie}+2N_{DG})}] \\ &Brood_j = \overline{X}_{best} + \beta \times (\overline{X}_{best} - Sp_i) \\ &j = 1, 2, \ldots, N_{Brood} \end{aligned} \tag{4}$$

In the improved HBMO, a new rule base is proposed to improve the brood generation that could be described in IHBMO as follows. By applying this new formula, we expect to solve the algorithm local search problem.

At first, three drones $(Sp_{m_1}, Sp_{m_2}, Sp_{m_3})$ are randomly extracted from the queen's spermathecal, so that $m_1 \neq m_2 \neq m_3$. Later, the vector of drone position is calculated as follows:

$$\begin{aligned} &X_{improved,1} = Sp_{m_1} + rand(\cdot) \times (Sp_{m_2} - Sp_{m_3}) \\ &X_{improved,1} = [x_{im1,1}, x_{im1,2}, \ldots, x_{im1,(N_{tie}+2N_{DG})}] \\ &X_{Brood,1} = [x_{br1,1}, x_{br1,2}, \ldots, x_{br1,(N_{tie}+2N_{DG})}] \\ &x_{br1,i} = \begin{cases} x_{im1,i}, & \text{if } \gamma_1 \le \gamma_2 \\ s_{m1,i}, & \text{otherwise} \end{cases} \end{aligned} \tag{5}$$

$$\begin{aligned} &X_{improved,2} = \overline{X}_{best} + rand(\cdot) \times (Sp_{m_2} - Sp_{m_3}) \\ &X_{improved,2} = [x_{im2,1}, x_{im2,2}, \ldots, x_{im2,(N_{tie}+2N_{DG})}] \\ &X_{Brood,2} = [x_{br2,1}, x_{br2,2}, \ldots, x_{br2,(N_{tie}+2N_{DG})}] \\ &x_{br2,i} = \begin{cases} x_{im2,i}, & \text{if } \gamma_3 \le \gamma_2 \\ x_{best,i}, & \text{otherwise} \end{cases} \end{aligned} \tag{6}$$

Where, $rand(\cdot)$, $\gamma_1$, $\gamma_2$, $\gamma_3$ are the random numbers in the range [0, 1].

The better answer between $X_{brood,1}$ and $X_{brood,2}$ is considered as a new brood.

## 4- MULTI-OBJECTIVE OPTIMIZATION PROBLEM

In this paper, the proposed optimization problem is a complex multi-objective optimization problem with constraints, and a multi-objective IHBMO algorithm is considered to solve it. To obtain a set of pareto-optimal solutions, the introduced algorithm must optimize several objective functions simultaneously in a single run. In general, a multi-objective problem is formulated as follows [18, 19]:

$$\begin{aligned} &\min F = [f_1(X), f_2(X), \ldots, f_n(X)]^T \\ &s.t. \\ &g_i(X) < 0 \qquad i = 1, 2, \ldots, N_{ueq} \\ &h_i(X) = 0 \qquad i = 1, 2, \ldots, N_{eq} \end{aligned} \tag{7}$$

The goal of multi-objective problem solving is to extract non-dominant solutions. A non-dominate solution must overcome the other solutions. In this regard, if the following two conditions are met, solution $X_1$ dominates solution $X_2$ [20]:

(1): All the objectives corresponding to the solution $X_1$ are better than the objectives corresponding to the solution $X_2$:

$$\forall j \in \{1, 2, \ldots, n\}, f_j(X_1) \le f_j(X_2) \tag{8}$$

(2): The solution $X_1$ is completely better than $X_2$ in at least one of the objectives:

$$\exists k \in \{1, 2, \ldots, n\}, f_k(X_1) < f_k(X_2) \tag{9}$$

## 5- FUZZY BASED CLUSTERING

In the proposed multi-objective improved HBMO algorithm (MIHBMO), the solutions obtained during search and evaluation is stored in a fixed size external memory. In order to keep the external memory size constant, the non-dominated solution must be ranked according to the objective functions. Moreover, the objectives functions of DNR problem are imprecise, therefore, to recognize the best compromise solution, a fuzzy-based clustering procedure is proposed. In (10), the membership function of each objective function is defined for each non-dominated solution:

$$\mu_{fi}(X) = \begin{cases} 1 & for \;\; f_i(X) \le f_i^{\min} \\ 0 & for \;\; f_i(X) \ge f_i^{\max} \\ \dfrac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}} & f_i^{\min} \le f_i(X) \le f_i^{\max} \end{cases} \tag{10}$$

where, the values of $f_i^{min}$ and $f_i^{max}$ are evaluated using the computed results of optimizing each objective function, separately.

For each solution in the external memory, the normalized membership value is evaluated using:

$$N\mu(j) = \frac{\sum_{k=1}^{n} \omega_k \times \mu_{fk}(X_j)}{\sum_{j=1}^{m} \sum_{k=1}^{n} \omega_k \times \mu_{fk}(X_j)} \tag{11}$$

Using (11), a type of decision-making criteria is obtained which its value is changed based on the decision maker priority.

## 6- SCENARIO APPROACH BASIS

In this paper, the uncertainty caused by wind and load is modeled using load and wind forecast error. In this way, typical probability distribution functions (PDF) of the load/wind forecast errors are implemented [21]. According to reference [22], we divided the probability distribution function curve into seven segments (it should be noted that the greater number of segments will result to more accurate prediction with more computational burden). Additionally, two roulette wheels mechanism are used to generate the scenarios. The steps of generating the final scenarios are as follows:

**Step 1:** the scenario generation. The initial scenarios are generated by applying the roulette wheel mechanism to the PDFs of load and wind [23]. The structure of each scenario and its probability is shown in (12) and (13), respectively.

$$\begin{aligned} &scenario\ n = \left\{ w_{1,s}^{L_i}, w_{2,s}^{L_i}, \ldots, w_{7,s}^{L_i}, w_{1,s}^{WTG_j}, w_{2,s}^{WTG_j}, \ldots, w_{7,s}^{WTG_j} \right\} \\ &i = 1,2,\ldots,N_L \\ &j = 1,2,\ldots,N_{WTG} \\ &s = 1,2,\ldots,N_S \end{aligned} \tag{12}$$

$$\begin{aligned} &p_{Scenario_n} = \frac{\prod_{j=1}^{N_{WTG}} \sum_{i=1}^{7} w_{i,n}^{WTG_j} . \alpha_{n,i,j} . \prod_{m=1}^{N_L} \sum_{r=1}^{7} w_{r,n}^{L_m} . \alpha_{n,r,m}}{\sum_{k=1}^{N_s} \left( \prod_{j=1}^{N_{WTG}} \sum_{i=1}^{7} w_{i,n}^{WTG_j} . \alpha_{n,i,j} . \prod_{m=1}^{N_L} \sum_{r=1}^{7} w_{r,n}^{L_m} . \alpha_{n,r,m} \right)} \\ &n = 1,2,\ldots N_s \end{aligned} \tag{13}$$

**Step 2:** the scenario reduction. In this step, in order to reduce the computational burden, we use a scenario reduction method, named the developed backward reduction method [24]. Using this method, the number of scenarios is reduced by maintaining the accuracy of the work. The proposed scenario reduction method works as follow:

**Step 2-1.** Construct the Kantorovich Distance matrix (KDM) [24]. First, the KD of each pair scenario must be calculated. The KD of each pair scenarios are calculated as:

$$KD(scenario_i, scenario_j) = \left( \sum_{s=1}^{N_{WTG}+N_L} \mathrm{v}(scenario_i, scenario_j) \right)^{0.5} \tag{14}$$

where $v(scenario_i, scenario_j)$ is a cost function, defined as vector distance between scenarios i and j subsets.

**Step 2-2.** Determine the next closest scenario to each scenario ( $\min\left\{KD(scenario_i, scenario_j)\right\}$ ).

**Step 2-3.** Compute $kp^{i,j}$ for each pair of scenarios in the previous step:

$$kp^{i,j} = \min\left\{KD(scenario_i, scenario_j)\right\} \times p_{scenario_i} \tag{15}$$

Compare the $kp^{i,j}$ for all scenario pairs in the KDM and locate which pair has the minimum value. From the two members of this pair, the deleting scenario is chosen based on: (i) relative closeness to other scenarios, and (ii) small probability of occurrence.

**Step 2-4.** After deleting one scenario, add the probability of the deleted scenario to the probability of the scenario which is closest to it and construct new KDM.

**Step 2-5.** Go to step 2 and eliminate 1 scenario during each iteration, until the desired number of final remaining scenarios is met.

**Step 3:** Generate aggregated Scenario. The scenario aggregation method is formulated as follows:

$$\sum_{s=1}^{N_s} \min \{p_{Scenario} f(\mathrm{X}_s)\} \quad i = 1,\ldots,N_s \tag{16}$$

After executing this equation, a decision maker can claim that the output control variables can optimize all scenarios while the constraints are met in them.

## 7- Stochastic MIHBMO algorithm

In the previous sections, different parts of the stochastic MIHBMO algorithm were presented. The flowchart of the proposed algorithm to solve the DNR problem in presence of WTGs is presented in Fig. 1.

## 8- SIMULATION RESULTS

### A. Assumption

In this paper, MIHBMO algorithm is proposed to solve multi-objective DNR problem containing WTG units. The studies have been implemented in MATLAB 2014 using an Intel(R) Core (TM) i7-7500 CPU, 2.7-GHz personal computer with 8 GB of RAM.

A practical case study is used in this section to analyze the performance of the proposed method. The proposed case study is IEEE 84-bus radial distribution Network [9], and its schematic is shown in Fig. 1. To optimize the multi-objective DNR problem containing DG units, 10 DG units are placed on the proposed distribution network. Five units of all DG units are considered as WTG and another five units are considered for backing WTGs that their specification is given in Table 1. Moreover, the emission factor corresponding to $NO_X$, $CO_2$ and $SO_2$ are shown in Table 2.

### B. Sensitivity analysis of IHBMO algorithm

The most important parameter of HBMO algorithm is the number of the initial population, which has a direct impact on the accuracy and execution time of the algorithm. Table 3 evaluates the sensitivity of the IHBMO algorithm to the initial population size compared to the original HBMO algorithm. For each case (number of population), both algorithms are run 20 times and their results are summarized from different points of view. According to the results of Table 3, it is clear that the IHBMO algorithm is robust and less sensitive than the HBMO algorithm.

It should be noted that in Table 3, the DNR problem is solved for loss minimization without considering DGs and WTGs.

### C. Comparison of IHBMO with Other Methods

In order to compare the results of the algorithm with other papers, Table 4 presents the results of the DNR problem on the original 84-bus network. Since the DNR problem has been solved without considering DGs in the previous papers, in this section DGs are omitted. In

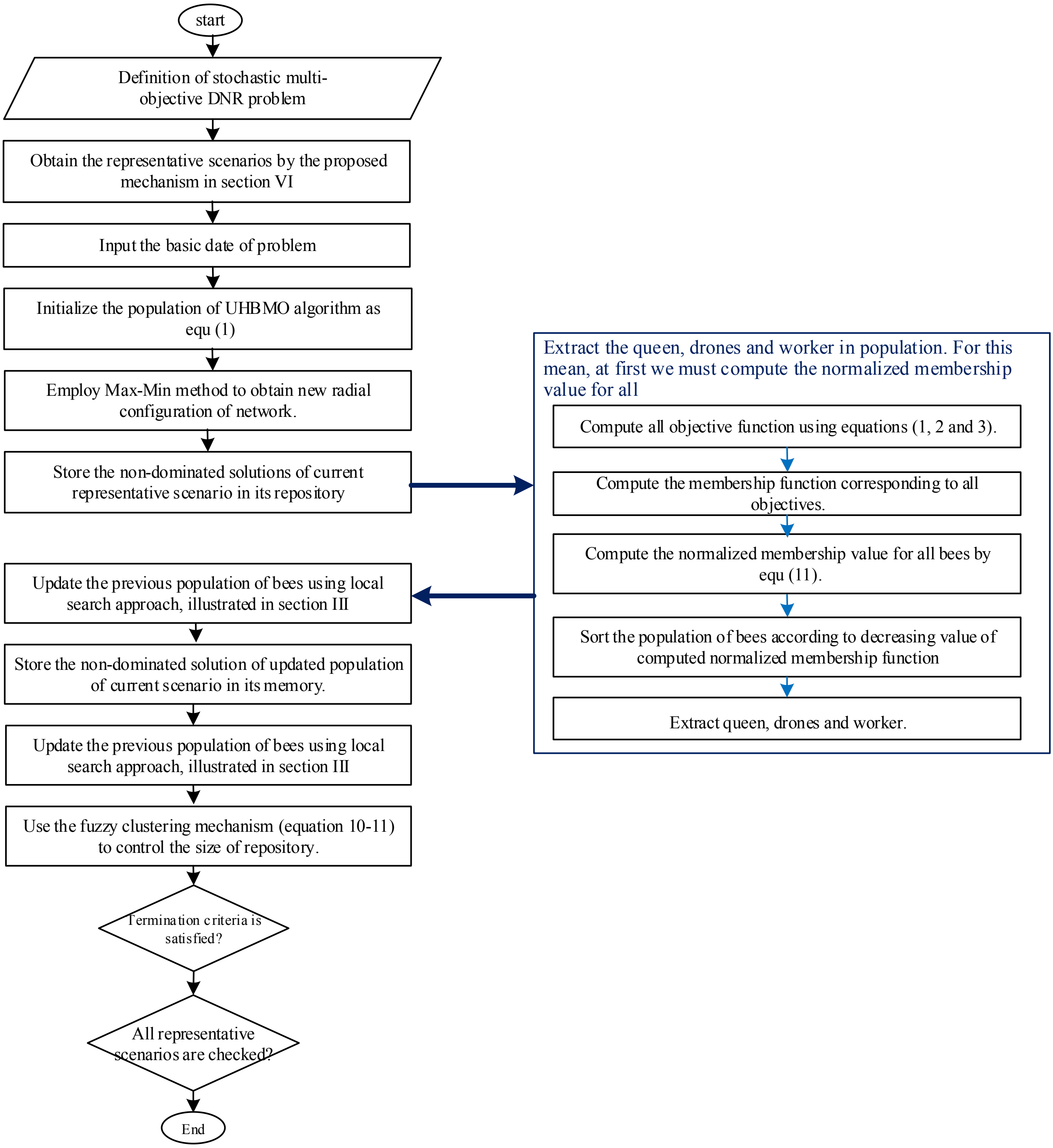



**Fig 1. Flowchart of proposed MIHBMO algorithm for stochastic multi-objective DNR problem**

this Table, the DNR problem is solved to minimize the networks losses. According to the results of Table 4, the proposed algorithm performs better than references [26, 27], and obtains the same results as references [28, 29], which confirms the efficiency of the proposed method.

To check the efficiency of IHBMO over the original HBMO algorithm, the objective functions including the total active power losses, the total cost of DG units and substation buses and the total emission produced by DG units and substation buses are minimized separately. The individually optimized results are shown in Tables 5, 6 and 7, respectively. By comparing the results of IHBMO algorithm in comparison to the original HBMO for 20 random tails, it is obvious that the IHBMO algorithm is able to find better solutions for each objective function.

D. Application of MIHBMO to solve Stochastic Multi-

**Table 1. Specification of DG units**

| DG number | Capacity (kw) | DG type | Location |
|---|---|---|---|
| $DG_1$ | 300 | Gas turbine | 3 |
| $DG_2$ | 300 | Gas turbine | 59 |
| $DG_3$ | 300 | Micro turbine | 21 |
| $DG_4$ | 300 | Micro turbine | 76 |
| $DG_5$ | 300 | Gas turbine | 46 |
| $WTG_1$ | 200 | Wind turbine | 54 |
| $WTG_2$ | 200 | Wind turbine | 11 |
| $WTG_3$ | 200 | Wind turbine | 71 |
| $WTG_4$ | 200 | Wind turbine | 36 |
| $WTG_5$ | 200 | Wind turbine | 82 |

**Table 2. Emission factor [25]**

| Emission type | Emission factors (kg/MWh) | | | |
|---|---|---|---|---|
| | Micro turbine | Gas turbine | Grid | WTG |
| **$NO_x$** | 0.44 | 0.03 | 2.2952 | 0 |
| **$CO_2$** | 1596 | 1078 | 921.25 | 0 |
| **$SO_2$** | 0.008 | 0.006 | 3.5824 | 0 |

**Table 3. Results for different population**

| Number of populations | Method | Average of loss (kW) | Standard deviation | Worst solution (kW) | Best solution (kW) | No of global solution |
|---|---|---|---|---|---|---|
| 20 | HBMO | 475.6 | 9.8 | 496.9 | 469.8 | 0 |
| | IHBMO | 467.7 | 3.2 | 471.0 | 463.2 | 4 |
| 40 | HBMO | 471.2 | 4.1 | 475.7 | 466.2 | 0 |
| | IHBMO | 466.1 | 1.9 | 471.0 | 463.2 | 7 |
| 80 | HBMO | 467.5 | 2.4 | 469.7 | 463.2 | 5 |
| | IHBMO | 464.5 | 1.1 | 466.2 | 463.2 | 10 |
| 160 | HBMO | 465.3 | 1.3 | 471.0 | 463.2 | 11 |
| | IHBMO | 463.2 | 0 | 463.2 | 463.2 | 20 |
| 320 | HBMO | 463.8 | 0.97 | 465.2 | 463.2 | 14 |
| | IHBMO | 463.2 | 0 | 463.2 | 463.2 | 20 |

**Table 4. Comparison of IHBMO with other method of DNR problem**

| Method | Loss (kW) | Loss Reduction (%) | Min Voltage (V) | Open Switches |
|---|---|---|---|---|
| IHBMO | 463.2 | 12.92 | 0.9532 | S55, S7, S86, S72, S88, S14, S90, S83, S92, S39, S34, S42, S62 |
| Chiou et al. [26] | 469.8 | 11.68 | 0.9285 | S55, S7, S86, S72, S88, S89, S90, S83, S92, S35, S34, S41, S62 |
| SA [27] | 469.8 | 11.68 | 0.9285 | S55, S7, S86, S72, S88, S89, S90, S83, S92, S35, S34, S41, S62 |
| Ahuja et al. [28] | 463.2 | 12.92 | 0.9532 | S55, S7, S86, S72, S88, S14, S90, S83, S92, S39, S34, S42, S62 |
| SAFWA [29] | 463.2 | 12.92 | 0.9532 | S55, S7, S86, S72, S88, S14, S90, S83, S92, S39, S34, S42, S62 |

**Table 5. Comparison of average and standard deviation for 20 trails (objective function f1)**

| Method | Best solution(kW) | Worst solution(kW) | Average(kW) | Time (Sec) |
|---|---|---|---|---|
| IHBMO | 428.7424 | 429.1095 | 428.9051 | ~396 |
| HBMO | 431.8361 | 436.1372 | 433.8189 | ~417 |

**Table 6. Comparison of average and standard deviation for 20 trails (objective function f2)**

| Method | Best solution(kg) | Worst solution(kg) | Average(kg) | Time (Sec) |
|---|---|---|---|---|
| IHBMO | 169640.52 | 170228.09 | 169802.93 | ~383 |
| HBMO | 169770.49 | 172166.77 | 171594.10 | ~411 |

**Table 7. Comparison of average and standard deviation for 20 trails (objective function f3)**

| Method | Best solution ($) | Worst solution ($) | Average ($) | Time (Sec) |
|---|---|---|---|---|
| IHBMO | 1552.513 | 1558.886 | 1553.810 | ~409 |
| HBMO | 1567.521 | 1574.040 | 1569.849 | ~437 |

**Table 8. The active power of WTG corresponding to 10 representative scenarios and aggregated scenario**

| Number | Active power (kW) | | | | | |
|---|---|---|---|---|---|---|
| | WTG1 | WTG2 | WTG3 | WTG4 | WTG5 | probability |
| 1 | 310.08 | 295 | 299.91 | 305 | 305 | 0.109 |
| 2 | 299.91 | 305 | 299.91 | 294.83 | 310 | 0.110 |
| 3 | 305 | 295 | 295 | 305 | 300 | 0.100 |
| 4 | 299.91 | 310 | 290.08 | 310.08 | 300 | 4.12e-5 |
| 5 | 299.91 | 300 | 290.08 | 310.08 | 295 | 1.05e-2 |
| 6 | 310.08 | 305 | 295 | 310.08 | 305 | 4.39e-03 |
| 7 | 310.08 | 305 | 290.08 | 305 | 305 | 1.74e-06 |
| 8 | 294.83 | 295 | 285.16 | 299.91 | 290 | 0.087 |
| 9 | 315.16 | 295 | 295 | 310.08 | 300 | 0.232 |
| 10 | 305 | 290 | 295 | 294.83 | 295 | 0.373 |
| Aggregated scenario | 306.48 | 294.12 | 295.10 | 300.92 | 298.73 | - |

objective DNR problem Considering Wind Turbines

To model the stochastic problem, first 1000 realizations of WTG production and loads value were developed as the initial scenario set. The developed backward reduction method was then used to obtain 10 representative scenarios. For this mean, 990 iterations of the scenario reduction method were run. The active power of WTG corresponding to final set of reduced scenarios is shown in Table 8. In the last rows of Table 8 the results of aggregated scenario are shown.

Table 9 shows the three solutions related to extreme trade-off points of the representative scenario. According to Table 9, the results obtained from the stochastic multi-objective DNR problem, differ from the deterministic results. This difference is due to the fact that in stochastic modeling, different cases of wind turbine production and load are considered for the proposed problem, but in the deterministic wind generation

**Table 9. Optimum results of each representative scenario**

| No | Power losses(kw) | Emission (kg) | Cost ($) | Open switches |
|---|---|---|---|---|
| | **425.42** | 177328.42 | 1625.07 | 1, 85, 11,87, 75, 12, 90, 91, 92, 29, 94, 41, 49 |
| 1 | 497.24 | **170473.10** | 1700.59 | 84, 85, 86, 65, 75, 12, 15, 91, 92, 93, 94, 95, 49 |
| | 460.06 | 179510.07 | **1566.45** | 84, 6, 86, 87, 75, 12, 15, 91, 92, 29, 94 95, 96 |
| | **426.02** | 172423.55 | 1649.79 | 1, 6, 86, 87, 88, 89,90, 91, 92, 93, 94, 95, 96 |
| 2 | 572.70 | **169792.25** | 1691.33 | 84, 85, 11, 65, 75, 89, 15, 77, 92, 29, 94, 95, 96 |
| | 649.12 | 183822.65 | **1553.02** | 84, 76, 11, 65, 75, 89, 15, 77, 25, 29, 94, 95, 96 |
| | **425.50** | 172797.93 | 1658.19 | 84, 85, 11, 87, 75, 12, 15, 91, 25, 93, 94, 41, 49 |
| 3 | 535.57 | **169069.81** | 1671.48 | 1, 85, 86,87, 88, 89, 15, 77, 25, 93, 94, 95, 96 |
| | 544.51 | 180546.64 | **1550.75** | 1, 85, 11,87, 75, 89, 90, 91, 92, 29, 94, 41, 96 |
| | **433.88** | 179010.68 | 1609.71 | 84, 6, 86,65, 75, 89, 90, 91, 92, 93, 94 41, 49 |
| 4 | 502.16 | **170953.00** | 1678.22 | 1, 6, 11, 87, 88, 17,15, 91, 25, 93, 94, 95, 49 |
| | 598.38 | 180857.54 | **1554.69** | 84, 6, 11, 65, 64, 89, 15, 91, 25, 93, 94, 95, 96 |
| | **443.90** | 179498.88 | 1418.86 | 84, 6, 86,65, 88, 89, 90, 91, 92, 29, 94, 41, 96 |
| 5 | 454.62 | **176025.91** | 1450.04 | 1, 6, 11, 65, 88, 89, 15, 91, 25, 29, 94, 41, 96 |
| | 534.17 | 189108.55 | **1313.34** | 1, 85, 11, 65, 88, 89, 90, 91, 92, 93, 94, 95, 96 |
| | **425.85** | 174016.11 | 1685.64 | 84, 6, 11, 87, 88, 89, 15, 91, 92, 93, 94, 41, 96 |
| 6 | 497.97 | **170962.18** | 1688.70 | 1, 6, 86, 65, 88, 89, 15, 77, 92, 93, 94, 95, 96 |
| | 613.30 | 181488.78 | **1566.52** | 1, 6, 86, 65, 75, 89, 90, 77, 25, 29, 94, 95, 96 |
| | **425.39** | 177345.86 | 1622.93 | 84, 6, 86, 87, 88, 89, 90, 91, 92, 93, 94, 41, 96 |
| 7 | 569.68 | **169866.34** | 1690.85 | 84, 6, 11, 87, 88, 89, 90, 77, 92, 29, 94, 41, 96 |
| | 679.77 | 181727.66 | **1552.63** | 1, 6, 86, 87, 88, 17, 90, 91, 25, 29, 94, 95, 96 |
| | **426.30** | 170538.66 | 1610.09 | 1, 6, 86, 87, 88, 89,90, 77, 92, 29, 94, 41, 96 |
| 8 | 464.57 | **169325.95** | 1657.21 | 84, 6, 11,87, 75, 12, 90, 77, 92, 29, 94, 41, 96 |
| | 472.46 | 180272.34 | **1536.55** | 1, 6, 86, 65, 88, 89,90, 77, 25, 93, 94, 95, 96 |
| | **430.41** | 178828.47 | 1609.37 | 84, 6, 86,87, 75, 12, 15, 91, 25, 93, 94, 95, 96 |
| 9 | 519.81 | **169130.85** | 1677.02 | 1, 85, 11,65, 75, 12, 90, 91, 92, 93, 94, 41, 49 |
| | 464.91 | 180241.75 | **1547.06** | 1, 6, 11, 65, 88, 89, 90, 91, 92, 93, 94, 41, 96 |
| | **425.94** | 173916.44 | 1609.01 | 84, 85, 11, 87, 75, 12, 15, 77, 25, 93, 94, 95, 49 |
| 10 | 475.40 | **170972.35** | 1667.30 | 1, 6, 11, 65, 75, 89,15, 77, 25, 29, 94, 41, 49 |
| | 672.08 | 180899.60 | **1545.24** | 84, 6, 86,87, 88, 89, 90, 91, 25, 93, 94, 41, 49 |

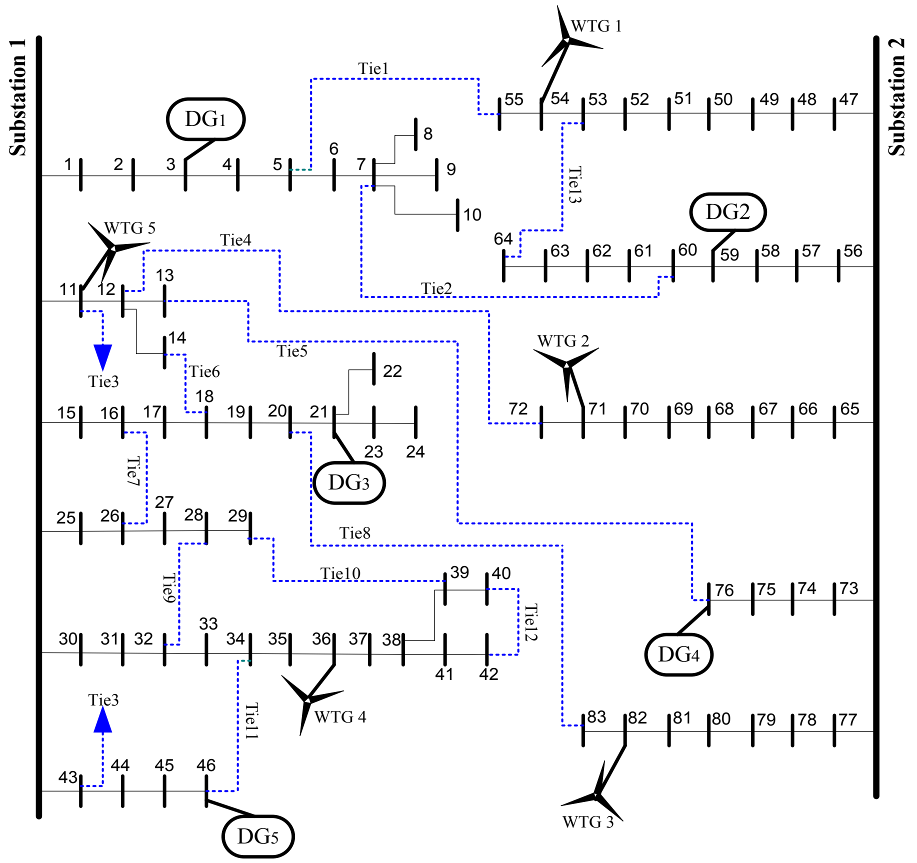
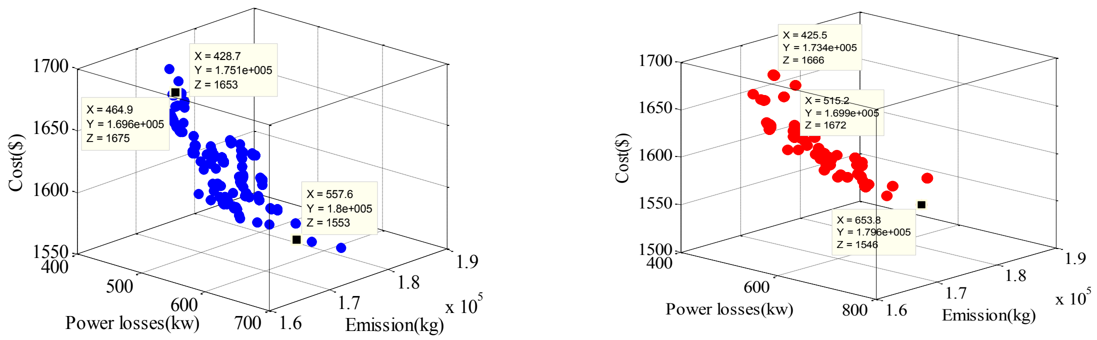



Fig 2. Single line diagram of distribution test system [9]




a) Deterministic scenario b) Aggregated scenario.

Fig 3. Obtained non-dominated solutions of multi-objective DNR problem.

and load model, only one scenario is considered. Fig. 2 shows the Pareto fronts obtained from the deterministic and the aggregated scenario. According to the presented results in Table 9 and Fig. 3, it is obvious that the difference between the results of the deterministic and the representative scenarios ignore the concern of proper WTG prediction and load in the DNR problemss.

According to the results presented of Table 9 and Fig. 3, there is a clear difference between the results of deterministic and stochastic analysis. The probability of occurrence of deterministic scenario 4.1% (among 1000 generated scenarios) and represented scenarios is the total of 10.4%. In other words, the probability of occurrence of aggregated scenario is 2.53 times the probability of occurrence deterministic scenario, and as a result the answer is closer to reality. It should be noted that if we want to increase the probability of occurrence of aggregated scenario, we should consider more representative scenarios that lead to an increase in the computational load of the problem.

The main goal of producing non-dominant solutions to

**Table 10: Objective functions values in all cases, (Aggregated scenario)**

| Case | Importance | | | | | |
|---|---|---|---|---|---|---|
| | $W_1$ | $W_2$ | $W_3$ | Power losses(kw) | Emission(kg) | Cost($) |
| I | 1 | 0 | 0 | **425.5052** | 173375.1 | 1666.02 |
| II | 0 | 1 | 0 | 515.2248 | **169863**.2 | 1672.20 |
| III | 0 | 0 | 1 | 653.7676 | 179551.2 | **1546.26** |
| | 0 | 0.5 | 0.5 | - | 171279.4 | 1643.83 |
| IV | 0 | 0.3 | 0.7 | - | 172109.1 | 1613.82 |
| | 0 | 0.7 | 0.3 | - | 171214.2 | 1644.20 |
| | 0.5 | 0 | 0.5 | 507.9013 | - | 1590.46 |
| V | 0.3 | 0 | 0.7 | 503.2578 | - | 1574.78 |
| | 0.7 | 0 | 0.3 | 442.4666 | - | 1592.59 |
| | 0.5 | 0.5 | 0 | 460.0125 | 177635.5 | - |
| VI | 0.7 | 0.3 | 0 | 446.8394 | 177311.2 | - |
| | 0.3 | 0.7 | 0 | 501.0477 | 176336.1 | - |
| | 0.33 | 0.33 | 0.33 | 462.1669 | 178910.9 | 1577.57 |
| | 0.2 | 0.4 | 0.4 | 527.8031 | 176274.6 | 1568.58 |
| | 0.4 | 0.2 | 0.4 | 457.9954 | 179053.6 | 1578.14 |
| VII | 0.4 | 0.4 | 0.2 | 457.8056 | 175099.1 | 1602.01 |
| | 0.2 | 0.2 | 0.6 | 503.7636 | 175615.3 | 1571.20 |
| | 0.2 | 0.6 | 0.2 | 463.1760 | 175033.7 | 1600.82 |
| | 0.6 | 0.2 | 0.2 | 445.9974 | 177092.9 | 1592.08 |

the proposed multi-objective DNR problem is to achieve the best compromise solution based on the needs of the networks. In this regard, the goal attainment optimization (GAO) approach [26] is used to select the best compromise solution among the existing solutions. It is stated that in the GAO, a vector of weights ($W=\{w_1,w_2,....,w_n\}$) is considered to control the importance of objectives that $\sum_{i=1}^{n} w_i=1$. In Table 8, the obtained results of the GAO method are presented.

Table 10 presents seven different solutions extracted by GAO from the total solutions. The proposed solutions indicate the different preferences of the decision maker in different network conditions. For example, the first solution (case 1) is for the case where the loss is an important solution and the operator has given all the weight to the losses ($w_1=1, w_2=0\, and\, w_3=0$). In the VII-1 case, all three objective functions are equally important and have equal weight ($w_1=0.33, w_2=0.33\ and\ w_3=0.33$).

## 9- CONCLUSION

In this paper, a multi-objective evolutionary algorithm based on the modification of HBMO algorithm, has been proposed to solve the multi-objective DNR problems. The objectives of the DNR problems were active power losses, total electrical energy costs and total emissions of DGs and substation busses. Additionally, the problem has been solved in the stochastic framework by generating stochastic scenarios to reach a more realistic solution. Moreover, to decrease the computational burden, a developed backward technique has been employed to decrease the number of produced scenarios. Finally, to extract the preferable non-dominant solutions, the GAO mechanism was applied on the proposed problem. The obtained results prove the following findings for the paper:

- Better performance of IHBMO than HBMO in local search.
- Efficient model for stochastic nature of load and wind in the DNR problem.
- The ability of decision maker in finding optimal

configuration based on the priority of operation.

Moreover, the other technical aspect of the network such as protection schemes, volt-var control and etc. could be added in the DNR problem.

## APPENDIX.

**Table.A. Three-phase load and line data of case study.**

| Bus to bus | Section resistance (Ω) | Section reactance (Ω) | End bus real load (kw) | End bus reactive load (kv Ar) | Bus to bus | Section resistance (Ω) | Section reactance (Ω) | End bus real load (kw) | End bus reactive load (kv Ar) |
|---|---|---|---|---|---|---|---|---|---|
| A-1 | 0.1944 | 0.6624 | 0 | 0 | 48-49 | 0.0655 | 0.1345 | 0 | 0 |
| 1-2 | 0.2096 | 0.4304 | 100 | 50 | 49-50 | 0.0393 | 0.0807 | 200 | 160 |
| 2-3 | 0.2358 | 0.4842 | 300 | 200 | 50-51 | 0.0786 | 0.1614 | 800 | 600 |
| 3-4 | 0.0917 | 0.1883 | 350 | 250 | 51-52 | 0.0393 | 0.0807 | 500 | 300 |
| 4-5 | 0.2096 | 0.4304 | 220 | 100 | 52-53 | 0.0786 | 0.1614 | 500 | 350 |
| 5-6 | 0.0393 | 0.0807 | 1100 | 800 | 53-54 | 0.0524 | 0.1076 | 500 | 300 |
| 6-7 | 0.0405 | 0.1380 | 400 | 320 | 54-55 | 0.1310 | 0.2690 | 200 | 80 |
| 7-8 | 0.1048 | 0.2152 | 300 | 200 | H-56 | 0.2268 | 0.7728 | 0 | 0 |
| 7-9 | 0.2358 | 0.4842 | 300 | 230 | 56-57 | 0.5371 | 1.1029 | 30 | 20 |
| 7-10 | 0.1048 | 0.2152 | 300 | 260 | 57-58 | 0.0524 | 0.1076 | 600 | 420 |
| B-11 | 0.0786 | 0.1614 | 0 | 0 | 58-59 | 0.0405 | 0.1380 | 0 | 0 |
| 11-12 | 0.3406 | 0.6944 | 1200 | 800 | 59-60 | 0.0393 | 0.0807 | 20 | 10 |
| 12-13 | 0.0262 | 0.0538 | 800 | 600 | 60-61 | 0.0262 | 0.0538 | 20 | 10 |
| 12-14 | 0.0786 | 0.1614 | 700 | 500 | 61-62 | 0.1048 | 0.2152 | 200 | 130 |
| C-15 | 0.1134 | 0.3864 | 0 | 0 | 62-63 | 0.2358 | 0.4842 | 300 | 240 |
| 15-16 | 0.0524 | 0.1076 | 300 | 150 | 63-64 | 0.0243 | 0.0828 | 300 | 200 |
| 16-17 | 0.0524 | 0.1976 | 500 | 350 | I-65 | 0.0486 | 0.1656 | 0 | 0 |
| 17-18 | 0.1572 | 0.3228 | 700 | 400 | 65-66 | 0.1703 | 0.3497 | 50 | 30 |
| 18-19 | 0.0393 | 0.0807 | 1200 | 1000 | 66-67 | 0.1215 | 0.4140 | 0 | 0 |
| 19-20 | 0.1703 | 0.3497 | 300 | 300 | 67-68 | 0.2187 | 0.7452 | 400 | 360 |
| 20-21 | 0.2358 | 0.4842 | 400 | 350 | 68-69 | 0.0486 | 0.1656 | 0 | 0 |
| 21-22 | 0.1572 | 0.3228 | 50 | 20 | 69-70 | 0.0729 | 0.2484 | 0 | 0 |
| 21-23 | 0.1965 | 0.4035 | 50 | 20 | 70-71 | 0.0567 | 0.1932 | 2000 | 1500 |
| 23-24 | 0.1310 | 0.2690 | 50 | 10 | 71-72 | 0.0262 | 0.0528 | 200 | 150 |
| D-25 | 0.0567 | 0.1932 | 50 | 30 | J-73 | 0.3240 | 1.1040 | 0 | 0 |
| 25-26 | 0.1048 | 0.2152 | 100 | 60 | 73-74 | 0.0324 | 0.1104 | 0 | 0 |
| 26-27 | 0.2489 | 0.5111 | 100 | 70 | 74-75 | 0.0567 | 0.1932 | 1200 | 950 |
| 27-28 | 0.0486 | 0.1656 | 1800 | 1300 | 75-76 | 0.0486 | 0.1656 | 300 | 180 |
| 28-29 | 0.1310 | 0.2690 | 200 | 100 | K-77 | 0.2511 | 0.8556 | 0 | 0 |
| E-30 | 0.1965 | 0.3960 | 0 | 0 | 77-78 | 0.1296 | 0.4416 | 400 | 360 |
| 30-31 | 0.1310 | 0.2690 | 1800 | 1600 | 78-79 | 0.0486 | 0.1656 | 2000 | 1300 |
| 31-32 | 0.1310 | 0.2690 | 200 | 150 | 79-80 | 0.1310 | 0.2640 | 200 | 140 |
| 32-33 | 0.0262 | 0.0538 | 200 | 100 | 80-81 | 0.1310 | 0.2640 | 500 | 360 |
| 33-34 | 0.1703 | 0.3497 | 800 | 600 | 81-82 | 0.0917 | 0.1883 | 100 | 30 |
| 34-35 | 0.0524 | 0.1076 | 100 | 60 | 82-83 | 0.3144 | 0.6456 | 400 | 360 |
| 35-36 | 0.4978 | 1.0222 | 100 | 60 | 5-55 | 0.1310 | 0.2690 | | |
| 36-37 | 0.0393 | 0.0807 | 20 | 10 | 7-60 | 0.1310 | 0.2690 | | |
| 37-38 | 0.0393 | 0.0807 | 20 | 10 | 11-43 | 0.1310 | 0.2690 | | |
| 38-39 | 0.0786 | 0.1614 | 20 | 10 | 12-72 | 0.3406 | 0.6994 | | |
| 39-40 | 0.2096 | 0.4304 | 20 | 10 | 13-76 | 0.4585 | 0.9415 | | |
| 38-41 | 0.1965 | 0.4035 | 200 | 160 | 14-18 | 0.5371 | 1.0824 | | |
| 41-42 | 0.2096 | 0.4304 | 50 | 30 | 16-26 | 0.0917 | 0.1883 | | |
| F-43 | 0.0486 | 0.1656 | 0 | 0 | 20-83 | 0.0786 | 0.1614 | | |
| 43-44 | 0.0393 | 0.0807 | 30 | 20 | 28-32 | 0.0524 | 0.1076 | | |
| 44-45 | 0.1310 | 0.2690 | 800 | 700 | 29-39 | 0.0786 | 0.1614 | | |
| 45-46 | 0.2358 | 0.4842 | 200 | 150 | 34-46 | 0.0262 | 0.0538 | | |
| G-47 | 0.2430 | 0.8280 | 0 | 0 | 40-42 | 0.1965 | 0.4035 | | |
| 47-48 | 0.0655 | 0.1345 | 0 | 0 | 53-64 | 0.0393 | 0.0807 | | |

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| | | | |
|---|---|---|---|
| $R_i$ | Resistance of the $i^{th}$ branch | $\beta$ | A random number between 0 and 1 |
| $I_i$ | Current of the $i^{th}$ branch | $Brood_j$ | The $j^{th}$ brood. |
| $N_{br}$ | Mumber of branches | $g_i(X)$ | Inequality constraints. |
| $Tie_j$ | State of the $i^{th}$ tie switch | $h_i(X)$ | Equality constraints. |
| $p_k$ | Active power of $k^{th}$ DG | $n$ | Number of objective functions. |
| $pf_k$ | Power factor of $k^{th}$ DG | $f_i^{min}$ | Lower limits of the $i^{th}$ objective function |
| $N_{tie}$ | Number of tie switches | $f_i^{max}$ | Upper limits of the $i^{th}$ objective function |
| $N_{DG}$ | Number of DGs | $m$ | number of non-dominated solutions |
| $Cost^i_{DG}$ | Cost of $i^{th}$ DGs | $\omega_k$ | weight for the $k^{th}$ objective function |
| $Cost_{Grid}$ | Cost of substation bus | $w_{k,s}^{L_i}$ | A binary parameter indicating whether the $k^{th}$ class interval of the $i^{th}$ load is selected ( $w_{k,s}^{L_i}=1$) or not ($w_{k,s}^{L_i}=0$) |
| $C^i_{DG}$ | Cost coefficient of $i^{th}$ DG | $w_{k,s}^{WTG_j}$ | a binary parameter indicating whether the $k^{th}$ class interval of the $j^{th}$ WTG is selected ($w_{k,s}^{WTG_j}=1$) or not ($w_{k,s}^{WTG_j}=0$). |
| $C_{Grid}$ | Cost coefficient of substation bus | $N_L$ | Number of loads. |
| $E^i_{DG}$ | Emission produced by the $i^{th}$ DG | $N_{WTG}$ | Number of WTGs. |
| $E_{Grid}$ | Emission produced by the substation bus. | $N_s$ | Number of initial scenarios. |
| $f_i(X)$ | The $i^{th}$ objective function. | $\alpha_i$ | probability of $i^{th}$ interval of PDF. |

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