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Belirsizlik ve Bulanık Etkileşme ile Dağıtım Ağı Yeniden Yapılanma Yönetimi

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Özet. Bu makale, güç kaybını minimize etmeye ulaşmayı, minimum voltaj sapmalarını ve dağıtılmış jeneratörlerde dairesel dağılım ağlarının denge faktörünü daha iyi yüklemeyi hedefleyen MPSO algoritmasına dayalı yeniden yapılandırma tekniğini önermektedir. A 33-bus sistemi konfigürasyonu optimize etmek ve DG üniteleri ile dağıtım sistemlerinin optimal değişim faaliyetlerini çözmek için sunulan tekniğin etkinliğini ispatlamak için seçilmiştir. Simülasyon sonuçları göstermiştir ki düşük sistem kaybı ve daha iyi yükleme dengesine DGsiz sistemler karşılaştırıldığında DGli sistemlerde ulaşılacaktır. Buna ek olarak, simülasyon sonuçları önerilen metodun başarısını onaylamaktadır ve kayıpları azaltma ve sistem performansını artırmada kayda değer etkisini göstermektedir.

Anahtar Kelimeler: Dağıtılmış Üretim (DG), dağıtım sistemi yeniden yapılandırılması, bulanık etkileşme, yük dengeleme indeksi iyileştirme, MPSO algoritması, güç kaybı azaltılması.

Management of the Distribution Network Restructuring Considering Uncertainty and Fuzzy Interaction

Abstract. This paper proposes a reconfiguration technique based on MPSO Algorithm that aims at achieving power loss minimization, minimum voltage deviation and better load balance factor of radial distribution networks in presence of distributed generators. A 33-bus distribution system was selected for optimizing the configuration and to demonstrate the effectiveness of the proposed technique for solving the optimal switching operation of distribution systems with DG units. The simulation results have shown that lower system loss and better load balancing will be achieved at a distribution system with distributed generation (DG) compared to a system without DG. In addition, the simulation results confirm the success of the proposed method and show significant impact in reducing losses and improving system performance.

Keywords: Distributed Generation (DG), Distribution system reconfiguration, Fuzzy Interaction, Load-balancing index improvement, MPSO Algorithm, Power loss minimization.

1. INTRODUCTION

Most of traditional power distribution systems have radial configuration. Types of switches used in distribution systems are sectionalizing-switches that remain normally closed,

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and tie-switches that remain normally open. There are several operational schemes in electrical distribution systems; one of them is "distribution feeder reconfiguration", which can bring nearly minimization of real loss, improvement in voltage profile, and mitigating of overloads in the network. In addition, distributed generation (DG) plays an important role in modern power systems. The admitted connection of large number of DG units to electrical power systems may cause serious problems in power system operation and planning. The conventional power distribution systems have radial networks with unidirectional power flows. However, with the development of DGs, power distribution systems would have ring networks with bidirectional power flows. The problems of operation and planning methods in power systems will be arising due to the increase of distribution generation units to the distribution power systems.

Several recent researches on network reconfiguration have focused on the minimum losses configuration problem in distribution systems. Different methods have been proposed for solving the minimum loss configuration. Each method has different advantages and disadvantages. For instance, the distribution system reconfiguration for loss reduction was first proposed by Merlin et al. [1] where they employed a combination of optimization techniques and heuristics to determine the minimal loss operation configuration. Since then, many techniques have been proposed: Baran and Wu's method [2] on feeder reconfiguration for loss reduction was based on branch exchange. This approach starts with a feasible configuration of the network; then one switch is closed and others are opened based on heuristics and approximate formulas for variation in losses. Nahman et al. [3] presented another heuristic approach; but this search scheme also does not guarantee global optimization.

A genetic algorithm (GA) is more likely to obtain the global optimal solution in comparison with heuristic search methods and takes less time than the exhaustive search [4]–[7]. The main advantage of using GA is representation of objects (strings) instead of manipulating the objects themselves, but the main problem of GA is the coding of the objects into strings. B. Venkatesh et al. [8] proposed a new optimal reconfiguration method for radial distribution systems. They proposed a method that based upon a maximum load ability index and uses fuzzy modeling methods for modeling two objectives of load ability margin maximization and obtaining the best voltage profile. In [9], [10], simulated annealing (SA) is proposed for solving combinatorial optimization problems. The SA has the ability of escaping local minima by incorporating a probability function in accepted or rejected new solutions. In [11], the artificial intelligent Petri nets were applied to find the optimal switching operation for service restoration

and feeder loading balance in distribution systems. After identification of fault location and isolating for a system fault contingency, the Petri nets model with inference mechanism is derived and applied to solve the optimal load transfer among distribution feeders. In [12], the variable scaling hybrid differential evolution (VSHDE) for solving network reconfiguration of distribution systems is a combination of genetic algorithm and a power flow method based on the heuristic algorithm for determining the minimum loss configuration of radial distribution networks.
The main advantage of this paper is to propose a novel feeder reconfiguration technology based on MPSO algorithm with DG considering load uncertainty and Fuzzy Interaction. In general, the PSO algorithm is a useful evolutionary algorithm with strong global search ability. Therefore, the proposed method in this paper can provide another useful algorithm for the feeder reconfiguration work.

2. DESCRIPTION OF THE PROBLEM

In this section, the original objective function and the security constraints are described in detail.

2.1. The objective functions

The total active power losses: The objective function used to reduce the ohmic losses is described below:

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

where R_i denotes the resistance of the branch i, Ii is the current for the i-th branch, and N_b is the number of branches in the network. X is the control vector control containing the state of the divider keys (Sectionalized) and connector keys (Tie) in the network as follows:

$$X = [Tie_1, Tie_2, .., Tie_{N_{Tie}}, SW_1, SW_2, .., SW_{N_{sw}}] \tag{2}$$

(Tie_i) is the state of the i-th key and (SW_i) is the state of the i-th key divider. (N_{Tie}) is the number of divider keys in the network, and (NSW) is the total number of keys in the network. It is obvious that (T_{iei}) can be between 0 and 1, which shows the open and closed positions, respectively.

Voltage deviation: This function is used to reduce the voltage deviation on the network and is as follows:

$$f_2(X) = dev(X) = \max[|1-V_{\min}|, |1-V_{\max}|] \tag{3}$$

where (V_{min}) and (V_{max}) correspond to the minimum and maximum voltage values, respectively.

Load balancing: This function is used to enhance the load balance in the branches of the network and is as follows:

$$f_3(X) = Balance(X) = -\min_i \left| \frac{I_{i,rate} - I_i}{I_{i,rate}} \right|, i = 1, 2, 3, ..., N_{br} \tag{4}$$

where (I_{irate}) is the nominal flow capacity of i-th line, and I_i is the value of current in the i-th line.

2.2. Restrictions and Limitations

Restrictions on distribution lines: Max load on each line is limited as follows:

$$\left|P_{ij}^{Line}\right| < P_{ij,\max}^{Line} \tag{5}$$

where ($P_{ij,\max}^{Line}$) is the maximum permitted transmission power that is passed between i-th and j-th buses, and (P_{ij}^{Line}) is the line transmitted power between i-th and j-th buses.

Equations for Distribution of load: Load distribution equations can be considered as constraints in the optimization problem.

$$\begin{aligned} P_i &= \sum_{i=1}^{N_{bus}} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) \\ Q_i &= \sum_{i=1}^{N_{bus}} |V_i||V_j||Y_{ij}|\sin(\theta_{ij} - \delta_i + \delta_j) \end{aligned} \tag{6}$$

where Pi and Qi are the active and reactive powers injected into the i-th bus. The i-bus voltage magnitude is V_j and δ_i is the i-bus voltage angles, and θ_{ij} is the angle of the branch admittance between buses i and j.

Maintaining the radial structure of the network: As previously mentioned, during the optimization process, the radial topology of the distribution system must be preserved. So every time a ring is formed in the distribution network, a key must be opened in the loop of the radial network load.

Limitation of the feeder current: the main feeder can feed a large current in the following way.

$$\left|I_{f,i}\right| \le I_{f,i}^{\max} \qquad ;i=1,2,...,N_f \tag{7}$$

where $I_{f,I}$ am the current of the i-th feeder streams i, i is the maximum current of the i-the racks, N_f number of feeders on the web.

3. PROPOSED (MPSO) ALGORITHM

The most powerful aspect of evolution based on optimization algorithms such as (PSO) is that they can be optimized for each type of problem regardless of whether the derivative or discontinuous. The first algorithm (PSO) to generate a random population consisting of particles starts. Each particle can be a solution to the problem is studied. Each particle has a position and speed. Flowchart of the proposed method is presented on the following page.

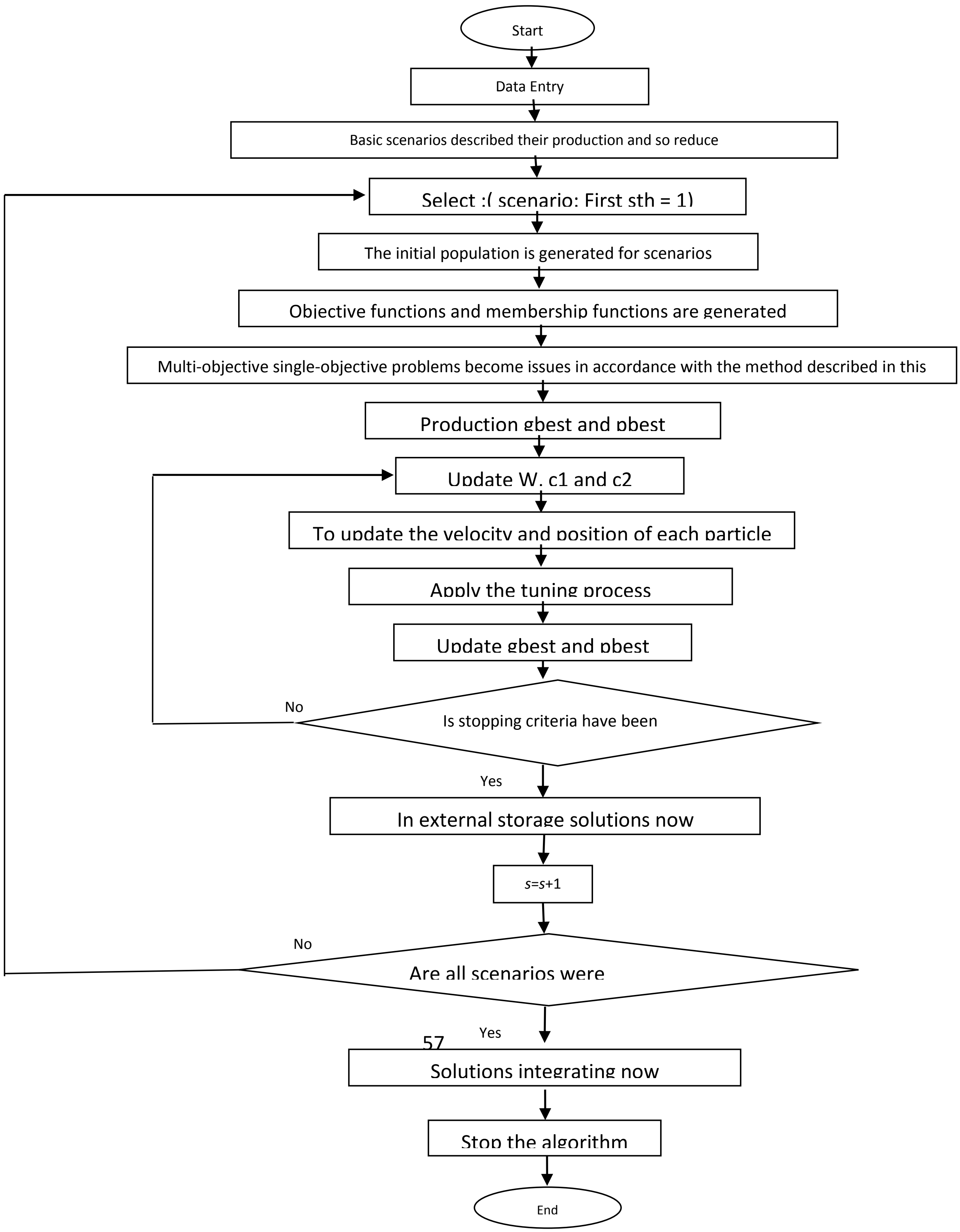
The main goal of a seamless update is to optimize the objective function. Update the status of each particle is influenced by three parameters:

1) The coefficient of the inertia weight (w),
2) The Global positioning (vel_i);
3) The position of the particle (X_{pbesti}).

Thus, the position of the i-th particle in the population can be updated as follows.

$$\begin{aligned} Vel_i^{new} &= W \times Vel_i + c_1 \times rand(.) \times (X_{pbest_i} - X_i) \\ &+ c_2 \times rand(.) \times (X_{gbest} - X_i) \\ X_i^{new} &= X_i + Vel_i^{new} \quad , i=1,2,...,N_{Sw} \end{aligned} \tag{8}$$

In the above equation, C_1 and C_2 are fixed parameters of the algorithm (PSO) and rand (.) is a random value in the interval [0, 1]. Algorithm (PSO) has many beneficial aspects such as simple concept, easy implementation, low tuning parameters, and others. However, in dealing with complex nonlinear optimization problems, the optimal position increases the possibility of trapping.



Here, a modified approach to improve the overall search capabilities of the algorithm (PSO) is proposed. The proposed method of mutation and crossover operators are used to increase the diversity of the population. In particular, at each iteration, and for each particle (X_i); three solutions (m_1, m_2 and m_3) were randomly selected from a population. Now, finding the correct solution we obtain:

$$\begin{aligned} X_{Test1} &= X_{m_1} + \beta_1 \times (X_{m_2} - X_{m_3}) \\ X_{Test1} &= [x_{Test1,1}, x_{Test1,2}, ..., x_{Test1,N_d}] \end{aligned} \tag{9}$$

where N_d is the length of the vector control. Using (X_{Test1}), (X_{gbest}) and (X_i) in the following test three solutions is established.

$$\begin{aligned} x_{Test2,j} &= \begin{cases} x_{Test1,j}, & \text{if } \beta_1 \le \beta_2 \\ x_{gbest,j}, & \text{Else} \end{cases} \\ x_{Test3,j} &= \begin{cases} x_{Test1,j}, & \text{if } \beta_3 \le \beta_2 \\ x_j \quad , & \text{Else} \end{cases} \\ X_{gbest} &= [x_{gbest,1}, x_{gbest,2}, ..., x_{gbest,N_d}] \\ X_{Test2} &= [x_{Test2,1}, x_{Test2,2}, ..., x_{Test2,N_d}] \\ X_{Test3} &= [x_{Test3,1}, x_{Test3,2}, ..., x_{Test3,N_d}] \end{aligned} \tag{10}$$

In equation (10) (β_1, β_2 and β_3) random values in the interval [0, 1] are. The solution of (X_{Test1}) and (X_{Test2}) and (X_{Test3}) with a (X_i) will be compared. If (X_i) should be replaced. If (X_i) will remain in his position. Thus, using this process, the entire population will be updated.

The second part of the reform of the inertia weight factor (W) initialized. In this regard, an adaptive formulation in order to update the value of (W) during the optimization process are as follows:

$$W^{new} = W^{\max} - \frac{Iter}{NI}(W^{\max} - W^{\min}) \tag{11}$$

where W_{max} and W_{min} are the maximum and minimum value of inertia weight factor, NI total number of iterations, I_{ter} is the number of iterations. In the above formulation, compliance, optimize the speed of convergence will increase effectively.

3.1. Fuzzy method to obtain interaction

As noted earlier, the lowest objective of this paper is to investigate the problem (DFR) is objective. The overall objective of limiting the problem can be formulated as follows:

$$\begin{aligned} &\min F = [f_1(X), f_2(X), \ldots, f_n(X)]^T \\ &s.t. \\ &g_i(X) < 0 \qquad i = 1, 2, \ldots, N_{ueq} \\ &h_i(X) = 0 \qquad i = 1, 2, \ldots, N_{eq} \end{aligned} \tag{12}$$

where g_i (X) and h_i (X) are non-uniform and function is limited. N_{ueq} and N_{eq} unlimited number of equations and inequality is limited.

Here's an interactive fuzzy satisfying method is proposed that allows the operator to the most optimal solutions from the lower set of choices. So using the concept of fuzzy set theory, the following equation is used.

$$F(X) = \min_{x \in \Omega} \left\{ \max_{i=1,\ldots,n} \left| \mu_{ref,i} - \mu_{f,i}(X) \right| \right\} \tag{13}$$

where μ_{fi} (X) values of fuzzy membership functions f_i (X); μ_{ref}, i satisfactory degree of f_i (X) is.

In this study, the membership function of a trapezoidal membership function [1] is obtained. [1] Shows that the trapezoidal membership function to model the objective function is a good place. Thus the operator can optimize the amount (μ_{fi}(X)) in the interval [0, 1] to adjust. Obviously, larger values of the objective functions, are more important.

4. RESULTS AND ANALYSIS

To evaluate the effectiveness and efficiency of the proposed method is satisfactory, a 33-bus radial distribution systems (IEEE) for the case study are used. Simulation for both single-objective and multi-objective structure of deterministic and stochastic done. In order to simulate the 33-bus test system in a single-objective deterministic structure, multi-structured deterministic, randomized, single-objective and multi-objective review, and the tables and charts, the results were compared. In most cases, the success of the proposed method (MPSO) is evident.

4.1. In the single-objective deterministic simulation results for 33-bus IEEE distribution system

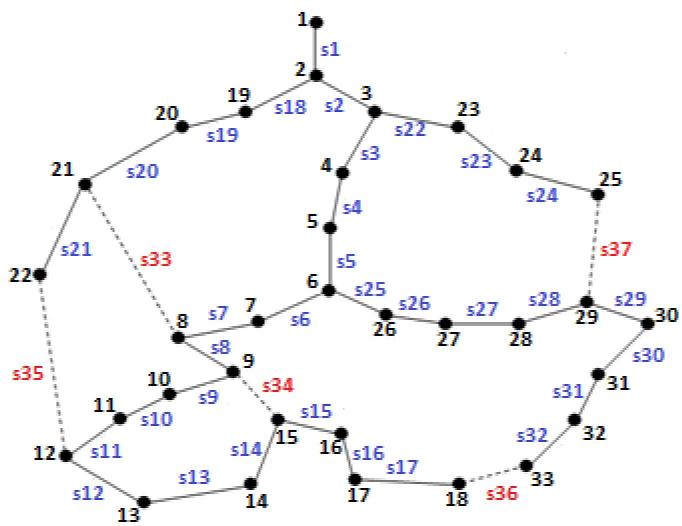


Figure 1. Schema linear 33-bus IEEE network

The test system consists of two racks and five branches of the loop [2]. Rated voltage kV 66/12 the system. Single-line diagram of the test system is shown in Figure 1. As can be seen from the figure, the Chinese have been shown to bind keys. About the proposed MPSO algorithm, the number of repetitions of the particle is assumed to have 20 100 iterations stopping criterion is considered. Since the proposed MPSO algorithm is first used in this study for the DFR problem, so at the moment of the single-objective optimization for each objective function has been performed. Table 1 shows the results of active power losses optimize the system.

Table 1. single-objective optimization objective function by the proposed method on the net loss of Deterministic

Method	Power loss [kW]	Open switches
Shirmohammadi [3]	140.26	s7, s10, s14, s32,s37
HBMO [4]	139.53	s7,s9,s14,s32,s37
DPSO–ACO [5]	139.53	s7,s9,s14,s32,s37
DPSO [5]	139.53	s7,s9,s14,s32,s37
DPSO–HBMO [6]	139.53	s7,s9,s14,s32,s37
MHBMO [6]	139.53	s7,s9,s14,s32,s37
Vanderson Gomes[7]	139.53	s7,s9,s14,s32,s37
McDermott *et al.* [6]	139.53	s7,s9,s14,s32,s37
The proposed MPSO	**139.53**	**s7, s9, s14, s32, s37**

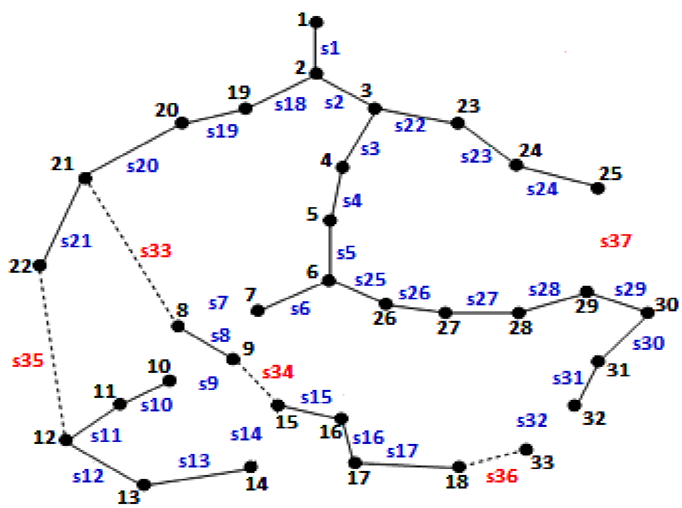


Figure 2. First test network, the keys s7, s9, s14, s32, s37 are open

Note that the total power loss before reconfiguration was kV 67/202. As can be seen from Table 1, the proposed MPSO algorithm is the optimal solution found by other known methods in this area is to be achieved.

Results of single-objective optimization of voltage deviation are presented in Table 2. Here again you can see that the proposed algorithm has achieved the optimal solution. Reconfiguration of the system before voltage deviation is 0869092/0 pu. Finally, Table 3 shows the results of single-objective optimization, where the goal is to balance the load on the system. It should be noted that the maximum current capacity of the lines S1 and S2 is 1200 A, lines S3, S4, and S5, is 426 A and the rest of the grid lines is 307 A. Before reconfiguration of the objective function value 5413236/0 load balancing. The simulation results are shown in Table 3, as can be seen, the proposed method can balance the load of the system 5413236/0 3437/0 to deliver optimal value. Should be kept in mind that the amount of reconfiguration can be achieved only by improving the load balancing and is an important achievement.

Table 2. single-objective optimization objective function of the voltage on the grid by the proposed method in the Deterministic

Method	Voltage deviation[p.u]	Minimum voltage	Open switches
DPSO [6]	0.0612031	0.93879681	s7,s9,s14,s32,s37
PSO–ACO [5]	0.0612031	0.93879681	s7,s9,s14,s32,s37
DPSO–HBMO [6]	0.0612031	0.93879681	s7,s9,s14,s32,s37
DPSO–ACO [5]	0.0612031	0.93879681	s7,s9,s14,s32,s37
GA [5]	0.0621809	0.93781902	s7,s10,s14,s32,s37
HBMO [8]	0.0612031	0.93879681	s7,s9,s14,s32,s37
The proposed MPSO algorithm	**0.0612031**	**0.93879681**	**s7,s9,s14,s32,s37**

Table 3. single-objective optimization objective function to balance the load feeders by the proposed method in the Deterministic Network

Method	Load Balance	Open switches
GA	0.344162601	s7,s11,s14,s36,s37
PSO	0.343929465	s7,s10,s14,s36,s37
The proposed MPSO algorithm	0.343774159	**s7,s9,s14,s36,s37**

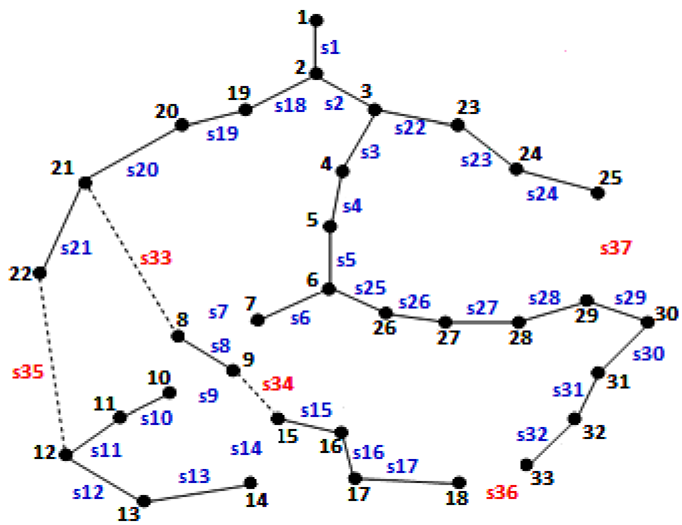


Figure 3. test network, the keys s7, s9, s14, s36, s37 are open

4.2. Simulation results confirm the structure of the 33-bus IEEE distribution system in the Deterministic Network

The proposed method has good performance was observed. Also, the positive impact of DFR optimize the real power loss, voltage deviation and load balancing is shown. However, multi-objective optimization is applied to the DFR. Here, the idea is to meet fuzzy interactive method is used. Values (values) to a degree meet all objective functions has been proposed. Obviously due to operator configuration, these values are in the range of (0, 1) change. As can be seen, the proposed method can achieve the right balance between the objective functions. DFR strategy in order to see the positive impact on system voltage, Figure 4 shows the voltage profiles before and after reconfiguration framework for multi-objective test shows.

Table 4. Multi-objective optimization framework and fuzzy objective functions by the proposed MPSO method in the Deterministic Network

Method	Power loss [kW]	Voltage deviation[p.u]	Load Balance	Open switches
GA	143.76196	0.06266643	0.40372161	s6,s9,s14,s36,s37
PSO	142.73916	0.062183436	0.36531157	s7,34,s11,s32,s37
The proposed MPSO	**139.5343**	**0.0621803**	**0.364086**	**s7,s9,s14,s32,s37**

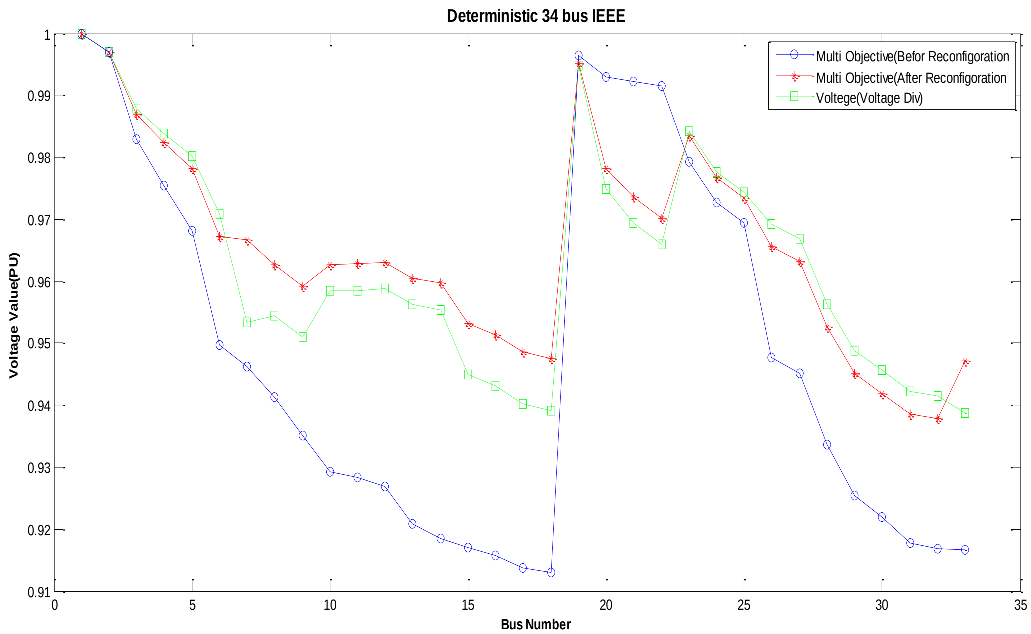


Figure 4. Comparison of the level of voltage before and after the 33-bus IEEE network reconfiguration in multi-objective optimization and voltage profile in single-objective

4.3. The simulation results of a randomized, single-objective and multi-objective to 33-bus IEEE distribution system

Due to the nature of events, in fact, most of the variables include the degree of uncertainty themselves. As a result of sampling error / measurement data may contain some uncertainties are associated with past events, while the error due to the uncertainty in the predictions can be expected in the future.

To run the simulation in this case, in the first moment, the scenario created in 2000. The scenario was produced in 2000, and the 20 scenarios with high probability elected. Each scenario has been applied on the network, and each finds the optimal solution. Each answer has a probability of occurrence and the probability of optimal responses to each of their occurrences are multiplied and then normalized (the sum of them is equal to 1).

Here is anticipated, active and reactive loads are anticipated, after a 33-bus system is expected to be 66 bit. Table 5 shows the results of single-objective optimization for 33-bus system in the context of deterministic and stochastic algorithms and fuzzy compares the proposed MPSO. Power losses, voltage deviation and load balancing issues that have been listed in the table

Table 5. Comparison of single-objective optimization objective functions in Stochastic and Deterministic structures by fuzzy framework proposed in MPSO algorithm on the test network

Framework	Power loss [kW]	Voltage deviation[p.u]	Load Balance
Deterministic	139.5300	0.0612003	0.3437741
Stochastic	**139.5130**	**0.0620543**	**0.3440466**
Max	141.8332	0.0624072	0.3453300
Mean	139.8799	0.0617124	0.3441456
Min	138.9183	0.0611687	0.3437466
STD	0.631	0.0005312	0.0012000

Similarly, Table 6 shows multi-objective optimization results for 33-bus system in the context of deterministic and stochastic fuzzy algorithms and compares the proposed MPSO. Power losses, voltage deviation and load balancing issues are also listed in the table.

Table 6. Comparison of Stochastic and Deterministic optimization of multi objective functions in the framework of fuzzy structures, and the proposed MPSO algorithm on the test network.

Framework	Power loss [kW]	Voltage deviation[p.u]	Load Balance
Deterministic	139.5343	0.0621803	0.364086
Stochastic	**139.6438**	**0.0621479**	**0.365609**
Max	140.6871	0.0625000	0.365400
Mean	139.7514	0.0622000	0.364200
Min	138.9184	0.0620000	0.363000
STD	0.4458	0.0001364	0.000672

5. CONCLUSION

In this paper, with the use of reconfiguration, the goal was to optimize the three important objective functions of the network, i.e. power losses, voltage deviation and the load balance. We introduced an algorithm (PSO) with respect to the non-linear and discrete nature of the problem and increased the search power by using an MPSO algorithm. In addition, for simultaneous solving of the multi-objective problem, a fuzzy structure based on the minimum and maximum method was provided. Moreover, to model the forecast error of the active and reactive loads and to minimize the computational mode, a method based on scenario production was presented which initially, various scenarios was provided by the role wheel. Twenty scenarios out of these was then selected and finally by multiplying the probability of each scenario by the collected answer of these scenarios, the overall response is obtained. According to the results of section 4, network reconfiguration strategy can, without any additional cost, improve voltage profile and load balancing from the point of view of losses. Compared to other algorithms including GA, PSO and conventional ...., the algorithm used in this paper is better in terms of performance and the results have been more acceptable. Finally, the reconfiguration of the voltage profile was implemented on all buses and the appropriate response was observed with the drawn simultaneous charts.

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