Reza SEDAGHATI et al./ IU-JEEE Vol. 14(2), (2014), 1817-1823

IMPLEMENTATION OF A NEW STOCHASTIC ALGORITHM OF NETWORK RECONFIGURATION IN DISTRIBUTION SYSTEMS FOR LOSSES AND COSTS REDUCTION

Reza SEDAGHATI*, Mohammad Bagher HADDADI, Mahdi HAYATDAVUDI, Mojtaba SAEEDIMOGHADAM

*Department of Electrical Engineering, Beyza Branch, Islamic Azad University, Beyza, Iran
*Reza_sedaghati@yahoo.com

Abstract: *In many countries the power systems are going to move toward creating a competitive structure for selling and buying electrical energy. This paper presents a new method based on Modified Firefly Optimization (MFO) algorithm to Distribution Feeder Reconfiguration (DFR) problems at the distribution networks considering Wind Turbines (WTs). The objectives consist of minimization of costs and losses of distributed system. The effectiveness of the proposed algorithm is demonstrated through IEEE 32 bus standard test systems. Also, regarding the uncertainties of the new complicated power systems such as the active and reactive loads in addition to the wind speed variations effectively, in this paper for the first time, the DFR problem is investigated in a stochastic environment by the use of probabilistic load flow technique based on Point Estimate Method (PEM). The feasibility of the MFO algorithm and the proposed DFR is demonstrated and compared with the solutions obtained by other approaches and evolutionary methods.*

Keywords: *Feeder reconfiguration, Point Estimate Method (PEM), multi-objective, firefly, wind turbines, distribution.*

1. Introduction

In recent years, the distributed generations predicated on renewable power source have already been among the most used problems to the electrical engineering researchers. Distributed generation units (DGs) are grid-connected or stand-alone electric generation units located within the electric distribution system at or near the end user [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]. Nevertheless, as the result of low emission, high efficiency, easy implementation and cleanness, WTs have attracted the most attentions among the researchers [2-3].

In fact, the recent progresses in the WT technology caused a rapid growth in the popularity of this type of renewable power sources [4]. This wide popularity will result in high penetration of WTs in the power systems which can affect almost all the network techniques from both the operation and planning points of view. In addition, wind as the input fuel to the WTs shows random behaviors in the forecasting problems such that significantly uncertainty may be encircled in the newest power networks. Optimization techniques should be employed for deregulation of the power industry, allowing for the best allocation of the distributed generation (DG).

The distribution feeder reconfiguration (DFR) is one of the most significant control schemes in the distribution networks which can be affected by WTs. 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 [5]. Because there are many candidate-switching combinations in the distribution system, network reconfiguration is a complicated combinatorial, non-differentiable constrained optimization problem.

The problem of minimizing losses through distribution system reconfiguration was first reported in 1975 by Merlin and Back [6], who modeled the distribution system as a spanning tree structure, with line sections represented by the arcs of a graph, and the buses by the nodes. The final configuration that minimized losses was determined from the values found for binary variables associated with switch status in which system constraints were neglected. A switch exchange type of heuristic method was suggested by Civanlar et al. [7] where a simple formula was developed for estimating change in losses due to a branch exchange. Aoki et al. [8] described a loss reduction strategy where a discrete optimization problem was solved. Merlin and Back [6] used a branch and bound method for an optimal solution

Received on: 07.06.2014
Accepted on: 17.09.2014

of minimum losses. Celli et al. [9] proposed a multiobjective formulation for the siting and sizing of DG resources into existing distribution networks. This methodology permits the planner to decide the best compromise between cost of network upgrading, cost of power losses, and cost of energy not supplied, and cost of energy required by the served customers. In [10], an expert system on the basis of the heuristic search was proposed to obtain utilization of the DFR technique to reduce the active power losses.

Based on the above discussion, the main target of the paper would be to examine the suitable operation management of the DFR technique in a new probabilistic structure such as the uncertainty of the active and reactive loads and the WT output variations, simultaneously. In this respect, the two point estimate method (2m PEM) as an approach and basic probabilistic strategy can be used to model the uncertainty outcomes in the problem. In this paper, a new DFR approach based on Modified Firefly Optimization (MFO) algorithm is presented for a distribution network containing WT units. The proposed methodology is tested on the IEEE 32-bus standard test system and comparisons of these results with earlier methods indicate encouraging results. MFO algorithm equipped with a fuzzy decision making tool has been used to cope with the Pareto-based multi objective optimization problem.

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 two-objective related to: minimize real power losses and costs. The feasibility and satisfying performance of the proposed method is examined on the 32-bus IEEE distribution test system.

2. Modeling of Distribution Feeder Reconfiguration

In this part, the objective functions 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.

2.1. Objective Functions

- *Minimization of the total active power losses*

Total active power Losses objective function could be determined by the bellow formula:

$$f_1(X) = P_{loss}(X) = \sum_{i=1}^{N_{br}} R_i \times \left|\tilde{I}_i\right|^2 \tag{1}$$

wherever I_i is the present of the i^{th} branch, R_i is the resistance of i^{th} branch, N_{br} may be the number of branches. Also X since the control vector is as follows:

$$X = \left[Tie, Sw, P_{Wind} \right] \tag{2}$$

$$Sw = \left[Sw_1, Sw_2 Sw_2, \ldots, Sw_{Nsw} \right] \tag{3}$$

$$Tie = \left[Tie_1,\ Tie_2,\ Tie_3, \ldots, Tie_{tie} \right] \tag{4}$$

$$P_{Wind} = [P_{Wind,1}, P_{Wind,2}, \ldots, P_{Wind,N_{WT}}] \tag{5}$$

In this formula, Tie_i and Sw_i will be the closed/open position of the i^{th} tie switch and sectionalizing switch, respectively. Also, $P_{Wind,j}$ reveals the quantity of active power value produced by the j^{th} WT; N_{sw} is the number of sectionalizing switches; N_{tie} is the number of tie switches and N_{WT} is the number of WTs in the network. It is specified that the Tie_i is between 0 and 1 which indicate the open and closed statuses for the related switch respectively.

- *Minimization of the total cost*

The total network cost objective function includes the cost of power made by the grid and the cost of power produced by WTs the following [11]:

$$f_3\ X = \sum_{i=1}^{N_{WT}} C_{Wind,i} + Cost_{grid} \tag{6}$$

The grid cost could be determined the following:

$$Cost_{grid} = C_{grid} \times P_{grid} \tag{7}$$

where's C_{grid} is the expected cost coefficient to purchase the power made by the grid and P_{grid} is the expected amount of power created by the grid. The cost of power generation by the WTs includes three main variables [12]: (1) investment cost (2) operation and maintenance cost (3) Fuel cost. Which means full cost of power generation by each WT is the following [12]:

$$C_{wind,i} = a_0 + a_1 \times P_{wind,i} \tag{8}$$

$$a_0 = \frac{Capital\cos t(\$/kW) * Capacity(kW) * Gr}{Life\ time(Year) * 365 * 24 * LF}$$

$$a_1 = Fuel\ \cos t(\$/kWh) + O\&MCost(\$/kWh)$$

It should be thought about that the fuel cost of WTs (wind) is zero. None the less, the WT cost function is principally considered by contemplating the initial investment cost along with the operation and maintenance cost.

2.2. Constraints

- *Distribution line limits*

Each feeder can transmit a maximum power according to the following formula:

$$\left|P_{ij}^{Line}\right| < P_{ij,\max}^{Line} \tag{9}$$

wherever $P_{ij,\max}^{Line}$ is the maximum active power flow between the buses *i* and *j*; $\left|P_{ij}^{Line}\right|$ is the absolute rate of the active power flow between the buses *i* and *j*.

- *Power flow equations*

The equations of load flow can be considered as equality limitations the following:

$$P_i = \sum_{i=1}^{N_{bus}} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) \qquad (10)$$
$$Q_i = \sum_{i=1}^{N_{bus}} |V_i||V_j||Y_{ij}|\sin(\theta_{ij} - \delta_i + \delta_j)$$

wherever V_i is the voltage value of the i^{th} bus; Y_{ij} is the admittance of the line involving the buses *i* and *j*; θ_{ij} is the admittance angle of the line involving the buses *i* and *j*; δ_i could be the voltage phase angle of the i^{th} bus; P_i and Q_i are the net active and reactive power injected to the i^{th} bus.

- Feeder current limitation

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

$$\left|\tilde{I}_{f,i}\right| \le I_{f,i}^{\max} \qquad ; i = 1, 2, ..., N_f \qquad (11)$$

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

- WTs limitations on active power production

$$p_{WT,i}^{\min} \le p_{WT,i} \le p_{WT,i}^{\max} \qquad (12)$$

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

- Radiality of the network

Techniqually, all of the distribution systems are created radial. This kind of framework can produce many advantages such as for instance simple notion, easy implementation, high protection, etc. Thus, this part of the network must certanly is maintained through the DFR optimization process. Thus, every time that a loop is formed in the network, a switch must certanly be exposed in a way that the radiality of the system is preserved.

3. Probabilistic Load Flow

The majority of the engineering issues are solved within an uncertain environment in a way that the the ultimate solutions may possibly incorporate a certain degree of uncertainty. Recently, among different ways which are proposed to think about the uncertainty consequences, PEMs stand out. The key effective part of these techniques is that they need just the first few moments of the random variable to model its uncertainty [13]. Also, in comparison to the well-known Monte Carlo Simulation (MCS) approach [14], it requires much less computational burden. In this study we get utilization of two PEM to reach a proper probabilistic load flow. Simply, the load flow equations could be revealed the following:

$$S = F(z) \qquad (13)$$

In the above mentioned formula, the input vector *z* is provided to the load flow equations (such as bus information, branch data, network topology, etc) to obtain the state variables. It's apparent that the uncertainty in the input variable *z* is utilized in the output variable *S* easily. In 2*m* PEM, the key strategy is to obtain the first moments of *S* by the utilization of several deterministic load flow runs. In this respect, for each random variable z_l, the probability density function f_{zl} is supposed. Today, the 2*m* PEM may use two new probability concentrations to displace f_{zl} by matching the mean, difference and skewness coefficient of f_{zl} [14]:

$$z_{l,k} = \mu_{z_l} + \xi_{l,k}.\sigma_{z_l}; \quad k = 1,2 \qquad (14)$$

wherever μ_{zl} and σ_{zl} will be the mean and the standard deviation of the probability density function f_{zl} respectively. Supposing *m* random parameters in the issue, 2*m* PEM will solve the deterministic power flow 2*m* times. Also, $\zeta_{l,k}$ as the standard place is computed as under [15]:

$$\xi_{l,k} = \frac{\lambda_{l,3}}{2} + (-1)^{3-k}\sqrt{m - (\lambda_{l,3}^2/2)^2}\ , \quad k = 1,2 \qquad (15)$$

wherever $\lambda_{l,3}$ may be the skewness coefficient and is determined the following [15]:

$$\lambda_{l,3} = \frac{E\left[\left(z_l - \mu_{z_l}\right)^3\right]}{\sigma_{z_l}^3} \qquad (16)$$

In the aforementioned formula, *E* reveals the estimated value. The graphic description of two-point calculates technique is represented in Fig. 1.

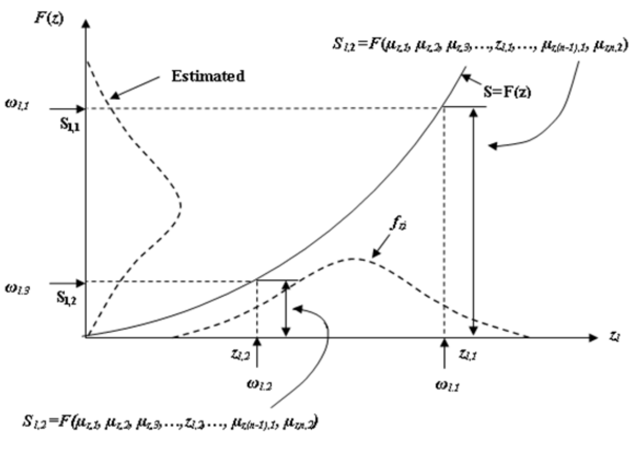

Figure 1. The Conceptual illustration of 2m PEM

In accordance with Fig. 1, the focus points of $z_{l,1}$ and $z_{l,2}$ are utilized in the output information $S_{l,1}$ and $S_{l,2}$. In the 2*m* PEM, the weighting factors $\omega_{l,1}$, $\omega_{l,2}$ are accustomed to determine the impact of the uncertain parameters $z_{l,1}$ and $z_{l,2}$ to find out the output data. Eventually, the estimated value as well as the standard deviation of the output information S_i is determined as bellow [15]:

$$\sigma = \sqrt{\mathrm{Var}(S_i)} = \sqrt{E(S_i^2) - E(S_i)^2} \tag{17}$$
$$E(S_i^j) = \sum_{l=1}^{m}\sum_{k=1}^{2}(\omega_{l,k} \times S_i^j(\mu_{z1}, \mu_{z2}, ..., z_{l,k}, ..., \mu_{zm}))$$
$$\omega_{l,k} = \frac{1}{2m}$$

As discussed earlier, in this perform, the relationship between the WTs can also be considered. In this respect, the extensive 2*m* 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 Eqs. 14 to 17 are solved for the new transformed variables. Eventually, before evaluating the objective function, the parameters are shifted to their fundamental space.

4. Solution Technique

4.1. 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 [16]. This algorithm imitates the fireflies' behavior in exotic regions predicated on three main key ideas [17]: 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:

$$\beta(r) = \beta_0 \times \exp(-\gamma r^m) \quad ; m \geq 1 \tag{18}$$

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:

$$r_{ij} = \left\| X_i - X_j \right\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \tag{19}$$
$$X_i = [x_{i,1}, x_{i,2}, ...x_{i,k}, ..., x_{i,d}]$$
$$X_j = [x_{j,1}, x_{j,2}, ...x_{j,k}, ..., x_{j,d}]$$

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:

$$X_j = X_j + \beta(r) \times (X_i - X_j) + U_j \tag{20}$$
$$U_j = \alpha(rand - \frac{1}{2})$$

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.

4.2. Modified FA(MFA)

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. 20. 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:

$$\alpha^{k+1} = (\frac{1}{2k_{\max}})^{1/k_{\max}} \alpha^k \tag{21}$$

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 $q_1 \neq q_2 \neq q_3 \neq i$. Today, a new test firefly is produced the following:

$$X_{Test} = [x_{Test,1}, x_{Test,2}, ..., x_{Test,d}] \tag{22}$$
$$X_{Test} = X_{q_1} + \sigma_1 \times (X_{q_2} - X_{q_3})$$

In equations 22 to 24, the parameters σ_1,…, σ_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:

$$x_{new1,j} = \begin{cases} x_{Test,j}, & \text{If } \sigma_1 \leq \sigma_2 \\ x_{best,j}, & Else \end{cases} \tag{23}$$

$$X_{new,2} = \sigma_3 \times X_{best} + \sigma_4 \times (X_{best} - X_j) \tag{24}$$

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

4.3. Multi-objective approach using Pareto dominance criterion

In a multi-objective optimization issue, there could be several contradictory objective functions in a way that optimizing one can lead to destroying another one. Usually, a limited multi-objective optimization problem could be created the following:

$$\min F = [f_1(X), f_2(X), ..., f_n(X)]^T$$
$$s.t.$$
$$g_i(X) < 0 \quad i = 1,2,...,N_{ueq}$$
$$h_i(X) = 0 \quad i = 1,2,...,N_{eq} \tag{25}$$

wherever n is the number of the objective functions, $g_i(X)$ could be the inequality constraint, $h_i(X)$ is the equality limitation, N_{ueq} could be the number of inequality limitation and N_{eq} is the number of equality limitation[18]. As discussed earlier, in this paper the notion of non-dominated solution (Pareto optimality) is applied to deal with all of the objective functions properly. Based on the explanation, the solution X_1 dominates the solution X_2 if both the next conditions are satisfied:

$$1)\ \forall j \in 1,2,...,n \ , f_j(X_1) \le f_j(X_2) \tag{26}$$
$$2)\ \exists k \in 1,2,...,n \ , f_k(X_1) < f_k(X_2)$$

Thus, the solution X^* is named a non-dominated solution (Pareto optimal solution), when there is no solution X in the search space Ω accessible in a way that X dominates X^*. 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 [19]. In this regard, the trapezoidal membership function type can be used for the objective functions. Today, by considering the satisfying level of every objective function, the repository is sorted utilizing the bellow formula:

$$N\mu(j) = \frac{\sum_{i=1}^{n} \Delta_i \times \mu_{fi}(X_j)}{\sum_{j=1}^{Np} \sum_{i=1}^{n} \Delta_i \times \mu_{fi}(X_j)} \tag{27}$$

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

5. Application of MFA in the DFR

***Step* 1:** Determine the input data.

***Step* 2:** Change the limited multi-objective optimization issue to a non-constrained one utilizing the penalty functions the following:

$$F(X) = \begin{bmatrix} f_1(X) + L_1 \sum_{i=1}^{N_{eq}} (h_i(X))^2 + L_2 (\sum_{i=1}^{Nueq} (Max[0, -g_i(X)])^2) \\ f_2(X) + L_1 \sum_{i=1}^{N_{eq}} (h_i(X))^2 + L_2 (\sum_{i=1}^{Nueq} (Max[0, -g_i(X)])^2) \end{bmatrix}_{2\times 1} \tag{28}$$

In the paper, L_1 and L_2 will be the penalty factors which in this study are allowed to be be 10^{10}.

***Step* 3:** Produce the initial firefly population randomly.

***Step* 4:** Examine all of the objective functions for the population. Here the stochastic power flow predicated on 2*m* 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 4.1.

***Step 8*:** Update the firefly population, the repository and the best firefly.

***Step* 9:** Use the planned modification approach as explained in part 4.2.

***Step* 10:** Update the repository. Also, check the size of the repository to become too large as explained in part 4.3.

***Step* 11:** Check the termination criterion. If the termination criterion is pleased finish the algorithm, if not come back to stage 6.

6. 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 [20]. The schematic diagram of the test system is revealed in Fig. 2. The initial active power loss before reconfiguration is 201.46 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.

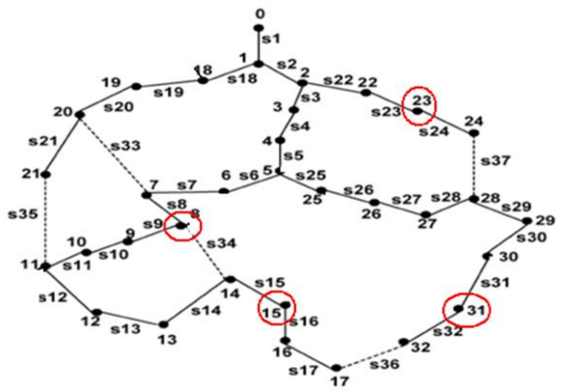

Figure 2. Single line diagram of 32-bus test system including WTs revealed by red circle

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 1 shows the results of single objective optimization of the active power losses neglecting WTs.

Table 1. Deterministic optimization of the active power losses objective function by different methods neglecting WTs

Method	Power loss [KW]	Open switches
PSO–ACO [21]	139.53	s7,s9,s14,s32,s37
DPSO–HBMO [22]	139.53	s7,s9,s14,s32,s37
McDermott et al [23]	139.53	s7,s9,s14,s32,s37
Vanderson Gomes[24]	139.53	s7,s9,s14,s32,s37
PSO-SFLA [25]	139.53	s7,s9,s14,s32,s37
Shirmohammadi [26]	140.26	s7,s10,s14,s32,s37
Original FA	139.53	s7,s9,s14,s32,s37
The proposed MFA	**139.53**	**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 1 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. Since it is observed, the DFR technique alone may reduce the amount of active power losses from 201.46 kW to the optimal value of 139.53 which means increasing the system efficiency without paying any extra cost. Actually, just changing the direction of the power flow in the system may reduce the cost of MW losses. Table 2 reveals the outcome of single-objective optimization of every objective function independently contemplating WTs.

Table 2. Estimated values of the single objective optimization considering WTs (probabilistic Framework)

Objective function	Method	Best solution	States of the switches
Power Losses [kW]	GA	101.32482	s6,s14,s35,s17,s37
	PSO	101.69487	s7,s14,s35,s32,s37
	Original FA	96.936722	s7,s14,s11,s30,s37
	MFA	**94.460261**	**s7,s14,s10,s30,s37**
Cost [$]	GA	154.21831	s6,s11,s35,s36,s37
	PSO	154.32323	s7,s14,s10,s32,s37
	Original FA	154.01164	s7,s14,s11,s32,s37
	MFA	**153.53290**	**s7,s14,s10,s30,s37**

As discussed earlier, the normal probability density function (PDF) with zero mean value is designed to model the forecasting errors of the active and reactive loads. In the event of WT output power generation, the Weibull PDF function can be used here. For better contrast, the outcomes of optimization by the PSO, GA and original FA are revealed comparatively. Based on the Table 2, the existence of WTs in the system has occurred to significant improvement in all the objective functions. In the event of active power losses, this improvement is approximately (139.53-94.46=45.07) 45.07 kW which is a good reduction. Similar improvements is visible in another objective functions. From the stochastic evaluation point of view, the new optimal points revealed in Table 2 are more dependable. Actually, the values of the objective functions in this table are the estimated values maybe not the utter values! In other words, the proposed stochastic construction deduces that by the optimal management of the DFR technique as well as the WTs, these optimal values are expected to be performed for the objective functions. For better contrast, Table 3 reveals the standard deviation values of the objective functions before and after optimization process. Lower value for the standard deviation value reveals more reliable optimal solution. In accordance with Table 3, the proposed stochastic approach could reduce the standard deviation values of the objective functions suitably.

Table 3. The standard deviation value of each objective function in the multi-objective stochastic DFR problem

Standard Deviation	Power Losses [kW]	Cost [$]
Initial σ	4.3641	6.5089
final σ	3.0327	5.1034

7. Conclusions

This paper presented a new multi-objective probabilistic algorithm based on modified FA for multi-objective DFR problem while the effect of the WTs is considered. In the proposed method, the concept of the Pareto optimality is utilized to take advantage of the non-dominated solutions evaluated during the optimization process so that to allow the decision maker to apply his/her preferences in the implementation. In order to control the size of the repository, a fuzzy-based technique is proposed and utilized in the optimization. Also, In order to consider the uncertainties of the new market driven power systems, in this paper for the first time, the DFR problem is investigated in a stochastic environment based on Point Estimate Method (PEM). The simulation results illustrated that the multi-objective evolutionary algorithm is suitable for use in the large-scale integer optimization problems such as the optimal feeder reconfiguration problem; also it does not need complex mathematical programming. The proposed method has been extended for losses and costs of electrical power generation reduction. The results of the proposed algorithm in comparison with the other optimization methods in the area show the superiority of the method in the viewpoint of the accuracy and calculation speed.

8. References

[1] T. Ackerman, G. Anderson, L. Soder, “Distributed generation: a definition,” *Elsevier Sci*. 195–204, 2003.

[2] D. Zhu, R.P. Broadwater, K. Tam, R. Seguin, H. Asgeirsson, “ Impact of DG placement on reliability and efficiency with time-varying loads,” *IEEE Transactions on Power Systems* 21 (1) , 419–427, 2006.

[3] "Distributed Energy Resources Guide," The California Energy Commission, 2003. [Online]. Available: http://www.energy.ca.gov/.

[4] "Wind power systems," in *Encyclopedia of Physical Science and Technology*, 3rd ed. New York: Academic, 2006.

[5] Y.T. Hsiao, C.Y. Chien, "Multiobjective optimal feeder reconfiguration," *IEE Proceedings Generation, Transmission and Distribution*, 148(4):333–336, 2001.

[6] H. Merlin, "Search for a minimal-loss operating spanning tree configuration in an urban power distribution system," in: *Proceedings of the Fifth Power System Computation Conference*, Cambridge, UK, pp. 1–18, 2008.

[7] S. Civanlar, J.J. Grainger, H. Yin, S.S.H. Lee, "Distribution feeder reconfiguration for loss reduction," *IEEE Trans Power Deliver*; 3(4):1217–23, 2010.

[8] K. Aoki, H. Kawabara, T. Satoh, M. Kanezashi, "An efficient algorithm for load balancing of transformers and feeders," *IEEE Trans Power Deliver*; 3(4):1865–72, 2002.

[9] G. Celli, E. Ghiani, S. Mocci, F. and Pilo, F., "A multiobjective evolutionary algorithm for the sizing and siting of distributed generation," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 750–757, May 2009.

[10] T. Taylor, D. Lubkeman, "Implementation of heuristic search strategies for distribution feeder reconfiguration," *IEEE Trans. Power Del*, vol. 5, pp. 239 – 245, 1990.

[11] P. Agalgaonkar, S.V. Kulkarni, S.A. Khaparde, S.A. Soman, "Placement and penetration of distributed generation under standard market design," *Int J Emerg Electr Power Syst*;1(1), 2004.

[12] J. Olamaie, T. Niknam, G. Gharehpetion, "Application of particle swarm optimization for distribution feeder reconfiguration considering distributed generators," *Appl Math Comput* ;20(1):575–86, 2008.

[13] J.M. Morales, J. Perez-Ruiz, "Point estimate schemes to solve the probabilistic power flow," *IEEE Transactions on Power System*, vol. 22, pp. 1594-1601, .2007.

[14] R. Billinton, and P. Wang, "Teaching Distribution System Reliability Evaluation Using Monte Carlo Simulation," *IEEE Transactions on Power Systems*, vol. 14, no. 2, pp. 397-403, May 1999.

[15] A. Soroudi, M. Ehsan, R. Caire, N. Hadjsaid, "Possibilistic evaluation of distributed generations Impacts on distribution networks," *IEEE Trans on Power Syst*, vol. 26, pp. 2293 – 2301, 2011.

[16] X.S. Yang, "Nature-Inspired Metaheuristic Algorithms," *Frome: Luniver Press*. ISBN 1905986106, 2008.

[17] T. Apostolopoulos, A. Vlachos, "Application of the Firefly Algorithm for Solving the Economic Emissions Load Dispatch Problem," *International Journal of Combinatorics*, ID: 523806, 2011.

[18] Y.P. Cai, G.H. Huang, Z.F. Yang, Q. Tan, "Identification of optimal strategies for energy management systems planning under multiple uncertainties," *Appl Energy* 9;86(4):480–95, 2009.

[19] R.R. Tan, K.B. Aviso, I.U. Barilea, A.B. Culaba, J.B. Cruz, " A fuzzy multi-regional input-output optimization model for biomass production and trade under resource and footprint constraints,"*Appl Energy*, in press. ISSN: 0306-2619.

[20] M.E. Baran, F.F. Wu, " Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Trans on Power Del*, vol. 4, pp. 1401 – 1407, 1989.

[21] T. Niknam, "An efficient hybrid evolutionary based on PSO and ACO algorithms for distribution feeder reconfiguration," *European Trans on Elect Power*, vol. 20, pp. 575 – 590, 2010.

[22] T. Niknam, S.I. Taheri , J. Aghaei, S. Tabatabaei, M. Nayeripour, " A modified honey bee mating optimization algorithm for multiobjective placement of renewable energy resources," *Applied Energy* , vol. 88 , pp. 4817-4830, 2011.

[23] T.E. McDermott, I. Drezga, R.P. Broadwater, "A heuristic nonlinear constructive method for distribution system reconfiguration," *IEEE Trans on Power Sys*, vol. 14, pp. 478 – 483, 1999.

[24] S.Jr. Carneiro, J.L.R. Pereira, M.P. Vinagre, P.A.N. Garcia, L.R. Araujo, " A New Heuristic Reconfiguration Algorithm for Large Distribution Systems," *IEEE Tran on Power sys*, vol. 20 , pp. 1373 – 1378, 2005.

[25] T. Niknam, A. Kavousifard, A. Seifi, "Distribution feeder reconfiguration considering fuel cell/wind/photovoltaic power Plants," *Journal of Renewable Energy*, vol. 37, pp. 213-225, 2011.

[26] D. Shirmohammadi, H.W. Hong, "Reconfiguration of electric distribution networks for resistive line loss reduction," *IEEE Trans, Power System*, vol. 4, pp. 1492 – 1498, 1989.