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# A new multiobjective fuzzy shuffled frog-leaping algorithm for optimal reconfiguration of radial distribution systems in the presence of reactive power compensators

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**Abstract:** This paper presents a new approach for the optimal reconfiguration of radial distribution systems in the presence of reactive power compensators (RPCs). The proposed method is based on the simultaneous reconfiguration and RPC allocation for the mitigation of losses, equalizing the feeder load balancing as well as improving the voltage profile in power distribution networks. In this paper, the compensators are the capacitor bank and distribution static compensator, which is a type of distribution flexible alternating current transmission system device representative of conventional and modern RPCs. In this regard, the optimal states of the distribution system tie switches are determined taking into consideration the best size and location of the RPCs. In order to facilitate the algorithm for multiobjective search ability, the optimization problem is formulated for minimizing fuzzy performance indices. Since the optimization problem is nonlinear, using intelligent search methods such as the shuffled frog-leaping (SFL) algorithm can overcome the limitations of conventional analytic methods. In addition, to enhance the performance of the standard SFL, the fuzzy frog-leaping rule is used in this paper. This algorithm is more accurate and has an efficient convergence property compared to other intelligent search algorithms. The proposed method is validated using the IEEE 33-bus test system and a Tai-Power 11.4-kV distribution system as a real distribution network. The obtained results indicate that multiobjective simultaneous placement of RPCs along with reconfiguration can be more beneficial than separate single-objective optimization.

**Key words:** Optimal reconfiguration, reactive power compensator, network losses, voltage profile, load balancing, shuffled frog-leaping algorithm, fuzzy system

## 1. Introduction

Reactive power compensators (RPCs) are generally used to reduce network losses, improve the voltage profile, and even reduce the unbalance rate of a feeder's load in distribution networks. The efficiency of these compensators depends to a large extent on their magnitude and location in the network, and any improper placement may lead to a reduction of their expected performance in the network. Distribution networks include a group of feeders that are radially connected to each other. Most network feeders have switches by which they connect to the network or disconnect from it. Generally, 2 types of switches are used for network reconfiguration management purposes: normal open and normal close. Network reconfiguration is considered as the process of changing the topology of the distribution network through varying the positions of the open and close switches. Various approaches have been proposed for network reconfiguration and defining the optimum capacities for RPCs. In [1,2], this problem was formulated as a nonlinear program regarding the magnitudes and locations of the compensators. In [3], the method considered the magnitudes of the compensators as discrete variables and used

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dynamic programming in order to solve the problem in an optimum manner. In [4,5], sensitivity-based methods were suggested for finding the optimal locations for the capacitors. Some methods were developed based on the simulated annealing algorithm to define the optimum positions and values for the capacitors [6]. Researchers in [7–9] employed the genetic algorithm (GA) in order to obtain the defined objects for radial networks. In [10], an evolutionary programming algorithm was used in order to optimally assign RPCs. The distribution static compensator (DSTATCOM) is a type of flexible alternating current transmission system (FACTS) device and is considered to be one of the most important RPCs, connecting to the system in parallel. The primary object of DSTATCOM is to support the bus voltage by injecting reactive power. It also has the ability to improve the system's stability and losses [11,12]. In practice, it is worth mentioning that parallel FACTS devices placed in distribution buses offer the best advantages by ensuring stable voltages [13,14]. In [15], recent studies on network reconfiguration carried out for reducing network loss purposes were presented. In [16], reconfiguration was done in order to reduce network losses and balance feeder loads. Other methods have also been employed for the optimal reconfiguration of distribution networks, including power flow based on intelligent algorithms [17], the simulated annealing algorithm [18], the hybrid differential revolution algorithm [19], particle swarm algorithm (PSO) [20], and improved GA [21], and in [22], a fuzzy multiobjective approach was presented.

Although most of the above-mentioned methods consider the problem of the placement of the RPC and the reconfiguration problem as 2 separate problems, some recent studies, however, consider them simultaneously [23,24].

This paper discusses the multiobjective reconfiguration of a system in the presence of DSTATCOM, which is an innovative approach, and compares the obtained results through this method with the results of the reconfiguration in the presence of the capacitor. The method uses the shuffled frog-leaping (SFL) algorithm, which is a combination of PSO and the GA, to solve the problem. The method also employs a fuzzy system in order to improve the SFL algorithm. There are a number of approaches for solving the multiobjective optimization problem. Since reconfiguration and RPC allocation placement according to the multiobjective functions is difficult with an analytical method, a fuzzy logic technique is proposed in this paper to achieve a trade-off between the objective functions. The multiobjective optimization problem is transformed into a fuzzy inference system (FIS), where each objective function is quantified into a set of fuzzy objectives selected by fuzzy membership functions. The proposed algorithm was examined on the IEEE 33-bus and Tai-power 83-bus distribution systems and the obtained results confirm the ability of this approach in solving the nonlinear problems and show the effectiveness of the concurrent application of reconfiguration and reactive power planning in distribution networks.

## 2. Problem formulation

The objective function is a constrained optimization problem to find an optimal arrangement for the distribution system and RPC placement in which the value of function F(x) is minimized.

The objective function F(x) consists of 3 goals: reducing the loss, increasing the load balancing, and improving the voltage profile in distribution systems.

The first term of the objective function reflects losses that are defined by Eq. (1):

$$P_{loss} = \sum_{i=1}^{nf} r_i \frac{P_i^2 + Q_i^2}{V_i^2}, \tag{1}$$

where $P_i$ and $Q_i$ are the active and reactive power passing through the feeders, respectively; $n_f$ is the number of feeders; and $r_i$ and $V_i$ are the resistance and voltage amplitude, respectively.

The second term of the objective function is considered for reducing the equal load balancing (ELB) index of the feeders, which is shown in Eq. (2).

$$ELB = \sum_{F_j} \left( \frac{I_{F_j}}{I_{Favg}} \right)^2, \tag{2}$$

Here, $I_{F_j}$ is the current passing through feeder j and $I_{Favg}$ is defined by Eq. (3):

$$I_{Favg} = \frac{1}{n_f} \sum_{j=1}^{n_f} I_{F_j}. \tag{3}$$

The third term of the objective function reflects the improvement of the voltage profile, which is shown by Eq. (4):

$$IV = \sum_{i \in LB}^{|V_i - V_{ref.i}|}, \tag{4}$$

where LB is the collection of all of the load buses, and $V_i$ and $V_{ref.i}$ are the voltage magnitude and the nominal or reference voltage at load bus i, respectively.

The different terms of the objective function are in various ranges, and so a fuzzy system is employed in order to balance these terms.

### 2.1. Membership function for terms of the objective function

Clearly, the different terms of the objective function have different dimensions. Hence, it is necessary to make a simple structure to compare these terms during reconfiguration and RPC placement. For achieving this purpose, a fuzzy framework is used for the objective function variables. Each variable has a membership function ($\mu$) in this fuzzy structure that determines the rank and effectiveness of its variable. The membership values for each variable are between zero and unity in the fuzzy domain and may be different for each element. Hence, it becomes possible to compare the variables in this domain [25].

The membership function is formulated as given in Eq. (5) and is depicted in Figure 1.

$$\mu_{f_i}(X) = \begin{cases} 1, f_i(X) \le f_i^{\min} \\ \frac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}}, f_i^{\min} \le f_i(X) \le f_i^{\max} \\ 0, f_i^{\max} \le f_i(X) \end{cases} \tag{5}$$

The F(x) parameter is also defined as the index of the system's real power losses, or the equal load balancing of the feeders or improvement of the maximum loading. In order to determine the maximum ($f_i^{\max}$) and minimum ($f_i^{\min}$) values of the F(x) parameter, the proposed method uses the best and worst solutions, individually optimized for each objective function.

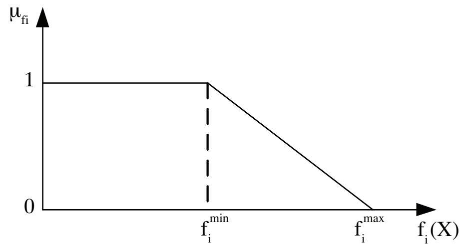


**Figure 1.** Fuzzy system for making compromises among different terms of the objective function.

## 3. DSTATCOM model

Due to its topological structure and controllability, the DSTATCOM used in this paper has the ability to operate in the voltage or power control modes. If the voltage control mode is considered, a DSTATCOM can impose the connected bus voltage into the indicated values. However, in the power control mode, a DSTATCOM can generate the specified reactive power with respect to the bus voltage. Since the steady-state operation principles of a DSTATCOM are similar to those of a STATCOM structure, which is used in transmission networks, a STATCOM model is appropriate for the power flow analysis of a DSTATCOM. In this condition, the DSTATCOM acts like a source of reactive power connected to a bus with a load equal to $P_{Li}+ jQ_{Li}$. From a load flow calculation point of view, the performance of a DSTATCOM installed in bus i in the voltage or power control mode can be modeled like a new PV or PQ bus j with zero active power, respectively. For more accurate modeling of a DSTATCOM, it is necessary to consider its steady state losses, such as inverter and coupling transformer losses. For this purpose, the coupling transformer can be modeled using its leakage reactance ($X_T$) and resistance ($R_T$). The illustrated model is depicted in Figure 2. The transformer loss will be calculated at each iteration of the load flow analysis [26,27].

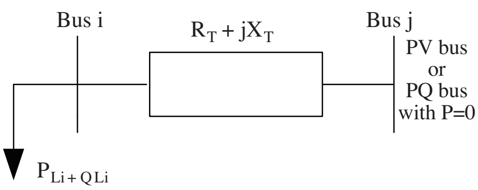


**Figure 2.** DSTATCOM load flow model.

## 4. Optimization procedure

In order to investigate the capability of the proposed fuzzy-SFL method, the results obtained by this method have been compared with those obtained through conventional SFL and well-known PSO methods. In addition, the convergence properties and best fitness values of these methods are compared and discussed through single-objective and multiobjective formulation for most useful cases. In the next sections, the SFL, fuzzy-SFL, and PSO methods are introduced concisely.

### 4.1. SFL algorithm

The SFL method is a metaheuristic iterative search algorithm that is based on the memetic evolution of a set of frogs when looking for food. The first proposal for the SFL method was introduced by Eusuff et al. in 2006 [28]. The object of presenting this algorithm was to obtain an algorithm by which complex problems could be handled with no need for mathematical formulations. It could be said that this algorithm is a combination of the memetic algorithm (MA)-based GA and PSO. Indeed, it is generated through mixing the advantages of the MA and PSO algorithms.

In this method, the initial population is divided into several separate groups. Each group contains the same number of frogs. This algorithm has 2 search techniques based on this grouping: a) a local search technique in which each frog gets a better position to find food, i.e. the best solution, through information exchange; and b) the process of information exchange among the memeplex, by which the results of all of the memeplexes obtained through local searches are compared with each other [29].

In each memeplex, the frogs with the best and the worst fitness are called $L_b$ and $L_w$, respectively. Moreover, the frog with the best fitness out of all of the memeplexes is considered as $L_g$. Next, a process similar to PSO is performed to improve only the frog with the worst fitness (not all of the frogs) in each iteration. In a suitable manner, the location of the frog with the worst fitness is adjusted as follows [29]:

$$D = r \times (L_b - L_w), \tag{6}$$

$$L = L + D; -D_{\max} < D < D_{\max}, \tag{7}$$

where D is the change in the frog's position, L is the location of the frogs, r is a random number between 0 and 1, and $D_{\max}$ is the maximum allowed change in a frog's position. If this process outputs a better solution, it substitutes for the worst frog. Otherwise, the calculations in Eqs. (6) and (7) are done over again. In addition, to make an opportunity for the random generation of the improved information, random virtual frogs are produced and replaced in the population if the local search cannot achieve better solutions, respectively, in each iteration. After a number of iterations, the different groups come together and share their ideas with each other through a shuffling process. The local search algorithm and the shuffling processes continue until the specified convergence criteria are met. The aim of the overall process is to find global optimal solutions.

The steps of this algorithm proceed as follows:

1. The initial population is generated randomly.

2. The frogs are divided into several groups. Each group has n frogs.

3. The local research proceeds as follows. At first, within each group, the frogs with the best and the worst solutions are recognized. Moreover, the frog that has the best solution within the population is also recognized. Next, the position of the worst frog is corrected towards the best frog within each group.

4. Step 3 is repeated for a predefined number of iterations.

5. Following the improvement of the positions of the frogs, the new population is sorted from the best to the worst solution.

6. If the stop condition of the algorithm is met, the algorithm is ended; otherwise, it goes to step 2.

Figure 3 shows the general flowchart of this algorithm.

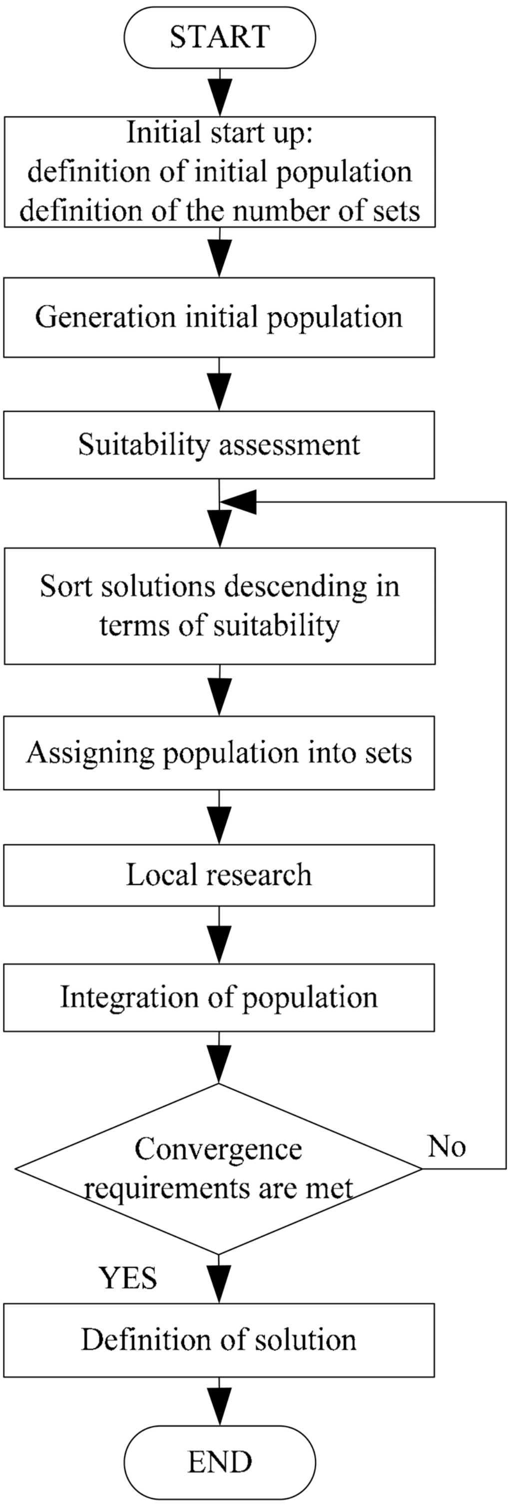


**Figure 3.** General flowchart of the SFL algorithm.

### 4.2. Fuzzy-SFL algorithm description

In this paper, the authors propose the implementation of a hybrid fuzzy-SFL algorithm for distribution reconfiguration and VAr planning with multiobjective optimization. In the conventional SFL algorithm, due to imperfect perception [30], the worst frog cannot exactly place the best frog's position, and because of the inexact action, the worst frog cannot leap right to its goal position. Considering these uncertainties, and taking into account the fact that the worst frog could leap over the best one, a modified frog leaping rule can be defined as:

$$L(new) = L + M \times D. \tag{8}$$

In this paper, a simple rule is used to determine the value of M using the fuzzy theory. For this purpose, the membership function of the M index is selected as a generalized semibell-shaped built-in membership function, which is formulated as given in Eq. (5):

$$M = \begin{cases} \frac{D_{\max}}{\sqrt{D^T D}} & D > D_{\max} \text{ or } D < -D_{\max} \\ 1 & -D_{\max} \le D \le D_{\max} \end{cases}, \tag{9}$$

where $D_{\max}$ is the highest permitted distance of one jump.

### 4.3. PSO algorithm

PSO is a population-based algorithm that uses a population of individuals to investigate the favorable region of the search space. With this particular context, the population is considered as a swarm and the individuals are considered as particles. Widespread application of PSO for solving the optimization problem is due to its fast convergence properties and its capability of finding the global optimum, in which a great number of local optimum points may exist. In addition, this algorithm has easy programming and can adapt to constrained problems [31].

For a fair comparison, PSO parameters such as the number of populations and iterations have been selected in accordance with the SFL algorithm. In this regard, and also preventing explosion of the swarm, the highest permitted velocity is considered as 4 times the variable number.

## 5. Multiobjective optimization based on fuzzy system

In the next step, the fuzzy theory is employed to balance the ranges of different terms of the objective function changes, by which all of the objective functions are combined with each other in the form of a FIS, using expert knowledge.

Hence, a multiobjective optimization problem will be converted into a single-objective one. To achieve this purpose, at first, the value of each objective function, which is considered as an input in the FIS, is divided into several regions using fuzzy membership functions. Next, relations between the inputs and the final output, i.e. the final objective function that wants to optimize it, are made through the appropriate rules [32].

In this algorithm, it is possible to select different membership functions and different rules, which may change the final objective function, which in turn leads to obtaining different solutions. Since in this method the object-combining procedure is carried out based on verbal-linguistic variables, it would be more realizable to users compared to weight-based combining methods.

Figures 4–7 show the membership functions of the inputs and outputs of the fuzzy system. Tables 1–3 show the fuzzy rules that were employed for defining the optimum location of the compensator while simultaneously carrying out the reconfiguration process.

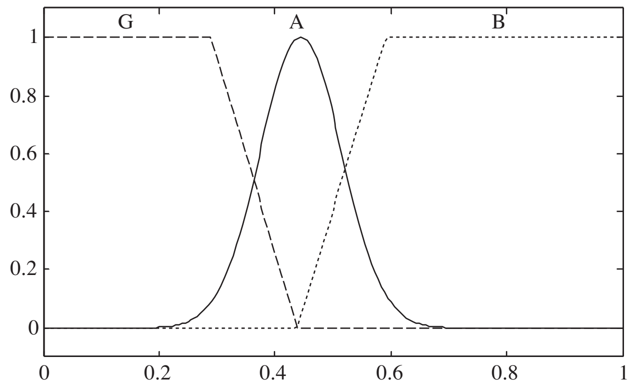


**Figure 4.** Membership function for $P_{loss}$.

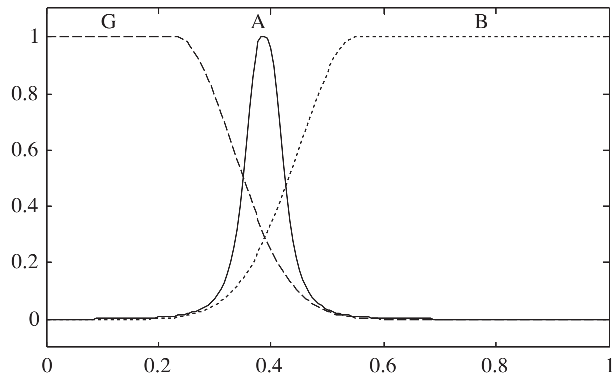


**Figure 5.** Membership function for ELB index.

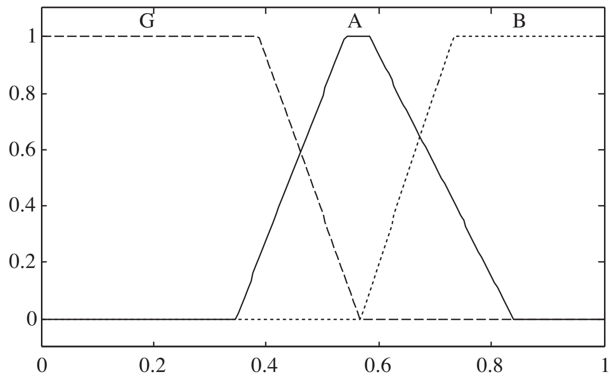


**Figure 6.** Membership function for IV index.

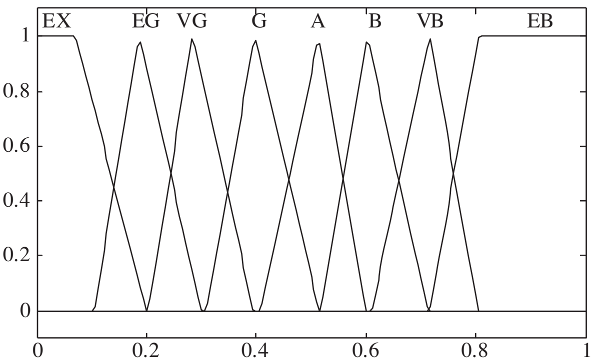


**Figure 7.** Membership function for the output of the fuzzy system.

**Table 1.** Fuzzy rules when the ELB index is bad.

| | | IV | | |
|---|---|---|---|---|
| | | G | A | B |
| $P_{loss}$ | G | G | B | EB |
| | A | A | VB | EB |
| | B | B | EB | EB |

**Table 2.** Fuzzy rules when the ELB index is medium.

| | | IV | | |
|---|---|---|---|---|
| | | G | A | B |
| $P_{loss}$ | G | EG | A | VB |
| | A | VB | B | EB |
| | B | G | EB | EB |

For the case study in Table 3, when the ELB index is bad for low $P_{loss}$ and IV is good, the level of fitness is extremely good. In these sections, B, A, G, VB, EB, VG, EG, and EX stand for bad, average, good, very bad, extremely bad, very good, extremely good, and excellent, respectively.

**Table 3.** Fuzzy rules when the ELB index is good.

| | | IV | | |
|---|---|---|---|---|
| | | G | A | B |
| $P_{loss}$ | G | EX | A | VB |
| | A | EG | A | VB |
| | B | VG | VB | EB |

## 6. Solution algorithm by fuzzy-SFL

Since the introduced multiobjective problem for reconfiguration and RPC allocation in radial distribution systems is a nonlinear optimization problem with increased numbers of local optima, it is necessary to solve the problem using a very robust and precise algorithm to find global optimum solutions in a minimum processing time. The plan is to discover the optimum combination of the tie switch states, RPC location, and size for mitigating power loss and improving equal load balancing of the feeders and voltage profile. Therefore, the variables including the tie switch states, size, and location of the RPC are arranged in a variable string.

Figure 8 shows the problem-solving block diagram using the SFL algorithm. The stop condition of this algorithm is met when, after some limited iterations, we see no improvement in the final solution.

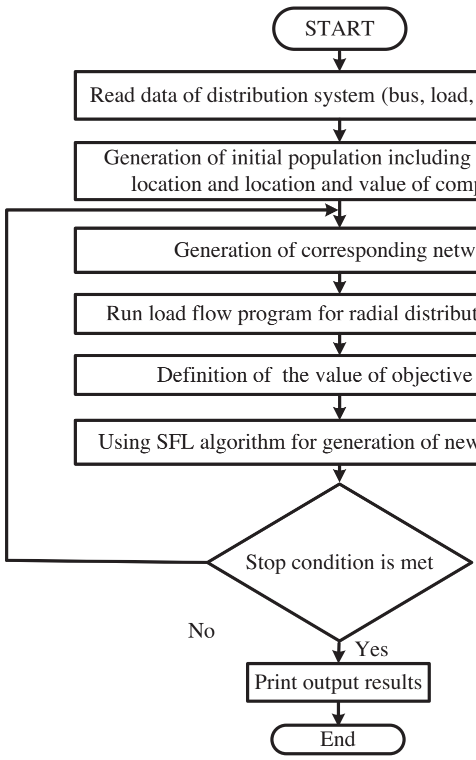


**Figure 8.** Proposed algorithm and computational flowchart.

## 7. Results

The proposed reconfiguration and RPC allocation algorithm using the fuzzy-SFL method has been developed and implemented in MATLAB 2010b.

Because of distribution network characteristics such as the radial structure and high R/X ratio, a forward/backward sweep-based power flow [33,34] is used for the distribution system analysis during the compensation and reconfiguration.

The effectiveness of the proposed multiobjective optimization method for this particular problem is illustrated using 2 case studies. Case study 1 was prepared for a single feeder 33-bus IEEE distribution system and case study 2 is for a network from the Taiwan power company (TPC) with 11 feeders and 83 buses. The results and discussions are presented through 5 different cases in each example.

At the beginning, in Case 1, the system is estimated under normal operating conditions. In Case 2, the system is reconfigured without compensating. In Case 3, the processes of the system reconfiguration and capacitor placement are carried out simultaneously. Similarly, in Case 4 the processes of the system reconfiguration and the DSTATCOM placement are carried out simultaneously and the DSTATCOM is used in its voltage control mode. Finally, in Case 5, the processes of the system reconfiguration and the DSTATCOM placement are carried out simultaneously and the DSTATCOM is used in its power control mode.

### 7.1. Case study 1

The first example is shown in Figure 9. This 33-bus, 12.66-kV test system consists of 37 branches that are equipped with 5 tie switches. The system has total load including 3.17 MW and 2.3 MVAr, while it is supposed to be constant. The other information for this test system can be found in [35]. The power flow calculation is performed using $S_{base}$ = 100 MVA and $V_{base}$ = 12.66 kV. Since this case study is a small distribution network, only a single RPC is considered for placement.

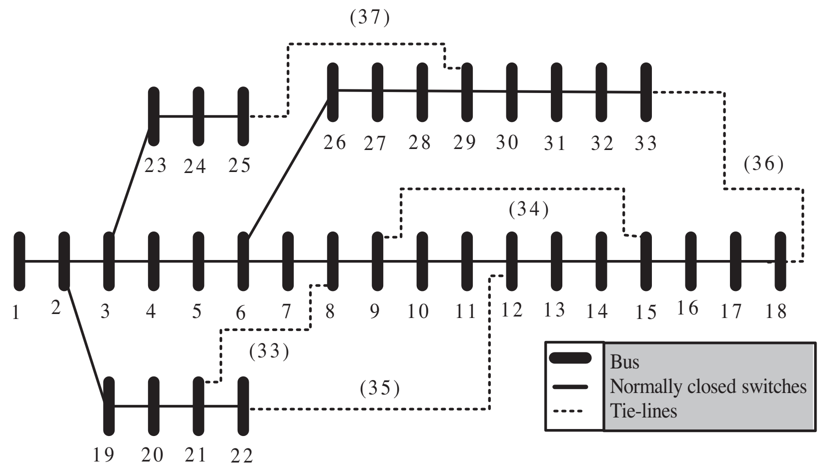


**Figure 9.** The IEEE 33-bus test distribution system.

The results obtained through these cases are shown in Tables 4 and 5; Figure 10 shows the voltage profile of the network in various exploiting conditions.

As it is shown in the results for Case 2, only by reconfiguration can a decrease in the optimal fitness from 0.67 (base case) to 0.398 be obtained. However, in Case 3, which is dedicated to both a capacitor bank installation and reconfiguration simultaneously, the optimal fitness decreases to 0.301. In Case 4, which is dedicated to both a DSTATCOM in its voltage control mode installation and reconfiguration simultaneously, the optimal fitness decreases to 0.261. This is because, unlike the capacitor, the output reactive power of a DSTATCOM is independent from the voltage of the power system. This advantage implies that a DSTATCOM is a more proper tool than a capacitor. In Case 5, which is the same as Case 4 except that the DSTATCOM is used in its power control mode, the optimal fitness decreases to 0.255. It seems that the results are better than those in the voltage control mode because there is no need to force the connected bus voltage to a specified value; however, in the voltage control mode, the system voltages are more appropriate than in the power control mode. Since reconfiguration and RPC allocation change power flow paths in the network, both can reduce power loss and improve the voltage profile as well as the load balancing.

**Table 4.** Comparison of results (case study 1).

| | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 |
|---|---|---|---|---|---|
| Active losses (kW) | 202.5 | 151.4 | 114.0 | 118.1 | 115.8 |
| ELB | 67.71 | 58.07 | 60.78 | 50.91 | 48.06 |
| IV | 1.7 | 1.328 | 1.0887 | 0.8379 | 0.9815 |
| Worst bus voltage (p.u.) | 0.9131 | 0.9318 | 0.9244 | 0.9423 | 0.9461 |
| Tie switches | 33, 34, 35, 36, 37 | 6, 8, 12, 36, 37 | 7, 9, 14, 31, 37 | 11, 28, 30, 33, 34 | 7, 10, 14, 32, 37 |
| RPC location (bus no.) | - | - | 30 | 10 | 7 |
| RPC rating (MVA) | - | - | 1.1237 | 1.1102 | 0.9947 |

**Table 5.** Comparison of results in percent (case study 1).

| | Case 2 | Case 3 | Case 4 | Case 5 |
|---|---|---|---|---|
| Loss reduction (%) | 25.23 | 43.7 | 41.68 | 42.81 |
| ELB improvement (%) | 14.23 | 10.23 | 28.81 | 29.02 |
| IV improvement (%) | 21.88 | 35.96 | 50.71 | 42.26 |
| Increment in worst voltage (%) | 2.04 | 1.23 | 3.19 | 3.61 |
| No. of tie switches changed | 3 | 4 | 3 | 4 |

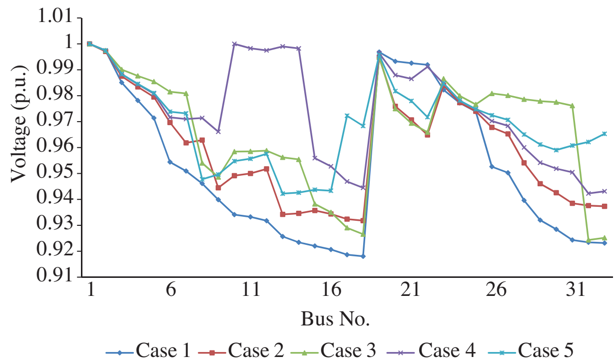


**Figure 10.** Voltage magnitude in different cases of case study 1.

From the results of the 33-bus test system, it can be seen that the RPC has the effect of improving the optimal fitness over the feeders in this particular case, and the topological structures of the optimum network without the RPC are different from those with the RPC. Based on the 33-bus system with the RPC, the proposed DSTATCOM installation in this paper has lower optimal fitness than the method proposed in the capacitor bank installation.

Now the proposed fuzzy-SFL method is compared with other methods, the SFL and PSO. In Table 6, the setting parameters for the fuzzy-SFL and SFL methods are depicted. The number of memeplexes (NM) is set to 5; the number of frogs in each memeplex (NFM) is equal to 30; the number of iterations in each memeplex (NIM) is selected as 50, and the number of iterations is set to 150. In order to have a fair comparison, the considered parameters for the PSO are the same as those of the fuzzy-SFL method. The results are shown in Table 7, where it can be seen that the proposed method gives the best configuration. In Figure 11, the convergence characteristics of the aforementioned evolutionary algorithms are depicted. As is shown, the fuzzy-SFL method has better performance than the others because of the lowest optimal fitness (0.255) in comparison with the SFL (0.285) and PSO (0.318) methods, which confirms the ability of this algorithm. It is obvious that the SFL and PSO methods cannot find the optimum solution in a specified number of iterations. Furthermore, the convergence behavior of the fuzzy-SFL method was found to be more reliable in comparison to the SFL and PSO methods because it does not get trapped in local optimum points. In order to investigate the effect of each objective function on the other objective functions, a single-objective problem based on the loss minimization is solved and the results are shown in Table 8. Although it can be seen that the $P_{Loss}$ and IV index values are decreased, the LBI index value has been increased in comparison with the multiobjective solution. It is obvious that the results of the multiobjective solution, which consider all of the objective functions with the appropriate weights, have better performance than the single-objective cases. The proposed multiobjective method was not considered, and so the comparison of the obtained results with other references is impossible. However, for the method evaluation, the single-objective results for Case 2 are compared with those obtained in [15] and [36], as is shown in Table 9.

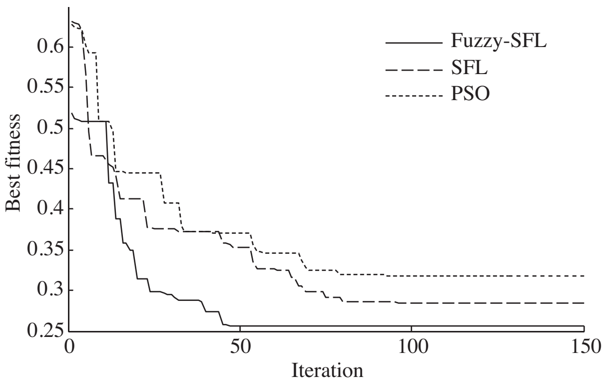


**Figure 11.** Convergence characteristics of case study 1, Case 5.

**Table 6.** Results obtained from various methods (case study 1, Case 5).

| | Fuzzy-SFL | SFL | PSO |
|---|---|---|---|
| Optimal fitness | 0.255 | 0.285 | 0.318 |
| Active losses (kW) | 115.8 | 128.1 | 130.2 |
| ELB | 48.06 | 47.91 | 53.76 |
| IV | 0.9815 | 0.8379 | 1.0678 |
| Worst voltage (p.u.) | 0.9461 | 0.9423 | 0.9240 |
| Tie switches | 7, 10, 14, 32, 37 | 8, 14, 31, 33, 37 | 6, 10, 14, 31, 37 |
| RPC location (bus no.) | 7 | 10 | 30 |
| RPC rating (MVA) | 1.6647 | 1.5102 | 1.2281 |

**Table 7.** SFL algorithm parameters.

| NM | NFM | NIM | Iterations |
|---|---|---|---|
| 5 | 30 | 50 | 150 |

**Table 8.** Single-objective results for minimization of power loss (case study 1).

| | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 |
|---|---|---|---|---|---|
| Active losses (kW) | 202.5 | 139.9 | 101.0 | 112.0 | 98.9 |
| ELB | 67.71 | 77.24 | 64.79 | 54.73 | 62.83 |
| IV | 1.7 | 1.0758 | 0.9339 | 0.6932 | 0.9540 |
| Worst bus voltage (p.u.) | 0.9131 | 0.9413 | 0.9545 | 0.9377 | 0.9538 |
| Tie switches | 33, 34, 35, 36, 37 | 7, 9, 14, 28, 32 | 7, 9, 14, 37 | 6, 9, 34, 36, 37 | 7, 9, 14, 32, 37 |
| RPC location (bus no.) | - | - | 30 | 14 | 28 |
| RPC rating (MVA) | - | - | 1.0702 | 1.401 | 1.1074 |

**Table 9.** Comparison of results of the 33-bus test system (Case 2).

| Methods | Tie switches | Total power loss (kW) | Loss reduction (%) |
|---|---|---|---|
| Base case | 37, 36, 35, 34, 33 | 202.5 | - |
| Proposed fuzzy-SFL | 7, 9, 14, 28, 32 | 139.9383 | 0.3090 |
| ACS | 7, 9, 14, 28, 32 | 139.9383 | 0.3090 |
| AS | 37, 32, 14, 9, 7 | 163.2949 | 0.1936 |
| GA | 36, 34, 33, 28, 9 | 146.3209 | 0.2774 |

### 7.2. Case study 2

The next example is a real distribution network from the TPC, which is shown in Figure 12. This practical 11.4-kV system with 11 feeders is equipped with 83 sectionalizing switches and 13 tie switches. The total

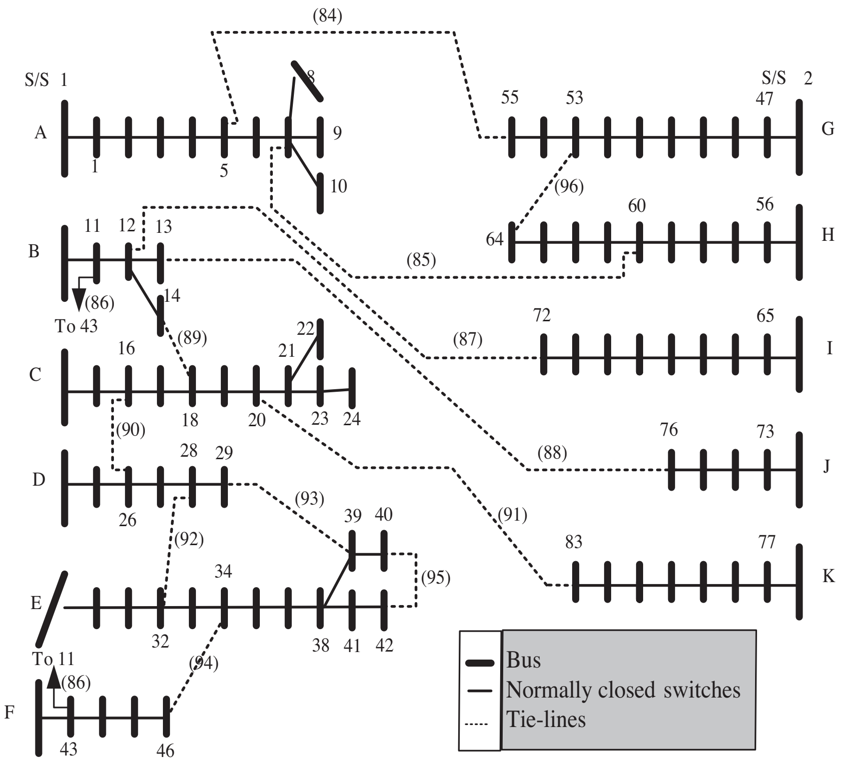


**Figure 12.** The Taiwan Power Company distribution system.

system load, which is considered as balanced and constant, is 28.35 kW and 20.7 kVAr. Other information can be derived from [37]. The power flow calculation is performed based on $S_{base}$ = 100 MVA and $V_{base}$ = 11.4. In this case, 2 RPCs are considered for installation because of the larger scale order compared to case study 1.

The results obtained through these cases are shown in Tables 10 and 11, which reveal that the optimal reconfiguration in the presence of the DSTATCOM will lead to a reduction of the network's loss, improvement of the voltage profile, and the improvement of equal load balancing of the feeders.

**Table 10.** Comparison of results (case study 2).

| | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 |
|---|---|---|---|---|---|
| Active losses (kW) | 532 | 484.4 | 447.8 | 408.5 | 402.8 |
| ELB | 140.35 | 133.73 | 131.40 | 128.80 | 126.85 |
| IV | 2.55 | 2.38 | 1.63 | 1.22 | 1.49 |
| Vorst voltage (p.u.) | 0.9285 | 0.9479 | 0.9481 | 0.9557 | 0.9532 |
| Tie switches | 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96 | 7, 13, 34, 39, 54, 62, 86, 87, 89, 90, 91, 92, 95 | 7, 13, 34, 39, 42, 54, 62, 72, 83, 86, 89, 90, 92 | 7, 13, 34, 39, 55, 62, 72, 83, 86, 89, 90, 92, 95 | 7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96 |
| RPC location (bus no.) | - | - | 61 | 61 | 63 |
| RPC rating (MVA) | - | - | 2.3173 | 2.4410 | 2.13 |
| RPC location (bus no.) | - | - | 20 | 79 | 20 |
| RPC rating (MVA) | - | - | 2.57 | 2.58 | 2.71 |

**Table 11.** Comparison of results in percent (case study 2).

| | Case 2 | Case 3 | Case 4 | Case 5 |
|---|---|---|---|---|
| Loss reduction (%) | 8.95 | 15.83 | 23.21 | 24.2857 |
| ELB improvement (%) | 4.71 | 6.38 | 8.23 | 9.6188 |
| IV improvement (%) | 6.67 | 36.08 | 52.16 | 41.5686 |
| Increment in worst voltage (%) | 2.09 | 2.11 | 2.93 | 2.6602 |
| No. of tie switches changed | 6 | 9 | 8 | 7 |

Figure 13 shows the voltage profile of the network in various exploiting conditions. Based on the following figures, it is obvious that the optimal reconfiguration in the presence of the DSTATCOM is the optimum method for reaching our objectives.

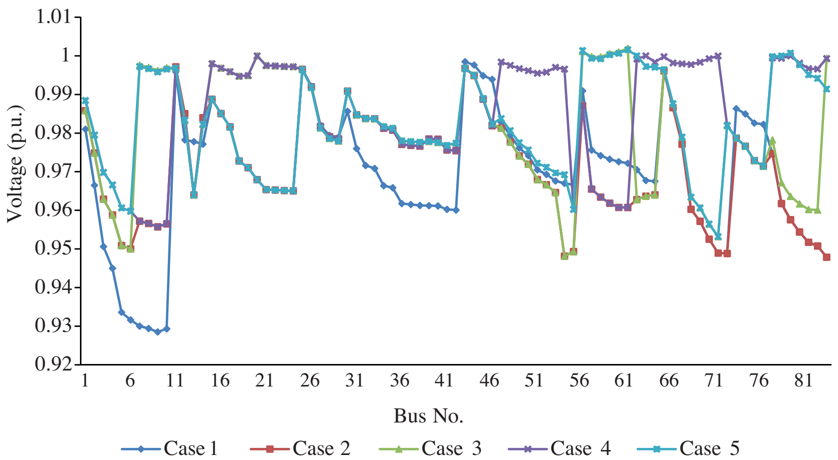


**Figure 13.** Voltage magnitude in different cases of case study 2.

**Table 12.** Results obtained from various methods (case study 2 , Case 5).

| | Fuzzy-SFL | SFL | PSO |
|---|---|---|---|
| Optimal fitness | 0.3008 | 0.3014 | 0.3125 |
| Active losses (kW) | 402.8 | 402.7 | 409.6 |
| ELB | 126.85 | 126.81 | 124.5021 |
| IV | 1.49 | 1.50 | 1.6554 |
| Worst voltage (p.u.) | 0.9532 | 0.9530 | 0.9488 |
| Tie switches | 7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96 | 7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96 | 7, 13, 34, 39, 41, 61, 84, 86, 87, 89, 90, 91, 92 |
| RPC location (bus no.) | 63 | 61 | 53 |
| RPC rating (MVA) | 2.13 | 2.2611 | 2.2883 |
| RPC location (bus no.) | 20 | 79 | 79 |
| RPC rating (MVA) | 2.71 | 2.6930 | 2.6797 |

**Table 13.** Single-objective results for minimization of power loss (case study 2).

| | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 |
|---|---|---|---|---|---|
| Active losses (kW) | 532 | 469.8 | 423.9 | 410.5 | 398.3 |
| ELB | 140.35 | 137.16 | 135.61 | 131.01 | 130.9532 |
| IV | 2.55 | 2.31 | 1.84 | 1.2468 | 1.94 |
| Vorst voltage (p.u.) | 0.9285 | 0.9532 | 0.9532 | 0.9557 | 0.9532 |
| Tie switches | 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96 | 7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92 | 7, 33, 55, 61, 72, 83, 86, 88, 89, 90, 92, 93, 95 | 7, 13, 34, 39, 40, 54, 61, 72, 86, 89, 90, 91, 92 | 7, 13, 34, 39, 41, 55, 62, 72, 83, 86, 89, 90, 92 |
| RPC location (bus no.) | - | - | 83 | 79 | 18 |
| RPC rating (MVA) | - | - | 2.0456 | 2.1942 | 2.31 |
| RPC location (bus no.) | - | - | 53 | 55 | 51 |
| RPC rating (MVA) | - | - | 2.1942 | 1.5769 | 1.56 |

From the results of the TPC case study, it can be seen that the RPC has the effect of a loss reduction improvement over the feeders in this particular case, and the topological structures of the optimum network without the RPC are different from those with the RPC.

In order to compare the proposed fuzzy-SFL, SFL, and PSO techniques in case study 2, based on our simulation results shown in Table 12 and Figure 14, the difference in the loss reduction between the fuzzy-SFL

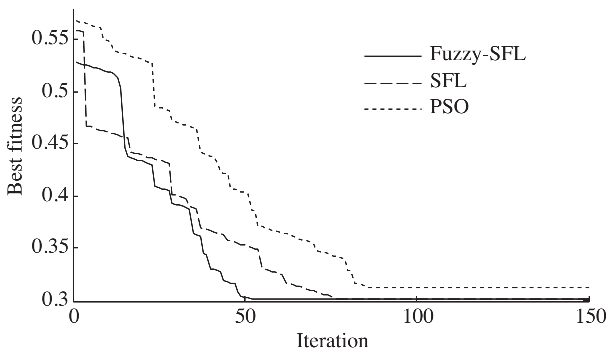


**Figure 14.** Convergence characteristics of case study 2, Case 5.

and SFL methods is very small. Since the reconfiguration problem does not have an infinite optimal search area, the fuzzy-SFL and SFL methods can achieve almost the same optimal solution if the algorithm iterations are large enough.

In a similar way as in Case 1, the single-objective results for the TPC distribution system are presented in Table 13. As is shown, the power loss index is decreased in spite of the ELB index in comparison with the multiobjective solution. For the method evaluation, the single-objective results for Case 2 are compared with those obtained in [15] and [36]. The method evaluation is shown in Table 14.

**Table 14.** Comparison of results of Tai-power system (Case 2).

| Methods | Tie switches | Total power loss (kW) | Loss reduction (%) |
|---|---|---|---|
| Base case | 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96 | 531.99 | – |
| Proposed fuzzy-SFL | 7, 13, 34, 39, 42, 55, 62, 72 ,83, 86, 89, 90, 92 | 469.81 | 0.1169 |
| ACS | 7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92 | 469.81 | 0.1169 |
| AS | 7, 13, 33, 39, 54, 61, 71, 86, 89, 90, 91, 92, 95 | 516.53 | 0.0290 |
| GA | 7, 33, 55, 61, 72, 83, 86, 88, 89, 90, 92, 93, 95 | 470.09 | 0.1163 |

## 8. Conclusion

This paper discusses an appropriate method for optimal multiobjective reconfiguration of distribution networks in the presence of RPCs. In this paper, the compensators used are a capacitor bank and DSTATCOM. At first, the objective function is defined with the following objectives: a) improvement of the voltage profile, b) reduction of the network losses, and c) improvement of the equal load balancing of the feeders. In order to solve the optimization problem for different cases, the fuzzy-SFL algorithm is used in this paper. In this study, the searching performance of the fuzzy-SFL algorithm is improved due to a new frog-leaping rule that considers uncertainties. The proposed algorithm was examined on 33- and 83-bus distribution test systems. The obtained results show that accurate placement of even small ratings of the DSTATCOM simultaneously with the optimal reconfiguration of system will lead to an improvement of the voltage profile, a further reduction of the losses, and improvement of the equal load balancing of the feeders. To investigate the validity of the results and the effectiveness of the fuzzy-SFL algorithm, the problem has also been solved with the SFL and PSO algorithms for an appropriate case.

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