

# Solving The Active Distribution Network Reconfiguration (ADNR) Problem Taking Into Consideration A Stochastic Wind Scenario and Load Uncertainty By Using HBFDE Method

Mr. Peter Musau Moses<sup>1</sup>, Dr. Nicodemus Abungu Odero<sup>2</sup>

<sup>1</sup>Post Graduate Student, <sup>2</sup>Senior Lecturer, Department of Electrical and Information Engineering, The University of Nairobi-Kenya, P.O Box 30197-00100 GPO

**Abstract--** Past literature has attempted to solve the problem of network reconfiguration with Distributed Generators (DGs) without taking into consideration the intermittent renewable at a close proximity. Distribution Network Reconfiguration (ADNR) must account uncertain behavior of loads and wind when the commercial wind based DG, Doubly Fed Induction Generators (DFIG) supports a significant part of network. In this paper, a new Hybrid Bacterial Foraging and Differential Evolution (HBFDE) algorithm is considered for the ADNR problem with minimum loss and an improved voltage profile. In the HBFDE algorithm the Differential Evolution (DE) algorithm is combined with the Bacterial Foraging (BF) algorithm to overcome slow and premature convergence of BF. Indeed, the proposed algorithm is based on the evolutionary natures of BF and DE, to take their advantage of the compensatory property, and avoid their corresponding drawbacks. In addition, to cope with the uncertainty behavior of loads and wind, a stochastic model is presented to solve the ADNR problem when the uncertainty related to wind and load forecast is modeled in a stochastic framework on scenario approach basis. The proposed algorithm is tested on the IEEE 33-Bus Radial Distribution Test Systems. The results of the simulation show the effectiveness of proposed algorithm real time and real world optimization problems facing the smart grid.

**Keywords--** Active Distribution Network Reconfiguration (ADNR), Bacterial Foraging (BF), Differential Evolution (DE), Doubly Fed Induction Generators (DFIG), Hybrid Bacterial Foraging and Differential Evolution (HBFDE).

## I. INTRODUCTION

The configuration of electric distribution networks is mostly as radial for proper protection coordination. Due to some objectives such as: supply all of the loads, reduce power loss, increase system security and enhance power quality; the configuration of these networks may be changed with automatic or manual switching operations. Distribution network reconfiguration also relieves the overloading of network components.

This change is performed by opening sectionalizing (normally closed) and closing tie (normally open) switches of the network. These switching operations are performed in such a way that all of the loads are energized and the radiality of the network is preserved. From the impact of DG on power distribution networks, the distribution system reconfiguration is found to have more line losses and reduction of terminal voltage as compared to transmission network. For optimizing power loss, the new reconfiguration can be used as the feeder reconfiguration as a systematic method to operate the distribution system at minimum cost and with improved system reliability and security. By opening or closing the feeder switches, load currents can be transferred from feeder to feeder thus helping to study the effect of DG on the distribution networks with reference to network reconfiguration problems.

The algorithms dealing with feeder reconfigurations like heuristic based and modern optimization methods have been proposed to solve the problem. The GA based method and Ant Colony Optimization (ACO) were proposed for optimal reconfiguration in presence of DG for distribution system power loss reduction respectively. The other conventional methods like Honey Bee Colony Optimization (HBCO) and Dig Silent software were also suggested. The feeder reconfiguration and DG placement process not only reduce the power loss but also improve the voltage profile. DGs are not only employed to provide real and /or reactive power compensation in distribution systems but also to reduce the power losses and to maintain the voltage profile within acceptable limits. This paper will focus on the wind specialized DFIG.

The numerous advantages of the DFIG in terms of their low or zero emission and their much smaller size than conventional central power plants have created more incentives than before to use these kinds of generators with free energy source.

Therefore, it is necessary to study the impact of DFIGs units on the distribution networks especially on the distribution network reconfiguration problem [1]-[2].

#### *A: General Review*

Many studies have undertaken the challenge of loss minimization in the area of the network reconfiguration. One of the first papers on this area had been introduced by Merlin and Back [3]. They solved the problem by the branch and bound method. But the introduced method has two drawbacks. Firstly, the convergence of the solution was not guaranteed, and secondly it required a huge amount of calculations for a real network. In [4], a simple innovative method for calculating loss through the network reconfiguration, which is based on some simplifications in order to calculate the change of loss in load transfer from one feeder to another, was proposed. Ajaja and Galiana improved the method in [4], with a few corrections. The main negative points of the method are that there is no guarantee to reach the global solution and the final solution depends on the initial status of the switches [5]. In [6, 10], a problem for loss reduction and load balancing as an artificial bee colony (ABC) problem was modeled. Qiwan et al introduced a power-flow-minimum heuristic algorithm for ADNR problem [8]. In [9], a model based automated strategy was considered the DNR problem taking the smart grid into consideration. Das proposed a GA and Spanning trees multi-objective approach to solve the ADNR problem [11].

Many papers have been used evolutionary algorithms to solve ADNR problem. In [7], an algorithm was considered for efficient and automatic network reconfiguration (EANR) based on the service restoration and load balancing in a real-time operation. The method was based on differential evolution. Chiou et al presented a variable scaling hybrid differential evolution (VSHDE) to solve the ADNR. In his work, minimizing the power loss was considered as the objective function [12]. Nuno and Susana proposed a method for network reconfiguration to minimize power loss by using the improved mixed-integer hybrid differential evolution [13]. In [14], a PSO based algorithm for multi-objective ADNR with fault restoration is proposed. Zhang et al proposed a hybrid algorithm based on GA and PSO for ADNR problem [15]. Yu et al [16] proposed an improved genetic algorithm with infeasible solution disposing for DNR problem. In all mentioned papers, the ADNR problem has been solved without considering the DFIG units, and in this paper, is considered for the first time

#### *B: ADNR with DFIG*

Recent studies on the ADNR problem with wind has been done by considering general wind turbines. To achieve the reconfiguration of distribution network with wind turbine, Shuang et al [17] raised a probability-based scenario analysis to form typical scenarios of wind turbine with consideration of statistical characteristics of wind energy output. By generating the switch state graph of distribution system, network reconfiguration was simplified to the optimization problem of network switch state combination. For model solution, a genetic algorithm (GA) and the way of "breaking circle" was employed to seek optimal network reconfiguration scheme with wind turbine under mono-scenario and the multiscenario.

In [18] a chance constrained programming formulation for distribution reconfiguration with wind power generator (WPG) was proposed that aims at minimum power loss and increment voltage quality. A scenario analysis method was applied to describe the random output of WPG through the scenario probability and scenario output. A multiple objective particle swarm algorithm (MOPSO) was employed to solve the multi-objective discrete nonlinear optimization problem. The dedicated particle encoding with the mesh information of the distribution network can effectively avoid producing a large amount of invalid solutions. With MOSPO, it was possible to obtain the optimum solution set of each objective while helping the operator to choose the most appropriate plan for reconfiguration.

In [19], a novel scenario distribution network reconfiguration model was presented in which the scenario analysis method was applied to describe the random output of the wind power generator (WPG) and its influence through the scenario selection and scenario voltage. Multiple WPGs and wind farms connected with a network was also considered in this model. And then, an efficient genetic algorithm (GA) was presented for the scenario distribution network reconfiguration model. Through the no unfeasible coding rule in the initial population strategy, cross strategy and eugenic strategy, individuals in the evolution always form the feasible solutions which can meet the requirement of the actual distribution network. Physical optimization based on scenario voltage in the process of evolution reduces the optimization time and the dependence of the initial population. All these studies are based on general wind turbine generators and are therefore not suitable for the commercial DFIG. In Addition the hybrid optimization methods are the state of the art means for a real time and real world power system.

In [20] a joint optimization algorithm of combining reactive power control of wind farm with DFIG and network reconfiguration was proposed. In the proposed joint optimization algorithm, an improved hybrid particle swarm optimization with wavelet mutation algorithm (HPSOWM) was developed for voltage profile improvement which utilized reactive power output of wind farm as the control variable. In each particle updating instance at each iteration of reactive power output optimization algorithm, a binary particle swarm optimization algorithm (BPSO) is utilized to find the optimal network structure. This problem will be revisited in this paper by using an HBFDE algorithm

In the distribution system, due to many candidate switching combinations and also presence of DFIG units, the ADNR problem is modeled as a mixed-integer nonlinear programming problem. Various methods such as linear programming, mixed-integer programming, quadratic programming, can be used to solve this problem. However, in many cases, the classical methods fail to provide the global optimum solution and only reach local solution. In recent years, The BF and DE algorithms have been proposed as two powerful optimization evolutionary algorithms in the field of optimization [21]-[22]. Although in many cases, BF eventually determines the desired solution; its convergence rate is slow and its local search is weak. In other side, DE algorithm has a good performance in the local search area; but its global search is weak and its performance depends on the proper selection of the initial population. In this paper, hybrid method is employed to combine the BF and DE algorithms (HBFDE) based on the evolutionary natures of them, to take the advantage of the compensatory property of them, and avoid their negative points. Most important advantage of proposed HBFDE algorithm is high accuracy in finding the optimal switching combination of the distribution system to minimize the network loss.

In addition, the decision maker must be able to balance the consumption and generation of energy at both short and long time intervals. Due to intermittent nature of wind and loads, this is difficult for the network operator to balance the consumption and production of energy when the wind turbines are feeding the electrical network [23]-[25]. This is the main reason why a good prediction has a significant role in handling of the DFIG and loads in electrical networks. Hence, in this paper, the system uncertainty including the DFIGs and loads are modeled in a stochastic approach based on scenarios.

The scenarios are generated using the roulette wheel mechanism and Monte Carlo Simulation (MCS) which model the stochastic behaviors of the wind speed and loads uncertainty. Moreover, an aggregation method is used to decrease the computation burden and extract one scenario among all generated scenario so that the uncertainty of all scenarios are considered in aggregated scenario based on their probability. Finally, the HBFDE algorithm is used to optimize the problem for deterministic and stochastic (aggregated) scenarios.

## II. ADNR PROBLEM WITH WIND

The ADNR problem considering the DFIG is a mixed integer nonlinear optimization problem. In this problem, there are many different objective functions including loss minimization, balancing the load on transformers, balancing the load on feeders, maximum loading of feeders and minimizing the deviation of voltages from nominal value. In this paper, loss minimization is considered as the objective of ADNR problem with regard to DFIG, while the other objectives are considered as constraints. The minimization of total real power loss is calculated as follows [23]:

$$f(\mathbf{X}) = \sum_{i=1}^{N_{br}} R_i \times |I_i|^2 \quad (1)$$

The vector  $\mathbf{X}$  has three sections:  $Tie_i$ , that represents the situation of tie switch in  $i$ th loop and get '0' and '1' values corresponding to open and close states, respectively. Indeed, if the  $Tie_i$  is 0, it means that the tie switch of  $i$ th loop must remain unchanged (open), also if it is '1', it means that tie switch of  $i$ th loop must be closed and the  $S_{W_i}$  (obtained in second part of vector  $\mathbf{X}$ ) that is one of the sectionalizing switches in  $i$ th loop, replace the tie switch of that loop. The third part of vector  $\mathbf{X}$  is the power factor of  $i$ th DFIG.

The constraints of the proposed problem are listed as follows [23, 24]:

- *Distribution line limits,*

$$\left| P_{ij}^{Line} \right| < P_{ij, \max}^{Line} \quad (2)$$

- *Distribution power flow equations,*

$$P_i = \sum_{j=1}^{N_{bus}} V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j)$$

$$Q_i = \sum_{j=1}^{N_{bus}} V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j) \quad (3)$$

- *Radial structure of the network*

In this paper, the main closed loops of the system are used to check the radial structure of the network. The number of main loops is calculated as follows:

$$N_{FL} = N_{br} - N_{bus} + 1 \quad (4)$$

- Limit on currents of transformers,

$$|I_{t,i}| \leq I_{t,i}^{\max} \quad i = 1, 2, \dots, N_t \quad (5)$$

- Limit on the current of feeders,

$$|I_{f,i}| \leq I_{f,i}^{\max} \quad i = 1, 2, \dots, N_f \quad (6)$$

- Active power constraints of the DFIG,

$$P_{\min,w,i} \leq P_{w,i} \leq P_{\max,w,i} \quad (7)$$

- Bus voltage amplitudes are limited as:

$$V_{\min} \leq V_i \leq V_{\max} \quad (8)$$

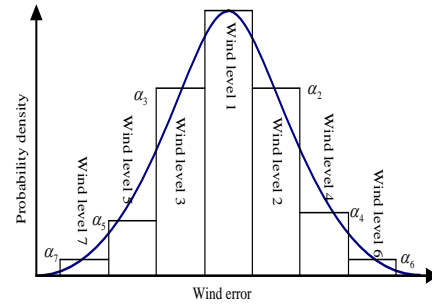
- Power factor constraints of the DFIG,

$$pf_{\min,i} \leq pf_i \leq pf_{\max,i} \quad (9)$$

### III. THE STOCHASTIC MODEL OF DFIG AND LOADS

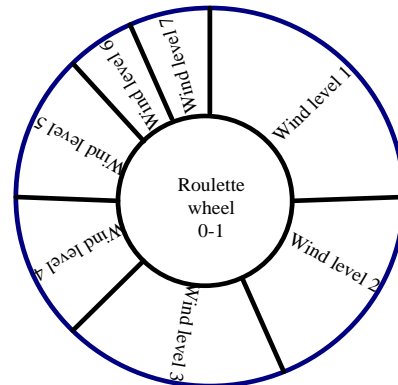
If decision maker wants to balance the consumption and production of energy in a system considering DFIG, he/she must make a good prediction of wind speed and loads. In this paper to make a good prediction of uncertainty parameters, the wind and loads uncertainty are considered based on the wind and loads forecast error [24, 25]. So, the probability distribution function (PDF) of the wind and loads forecast error should be constructed (In this paper a typical PDF has been considered.).

The continuous distribution function of the wind forecast error along with its discretization is shown in Fig. 1 according to which seven intervals are centered on the zero mean and each of intervals are one wind speed forecast error standard deviation, as presented in [26]. Finally, a roulette wheel mechanism [27] is implemented to generate scenarios for the proposed time. In the roulette wheel mechanism, scenarios are selected on the basis of different wind and loads forecast levels and their probabilities obtained from the PDF.



**Fig 1: Discretization of PDF of wind forecast error**

For this purpose, at first, the probabilities of different wind and loads forecast levels are normalized such that their summation becomes equal to unity. Then, by roulette wheel mechanism a scenario is obtained. In this regards, as shown in Fig. 2, the range of 0-1 is occupied by the normalized probabilities. After that, random numbers are generated between 0 and 1. Each random number falls in the normalized probability range in the roulette wheel. The selected interval is associated with a binary digit equal to 1, and other interval becomes zero.



**Fig 2: Roulette Wheel Selection**

After obtaining the wind and load forecast level for all DFIGs and loads, a scenario corresponding to all DFIGs and loads is produced. A scenario is a vector of binary parameters that identify the wind and loads intervals: This procedure is repeated until the desired number of scenarios is generated. The probability of all scenarios is calculated by equation [24]:

$$P_{\text{Scenario}_n} = \frac{\prod_{j=1}^{N_{WTG}} \sum_{i=1}^7 W_{n,i,j}^{WTG} \cdot \alpha_{n,i,j} \cdot \prod_{m=1}^{N_{load}} \sum_{r=1}^7 W_{n,r,m}^{load} \cdot \alpha_{n,r,m}}{\sum_{k=1}^{N_{sen}} \left( \prod_{j=1}^{N_{WTG}} \sum_{i=1}^7 W_{n,i,j}^{WTG} \cdot \alpha_{n,i,j} \cdot \prod_{m=1}^{N_{load}} \sum_{r=1}^7 W_{n,r,m}^{load} \cdot \alpha_{n,r,m} \right)}$$

$$n = 1, 2, \dots, N_{sen} \quad (10)$$

Finally, obtained wind speed is converted to the active power of DFIGs by following equation [30]:

$$P_w = \begin{cases} 0 & v_w \leq v_1, v_w \geq v_3 \\ \phi(v_w) & v_1 \leq v_w \leq v_2 \\ P_n & v_2 \leq v_w \leq v_3 \end{cases} \quad (11)$$

Where,  $v_1$ ,  $v_2$  and  $v_3$  are, cut in, rated and cut-out wind speeds respectively

#### IV. THE HBFDE ALGORITHM

##### A: Bacterial Foraging (BF) Algorithm

The Bacterial Foraging algorithm (BF) has been implemented in the global optimization field during the recent years. BF algorithm is based on the foraging behavior of the *E. coli* bacteria. Each bacterium by its selection behavior tries to eliminate the poor foraging strategy and modifies the successful foraging strategy. As the other evolutionary algorithms, this algorithm is designed to solve non-gradient optimization problems with non-differentiable and complex objective functions such as DNR problem. In BF algorithm, each possible solution is considered as bacteria. There are three main steps in the original BF algorithm, namely; chemotaxis, reproduction and elimination or dispersal [21]. Before going to the main steps, the initial population of bacteria must be produced in their search space as follows:

$$BF\_Population = \begin{bmatrix} X_1 \\ \vdots \\ X_{N_{BF}} \end{bmatrix}_{(N_{BF}) \times (2N_{tie} + N_{WTG})}$$

for,

$$X_i = [Tie_1, Tie_2, \dots, Tie_{N_{tie}}, Sw_1, Sw_2, \dots, Sw_{N_{tie}}, pf_1, pf_2, \dots, pf_{N_{WTG}}]_{1 \times (2N_{tie} + N_{WTG})}, i = 1, 2, \dots, N_{BF} \quad (12)$$

The **chemotaxis** step is composed of a set of consequence swimming following by tumble. At first, based on the rotation of the flagella, the bacterium selects the direction that it should move (tumbling). Then, if the new position of bacterium is better than previous, the bacteria will begin to move in the same previous direction (swimming). A unit length in a random direction represents a tumble;  $\phi(j)$ , this random direction specifies the direction of the movement after a tumble. The constant run-length unit,  $C(i, j)$ , determines the size of the step taken in the random direction. In the proposed algorithm, the location of the  $i$ th bacterium at the  $j$ th chemotactic step,  $k$ th reproduction step and  $l$ th elimination/dispersal event is represented by  $\theta^i(j, k, l)$ , and the objective function is shown by  $J(i, j, k, l)$ . After a tumble the location of  $i$ th bacteria is shown by the following equation [21]:

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i, j)\phi(j) \quad (13)$$

If the obtained objective function at  $\theta^i(j+1, k, l)$  is better (lower) than  $J(i, j+1, k, l)$ , another step of size  $C(i, j)$  in the same direction is taken. This swimming operation is repeated as long as a lower objective function is obtained until a maximum preset number of steps are reached.

The objective function of each bacterium in the population is affected by swarming, that is performed by the cell-to-cell signaling released by the bacteria groups to form swarm patterns. This procedure is expressed as follows [22]:

$$J_{cc}(\theta, P(j, k, l)) = \sum_{i=1}^s J_{cc}^i(\theta, \theta^i(j, k, l)) = \sum_{i=1}^s [-d_{attract} \exp(-w_{attract} \sum_{m=1}^p (\theta_m - \theta_m^i))] + \sum_{i=1}^s [h_{repellent} \exp(-w_{repellent} \sum_{m=1}^p (\theta_m - \theta_m^i)^2)] \quad (14)$$

Where,  $d_{attract}$ ,  $w_{attract}$ ,  $h_{repellant}$  and  $w_{repellant}$  are coefficients representing the characteristics of the attractant and repellant signals released by the cell and  $\theta_m^i$  is the  $m$ th component of  $i$ th bacteria position  $\theta^i$ . Also, the position of each member of the population of the  $S$  bacteria is show by  $p(j,k,l)$  and defined as:

$$p(j,k,l) = \left\{ \theta^i(j,k,l) \mid i=1,2,\dots,s \right\} \quad (15)$$

Where,  $S$  is the size of the bacteria population.

The function  $J_{cc}(\theta, P(j,k,l))$ , which represents the cell-to-cell signaling effect, is added to the  $J(i,j,k,l)$ .

After  $N_c$  steps of chemotactic, the **reproduction** process is performed. In this step, the population is halved so that the least healthy half dies and each bacterium in the other healthiest one splits into two bacteria that take the same position.

$$S_r = \frac{S}{2}$$

An **elimination/dispersal** process is performed after taking a maximum number of chemotactic steps,  $N_{re}$ . In this operation each bacterium could be moved to the new position of the search space

#### B: Differential Evolutionary (DE)Algorithm

Differential Evolutionary (DE) algorithm was proposed by D.Pal et al [7]. This algorithm is a very simple and straightforward optimization strategy. The main concept of DE is conducted by means of four main operations: 1- initialization, 2- mutation, 3- crossover, 4- selection.

In the **initialization** step,  $N_{DE}$  vertex points are randomly generated and the fitness of the objective function is evaluated. The generated population is sorted based on the objective function values as following matrix:

$$DE\_Population = \begin{bmatrix} X_1 \\ \vdots \\ X_{N_{DE}} \end{bmatrix} \quad (16)$$

$X_i = [Tie_1, Tie_2, \dots, Tie_{N_{de}}, Sw_1, Sw_2, \dots, Sw_{N_{de}}, pf_1, pf_2, \dots, pf_{N_{de}}]_{(2N_{de}+N_{pf})}$ ,  $i=1,2,\dots,N_{DE}$

In the **mutation** step, a donor vector  $Xm_i^{j+1}$  is created by adding the weighted difference between the two vectors to the third vector as following equation:

$$Xm_i^{j+1} = X_{r3,i} + \beta(X_{r1,i} - X_{r2,i}) \quad (17)$$

Where, indexes  $r1, r2, r3 \in [1, N]$  are selected randomly. It is noted that random indexes have to be different from each other and from the running index ( $i$ ). The  $\beta$  is a constant value in the range of 0 to 2 and controls the amplification of the difference vector of randomly chosen individuals and  $j$  is number of iteration. The  $\beta$  factor is determined based on performance of the optimization routine in previous experiments.

In the **crossover**, the new individuals are generated using the following scheme in crossover procedure:

$$u_i^{j+1} = \begin{cases} X_i^{j+1} & \text{if } r < CR \\ X_i^j & \text{if } r > CR \end{cases} \quad (18)$$

Where,  $r$  is a random number generator  $r \in [0,1]$  and  $u_i^{j+1}$  represents trial individuals.  $CR \in [0,1]$  is a constant value.

In the **selection** step, the equation (19), is used for the selection with the modification,

$$X_i^{j+1} = \begin{cases} u_i^{j+1} & \text{if } f(u_i^{j+1}) < f(X_i^j) \\ X_i^j & \text{otherwise} \end{cases} \quad (19)$$

Where,  $f(u_i^{j+1})$  and  $f(X_i^j)$  are the objective function value of  $u_i^{j+1}$  and  $X_i^j$ , respectively.

#### C: The HBFDE Algorithm

The combination of BF and DE algorithm with each other and other evolutionary algorithms has been considered by other authors in recent years. In [2] and [32], BF and DE has been combined to perform economic load dispatch with non-convex loads and improve the performance of algorithms by increasing the effect of swarming.

In [12], a variable scaling hybrid DE algorithm has been proposed to dominate the problem of the selection of a mutation operator. But, this paper aims at the integration of BF and DE algorithms, to combine their advantages and avoid their negative points. For example, DE algorithm is a very efficient local search procedure, but it is not always available since it is very sensitive to the choice of the initial condition and there is no guarantee to obtain the global optimization. Also, the accuracy of the BF algorithm is not very high and its local search is weak. But, by combining these algorithms, the new algorithm namely, HBFDE algorithm has a better convergence rate in comparison to original BF and DE algorithms.

The algorithm for the DFIG scenario generation is summarized as follows.

**Step 1:** Set  $I$  as the initial number of trials;  $i=i+1$

**Step 2:** Import the basic information; that is the bus and load data.

**Step 3:** Generate 1000 scenarios for the DFIGs speed.

**Step 4:** Determine the aggregate of the 1000 generated scenarios using equation (10).

**Step 5:** Use equation (11) to determine the DFIG output.

#### *The HBFDE Algorithm Mechanism*

**Step 6:** Generate the initial population.

**Step 7:** Let  $J$  be the number of HBFDE iterations,  $J=J+1$ .

**Step 8:** Evaluate the objective function for initial population; that is the power loss.

**Step 9:** Sort the initial population based on augmented objective function value.

**Step 10:** Devide the sorted population to BF and DE algorithms. The population size is set at  $3N$ , when solving an  $N$ -dimensional problem. The initial  $3N$  solutions are randomly generated and sorted by their fitness, and the top  $N=N_{DE}$  solutions fed into the DE method to improve their positions. The other  $2N=N_{BF}$  solutions are updated by the BF method.

In the BF algorithm  $N$  neighborhood of bacterium is proposed to expand the local search area. The neighborhoods best bacterium are selected by first evenly dividing the  $2N$  bacterium into  $N$  neighborhoods and designating the bacterium with the better fitness value in each neighborhood as the neighborhood's representative. After first iteration of BF and DE, the first combination is completed. In the second combination, the  $3N$  updated solutions are sorted again for repeating the entire run. This process is performed after taking a maximum number of combinations.

**Step 11:** Combine the updated population from **step 10** to generate the HBFDE population

**Step 12:** Compare the HBFDE iterations  $J$  and the initial number of trials i.e.  $J < J_{max}$  then update the HBFDE iterations to  $J=J+1$  and go back to **Step 7**. Otherwise go to **Step 13**.

**Step 13.** If  $i > i_{max}$  then output results, otherwise go back to **Step 1**.

The HBFDE algorithm is employed to solve the ADNR problem, considering stochastic model of wind and loads. As seen above steps, the proposed approach is a two stage optimization method. In the first stage, the stochastic scenario is produced for DFIGs and loads, and in the second step, using of the HBFDE algorithm the optimal configuration of network is obtained for deterministic and stochastic scenarios when power losses is objective function.

## V. SIMULATION RESULTS

### *A: IEEE 33-bus Radial Distribution Network*

In this paper to evaluate the feasibility of the proposed approach, we use IEEE 33-bus Radial Distribution Network [15,33], which is a practical distribution network. The schematic of this network is shown in Fig 3a). The distribution network for reconfiguration consists of 33buses and 5 tie lines; the total loads are 5084.26 kW and 2457.32 kVAr. The normally open switches are 33, 34, 35, 36, and 37 represented by the dotted lines and normally open switches 1 to 32 are represented by the solid lines. For this base case, the initial losses are 221.71 kW.

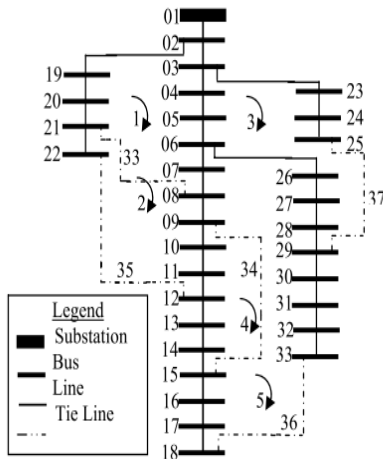


Figure 3a)

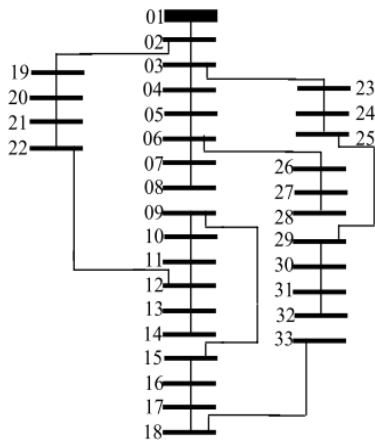


Figure 3b)

Fig. 3. 33-Bus IEEE, Radial distribution network a) in the initial reconfiguration b) after reconfiguration with DFIG

**B: A Comparison of BF DE and HBFDE without DFIG**

In Table 1 a comparison between, HBFDE, BF and DE algorithms for 10 trials is given for DNR problem without DFIG units. According to this table, the hybrid HBFDE algorithm is more effective than original BF and DE algorithms in that the standard deviation of proposed HBFDE algorithm is less than of BF and DE algorithms. Indeed, the HBFDE algorithm could obtain optimum solution in 9 trials of 10 trials and only in one trial the obtained results are different.

**Table.1**  
Comparison of average solutions of 10 trials without considering DFIGs.

Algorithm	Initial population	Iterations	Best solution	Worst solution	Average	CPU Time(s)
BF	100	500	195.398	198.96	197.179	~29
DE	100	500	195.398	198.90	197.649	~24
HBFDE	100 $N_{BF}=60$ $N_{DE}=40$	External loop=10 BF loop=30 DE loop=20	135.498	136.99	135.78	~26

*C: ADNR problem with Wind*

The ADNR problem considering DFIG has not been studied so far. Hence, in the Table 2 to demonstrate the performance of proposed HBFDE algorithm, the total active power loss of the proposed distribution system optimized without considering DFIG units is shown.. According to this table, the obtained results by HBFDE algorithm are better than others in terms of loss reduction, CPU time and load flow iterations.

To obtain the minimum power losses corresponding to stochastic situation, 1000 realizations of DFIGs and loads have been developed .In this case, it can be possible to solve the problem for each scenario separately, but it is questionable which scenario must be followed by decision maker. For this mean, all 1000 generated scenarios is aggregated using equation (20) to extract a scenario which includes the uncertainty in all scenarios based on their occurrence probability.

$$Aggregated\ Scenario = \sum_{s=1}^{N_s} \{P_{scenario_s} (\xi^s)\} \quad (20)$$

After implementation of the above equation, a decision maker can claim that the output control variables can optimum all scenarios while the constraints in all scenarios are satisfied.

In Table 2, the obtained aggregated scenario including loads and DFIGs active power is shown to illustrate the importance of the uncertainty parameters in DNR problem, by comparing the deterministic and stochastic situations.



In this table, to show the impacts of DFIGs in DNR problem, the deterministic situation includes two cases; DNR considering the DFIG and without considering the impact of DFIGs in network. In last columns of Table 3 the optimum tie switches corresponding to each scenario is shown.

**Table.2.**  
**The Simulation Results for DFIG in Stochastic Scenario**

Loss in the base configuration	222.71kw
Loss in the optimal configuration	155.78
Optimal configuration	s33,s14,s8,s32,s28
Loss reduction	86.93kw
Loss reduction (%)	39.1%
CPU time	0.42 sec
Number of load flow iterations	26

The optimal radial configuration of the network after all the switching operations is shown in Figure 3b). Table 2 shows the simulation results of the base configuration and the optimal configuration. The minimum and the maximum voltages of the two configurations are depicted in Fig. 4. The power loss before reconfiguration is 222.71 kW and reconfiguration is 155.78 kW. From the results it is observed that reduction in power loss is 86.93 kW which is approximately 39.1 %. The number of all load flow runs required for the entire process is 26

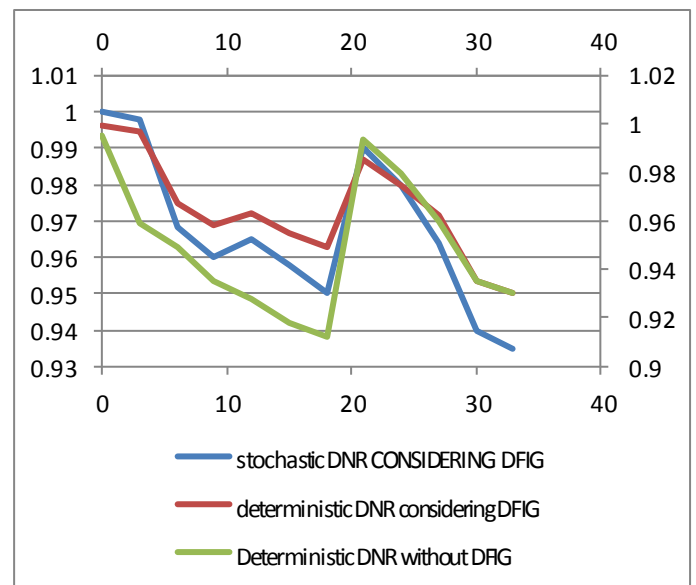
**Table.3.**  
**The optimum results of deterministic and stochastic situations**

Case		Power losses [kW]	Optimum tie Switches
DNR considering DFIG	Stochastic	135.89	s34,s14,s8,s32,s28
	Deterministic	138.97	s35,s14,s8,s32,s28
DNR without DFIG	Deterministic	197.398	s37,s14,s8,s32,s28

By comparing the obtained results in Table 1 and Table 3, it is clear that there are differences between the results of deterministic and stochastic scenarios. In other side, the probability of the deterministic scenario is about 4.1% (among 1000 produced scenarios). This means that the deterministic solution may happen with the low probability of 4.1%. Consequently, the deterministic scenario cannot be an acceptable solution by itself. On the other hand, using the obtained aggregated scenario, all 1000 scenarios contribute into determining the ADNR results according to their probability values. So, the ADNR results of the stochastic framework are more realistic than the deterministic one. In other word, the most important advantage of stochastic scenario is that individual scenario problems become simple to interpret and with aggregation the 1000 scenarios the underlying problem structure is preserved

#### *D: The voltage profile*

The voltage profiles before and after reconfiguration is shown in from Fig.5. It is observed that the minimum voltage before reconfiguration is 0.9131 p.u for deterministic DNR without DFIG and after reconfiguration taking into consideration DFIG under both deterministic and stochastic scenarios, the minimum voltage is 0.9391 p.u. This shows that the minimum voltage in the network is improved by 2.78 % after the reconfiguration.



**Fig.4: The profile voltages of three situations mentioned in Table 3**

*E: Comparison with other methods*

The HBFDE method is compared with the methods proposed by Chiou et al [12] and Jingjing Zhao et al [20] for the same 33-bus test system. For effective comparison, the results of the proposed method along with other methods are shown in Table 4. The saving in total loss by the proposed method is higher than all other methods. The number of tie switch operations obtained by the HBFDE and all other methods is 5. The CPU Time for the HBFDE method is the best compared to the other methods.

**Table.4.**

**A Comparison of results obtained by optimizing active power loss**

<b>Method</b>	<b>Final open switches</b>	<b>Total loss savings (%)</b>	<b>CPU time</b>
<b>HBFDE</b>	s33,s14,s8, s32,s28	33.1	0.42
<b>Jingling Zhao et al [20]</b>	s7,s9,s14, s32,s37	32.6	0.87
<b>Chiou et al [12]</b>	s7,s9,s14, s32,s37	32.6	1.66

**VI. CONCLUSION**

In this paper, a hybrid evolutionary algorithm based on the combination of BF and DE algorithms called HBFDE has been proposed to obtain the optimal configuration of radial distribution systems, when the objective function is power loss and holding all the other objectives of ADNR as constraints. An ADNR has been studied considering the wind based DFIG. To reach a more realistic solution than the deterministic situation, a stochastic framework has been considered to model the stochastic behavior of the wind speed and loads. Additionally, the simulation results have shown the effectiveness of HBFDE algorithm and the stochastic approach which can lead to a more efficient utilization of energy in the distribution systems and permit decision makers to select the possible actions to cope with the wind uncertainty in the modern power system.

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