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Study of Network Reconfiguration in Distribution Systems Using an Adaptive Modified Firefly Algorithm

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Original scientific paper

This paper suggests a new method based on the probabilistic load flow and Adaptive Modified Firefly Algorithm (AMFA) in order to evaluate the optimal management of the Distribution Feeder Reconfiguration (DFR) operation problems by considering a few Wind Turbines (WTs) in system and performance satisfaction of the proposed method is examined on the IEEE 32-bus standard test system. The significant objective functions in this paper includes: 1) Minimizing the total cost of active power losses in the network, 2) voltage profile improvement, 3) decreasing the present network total costs such as power production cost by the main network and distributed generations. Furthermore, a new stochastic solution based on Point Estimate Method (PEM) is proposed to effectively deal with the uncertainty related to the important random parameters such as active and reactive loads in addition to the wind speed variations. Thus, the suggested probabilistic framework must be considered in order to solve the reconfiguration problem with regard to uncertainties which caused by the wind turbines.

Key words: Reconfiguration, Probabilistic Load Flow, Adaptive Modified Firefly Algorithm (AMFA)

Studija o rekonfiguraciji mreže distributivnog sustava korištenjem adaptivnog modificiranog *firefly* algoritma. U radu se predlaže novi pristup za optimalno rekonfiguriranje napojnih vodova u elektroenergetskim distributivnim sustavima temeljen na adaptivnom modificiranom *firefly* algoritmu. Primjena obuhvaća problem s par vjetroagregata u sustavu, a učinkovitost je provjerena korištenjem standardnog testa za IEEE 32 sabirnicu. Značajniji razmatrani kriteriji su: 1) smanjenje ukupne cijene gubitaka aktivne snage u mreži, 2) poboljšanje profila napona, 3) smanjenje ukupne cijene postojeće mreže kroz smanjenje cijene proizvodnje snage glavne mreže i distribuiranih izvora. Nadalje, novo stohastičko rješenje temeljeno na *Point estimate* metodi predloženo je za učinkovito savladavanje nesigurnosti povezanom s važnim stohastičkim parametrima kao što su aktivni i reaktivni teret u dodatku s varijacijama brzine vjetra. Predloženi stohastički okvir mora biti uzet u obzir prilikom rješavanja problema rekonfiguracije s obzirom na neodređenosti koje proizlaze iz vjetroagregata.

Ključne riječi: rekonfiguracija, vjerojatnosni model tereta, adaptivni modificirani *firefly* algoritam

1 INTRODUCTION

Lately, the distributed generations which are predicated on renewable power sources have already been among the most used problems to the electrical engineering researchers. In this group, there are several desirable power sources such as WTs, Fuel Cells (FCs), Photovoltaics (PVs), geothermal based sources, etc. Nonetheless, the consequence of low emission, high performance, easy implementation and cleanness, WTs have attracted probably the most attentions among scientists [1-2].

In reality, the recent progresses in the WT technology have caused a rapid development in recognition of this sort of renewable power sources [3]. This wide recognition can lead to high penetration of WTs in the power systems which nearly could influence both operation and planning techniques of the network. Furthermore, while the input fed with wind, the WTs reveal random behaviors in the forecasting problems such that significantly may be encircled in the newest power networks. Certainly the appearance of WTs in the network can affect the total reconfiguration strategy greatly.

The Distribution Feeder Reconfiguration (DFR) is described as the procedure of changing the topology of the radial distribution system through a few sectionalizing and tie switches such that the maximum efficiency is accomplished [4,5]. The term “maximum efficiency” refers to various objectives such as loss reduction, voltage profile improvement, load balance increment, reliability improvement, etc. [6, 7, 8]. In this respect, a number of valuable researches have been implemented in recent years which some of the most significant ones are reviewed bellow.

In [9], the simultaneous effect of different renewable power sources and the DFR strategy was investigated in a multi-objective framework. In [10], an expert system based on heuristic search was proposed to obtain utilization of the DFR technique in order to reduce the active power losses. In [11], a discrete measurement was proposed to first find a loop in the system (through closing some of the tie switches) and find the best switching scheme to make the system radial. In [12], the DFR technique was applied, to increase the system load balance and service restoration simultaneously.

Based on above discussion, the main target of this paper would be evaluation of DFR operation management technique suitability in a new probabilistic structure such as uncertainty of active and reactive loads and the WT output variations, simultaneously.

In this regard, the two point estimate method (2*m* PEM) as an approach and basic probabilistic strategy can be used to model the uncertainty outcomes of the problem [13]. In order to consider the correlated effect of the WT on each other, the extensive PEM is used here [14].

The problem is then formulated in a multi-objective framework by optimizing the total active power losses, the maximum bus voltage change and the total system cost. To optimize all the target functions appropriately, the Pareto optimality strategy (Non-dominated solutions) is utilized.

Since the investigated problem is categorized in discrete, nonlinear and complex optimization problem[15], a new optimization algorithm which is predicated on adaptive modified firefly algorithm is proposed. The feasibility and gratifying efficiency of the planned technique is analyzed on the 32-bus IEEE distribution test system.

2 DISTRIBUTION FEEDER RECONFIGURATION MODELING

In this part, objective functions and the appropriate equality and inequality constraints are explained. Notice that in this paper, the symbol $\tilde{}$ is employed to exhibit the expected value of the corresponding variable.

2.1 Objective Functions

- Minimization of total active power losses Total active power Losses objective function could be determined by the following formula:

$$\widetilde{f}_1(X) = \widetilde{P}_{loss}(X) = \sum_{i=1}^{N_{br}} R_i \times \left|\widetilde{I}_i\right|^2 \tag{1}$$

Here I_i is the current of the i^{th} branch, R_i is the resistance of i^{th} branch, and N_{br} consider as a number of branches. Where *X* as a control vector would be defined as follows:

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

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

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

$$\widetilde{P}_{Wind} = [\widetilde{P}_{Wind,1}, \widetilde{P}_{Wind,2}, ..., \widetilde{P}_{Wind,N_{WT}}]. \tag{5}$$

In this formula, Tie_i and Sw_i will be the close/open position of the i^{th} tie switch and sectionalizing switch, respectively. Also, $P_{Wind,j}$ demonstrates the quantity of active power value which is 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. The values of 0 and 1 are used for to show the open and closed status, respectively.

- Minimizing the bus voltage deviation Maximum bus voltage deviation is explained as bellow:

$$\widetilde{f}_2(X) = \max\left[\left|\ 1 - \widetilde{V}_{\min}\right| \text{ and } \left|\ 1 - \widetilde{V}_{\max}\right|\right]. \tag{6}$$

Here $\widetilde{V}_{\min}$ and $\widetilde{V}_{\max}$ would be the minimum and maximum expected voltage magnitudes of buses.

- Minimization of the total cost The total network cost objective function includes the cost of power produced by the grid and the cost of power produced by WTs as it has shown bellow [16]:

$$\widetilde{f}_3\left(X\right) = \sum_{i=1}^{N_{WT}} \widetilde{C}_{Wind,i} + \widetilde{C}ost_{grid}. \tag{7}$$

The grid cost could be determined as follow:

$$\widetilde{C}ost_{grid} = \widetilde{C}_{grid} \times \widetilde{P}_{grid}. \tag{8}$$

Where $\widetilde{C}_{grid}$ is the expected cost coefficient of the grid and$\widetilde{P}_{grid}$is the expected amount of power supplied by the grid.

The generated power cost by means of WTs includes three main variables [17]: (1) investment cost (2) operation and maintenance cost (3) fuel cost, which means full cost of power generation by each WT is calculated as follow [17]:

$$\widetilde{C}_{wind,i} = a_0 + a_1 \times \widetilde{P}_{wind,i}, \tag{9}$$

$$a_0 = \frac{\text{Capital cost [\$/kW]} \times \text{Capacity [kW]*Gr}}{\text{Life time [Year]} \times 365 \times 24 \times LF},$$

$$a_1 = \text{Fuel cost [\$/kWh]} + \text{O\&MCost[\$/kWh]}.$$

It should be mentioned that the fuel cost of WTs (wind) is zero. Nonetheless, the WT cost function is principally calculated by contemplating the initial investment cost along with operation and maintenance cost.

2.2 Constraints

- Distribution line limits Each feeder can transmit a maximum power according to the following formula:

$$\left|\widetilde{P}_{ij}^{Line}\right| < P_{ij,\max}^{Line}, \tag{10}$$

where $P_{ij,\max}^{Line}$ 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 *i* and *j* busses.

- Power flow equations Load flow equations are considered as equality limitations and described by following equations:

$$\widetilde{P}_i = \sum_{i=1}^{N_{bus}} \left|\widetilde{V}_i\right| \left|\widetilde{V}_j\right| |Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j), \tag{11}$$
$$\widetilde{Q}_i = \sum_{i=1}^{N_{bus}} \left|\widetilde{V}_i\right| \left|\widetilde{V}_j\right| |Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j).$$

Where V_i is the voltage value of the *i*th bus; Y_{ij} is the admittance of the line between the buses *i* and *j* buses; θ_{ij} is the admittance angle of the line between the buses *i* and *j*;δ_i consider as an *i*th bus voltage phase angle; P_i and Q_i represent injected net active and reactive power into the *i*th bus.

- Feeder current limitation According to the thermal limitations, each feeder should not exceed its maximum current capacity. Therefore, each time that the load flow is done, this constraint should be checked to be satisfied. In the probabilistic power flow, the expected value of the current should be calculated and satisfied in this constraint:

$$\left|\widetilde{I}_{f,i}\right| \leq I_{f,i}^{\max} \qquad ;i = 1, 2, ..., N_f. \tag{12}$$

Here $|I_{f,i}|$ 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

$$p_{WT,i}^{\min} \leq \widetilde{p}_{WT,i} \leq p_{WT,i}^{\max}. \tag{13}$$

Where $p_{WT,i}^{\max}$ and $p_{WT,i}^{\min}$ represent the maximum and the minimum of generating power capacity for the *i*th WT.

- Bus voltage limitation

$$V_{\min} \leq \widetilde{V}_i \leq V_{\max}. \tag{14}$$

Here $V_{\max}$ and $V_{\min}$ represent the maximum and minimum values of the buses voltage.

- Radiality of the network Technically, majority of distribution systems are created radial. This kind of framework has many advantages, for instance simple notion, easy implementation, high protection, etc. Thus, this aspect of the network should be preserved during the DFR optimization process. Thus, whenever a loop is formed in the network, a switch should be opened such that the radiality of the network is preserved.

3 PROBABILISTIC LOAD FLOW

The majority of engineering issues are solved within an uncertain environment in a way that the ultimate solutions are possibly incorporating a specific degree of uncertainty. Recently, among different methods which are proposed to consider the uncertainty effects, PEMs stand out. The prominent feature of these techniques is that they need just the first few moments of the random variable to model its uncertainty [18]. Also, in comparison to the well-known Monte Carlo Simulation (MCS) approach, it requires much less computational burden. In this study we utilize two PEM in order to reach a proper probabilistic load flow. Simply, the load flow equations are considered as follow:

$$S = F(z). \tag{15}$$

In equation (15), the input vector *z* is provided for the load flow equations (such as bus data, branch data, network topology, etc) to obtain the state variables. It's apparent that uncertainty in the input variable *z* is transferred to the output variable *S* easily. In 2*m* PEM, the key strategy is to obtain the first moments of *S* by utilizing several deterministic load flow runs. With respect to what have been mentioned, for each random variable *zl*, the probability density function *fzl* is supposed. Nowadays, the 2*m* PEM may use two new probability concentrations to displace *fzl* by matching the mean, difference and skewness coefficient of *fzl*[18]:

$$z_{l,k} = \mu_{z_l} + \xi_{l,k}.\sigma_{z_l}; \quad k = 1, 2. \tag{16}$$

Here μ_{z_l} and σ_{z_l} are the mean and the standard deviation of the probability density function f_{z_l} respectively. Supposing *m* as random parameters in the problem, 2*m* PEM will solve the deterministic power flow 2*m* times. Also, $\zeta_{l,k}$ as the standard place is computed as below [19]:

$$\xi_{l,k} = \frac{\lambda_{l,3}}{2} + (-1)^{3-k}\sqrt{m - (\lambda_{l,3}^2/2)^2}\ , \quad k = 1,\ 2. \tag{17}$$

Where $\lambda_{l,3}$ demonstrate the skewness coefficient and determined by the following equation [19]:

$$\lambda_{l,3} = \frac{E\left[(z_l - \mu_{z_l})^3\right]}{(\sigma_{z_l})^3}. \tag{18}$$

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

According to Fig. 1., the $z_{l,1}$ and $z_{,l,2}$ focus points are utilized in $S_{l,1}$ and $S_{l,2}$ output information. In 2*m* PEM, the $\omega_{l,1}$, $\omega_{l,2}$ weighting factors are accustomed to determine the impact of the uncertain parameters $z_{l,1}$ and $z_{l,2}$ to

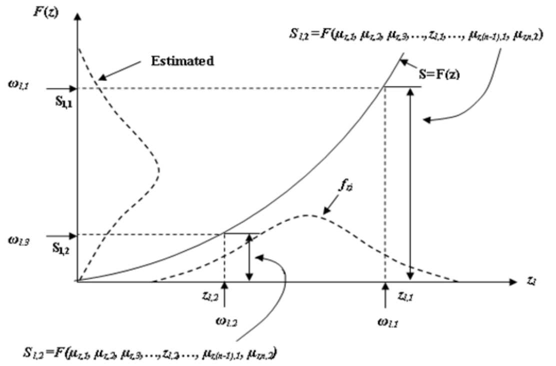

Fig. 1. Conceptual illustration of 2m PEM

find out the output data. Eventually, the desired value as well as the standard deviation of output information *Si* is determined as follow [19]:

$$\sigma = \sqrt{\mathrm{Var}(S_i)} = \sqrt{E(S_i^2) - [E(S_i)]^2}, \qquad (19)$$
$$E(S_i^j) = \sum_{l=1}^{m}\sum_{k=1}^{2}(\omega_{l,k} \times S_i^j(\mu_{z1}, \mu_{z2}, ..., z_{l,k}, ..., \mu_{zm})),$$
$$\omega_{l,k} = \frac{1}{2m}.$$

As it has been mentioned, in this research, the correlation between the WTs is also considered. In this respect, the extensive 2*m* PEM is employed. The prominent strategy behind this process is to transform the correlated output power of the WTs into uncorrelated kinds by utilizing the orthogonal transformation. Then Equations 17 to 20 are solved for new transformed variables. Eventually, before evaluating the objective function, the parameters are shifted to their fundamental space.

4 SOLUTION TECHNIQUE

4.1 Original FA

Actually the FA is 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 which 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 would fly randomly in the air. In the optimization problem, the objective function value determines the brightness of the fireflies. Compared to another well-known progressive technique like PSO and GA, the FA has especial characteristics such as simple concept, easy implementation, low dependency on the initial variables, common idea, etc.

In the FA, as the exact distance between any two fireflies increase, the brightness of one firefly to the eyes of another firefly will decrease. Thus, for every firefly, an attractiveness parameter is described as bellow:

$$\beta(r) = \beta_0 \times \exp(-\gamma r^m) \quad ; m \geq 1. \qquad (20)$$

Here *r* defined as an exact distance between two fireflies, β_0 consider as an initial attractiveness at $r = 0$ and γ is the absorption coefficient to model the brightness reduction rate (called light intensity). In the Cartesian distance, the exact distance between both *i* and *j* fireflies shown by r_{ij} and determined as follow:

$$\begin{aligned} r_{ij} &= \|X_i - X_j\| = \sqrt{\textstyle\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2}, \\ X_i &= [x_{i,1}, x_{i,2}, ...x_{i,k}, ..., x_{i,d}], \\ X_j &= [x_{j,1}, x_{j,2}, ...x_{j,k}, ..., x_{j,d}]. \end{aligned} \qquad (21)$$

Dimension is designated by *d* in formula (21). By utilizing both aforementioned equations; the firefly with less brightness (X_j) is moved toward the brighter firefly (X_i) as bellow:

$$\begin{aligned} X_j &= X_j + \beta(r) \times (X_i - X_j) + U_j, \\ U_j &= \alpha(rand - \tfrac{1}{2}), \end{aligned} \qquad (22)$$

Where α is the randomization parameter that is fixed in the range of (0,1). According to above formula, it can be observed that updating method of each 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 mentioned before, each time that a firefly can not see any firefly in the near neighboring, it should fly randomly. In this formula, the term U_j has been utilized to simulate this random movement. The aforementioned formula is repeated before entire population became update.

4.2 Adaptive Modified FA (AMFA)

While the original FA has several advantages to deal with complicated optimization problems, in this part, a new two-phase modification strategy is proposed to increase the total search capacity of the algorithm effectively. The first section of the modification approach is definitely an adaptive formulation to update the value of the randomization parameter in Equation 22. A small value of α will encourage the FA to search more locally while a large value of α will motivate the algorithm to search in the unfamiliar sections. Therefore, after running the algorithm several times, the bellow adaptive formulation is available for α:

$$\alpha^{k+1} = (\frac{1}{2k_{\max}})^{1/k_{\max}}\alpha^k. \qquad (23)$$

Where k demonstrates the iteration number and $k_{\max}$ is the maximum number of iteration. The next part of the optimization approach is planned to add to the diversity of the FA population by utilizing mutation and crossover operators. Here we have used the crossover and mutation operators from genetic algorithm to increase the possibility of escaping from local optima. This event can be achieved by the use of powerful operators and creating new test solutions. Thus, for each firefly X_i, three random fireflies (q_1,q_2,q_3) are selected from the population in a way that $q_1 \neq q_2 \neq q_3 \neq i$. Now, a new test firefly is produced as bellow:

$$\begin{array}{l} X_{Test} = [x_{Test,1}, x_{Test,2}, ..., x_{Test,d}], \\ X_{Test} = X_{q_1} + \sigma_1 \times (X_{q_2} - X_{q_3}). \end{array} \tag{24}$$

In equations 25 to 27, the $\sigma_1,\ldots, \sigma_4$ parameters have random values in the range [0,1]. By utilizing the aforementioned formula, two new test fireflies are produced as follows:

$$x_{new1,j} = \begin{cases} x_{Test,j}\,, & \text{If } \sigma_1 \le \sigma_2 \\ x_{best,j}\,, & Else \end{cases} \tag{25}$$

$$X_{new,2} = \sigma_3 \times X_{best} + \sigma_4 \times (X_{best} - X_j). \tag{26}$$

Now, the best firefly among X_{new1} and X_{new2} is chosen to be compared with the i^{th} firefly (X_i). If it better than X_i, then replaces X_i otherwise X_i will stay put in its current position.

5 MULTI-OBJECTIVE APPROACH USING PARETO DOMINANCE CRITERION

In a multi-objective optimization problem, there could be several contradictory objective functions in a such that optimizing one will result in destroying the other one. Usually, a limited multi-objective optimization problem could be written as bellow:

$$\begin{array}{ll} \min F = [f_1(X), f_2(X), ..., f_n(X)]^T & \\ s.t. & \\ g_i(X) < 0 & i = 1, 2, ..., N_{ueq} \\ h_i(X) = 0 & i = 1, 2, ..., N_{eq} \end{array} . \tag{27}$$

Here n is the number of the objective functions, $g_i(X)$ demonstrates the inequality constraint, $h_i(X)$ is the equality limitation, N_{ueq} is the number of inequality limitation and N_{eq} is the number of equality limitation [22]. As discussed earlier, in this paper the notion of non-dominated solution (Pareto optimality) is applied to deal with all of objective functions properly. Based on definition, the solution X_1 dominates the solution X_2 if both of the next following conditions are satisfied:

$$\begin{array}{l} 1)\forall\ j \in \{1, 2, ..., n\}\,, f_j(X_1) \le f_j(X_2) \\ 2)\exists\ k \in \{1, 2, ..., n\}\,, f_k(X_1) < f_k(X_2) \end{array} \tag{28}$$

The solution X^* is named as non-dominated solution (Pareto optimal solution), if there is no solution X in the search space Ω accessible in a way that X dominates X^*. During the optimization process, the non-dominated solutions which had been found are stored in an additional memory named repository. In order to prevent the repository size from growing too large, a fuzzy clustering approach which is predicated on membership function is applied [23]. So, the trapezoidal membership function type can be used for all objective functions. Now, by considering the satisfying level of each objective function, the repository is sorted by utilizing the following formula:

$$\begin{array}{l} N\mu(j) = \frac{\sum_{i=1}^{n} \Delta_i \times \mu_{fl}(X_j)}{\sum_{j=1}^{Np} \sum_{i=1}^{n} \Delta_i \times \mu_{fl}(X_j)} \\ \mu_{f_i}(X) = \begin{cases} 1 \text{ for } f_i(X) \le f_i^{\min} \\ 0 \text{ for } f_i(X) \ge f_i^{\min} \\ \frac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}}, \text{ for } f_i^{\min} \le f_i(X) \le f_i^{\max} \end{cases} \end{array} \tag{29}$$

Here 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 decision maker to utilize each objective function individually.

6 AMFA APPLICATION IN THE DFR

***Stage* 1:** Defining the input data.

***Stage* 2:** Changing the limited multi-objective optimization problem to a non-constrained one by utilizing the penalty functions as bellow:

$$F(X) = \ldots$$
$$\begin{bmatrix} f_1(X) + L_1 \sum\limits_{i=1}^{N_{eq}} (h_i(X))^2 + L_2(\sum\limits_{i=1}^{Nueq} (Max[0, -g_i(X)])^2) \\ f_2(X) + L_1 \sum\limits_{i=1}^{N_{eq}} (h_i(X))^2 + L_2(\sum\limits_{i=1}^{Nueq} (Max[0, -g_i(X)])^2) \\ f_3(X) + L_1 \sum\limits_{i=1}^{N_{eq}} (h_i(X))^2 + L_2(\sum\limits_{i=1}^{Nueq} (Max[0, -g_i(X)])^2) \end{bmatrix}_{3\times 1} . \tag{30}$$

Where, L_1 and L_2 are considered as penalty factors which in this study are allowed to be 1010.

***Stage* 3:** Generating the initial firefly population haphazardly.

***Stage* 4:** Evaluating the objective functions population. Here the stochastic power flow which is predicated on 2m PEM is implemented.

***Stage* 5:** Constructing the repository by utilizing the non-dominated solutions in the population.

***Stage* 6:** Best firefly selection from the repository randomly.

***Stage* 7:** Move a firefly with less brightness toward the one which has more brightness as explained in part 4.1.

***Stage* 8:** Update the firefly population, the repository and

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

the best firefly.

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

Stage 10: Update the repository. Also, check the size of the repository to become too large as explained in part 5.

***Stage* 11:** Check the termination criterion. If the termination criterion to finish the algorithm satisfied, finish the algorithm; else return to stage 6.

7 SIMULATION RESULTS

In this part, the 32-bus IEEE test system has been utilized 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 has been demonstrated in Fig. 2. The initial active power loss before reconfiguration is 202.67 kW. As it could be seen from Fig. 2, solid and dotted lines have been depicted as a symbol for sectionalizing and tie switches respectively. In this paper, the WTs are located in the network such that they will be near the high load points and preserve proper distance from each other.

The maximum power capacity of WTs is expected to be 250 kW. The evaluation is executed in both the deterministic and probabilistic frameworks. Furthermore, in order to investigate the satisfying performance of the proposed algorithm, initially, the single objective optimization is done. This evaluation reveals suitable results in comparison with other well-known methods. Table 1 shows the results of single objective optimization of the active power losses neglecting WTs.

It could be observed that WTs have been ignored in order to make a comparison 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.

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

Method	Power loss [KW]	Minimum voltage	Open Switches
PSO–ACO [26]	139.53	0.9378964	s7, s9, s14, s32, s37
DPSO [27]	139.53	0.93781964	s7, s9, s14, s32, s37
DPSO–HBMO [27]	139.53	0.93781964	s7, s9, s14, s32, s37
McDermott et al [28]	139.53	0.93781964	s7, s9, s14, s32, s37
Vanderson Gomes[29]	139.53	0.93781964	s7, s9, s14, s32, s37
PSO-SFLA [30]	139.53	0.93781964	s7, s9, s14, s32, s37
DPSO–ACO [31]	139.53	0.93781964	s7, s9, s14, s32, s37
MSFLA [16]	139.53	0.93781964	s7, s9, s14, s32, s37
Shirmohammadi [32]	140.26	0.93787634	s7, s10, s14, s32, s37
Original FA	139.53	0.93781964	s7, s9, s14, s32, s37
The proposed AMFA	**139.53**	**0.93781964**	**s7, s9, s14, s32, s37**

From Table 1 it is obvious that the proposed modified FA has discovered the best optimal solution which was discovered by other well-known techniques in the area. In addition the related optimal switching has been shown in Table 1. It's obvious that just the DFR technique is able to reduce the amount of active power losses from 202.67 kW to the optimal value of 139.53 which means increasing the system efficiency without paying any extra cost. In fact, just changing the direction of the power flow in the system can reduce the cost of MW losses. Table 2 reveals the results of single objective optimization of the voltage deviation target.

Here again the suggested algorithm has achieved to the best switching which have been discovered up to date. So far, the existence of WTs in the system was neglected. Table 3 reveals the outcome of single-objective optimization of each objective function while independently contemplating WTs.

Here the results are in the stochastic framework. 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 case

Table 2. Deterministic optimization of the voltage deviation objective function by different methods neglecting WTs

Method	Voltage deviation [p.u.]	Minimum voltage	Open Switches
DPSO–ACO [31]	0.06120031	0.93879681	s7, s9, s14, s32, s37
PSO–ACO [26]	0.06120031	0.93879681	s7, s9, s14, s32, s37
DPSO [27]	0.06120031	0.93879681	s7, s9, s14, s32, s37
DPSO–HBMO [27]	0.06120031	0.93879681	s7, s9, s14, s32, s37
GA	0.06218097	0.93781902	s7, s10, s14, s32, s37
PSO	0.06120031	0.93879681	s6, s9, s14, s32, s37
Original FA	0.06120031	0.93879681	s7, s9, s14, s32, s37
The proposed AMFA	**0.93879681**	**0.06120031**	**s7, s9, s14, s32, s37**

Table 3. Estimated values of the single objective optimization considering WTs (probabilistic Framework)

Objective function	Method	Best solution	States of the switches
Power Losses [kW]	GA	101.12192	s6, s14, s35, s17, s37
	PSO	101.39677	s7, s14, s35, s32, s37
	Original FA	96.824722	s7, s14, s11, s30, s37
	AMFA	**93.970231**	**s7, s14, s10, s30, s37**
Voltage Deviation [p.u.]	GA	0.0491258	s6, s34, s10, s32, s37
	PSO	0.0488549	s6, s34, s10, s32, s37
	Original FA	0.0473932	s6, s14, s11, s32, s37
	AMFA	**0.0471888**	**s6, s14, s11, s32, s37**
Cost [$]	GA	154.11901	s6, s11, s35, s36, s37
	PSO	154.09343	s7, s14, s10, s32, s37
	Original FA	154.01094	s7, s14, s11, s32, s37
	AMFA	**153.96090**	**s7, s14, s10, s30, s37**

of WT output power generation, the Weibull PDF function can be used here. For better comparison, the outcomes of optimization by the PSO [25], GA and original FA are demonstrated comparatively. Based on the Table 3, the existence of WTs in the system leads to significant improvement in objective functions. In the case of active power losses, this improvement is about (139.53-93.97=45.56) 45.56 kW and this is a good reduction. Similar improvements can be seen in the other objective functions. From the stochastic evaluation point of view, the new optimal points revealed in Table 3 are more reliable.

Actually, the values of the objective functions in this table are desired values not absolute values! In other words, the proposed stochastic construction deduces that by optimal management of the DFR technique as well as the WTs, these optimal values are expected to be gained for objective functions. To have a better comparison, standard deviation values of the objective functions before and after optimization process are considered in Table 4. Lower value for standard deviation value reveals more reliable optimal solution. In accordance with Table 4, the proposed stochastic approach could properly reduce the standard deviation values of the objective functions.

8 CONCLUSION

In this paper, a stochastic structure which is predicated on 2*m* PEM and AMFA was proposed to solve the optimal operation administration of the DFR strategy. In this regard, the uncertainty related to active and reactive loads along with the WTs output power generation was considered in the analysis. Also, a new modification method based on FA was suggested to 1) increase the convergence speed of the algorithm, 2) avoid premature convergence.

The efficiency of the suggested approach was analyzed on the 32-bus IEEE standard distribution test system. Based on the results, the suggested stochastic structure can increase the reliability of the suitable solutions effectively. On the other hand by utilizing the DFR technique along with considering the WTs in the system can improve all of the objective functions individually. From the optimization ability, the proposed AMFA showed better performance

Table 4. The standard deviation value of each objective function in the multi-objective stochastic DFR problem

Cost [$]	Voltage Deviation [p.u]	Power Losses [kW]	Standard Deviation
6.7021	0.00792	4.3821	Initial σ
5.2011	0.00313	3.0201	Final σ

over other well-known methods in the area. The feasibility and satisfying performance of the proposed method was demonstrated too.

APPENDIX

The test system load data are as follows:

Branch Number	Pload (KW)	Qload (KVAR)	Branch Number	Pload (KW)	Qload (KVAR)
1	0	0	18	90	40
2	100	60	19	90	40
3	95	40	20	90	40
4	120	80	21	90	40
5	60	30	22	90	40
6	60	20	23	90	50
7	200	100	24	420	200
8	200	100	25	420	200
9	60	20	26	60	25
10	60	20	27	60	25
11	45	30	28	60	20
12	60	35	29	120	70
13	60	35	30	200	600
14	120	80	31	150	70
15	60	10	32	210	100
16	60	20	33	60	40
17	60	20			

All loads are considered with normal PDF as follows:

A random variable *X* is said to be normally distributed with mean μ and variance$\sigma_2$if its probability density function (pdf) is:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{(x-\mu)^2}{2\sigma^2})$$

The PDF of WTs are Weibull as follows:

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}(\frac{x}{\lambda})^{k-1}e^{-(\frac{x}{\lambda})^k}, x \geq 0 \\ 0, x \prec 0 \end{cases}$$

Where $k \succ 0$ is the shape parameter and $\lambda \succ 0$ is the scale parameter of the distribution.

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