A New Approach for Network Reconfiguration Problem in Order to Deviation Bus Voltage Minimization with Regard to Probabilistic Load Model and DGs

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Abstract—Recently, distributed generation technologies have received much attention for the potential energy savings and reliability assurances that might be achieved as a result of their widespread adoption. The distribution feeder reconfiguration (DFR) is one of the most important control schemes in the distribution networks, which can be affected by DGs. This paper presents a new approach to DFR at the distribution networks considering wind turbines. The main objective of the DFR is to minimize the deviation of the bus voltage. Since the DFR is a nonlinear optimization problem, we apply the Adaptive Modified Firefly Optimization (AMFO) approach to solve it. As a result of the conflicting behavior of the single- objective function, a fuzzy based clustering technique is employed to reach the set of optimal solutions called Pareto solutions. The approach is tested on the IEEE 32-bus standard test system.

Keywords—Adaptive Modified Firefly Optimization (AMFO), Pareto solutions, feeder reconfiguration, wind turbines, bus voltage.

I. INTRODUCTION

OVER the last decade, distribution systems have seen a significant increase in small-scaled generators as they can compensate the disadvantages encountered in the centralized generation dispatch. These generators, also known as distributed generation (DG), are installed in the network to serve as a source of power at on or near the site where they are to be used [1]. Therefore, the use of renewable types of distributed generations such as wind, photovoltaic, geothermal or hydroelectric power can also provide significant environmental benefits [2]. Therefore, it is of crucial importance to study their impacts on the distribution networks. In this situation, the DFR problem as one of the most significant control schemes in the distribution networks can be affected by DG units.

Generally, DFR is defined as altering the topological structure of the distribution feeders by changing the open/close states of sectionalizing and tie switches so that the objective function is minimized and the constraints are met[3], [4]. Because there are many candidate-switching combinations in the distribution system, network reconfiguration is a complicated combinatorial, non-differentiable constrained optimization problem.

Merlin and Back [5] introduce a branch and bound technique to develop a solution technique for the minimum losses reconfiguration in 1975. Since then, many reconfiguration techniques have been proposed. In [6], Gomes et al. have presented a new method based on heuristic search technique to determine the best structure of the system. In [7] switch placement for the reliability improvement of radial distribution systems with distributed generation is discussed. The objective is minimizing the number of switches and maximizing the reliability. A particle swarm optimization based method is proposed in [8] for the reliability improvement and loss reduction of radial distribution systems. In this paper, an algorithm has been proposed for optimal network configuration of the radial distribution systems with distribution generation. Initially at the terminal nodes of the system, tie-switch placement has been carried considering geographical constraints and at these tie-switch locations DGs are placed with at least one DG at a tie-switch as constraint. The objective of the reconfiguration problem is the power loss reduction and voltage profile improvement. Civanlar et al. [9] suggested a heuristic algorithm to determine change in power loss due to a branch exchange. The disadvantage of this method is only one pair of switching operations is considered at a time and reconfiguration of network depends on the initial switch status. Nara et al. [10] presented a solution using a genetic algorithm (GA) to look for the minimum loss configuration in distribution system. Zhu [11] presented a refined genetic algorithm (RGA) to reduce losses in the distribution system. Rao et al. [12] proposed Harmony Search Algorithm (HSA) to solve the network reconfiguration problem to get optimal switching combinations simultaneously in the network to minimize real power losses in the distribution network.

In this paper, a novel DFR technique based on adaptive modified firefly algorithm in a new probabilistic structure such as the uncertainty of the active and reactive loads and the WT output variations, simultaneously. The problem formulation proposed here in considers single-objective related to: Minimizing the deviation of the bus voltage.

II. PROBLEM FORMULATION

In this part, the objective function and the appropriate equality and inequality limitations are explained. Notice it that in this paper, the symbol ~ is employed to exhibit the expected value of the corresponding variable.

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A. Objective Function

1. Minimizing the Deviation of the Bus Voltage

The maximum voltage deviation of the buses is explained the following:

$$\widetilde{f}_1(X) = \max\left[\left|1-\widetilde{V}_{\min}\right| \quad and \quad \left|1-\widetilde{V}_{\max}\right|\right] \qquad (1)$$

wherever $\widetilde{V}_{\min}$ and $\widetilde{V}_{\max}$ would be the minimum and the maximum expected voltage magnitude of the buses[13].

B. Constraints

1. Feeder Current Limitation

The maximum current which each main feeder can hold is explained the following:

$$\left|\widetilde{I}_{f,i}\right| \le I_{f,i}^{\max} \qquad ;i=1,2,...,N_f \qquad (2)$$

wherever $\left|I_{f,i}\right|$ is the current magnitude of the ith line; $I_{f,i}^{\max}$ is the maximum current capacity of the ith line and N_f is the number of main feeders.

2. Wts Limitations on Active Power Production

$$p_{WT,i}^{\min} \le \widetilde{p}_{WT,i} \le p_{WT,i}^{\max} \qquad (3)$$

where $p_{WT,i}^{\max}$ and $p_{WT,i}^{\min}$ are the maximum and the minimum power generation capacity of the ith WT.

3. Bus Voltage Limitation

$$V_{\min} \le \widetilde{V}_i \le V_{\max} \qquad (4)$$

where $V_{\max}$ and $V_{\min}$ are the maximum and minimum voltage of the buses.

4. Keeping the Radiality of the Network

Since the distribution networks are assumed as radial networks, thus during the reconfiguration, this quality of the network should be preserved carefully. Each loop in the network is consisted of a sectionalizing switch and a tie switch. Each time that a loop is formed in the network; one of the switches should be opened in a way that the radiality of the network would be preserved.

III. STOCHASTIC DISTRIBUTION FEEDER RECONFIGURATION (SDFR)

A. Probabilistic Load Flow

In this section, the point estimate method (PEM) is explained completely.

1. Historical Background

As the result of the intrinsic randomness of the natural phenomena, most of the engineering problems are solved in a stochastic environment which involves much uncertainty. In a technical categorization, there are three different techniques to solve the engineering problems under the uncertainty [14]: 1) Monte Carlo Simulation (MCS) 2) analytical methods and 3) approximate methods. The main deficiency of MCS is the great number of runs which are needed to achieve convergence. On the other hand, analytical methods are computationally more efficient but require some mathematical assumptions to simplify the problem. Nevertheless, the approximate methods overcome these shortcomings and therefore can be more satisfying and useful. Among the most well-known approximate methods, first-order second-moment method (FOSMM) [15] and point estimate method stand out. In the original PEM [16], 2m algorithms should be solved to determine the statistical moments of a random variable. In [17], Hong attempted to simplify PEM by reducing the number of simulation runs from 2m to Km and Km1, in which Km is used to determine the type of Hong's PEM scheme. Finally, in [18], Su used Hong's 2m scheme to solve the probabilistic power flow.

$$S = F(z) \qquad (5)$$

In which the uncertain variable z is consisted of the network data, load consumption, generation dispatch, etc. Therefore, the uncertainty in the vector z is transferred to the output variable S (bus voltage or line flows). Suppose z_l as a random variable with the probability density function f_{zl}. Now by matching the first three moments of f_{zl}, the two-point estimate technique uses two probability concentrations to replace f_{zl} [19]. According to 2m PEM, (5) is solved 2m times. The two-dimension representation of the scheme is depicted in Fig. 1.

According to Fig. 1, the data of $z_{l,1}$ and $z_{l,2}$ are transformed to the output variables $S_{l,1}$ and $S_{l,2}$ by the use of the function S = F(z). The role of the two variables $u_{l,1}$, and $u_{l,2}$ is to scale the two estimates of variant S that is $\omega_{l,1}$, $\omega_{l,2}$. Each concentration point includes two pairs ($z_{l,k}$, $\omega_{l,k}$), k = 1, 2; in which $z_{l,k}$ and $\omega_{l,k}$ are the location and the weighting factor, respectively [19]. The location of each concentration can be calculated as follows:

$$z_{l,k} = \mu_{z_l} + \xi_{l,k}.\sigma_{z_l}; \quad k=1,2 \qquad (6)$$

where μ_{zl} and σ_{zl} are the mean and standard deviation of f_{zl}. Also, $\zeta_{l,k}$ is calculated as follows:

$$\xi_{l,k} = \frac{\lambda_{l,3}}{2} + (-1)^{3-k}\sqrt{m-(\lambda_{l,3}^2/2)^2} , \quad k=1,2 \qquad (7)$$

The variables $\lambda_{l,3}$ as the coefficient of skewness [19] is supposed as the third central moments of z_l and is defined as follows:

$$\lambda_{l,3} = \frac{E\left[\left(z_l - \mu_{z_l}\right)^3\right]}{\left(\sigma_{z_l}\right)^3} \qquad (8)$$

where E is the expectation operator. It should be noted that the standard deviation of each output variable S_i is calculated as follows:

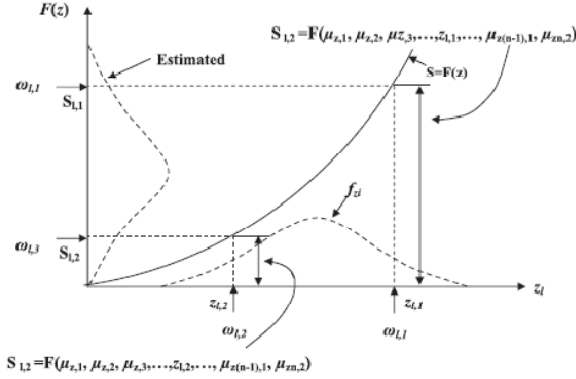$$\sigma = \sqrt{\text{var}(S_i)} = \sqrt{E(S_i^{\,2}) - [E(S_i^{\,2})]} \tag{9}$$

Fig. 1 Conceptual illustration of the 2m PEM

As discussed earlier, in this perform, the relationship between the WTs can also be considered. In this respect, the extensive $2m$ PEM is employed. The key strategy behind this process would be to transform the correlated output power of the WTs into uncorrelated kinds utilizing the orthogonal transformation. Then (6) to (9) are solved for the new transformed variables. Eventually, before evaluating the objective function, the parameters are shifted to their fundamental space.

IV. ADAPTIVE MODIFIED FIREFLY OPTIMIZATION ALGORITHM

A. Original FA

The FA is really a metahuristic population based optimization algorithm which was initially presented by Dr. Xin-She Yang at the Cambridge University [20]. This algorithm imitates the fireflies' behavior in exotic regions predicated on three main key ideas [21]: 1) all fireflies are unisex in a way that each firefly could be attracted by every other firefly; 2) the brighter firefly may attract the firefly with less brightness and 3) if a firefly can't see any other firefly in the near neighboring, it may fly randomly in the air. In the optimization issue, the objective function value may determine the brightness of the fireflies. Compared to another well-known major technique like PSO and GA, the FA has especial characteristics such as simple notion, easy implementation, low dependence on the initial variables, common idea, etc.

In the FA, as the exact distance between any two fireflies is increased, the brightness of one firefly to the eyes of the other firefly is decreased. Thus, for every firefly, an attractiveness parameter is described the following:

$$\beta(r) = \beta_0 \times \exp(-\gamma r^m) \quad ; m \ge 1 \tag{10}$$

wherever r is the exact distance between the both fireflies, β_0 could be the initial attractiveness at r=0 and γ is the assimilation

coefficient to model the brightness reduction rate (called light intensity). In the Cartesian distance, the exact distance between the both fireflies i and j revealed by r_{ij} is determined the following:

$$r_{ij} = \|X_i - X_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2}$$
$$X_i = [x_{i,1}, x_{i,2}, \ldots x_{i,k}, \ldots, x_{i,d}]$$
$$X_j = [x_{j,1}, x_{j,2}, \ldots x_{j,k}, \ldots, x_{j,d}] \tag{11}$$

wherever d is the issue dimension. By the utilization of the aforementioned two equations; the firefly with less brightness (X_j) is moved toward the brighter firefly (X_i) the following:

$$X_j = X_j + \beta(r) \times (X_i - X_j) + U_j$$
$$U_j = \alpha(rand - \frac{1}{2}) \tag{12}$$

wherever α could be the randomization parameter that is fixed in the range of (0,1). Since it is observed from the above mentioned formula, the updating method of every firefly includes three terms: 1) the present place of the firefly X_j; 2) the movement of the firefly X_i toward the firefly X_j and 3) the random movement. As discussed earlier, every time that a firefly can't see any firefly in the near neighboring, it will fly randomly. In this formula, the role of the term U_j would be to simulate this random movement. The aforementioned formula is repeated before entire population is updated.

B. Adaptive Modified FA

While the original FA has several advantages to deal with complicated optimization issues, in this part, a new two-phase modification strategy is planned to increase the total search capacity of the algorithm effectively. The first area of the modification approach is definitely an adaptive formulation to update the value of the randomization parameter in Eq. 12. A small value of α may encourage the FA to search more locally while a large value of α will motivate the algorithm to search in the not known areas. Therefore, after several running of the algorithm, the bellow adaptive formulation is available for α:

$$\alpha^{k+1} = (\frac{1}{2k_{max}})^{1/k_{max}} \alpha^k \tag{13}$$

wherever k could be the iteration number and k_{max} is the maximum number of iteration. The next part of the modification approach is planned to add to the diversity of the FA population though the utilization of the mutation and crossover operators. Thus, for each firefly X_i, three random fireflies (q_1, q_2, q_3) are selected from the population in a way that $q_1 \ne q_2 \ne q_3 \ne i$. Today, a new test firefly is produced the following:

$$X_{Test} = [x_{Test,1}, x_{Test,2}, \ldots, x_{Test,d}]$$
$$X_{Test} = X_{q_1} + \sigma_1 \times (X_{q_2} - X_{q_3}) \tag{14}$$

$$x_{new1,j} = \begin{cases} x_{Test,j}, & \text{If } \sigma_1 \le \sigma_2 \\ x_{best,j}, & Else \end{cases} \qquad (15)$$

$$X_{new,2} = \sigma_3 \times X_{best} + \sigma_4 \times (X_{best} - X_j) \qquad (16)$$

In (14) to (16), the parameters $\sigma_1, \ldots, \sigma_4$ are random values in the range [0,1]. By the utilization of the above mentioned formula, two new test fireflies are produced the following:

Today, the best firefly among X_{new1} and X_{new2} is selected to be in contrast to the ith firefly (X_i). When it better than X_i, then replaces X_i otherwise X_i will stay place in their recent position.

V. Optimization Using Pareto Dominance Criterion

In the optimization problems the concept of optimality is replaced with that of efficiency or Pareto optimality. The efficient (or Pareto optimal, non-dominated, non-inferior) solution is the solution that cannot be improved in single-objective function without deteriorating its performance in at least one of the rest [22]. It can be expressed as: If point X^* is Pareto-optimal solution and v is the search space:

$$\forall k \in \{1,2,3,\ldots,K\} : \forall X \in \chi - \{X^*\},$$
$$f_k(X^*) \le f_k(X) \text{ and } \exists m \in \{1,2,3,\ldots,K\} : \qquad (17)$$
$$f_m(X^*) \prec f_m(X)$$

where K is the number of objective function. In other words for a objective minimization problem given

$$\min F(X) = [f_i(X)] \qquad (18)$$

where $f_i(X)$ is a objective function and X is a feasible solution. For any two solutions X_1 and X_2 can have one of two possibilities: one dominates the other or none dominates the other. In a minimization problem, a solution X_1 dominates X_2 if the following two conditions are satisfied:

$$\begin{aligned} &1) \ \forall j \in \{1,2,\ldots,n\}, f_j(X_1) \le f_j(X_2) \\ &2) \ \exists k \in \{1,2,\ldots,n\}, f_k(X_1) < f_k(X_2) \end{aligned} \qquad (19)$$

If the above two mentioned conditions are validated, X_1 dominates X_2. The solutions that are non-dominated within the entire feasible search space are denoted as Pareto-optimal and known the Pareto optimal set or Pareto-optimal front.

Through the optimization method, the non-dominated solutions which are observed are stored in an additional memory named repository. To be able to hold the size of the repository from growing too large, a fuzzy clustering approach predicated on membership function is applied. In this regard, the trapezoidal membership function type can be used for the objective function. Today, by considering the satisfying level of every objective function, the repository is sorted utilizing the following:

$$N\mu(j) = \frac{\sum_{i=1}^{n} \Delta_i \times \mu_{fl}(X_j)}{\sum_{j=1}^{Np} \sum_{i=1}^{n} \Delta_i \times \mu_{fl}(X_j)} \qquad (20)$$

wherever Np is the number of Pareto solutions in the repository. By adjusting the value of Δ_i (weighting factors), experiences or preferences can be used by the decision producer to use each objective function individually.

VI. Application of AMFA to DFR

Step 1. Determine the input data.
Step 2. Change the limited one-objective optimization issue to a non-constrained one utilizing the penalty function the following:

$$F(X) = \left[f_1(X) + L_1 \sum_{i=1}^{N_{eq}} (h_i(X))^2 + L_2 (\sum_{i=1}^{Nueq} (Max[0, -g_i(X)])^2) \right] \qquad (21)$$

In the paper, L_1 and L_2 will be the penalty factors which in this study are allowed to be 10^{10}.
Step 3. Produce the initial firefly population randomly.
Step 4. Examine all of the objective function for the population. Here the stochastic power flow predicated on $2m$ PEM is implemented.
Step 5. Construct the repository utilizing the non-dominated solutions in the population.
Step 6. Select the best firefly from the repository randomly.
Step 7. Move the firefly with less brightness toward the firefly with more brightness as explained in part IV. *A*.
Step 8. Update the firefly population, the repository and the best firefly.
Step 9. Use the planned modification approach as explained in part IV. *B*.
Step 10. Update the repository. Also, check the size of the repository to become too large as explained in part V.
Step 11. Check the termination criterion. If the termination criterion is pleased finish the algorithm, if not come back to stage 6.

VII. Simulation Results

In this part, the 32-bus IEEE test system is applied to study the efficiency of the planned method. The test system is Baran and Wu 12.66 kV test system including 32 sectionalizing switches and 5 tie switches [24]. The schematic diagram of the test system is revealed in Fig. 2. The initial active power loss before reconfiguration is 202.67 kW. As it could be seen from Fig. 2, the sectionalizing switches are revealed by solid lines and the tie switches are revealed by dotted lines. In this paper, the WTs are observed in the network such that they will be close to the high load points and maintain appropriate distance from each other.
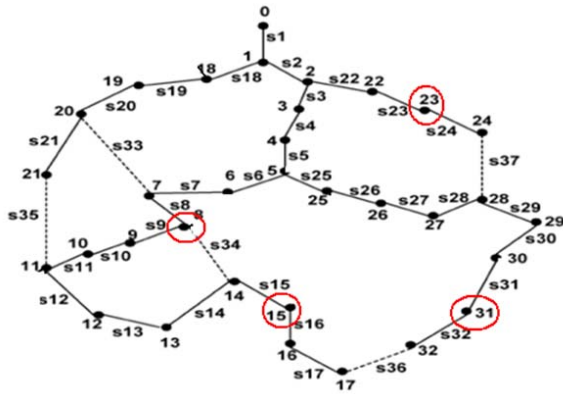
Fig. 2 Single line diagram of 32-bus test system including WTs revealed by red circle

The maximum power capacity of the WTs is allowed to be 250 kW. The evaluation is executed in both the deterministic and probabilistic frameworks. Furthermore, to be able to start to see the satisfying performance of the proposed algorithm, initially, the single-objective optimization is done. This evaluation can provide suitable results for contrast with the other well-known methods. Table I shows the results of single-objective optimization of the active power losses neglecting WTs.

TABLE I
DETERMINISTIC OPTIMIZATION OF THE OBJECTIVE FUNCTION BY DIFFERENT METHOD NEGLECTING WTS

Method	Minimum voltage	Open switches
PSO–ACO [23]	0.9378 964	s7,s9,s14,s32,s37
DPSO [24]	0.93781964	s7,s9,s14,s32,s37
DPSO–HBMO [24]	0.93781964	s7,s9,s14,s32,s37
Vanderson Gomes[25]	0.93781964	s7,s9,s14,s32,s37
PSO-SFLA [26]	0.93781964	s7,s9,s14,s32,s37
DPSO–ACO [27]	0.93781964	s7,s9,s14,s32,s37
Original FA	0.93781964	s7,s9,s14,s32,s37
The proposed AMFA	**0.93781964**	**s7,s9,s14,s32,s37**

TABLE II
DETERMINISTIC OPTIMIZATION OF THE VOLTAGE DEVIATION OBJECTIVE FUNCTION BY DIFFERENT METHOD NEGLECTING WTS

Method	Voltage deviation [p.u]	Minimum voltage	Open switches
DPSO–ACO [27]	0.06120031	0.93879681	s7,s9,s14,s32,s37
PSO–ACO [23]	0.06120031	0.93879681	s7,s9,s14,s32,s37
DPSO [24]	0.06120031	0.93879681	s7,s9,s14,s32,s37
DPSO–HBMO [24]	0.06120031	0.93879681	s7,s9,s14,s32,s37
GA	0.06218097	0.93781902	s7,s10,s14,s32,s37
Original FA	0.06120031	0.93879681	s7,s9,s14,s32,s37
The proposed AMFA	**0.06120031**	**0.93879681**	**s7,s9,s14,s32,s37**

It could be observed that ignoring WTs is to create a contrast with other well-known methods. Thus, here the length of the control vector X is restricted just to the position of the sectionalizing and tie switches. From Table I it is observed that the planned modified FA has discovered the best optimal solution which was discovered by the other well-known

techniques in the area. The appropriate optimal switching can also be revealed in this table. Table II reveals the results of single-objective optimization of the voltage deviation target.

Here again the planned algorithm has achieved to the best switching discovered to date. So far, the existence of WTs in the system was neglected. Table III reveals the outcome of single-objective optimization of every objective function independently contemplating WTs.

TABLE III
ESTIMATED VALUES OF THE SINGLE-OBJECTIVE OPTIMIZATION CONSIDERING WTS (PROBABILISTIC FRAMEWORK)

Objective function	Method	Best solution	States of the switches
Voltage Deviation [p.u]	GA	0.0483248	s6,s34,s10,s32,s37
	PSO	0.0476349	s6,s34,s10,s32,s37
	Original FA	0.0463952	s6,s14,s11,s32,s37
	AMFA	**0.0471213**	**s6,s14,s11,s32,s37**

Finally, Table IV shows a set of the Pareto solutions found in the proposed stochastic framework. In the operation management area, each of these solutions can be supposed as a promising optimal solution depending on the operator preferences. In fact, the operator can decide to choose any of these optimal solutions according to the system requirements. Nevertheless, if similar significance coefficients are supposed for the objective function, then the optimal solution which has found the most $N\mu$ in (20) should be used as the most compromised solution. It can be noted that here, the idea of fuzzy clustering is used to keep the size of the repository in the pre-determined specific values.

TABLE IV
SOME OF THE PARETO SOLUTIONS FOUND IN THE PROBABILISTIC SINGLE-OBJECTIVE DFR PROBLEM

	Voltage deviation (pu)
1	0.0507423
2	0.0517079
3	0.0507913
4	0.0511885
5	0.0513403
6	**0.0471888**
7	0.0508670
8	0.0548613
9	0.0513109
10	0.0515501
11	0.0511889
12	00507263
13	0.0514718
14	0.0509316
15	0.0521425
16	0.0511670
17	0.0518876
18	0.0513330
19	0.0507244
20	0.0506631
Best compromised solution	**0.0507913**

VIII. CONCLUSION

This paper presented a new single-objective evolutionary algorithm based on AMFO for single-objective DFR problem. The proposed algorithm utilized the concept of Pareto optimality. One of the most important advantages of the single-objective formulation is that it obtains several non-dominated solutions allowing the system operator to exercise his personal preference in selecting any one of those solutions for implementation. In the evolutionary algorithm, queens are considered as the non-dominated solutions. In order to control the size of the repository, a fuzzy- based clustering has been used.

The efficiency of the planned approach was analyzed on the 32-bus IEEE standard distribution test system. Based on the results, the planned stochastic structure can increase the dependability of the suitable solutions effectively. On the other hand, the using of the DFR technique along with considering the WTs in the system can improve all of the objective function individually. This improvement could be seen in both the economical and environmental criteria. From the optimization ability, the proposed MFA showed better performance over the other well-known methods in the area. The feasibility and satisfying performance of the proposed method was demonstrated too.

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