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USING AN IMPERIALIST COMPETITIVE ALGORITHM TO RECONFIGURE DISTRIBUTION SYSTEMS FOR INCREASED RELIABILITY AND DECREASED POWER LOSSES

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Abstract: There are several conceivable combinations of radial and loop feeders in distribution systems, which allows for numerous layouts to be run. Power losses and dependability in delivering electric energy to consumers are affected differently by each arrangement. The reconfiguration of electricity networks is approached as a multi-objective optimisation problem with various network operational constraints and goal functions in order to get the ideal configuration. Optimal network reconfiguration is suggested in this paper using a multi-objective framework that minimises power losses, SAIDI, AENS, and ASUI, the System Average Interruption Frequency Index and Standard Average Interruption Duration Index, respectively. One of the most up-to-date heuristic techniques, the Imperialist Competitive Algorithm (ICA), solves the optimisation issue. In this case, we use fuzzy membership to scale all objective functions to the same value, and then we use fuzzy fitness to find out how satisfied we are with the provided solution. The effectiveness of the suggested approach is validated by its testing on distribution test systems of 32 and 69 buses, respectively. In comparison to earlier techniques, the suggested one has a higher convergence rate and exhibits enhanced exploration capabilities, according to the simulation findings.

Keywords: Distribution System Reconfiguration, Distributed Generation, ICA, Multi-Objective Optimiza- tion, Reliability Indices.

1. Introduction

Distribution systems act as mediums providing final links between the electric utility and customers. Perhaps the occurrence of failures in power system components is one the most main reasons of unavailability in supplying electric energy to users. Most of failures occur in the distribution voltage level. There are some accessible strategies to enhance reliability in distribution system; some of which are[1], [2]: utilizing highly reliable equipment for protection; reclosing and switching; automation; acceleration of restore processes by employing faster crew; faster fault prophecy techniques; and fewer equipment failures to avoid contingencies. Distribution feeder reconfigura tion is also one of the most important strategies among reliability improvement schemes. Two types of switches are usually installed in distribution systems along the main feeders and laterals: normally closed switches (sectionalizing switches) and normally open switches (tie switches). A sectionalizing switch isolates a faulted section of the system so that the healthy part can still be electrically supplied,

while a tie switch recovers loads that have been disconnected by transferring some of loads to other supporting distribution feeders without violating operation and engineering constraints. The reconfiguration task of a distribution system, which is to change the open/close status of sectionalizing and tie switches, is done in order to achieve a radial operating structure that optimizes certain objectives while satisfying operational constraints without islanding any load [1]. Since the status of these switches has a vital effect on branch power flows as well as on interruption durations in the event of a system failure, power losses and reliability of a distribution system can be effectively improved by reconfiguration [1].

A great deal of work has been done in literature on network reconfiguration (also known as feeder reconfiguration) in distribution systems mainly with the objective

function of active power loss reduction due to the fact that the cost of active power losses occupies considerable amount of operation cost and therefore, even a small reduction in power losses is still attractive for electric power utilities. Abdelaziz et al. in [2] utilized the Improved Tabu Search (ITS) algorithm for network reconfiguration with the objective function of minimizing active power losses. Constraints consist of preserving the network radial structure and limits for bus voltages and line flows. Gupta et al. in [3] proposed a multi-objective network reconfiguration problem based on Adaptive Genetic Algorithm (AGA). Suggested objective functions include minimizing power losses, voltage violations, branch current violations, and number of switching. Objective functions are converted into fuzzy memberships with the same range of [0, 1] using truncated sinusoidal and trapezoidal fuzzy membership functions. The degree of overall satisfaction of the multi-objective solution is specified by the 'max-geometric mean' operator. The output of this operator is employed as the fitness function of the AGA method. To minimize power losses, Srinivasa Rao et al. in [4] proposed the Harmony Search Algorithm (HSA) for reconfiguration of distribution systems with constraints including voltage profile, feeder capacities, and radial structure of the network. Niknam et al. in [5] suggested a multi-objective optimization for reconfiguration of distribution networks equipped by fuel cells using probabilistic load flow. Shuaib et al. in [6] applied the Gravitational Search Algorithm (GSA) for distribution system reconfiguration problem with the objective functions of minimizing power losses and balancing loads in feeders subject to voltage profile and network radiality.

In literature, little attention has been paid to reliability enhancement in feeder reconfiguration. Duan et al. in [7] performed network reconfiguration for power loss reduction and reliability enhancement with constraints of voltage profile and network radiality. The algorithm used to solve the optimization problem is an enhanced Genetic Algorithm (GA). The basis for this work is the information of a single loop caused by closing a normally open switch and to develop the algorithm on crossover and mutation operations of the original GA. Shareef et al.in [8]applied the Quantum-Inspired Binary Firefly Algorithm (QBFA) to network reconfiguration to minimize the number of propagated voltage stages and other reliability indices such as System Average Interruption Frequency Index (SAIFI) and Momentary Average Interruption Frequency Index (MAIFI). The problem constraints are voltage profile and network radiality. Kavousi-Fard et al. in [9] utilized the self-adaptive modified optimization algorithm based on the Bat Algorithm (BA) for distribution network reconfiguration with considering several objectives of SAIFI, Average Energy Not Supplied (AENS), total active power losses, and total network cost. In order to observe the effect of distributed generation on the reli-

ability of the power system, wind power source is also considered in the method. This optimization is solved subject to constraints of voltage profile, feeder ratings, and radial structure of the network. Gupta et al. in [10] used an efficient GA to perform optimal distribution system reconfiguration. The objectives of optimization are feeder power losses and system's node voltage deviation reduction, and improvement of reliability indices such as SAIFI, system's average interruption unavailability index and energy not supplied. Zhang et al. in [11] presents a new reliability-oriented algorithm to distribution system reconfiguration. This method uses the interval analysis techniques to include data uncertainties and to maximize the possibility of reliability enhancement and/or loss reduction.

The problem of reconfiguring the network is formulated as a Nonlinear Programming (NLP) optimization problem that can be solved by a variety of solution methods. From viewpoints of optimality and accuracy, intelligent or evolutionary tools such as GA, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Imperialist Competitive Algorithm (ICA) may give better solutions compared with classical methods such as Lagrangian. In literature, some evolutionary algorithms are used to solve reconfiguration in distribution systems; for instance, we can refer to modified Tabu Search in [2], HSA in [4], AGA in[3], GSA in [6], QBFA in [8], Shuffled Frog Leaping Algorithm (SFLA) in [12]. Furthermore, ICA as one of new evolutionary methods has recently got more attention in power system applications [13-16] due to its special capabilities. The efficiency of ICA to solve optimization problems in other fields has confirmedits better performance compared with other evolutionary algorithms [14, 15].

According the features reviewed above, the contribution of this paper is to perform the optimal reconfiguration of distribution networks using a fuzzy-based multi-objective ICA algorithm to enhance reliability indices and reduce power losses[17]. The objective functions include minimization of power losses, SAIFI, System Average Interruption Duration Index (SAIDI), AENS, and Average Service Unavailability Index (ASUI). The optimal configuration of the distribution system is so obtained that power losses are minimized and reliability is enhanced at the same time. A fuzzy-based decision maker [18, 19] is used to transform objective functions into fuzzy memberships and then finally to combine them into a single objective function, which is optimized subject to a variety of power system operational constraints.

The paper is organized as follows. In Section 2, the multi-objective reconfiguration problem is formulated as an optimization problem with is objective functions and constraints. In section 3, the ICA algorithms are introduced to solve the problem. Section 4 explains how to apply the ICA algorithm to the reconfiguration problem.

Simulation results obtained from two test distribution systems are presented in Section 5. The results are compared with those of other approaches and they demonstrate the efficiency of the proposed algorithm. Finally, Section 6concludes the paper.

2. Proposed Multi-Objective Problem for Network Reconfiguration

The primary or main feeders and lateral distributors are two important parts of a distribution network. A primary feeder starts from a substation and ends to major load centers. Individual load points are connected to the main feeder through the lateral distributors with distribution transformers at their end point. A radial distribution network has a main feeder with components such as lines, cables, and transformers to supply load points. Review of failure statistics clarifies that overhead and underground cable failures contribute to a large part of customer interruptions. Indeed, underground cables have a high operating temperature and when the temperature of a cable exceeds its threshold, it can motivate insulation breakdown and thus exacerbate the component failure rates. Furthermore, with increasing operating temperature, the life expectation of dielectric materials reduce exponentially. There are the same issues for overhead lines. High levels of currents cause to increase the sag of overhead lines and to reduce the ground clearance and this results in raising the risk of happening an electric outage. So, any planning strategy that intends to enhance reliability of the

system should reduce the branch currents. In addition, total power losses are also reduced by reducing branch currents since losses are proportional with the square of currents. The branch currents can be reduced by altering the topology of the distribution network via distribution feeder reconfiguration. Consequently, the reliability indices and power losses are effectively managed by reducing the harmful impacts of the temperature. Regarding the above explanations, the distribution feeder reconfiguration can be a suitable strategy to reduce failure rates through reducing the temperature in overhead lines and underground cables by controlling the current magnitude. Then, after reconfiguration and current reduction, the failure rate of branches are improved. The new failure rate as a function of current magnitude can be expressed as [20]:

$$\lambda_i^{new} = \frac{I_{i,new}}{I_{i,old}} \left(\lambda_i^{old} - \lambda_i^{best} \right) + \lambda_i^{best} \tag{1}$$

where $I_{i,old}$ and $I_{i,new}$ represent branch i current magnitude before and after reconfiguration, respectively; λ_i^{old} and λ_i^{new} are the failure rate of branch i (failure /year) before and after reconfiguration, respectively; λ_i^{best} is the best failure rate which can be attained for

branch i by current reduction (this failure rate corresponds to the zero branch current $I_{i,new}$ =0).

As seen in (1), the failure rate of a branch is linearly related to the ratio of the feeder current after and before performing distribution feeder reconfiguration; this can be used as the failure rate reduction coefficient. By this strategy, branch currents are reduced by changing direction of power flow and as a result,the failure rate of whole network would be decreased.

2. 1. Reliability Indices

Reliability indices in a distribution system can be studied from two viewpoints: load point reliability indices and system reliability indices. For a load point P, basic reliability indices that can be defined include the average failure rate λ_p, average outage durationr_P, and annual outage time U_P. These reliability indices can be calculated assuming a series system as follows:

$$\lambda_p = \sum_{i=1}^{n} \lambda_i \tag{2}$$

$$U_p = \sum_{i=1}^{n} \lambda_i r_i \tag{3}$$

$$r_p = \frac{U_p}{\lambda_p} = \frac{\sum_{i=1}^{n} \lambda_i r_i}{\sum_{i=1}^{n} \lambda_i} \tag{4}$$

where n is number of outage events for load point P; r_i is repair time of component i (in hours).

Using the three basic load point indices in (2)-(4), customer-oriented reliability indices can be introduced as SAIFI, SAIDI, Average Service Availability Index (ASAI), ASUI, Energy Not Supplied (ENS), and AENS. In the next subsection, enhancement of these customer-oriented reliability indices and minimization of power losses are considered as objective functions of the proposed reconfiguration problem.

2. 2. Objective Functions
2. 2. 1. Minimization of Reliability Indices

A few reliability indices are optimized in the proposed method to ensure power quality in the network. The average number of interruptions that a customer experiences is measured by SAIFI. This index is the first objective function and expressed as:

$$SAIFI = \frac{\sum \lambda_i N_i}{\sum N_i} \tag{5}$$

where N_j is the number of customers supplied at load point j; λ_j is failure rate for load point j (failure/year); nl is number of load points.

The SAIDI is the reliability index utilized by electric power utilities; it gives the average outage duration time that a customer experiences and is defined as:

$$ \tag{6} $$

where U_j is unavailability of load j (failure/year).

The ASAI is the ratio of the total number of customer hours that service was accessible during a given time period to total customer hours; this is also referred as the service reliability index. The ASAI is usually computed on either a monthly basis (730 hours) or a yearly basis (8760 hours) and expressed as:

$$ \tag{7} $$

The third objective function of ASUI, which is the contrary of ASAI, is defined as:

$$ \tag{8} $$

Another reliability index is ENS, which is the energy not supplied to customers as a result of outages. It is defined for each load bus as:

$$ \tag{9} $$

where $L_{a(j)}$ is the average connected load to the load point j(kW).The Average Energy Not Supplied (AENS), as the last reliability objective function, is defined:

$$ \tag{10} $$

2. 2. 2. Minimization of Power Losses

Minimizing active power losses has been one of vital issues in distribution systems. It is computed as sum of power loss of branches as:

$$ \tag{11} $$

where R_k and I_k represent the resistance and current of branch k respectively; SBR is the set of branches.

The proposed multi-objective optimization problem has four reliability objective functions of $f_1(x)$, $f_2(x)$, $f_3(x)$, and $f_4(x)$ as formulated in (5), (6), (8), (10), respectively, and the power loss objective function as formulated by (11). By minimizing these objective functions simultaneously, it is ensured that the network after reconfiguration

have a higher reliability in supplying energy with a reduced power losses.

2. 3. Decision Variables

The decision variables of the proposed method for reconfiguration include the status of normally open switches (tie switches) and normally closed switches (sectionalizing switches).The corresponding binary vector is defined as:

$$ \tag{12} $$

where *ntie* and *nsw* are number of tie and sectionalizing switches, respectively.

2. 4. Fuzzy-Based Combination of Objective Functions

Using the proposed multi-objective programming method, all objective functions are optimized to find an optimal solution. In view of the fact that the five introduced objective functions have different scales, if they are simply combined into one objective function, It leads to the scaling problem. The fuzzi fication method can prevent scaling problems by converting objective functions into the same range. In this technique, all objective functions are fuzzi fied and transformed into the same range of [0, 1]. The membership function for minimizing objective function iis presented as:

$$ \tag{13} $$

where g_i^{ideal} and g_i^{nadir} represent the ideal and nadir values from the payoff table for objective function i, respectively; g_i is objective function value; β_i is its fuzzy membership value. A smaller value of the objective function causes a larger membership function; this is more favorable when the goal is minimization.

Ideal and nadir values characterize the best and worst

available value of each objective function, respectively, in the solution space of the problem. To obtain ideal and nadir values of an individual objective function, the best and the worst system configuration is obtained by individually optimizing each objective function regardless of other objective functions. Among the obtained values from single objective optimizations, the worst and best values of each objective function gives its nadir and ideal values.

In this paper, five memberships of β_{SAIFI}, β_{SAIDI}, β_{ASUI}, β_{AENS} and β_{Loss} are computed for objectives functions of SAIFI, SAIDI, ASUI and AENS, and power losses, respectively. There are several operators to determine an overall fuzzy satisfaction function, but some of them have disadvantages. For instance, when the "max-weighted addition" operator is used, the overall fitness function will not equal zero when one of membership functions is equal to zero. Another operator is "max-product" that cannot determine the distance of solutions from the ideal one. Soin this paper, to combine objective functions and provide the degree of overall fuzzy satisfaction, an operator named "max-geometric mean," [3, 21], is considered. This combining technique offers a better performance than other techniques. Its overall fuzzy satisfaction is defined as follows:

$$\mu_f = \quad (14)$$

where μ_f represents the overall fitness function of the solution. For our multi-objective problem, the overall fitness function is the objective function that should be maximized.

2. 5. Constraints of the optimization problem
The proposed multi-objective programming problem is optimized subject to different constraints as described in the following subsections.

2. 5. 1. Load flow equations
The following equations represent power balance at each node of the distribution system as equality constraints.

$$\quad (15)$$

$$\quad (16)$$

where PI_i and QI_i are active and reactive net injections at bus i; $|E_i|$ and δ_i represent the magnitude and angle of voltage phasor at bus i; N_b is number of buses; $|Y_{ij}|$ and

φ_{ij} are the magnitude and angle of entry ij from the admittance matrix.

2. 5. 2. Network Radiality and Connectivity
The conservation of network radiality is one of the most vital constraints in system reconfiguration. To keep simplicity in protection of distribution systems and other aspects, networks are designed as radial. Thus, this property should be retained during reconfiguration process. In radial networks, the number of fundamental loops is determined by closing all tie switches. It is calculated as [5]:

$$\quad (17)$$

where N_b is the total number of buses of the network; N_{Loop} is the number of tie switches of the system; N_{br} is the total number of network branches.

In the proposed algorithm, the number of switches to be opened to maintain feasible radial configurations is considered as a control variable as an integer number. In this paper, the radiality in the reconfiguration process is guaranteed by graph rules [13], where the distribution network is radial if there is neither any loop nor any isolated load point in the network. Mathematically, the topology of a graph with n nodes is radial if:

$$\quad (18)$$

where x_k is the status of branch k (equals to 1 if branch k is closed, otherwise 0); n is the number of nodes of the graph; SBR is the set of branches of the graph.

2. 5. 3. Branch capacity limits
For protection of cables and feeders against extreme currents, feeder currents should be limited to their permissible rating:

$$\quad (19)$$

where I_{ij} represents the current of branch ij; is the permissible rating of branch ij.

2. 5. 4. Bus voltage permissible range
In order to keep voltage of buses in their allowed range specified by the system operator after reconfiguration, the following limitation is considered:

$$\quad (20)$$

3. Imperialist Competitive Algorithm (ICA)

The policy of extending the power of an imperial beyond its own boundaries is named imperialism. An imperialist uses different policy for dominating other countries include direct rule or by less clear tools such as control of the market for goods or raw materials. Atashpaz-Gargari and Lucas [22] proposed the ICA in 2007. This algorithm as a socio-politically motivated global search strategy has recently been used for optimizing different optimization tasks [23, 24].

3. 1. Initialization Phase

This algorithm similar to other evolutionary algorithms is initialized by the population of Pcountries which are generated randomly within the search space. Each country is defined by contry$_i$=[p$_1$, p$_2$, …, p$_{nvar}$] which never is number of decision variables. The best countries with the best fitness function in the initial population are chosen as the imperialists and other countries are as the colonies of these imperialists. The initial empires are built by dividing colonies among imperialists based on imperialist's power. To divide the colonies among imperialists proportionally, the following normalized cost of an imperialist is defined [23]:

$$C_n = c_n - \max_i \{c_i\} \qquad (21)$$

where c_n and C_n are the cost of nth imperialist and its normalized cost, respectively. The normalized power of each imperialist can be calculated by the normalized cost of all imperialists according to the following equation [23]:

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \qquad (22)$$

The empires should be divided into the initial colonies based on their powers; consequently, the initial number of colonies belonging to the nth empires is as follows[23]:

$$N.C._n = round\{p_n \cdot N_{col}\} \qquad (23)$$

where $N.C._n$ is the initial number of colonies belonging to the nth empires; N_{col} is the total number of initial colonies. The initial number of colonies are randomly allocated to the nth imperialist. In this algorithm, the bigger empires have more number of colonies, while the weaker ones have less [23].

3. 2. Assimilation Phase

After clustering colonies among the imperialists, the assimilation phase is started. In this phase, the colonies start moving toward their empire. A vector x from the colony to the imperialist is determined for direction of the move-

ment. The vector x is a random variable with having uniform distribution.

$$x \sim U(0, \beta \times d) \qquad (24)$$

where d is the distance between the colony and the imperialist state; β is a number greater than one. The reason behind using $\beta > 1$ is that the colonies to get closerto the imperialist state from both sides. For realization this phase, it is not necessary that the colonies movement toward imperialists be done in straight line due to limitations of the searching capability [23]. For movement toward imperialists, the colonies can be diverted from straight line equal to θdegree. This fact increases the ability of searching more area around the imperialist. θ is a random angle with uniform distribution:

$$\theta \sim U(-\gamma, \gamma) \qquad (25)$$

where γ is parameter for regulating the deviation from the original direction. The amounts of β and γ are arbitrary. However, for good convergence of countries to the global minimum, a value of about two for β and about π/4 (rad) for γ are used in most of implementations [23].

3. 3. Exchanging Phase

When the colonies move toward imperialist, it is possible that a colony get a position with lower cost than the imperialist. In this situation, the colony and the imperialist exchange their positions. After that, the algorithm will progress by the imperialist in the new position and the imperialist will assimilate the colonies in its new position.

3. 4. Calculation of total power of an empire

Total power of an empire is summation of the power of imperialist country and a percentage of the power of the colonies of an empire as follows:

$$T.C._n = Cost(imperialist_n) + \delta \qquad (26)$$
$$mean\{Cost(colonies\ of\ empire_n)\}$$

where T.C. is the total cost of the nth empire; δ is participation factor of colonies in the total power of empire and it is a positive small number; δ represents good results with a value 0.1 in most of the implementations[23].

3. 5. Imperialistic competition

This phase is started by selecting a colony of the weakest empire and then finding the possession probability of each empire. The possession probability P_P and the total power of the empire have a proportional relation. The normalized

33

total cost of an empire is obtained as follows:

$$\text{(27)}$$

where $N.T.C._n$ and $T.C._n$ are the normalized total cost and the total cost of nth empire, respectively. The possession probability of each empire is determined by having the normalized total cost as follows:

$$\text{(28)}$$

The vector P is generated to clusterthe mentioned colonies among empires, this vector is as follows:

$$\text{(29)}$$

After that, the vector R is generated in the same size with P. The elements of this vector are uniformly distributed random numbers.

$$\text{(30)}$$

Finally, the vector D is created by subtracting R from P. The mentioned colony (colonies) belonging to an empire which relevant index in D has maximum value. The process of selecting an empire is similar to the roulette wheel process in Genetic Algorithm (GA) [23].

4. Application of the Proposed Algorithm to Distribution System Reconfiguration

The ICA algorithm is applied here to the problem of the multi-objective network reconfiguration as depicted in the flowchart of Fig. 1. In the first step, input data are given; they include network data and parameters of the ICA algorithm. Then, the initial countries is generated. In each candidate, one switch from each fundamental loop to be opened is randomly chosen. Afterwards, the radiality and bus islanding are checked for candidates. To check whether radiality is maintained as well as to make sure that all loads are in service to prevent load islanding, the graph theory is employed. If the network graph is not a tree, it means that either the network is not radial or at least one load has been isolated. In this state, the value of the fitness function is considered to be zero for the corresponding candidate. In the next stage, a distribution load flow is run in order to calculate the fitness function (μ_f) using (14) for each country.

To applying the proposed ICA to this problem, the following steps have been considered:

1. Define the input data. The input data which

should be provided includes system base configuration, line impedances, the number of countries, the number of empires, number of decision variables in the country, the maximum number of iterations, and the internal parameters of the algorithm (assimilation coefficient and assimilation angle).

2. Generate the initial population (countries). The initial individuals of the population must be generated randomly in this step.

3. Calculate the objective functions. For each individual in the countries, the overall fitness function
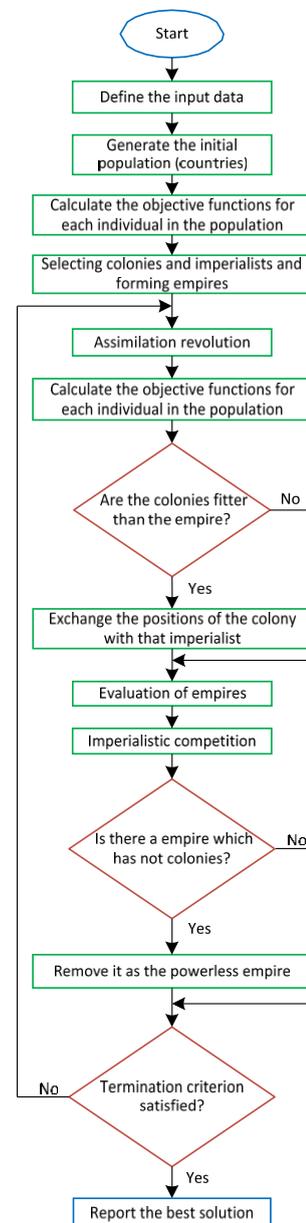

Fig. 1. Flowchart of the proposed ICA for distribution system reconfiguration

is calculated using (14). The violation of the constraints is also investigated in this step. For solutions that constraints are violated, fitness values are considered zero.

4. Selecting the colonies and imperialists and forming empires.

5. Moving the colonies toward their relevant imperialist (assimilation).

6. Exchanging the position of the colonywith its imperialist if the cost of the mentioned colony is lower than that imperialist.

7. Computing the total cost of all empires, regarding the power of the imperialist and its colonies.

8. Selecting the weakest colony (colonies) from the weakest empires and give it (them) to the empire that has the most likelihood to possess it (imperialistic competition).

9. Removing the powerless empires.

10. Check the termination criterion. The termination criterion is the maximum number of iterations. If the number of iterations is equal to the predefined number, go to the step 11; otherwise, go to the step 5.

11. Determine the best solution. After meeting the termination criterion, the process is finished.

5. Simulation Results

To demonstrate the performance of the proposed algorithm, it is tested on two case studies including 33-bus and 69-bus test systems and their numerical results are investigated and compared with other algorithms. The proposed method is implemented using the MATLAB software package. Parameters that are assumed for the ICA algorithms are listed in Table 1for the two case studies. These parameters are previously defined in section 3. Results are presented in two subsections for the two case studies in the following.

5. 1. Case Study 1 (33-bus test system)

The Baran and Wu [13] distribution network, whose one line diagram is shown in Fig. 2, is used as the first test system. The system consists 32 sectionalizing (normally closed) switches numbered S1-S32 and 5 tie switches (normally open) numbered S33-S37. The total real and reactive power loads of the system are 3715 kW and 2300 k VAR, respectively. In the base case (initial) load flow,

the network has power losses of 202.677 kW and the minimum bus voltage of 0.913 p.u. Regarding reliability indices, it is assumed here that the failure rate of the line with the greatest and the smallest length is 0.4 and 0.1 failure/year, respectively. Consequently, the failure rate of other lines is calculated proportional to their lengths between these two boundary failure rates [25].The time that is required for switching is supposed to be 0.5 h and the required time for repairing is assumed to be 6 h. In addition, it is assumed that components like transformers, breakers, and bus bars are entirely reliable because distribution system reconfiguration would just deal with the reliability of feeder sections. Another assumption is that the least failure rate, which can be acquired for a line by decreasing current, equals to 0.85 of its non-reduced failure rate. Moreover, the number of customers supplied in each load point, which is presented by N_j in (5)-(10), is shown in Fig. 3.

As mentioned before, the proposed method is a multi-objective programming with objective functions of minimizing power losses and reliability indices of SAIFI, SAIDI, AENS and ASUI. However, in order to compare the performance of the ICA with other methods in reconfiguration, the objective functions are optimized individually at first to get their single objective results and compare them with other methods. The results of single objective optimizations can be used for calculation of ideal and nadir
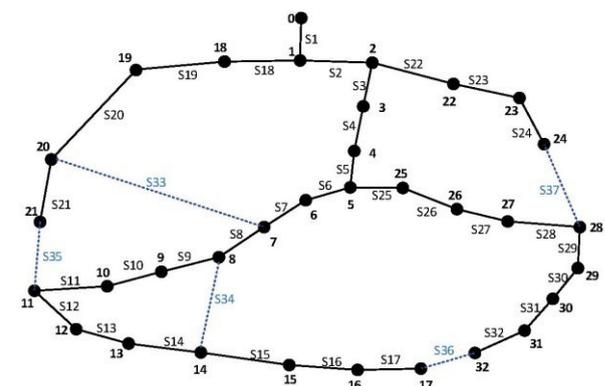

Fig. 2. One line diagram of the 33-bus Baran and Wu distribution test system

Table 1. Parameters of the proposed algorithm for the examined test systems

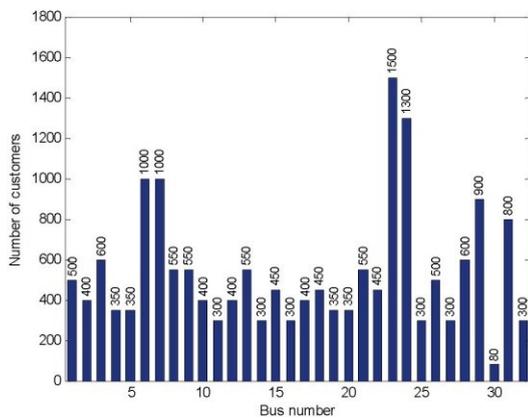| Test system	Number of countries	Number of empires	ق	ٻ	Max. iterations	□□□□□□□
IEEE 33-bus test system	50	6	2	0.5	60	30
IEEE 69-bus test system	50	6	2	0.5	100	30

Fig. 3. Number of customers at each bus of the 33-bus test system

values in (13). Results of the five single objective optimizations are shown in Table 2 and Table 3.

In Table 2, results of the optimizing four objective functions of f_1=SAIFI, f_2=SAIDI, f_3=ASUI, and f_4=AENS as single objective optimizations are presented. In the last column, open switches after optimal reconfiguration are also given. It is worthwhile to note that results of three objective functions (SAIFI, SAIDI and AENS) in this table are reported from [25] using different methods of GA, PSO, SFLA and Improved SFLA(ISFLA) to be compared with the proposed method. However, since there is

no other work to address the ASUI objective function, two well-known algorithms of GA and PSO are implemented in this paper and their results are reported also in Table 2. For optimization through GA, the algorithm needs the crossover and mutation probability, the initial population, and number of iterations; they have been chosen as 0.8, 0.08, 600, and 200, respectively [26]. Parameters used for the PSO algorithm include the initial number of particles, maximum number of iterations, the maximum velocity, and the inertia weight factor; they are considered as 40, 1000, 2, and 0.8, respectively, in simulations. As seen in Table 2, each method leads to an optimal value of the objective function with its status of open switches. Methods that result in the same status of open switches have the same optimal value of the objective function. As seen in this table, the proposed ICA offers the best value of reliability indices when it is optimized in its single objective mode.

The results of minimization of total active power losses or $f_5\,(x)$ as a single objective optimization are also shown in Table 3, where columns 2-4 represents results of optimization methods. Results from different methods are reported in this table including Honey-Bees Mating Optimization (HBMO), Discrete Particle Swarm Optimization (DPSO), and Adapted Ant Colony Optimization (AACO). As seen in this table, the least possible power losses that is obtained by some methods equals to 139.35kW and the proposed ICA method can optimally find the most optimal solution with the best switching op-

Table 2. Results of single objective optimization to minimize reliability indices by different methods in the 33-bus test system

Objective function	Method	Best solution	Open switches
$f_1 = SAIFI$ (f/customer/yr)	GA[25]	1.195432	S33, S14, S35, S17, S37
	PSO[25]	1.181065	S33, S12, S35, S36, S37
	SFLA[25]	1.178177	S33, S13, S35, S36, S37
	ISFLA[25]	1.178177	S33, S13, S35, S36, S37
	ICA	1.178177	S33, S13, S35, S36, S37
$f_2 = SAIDI$ (h/customer/yr)	GA[25]	9.8803979	S33, S14, S35, S17, S37
	PSO[25]	9.7617397	S33, S34, S35, S17, S37
	SFLA[25]	9.7617397	S33, S34, S35, S17, S37
	ISFLA[25]	9.6422849	S33, S34, S35, S16, S37
	ICA	9.6422849	S33, S34, S35, S16, S37
$f_3 = ASUI$	GA	0.00005	S33, S34, S35, S17, S37
	PSO	0.00005	S33, S34, S35, S17, S37
	ICA	0.00005	S33, S34, S35, S17, S37
$f_4 = AENS$ (kWh/customer/yr)	GA[25]	1.9168710	S33, S34, S35, S36, S37
	PSO[25]	1.9168710	S33, S34, S35, S36, S37
	SFLA[25]	1.9168710	S33, S34, S35, S36, S37
	ISFLA[25]	1.9052420	S33, S34, S35, S16, S37
	ICA	1.9052420	S33, S34, S35, S16, S37

Table 3. Comparison of single objective optimization of active power losses by ICA and other methods in the 33-bus test system

Method	$f_5 = P_{Loss}$(kW)	Minimum voltage(p.u.)	Open switches
Ref[27]	140.26	0.93781964	S7, S10, S14, S32, S37
HBMO [28]	139.53	0.93781964	S7, S9, S14, S32, S37
PSO–ACO [29]	139.53	0.93781964	S7, S9, S14, S32, S37
DPSO–ACO [30]	139.53	0.93781964	S7, S9, S14, S32, S37
DPSO–HBMO [31]	139.53	0.93781964	S7, S9, S14, S32, S37
DPSO [31]	139.53	0.93781964	S7, S9, S14, S32, S37
AACO [32]	139.53	0.93781964	S7, S9, S14, S32, S37
Ref[33]	139.53	0.93781964	S7, S9, S14, S32, S37
Fuzzy-ACO [34]	140.27	0.93781850	S7, S10, S14, S32, S37
HAS [4]	142.67	0.93358830	S7, S10, S14, S36, S37
ISFLA [25]	139.53	0.93781964	S7, S9, S14, S32, S37
ICA	139.53	0.93781964	S7, S9, S14, S32, S37

eration. As a result, Table 3 and Table 2 show that the proposed ICA method leads to the best performance in comparison with other methods.

After validating the efficiency of the proposed ICA method in its single objective cases in Table 2 and Table 3, it is time to run the proposed method in its multi-objective form. In order to fuzzify objective functions, their ideal and nadir values are needed. These values are obtained as reported in Table 4.

Results of the ICA method in the multi-objective mode are shown in Table 5. Since the proposed method has five objective functions and there is no other work in literature with the same objective functions to compare results, we here have implemented two well-known algorithms of PSO and GA with the same conditions and have solved the same multi-objective problem with these two methods to evaluate the proposed method in its multi-objective case.Parameters of the PSO algorithm including the initial number of particles, number of maximum iterations, the maximum velocity, and the inertia weight factor are assumed as 45, 1000, 2, and 0.8, respectively. For the GA algorithm, the crossover probability, mutation probability, the initial population, and number of iterations are con-

sidered as 0.8, 0.08, 600, and 1000, respectively. Inasmuch as these methods have stochastic nature and they are based on generation of random numbers, these methods are run multiple times and the results presentedin Table 5 are the best solutions after 50 times running of simulations.

In Table 5, the optimal value of five objective functions are reported in columns 2-6 as obtained by the three examined methods. As seen in the table, the three methods lead to different optimal sets of objective functions. It is noted that a less value for objective functions is more preferred since they are for minimization. In column 7 of the table, the overall fuzzy fitness of optimal solutions is presented. A higher value of the overall fitness implies a more optimal solution. As seen, the proposed ICAmethod offers a better fitness than PSO and GA algorithms (0.8691 against 0.7315 and 0.7859). Although the ICA algorithm offers a bit higher value for some objective functions, it can manage to make a better tradeoff considering all objective functions leading to a better overall fitness. In the last column of the table, CPU running times are given for examined methods. The PC used in simulations had a dual 2 GHz CPU with 1 GB RAM. As seen, the ICA algorithm

Table 4. Ranges of objective functions

Objective function	Ideal value	Nadir value
۹.□ ۱۵۰۳ ۵″ ۴ ۶۲ (f/customer/yr)	1.1782	1.3530
۹.□ ۵۱۵۰۳ ۵″ ۶۵۶ (h/customer/yr)	9.6423	11.7221
۹.□ ۱۵۰۳ ۵۲,	0.00005	0.1477
۹.□ ۱۵۰۳ ۵۵۵₀^{e}₀″ (kWh/customer/yr)	1.9052	2.3150
۹.□ ۱۵۰۳ ۹: □□₀₀(kW)	139.5300	204.0504

Table 5. Comparison of results from the proposed method with PSO and GA algorithms in the 33-bus test system

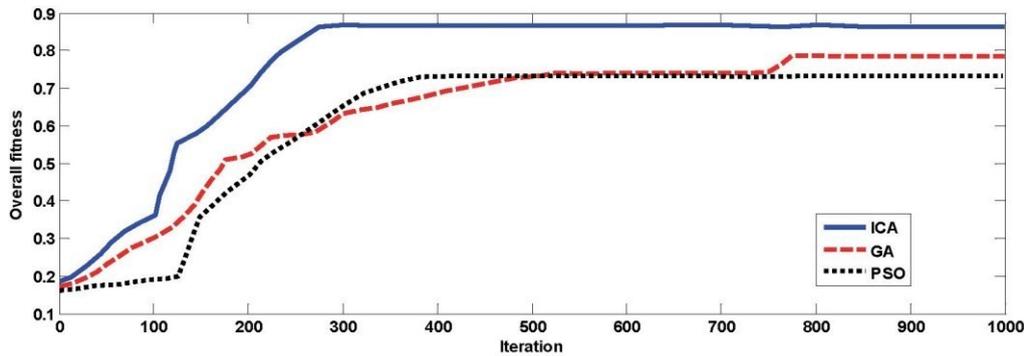| Method	$f_1 = SAIFI$ (f/customer/yr)	$f_2 = SAIDI$ (h/customer/yr)	$f_3 = ASUI$	$f_4 = AENS$ (kWh/customer/yr)	$f_5 = P_{Loss}$ (kW)	μ_f	CPU time (sec)
PSO	1.2894	9.7617	0.0050	2.031	146.984	0.7315	5.78
GA	1.2347	9.9982	0.0328	1.992	147.823	0.7859	13.67
ICA	1.1954	9.8803	0.0277	1.967	145.998	0.8691	4.76

Fig. 4. The convergence behavior of the proposed method along with PSO and GA algorithms in the 33-bus test system

is the fastest of the three ones.

The convergence behavior of the three algorithms is depicted in Fig. 4. According to this figure, the ICA algorithem converges to the fitness value of 0.8642 after 274 iterations (in the knee point), whilethe GA algorithm reaches to the fitness value of 0.7859 after 775 iterationsat its knee point and the PSO reaches to the fitness of 0.7291 at iteration 382 at its knee point. According to this figure, the proposed ICAalgorithmhas better a performance in comparison with GA and PSO algorithms from both computional burden and solution optimality.

5. 2. Case Study 2 (69-bus test system)
This case study is the practical distribution network of Taiwan Power Company [35] with the voltage level of

12.66 kV. Theone line diagram of this distribution system including 11 feeders, 69 buses, and 69 switchesis shown in Fig. 5. This system has 5tie switches, numbered S69 to S73 and shown by dotted lines, as well as 68 sectionalizing switches, numbered S1 to S63 and illustrated by solid lines. Power losses and minimum bus voltage in the initial configuration are 224.952 kW and 0.909 p.u, respectively. To calculate reliability indices, it is assumed that there is a breaker at the beginning of each feeder and a sectionalizer at the beginning of each section. The failure rate of the branch with the largest impedance and the branch with the smallest impedance are considered as 0.4 and 0.1, respectively. The failure rate of other branches is considered in the range between these two values. Switching time and repairing time are considered as 0.5 and 6 hours, respec-
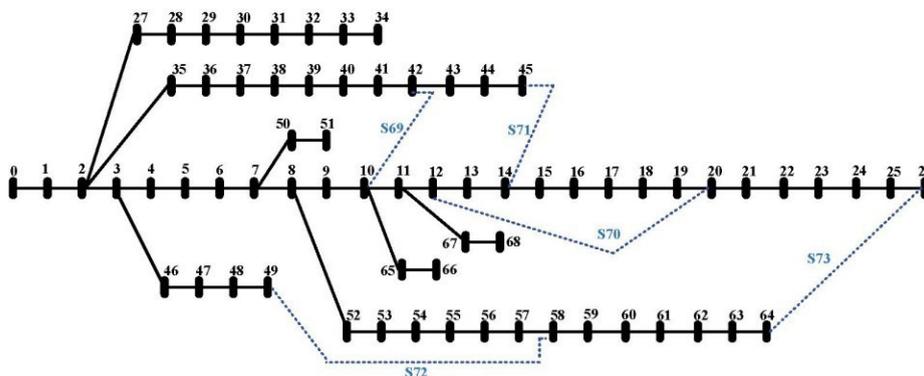
Page 19

Fig. 5. The one line diagram of 69-bus distribution system

Table 6. Comparison of single objective optimization of minimizing active power losses yielded by different methods

Method	$f_5 = P_{Loss}$(kW)	Open switches
Base case network	225.0	S11-S66,S13-S20,S15-S69,S27-S54,S39-S48
Ref[36]	102.6	S11-S66,S13-S20,S14-S15,S50-S51,S44-S45
Ref[37]	102.1	S11-S66,S13-S20,S14-S15,S50-S51,S47-S48
Ref[27]	106.63	S11-S66,S17-S18,S67-S68,S21-S22,S47-S48
Ref[38]	99.62	S11-S66,S13-S20,S14-S15,S50-S51,S47-S48
Ref[39]	99.62	S11-S66,S13-S20,S14-S15,S50-S51,S47-S48
SAMCSA [35]	99.62	S11-S66,S13-S20,S14-S15,S50-S51,S47-S48
Proposed (ICA)	99.62	S11-S66,S13-S20,S14-S15,S50-S51,S47-S48

tively.

Similar to the previous case study, at first, objective functions are individually optimized so that we can compare the ability of different methods in optimizing individual objective functions. Results of optimizing the active power-erloss objective function isshown in Table 6.From this table, it can be understood that the proposed method offers the most optimal power losses of 99.62 kW. In this table, the optimal open switches resulted by different methods are also shown in the last column.

Results of single objective optimization of SAIFI, SAIDI, AENS, and ASUI by a few methods are shown in Table 7. The values of SAIFI, SAIDI, and AENS before reconfiguration were 1.7193689 (fr/customer/yr), 14.27470 (h/customer/yr), and 3.168866 (kWh/customer/yr), respectively. After reconfiguration, all methods enhances reliability indices as seen in the table. Since the methods in Table 7 uses random number generations in their algorithm, they can result in a different solution in runs. Then, in this table, the problem is solved for 25 trials by each method and the values of the best solution, the worst solution, the average of the optimal solutions, the standard deviation of the optimal solutions, and the CPU time obtained are shown. Since there is no work addressing the ASUI objective function, two algorithms of GA and PSO are implemented here and their results are compared with

Table 7. Comparison of single objective optimization ofreliability indices by ICA and other methods in the 69-bus test system

Objective function	Method	Best solution	Worst solution	Average	Standard deviation (×10⁻³)	CPU Time (Sec)
$f_1 = SAIFI$ (f/customer/yr)	GA[35]	1.440030	1.48258	1.46730	25.94	17.62
	PSO [35]	1.425362	1.44002	1.43604	10.03	16.95
	CSA [35]	1.424326	1.43940	1.43118	7.51	17.22
	SAMCSA [35]	1.419796	1.42433	1.42002	3.53	15.44
	ICA	1.419796	1.42237	14.19957	3.21	13.06
$f_2 = SAIDI$ (h/customer/yr)	GA [35]	12.81103	12.88221	12.84933	41.00	17.28
	PSO [35]	12.73029	12.83062	12.81204	39.79	16.62
	CSA [35]	12.76283	12.83014	12.80346	38.11	17.52
	SAMCSA [35]	12.59105	12.64257	12.61086	17.52	13.62
	ICA	12.59105	12.63736	12.59921	14.38	10.67
$f_3 = ASUI$	GA	0.000455	0.03121	0.02344	12.56	14.79
	PSO	0.000353	0.02066	0.01566	11.47	11.26
	ICA	0.000275	0.01166	0.00504	9.94	10.47
$f_4 = AENS$ (kWh/customer/yr)	GA [35]	2.839291	2.90328	2.85931	24.39	17.84
	PSO [35]	2.817355	2.84077	2.82920	12.87	17.30
	CSA [35]	2.814327	2.83285	2.82676	9.01	17.29
	SAMCSA [35]	2.797363	2.79916	2.79814	0.67	15.23
	ICA	2.797363	2.79845	2.79792	0.36	12.45

Table 8. Multi-objective optimization results obtained by different methods in the 69-bus test system

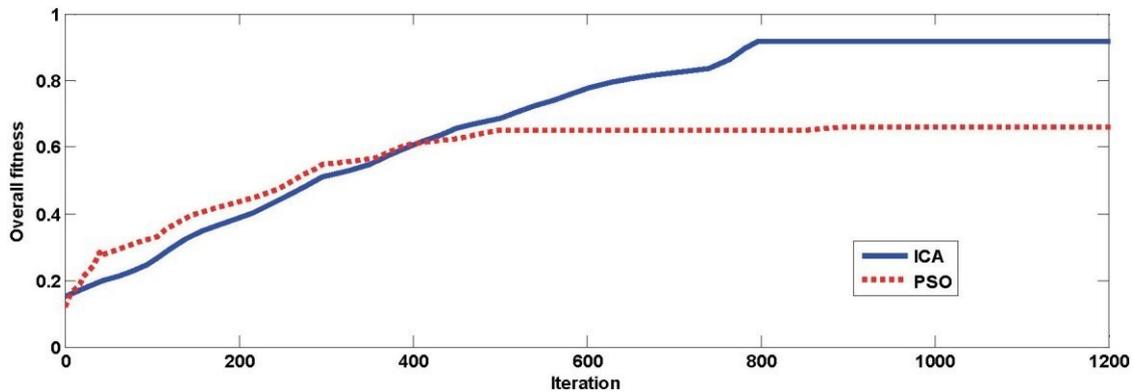| Method	$f_1 = SAIFI$ (f/customer/yr)	$f_2 = SAIDI$ (h/customer/yr)	$f_3 = ASUI$	$f_4 = AENS$ (kWh/customer/yr)	$f_5 = P_{Loss}$ (kW)	μ_f
PSO	1.5567	12.896	0.0235	3.24	105.76	0.6585
ICA	1.4326	12.672	0.0114	2.98	100.27	0.9203

Fig. 6. The convergence of multi-objective ICA and PSO algorithms in the 69-bus test system

ICA in Table 7 for the ASUI objective function. Considering Table 7, the proposed method offers its optimal solution and configuration like the SAMCSA method on objective functions of f_1, f_2, and f_4. However, the proposed method needs less CPU time for catching the optimal solution and also it has better results for the worst solution, average, and standard deviation. The simulation results reveal that the proposed method has more satisfying results in comparison to GA, PSO, and CSA methods in terms of robustness and CPU time.

Results of multi-objective optimization by the proposed method are shown in Table 8, where results from the multi-objective PSO algorithm are also reported. The results are reported in this table are the best solutions obtained after 50 times running of simulation. Objective functions obtained by the ICA in this table lead to the overall fitness of 0.9203, which is close to its ideal value of unity. However, the PSO algorithm results in a multi-objective solution with the overall fitness of 0.6585. This means that the proposed ICA can manage to find a more optimal solution than the PSO. This is due to the mutation operator used in the ICA that makes the method searches for a more optimal solution.

In Fig. 6, the convergence rates of the proposed ICA and the PSO algorithms are depicted. As seen from this figure, the ICA method reaches to its ultimate overall fitness of 0.9176 (almost optimal) at iteration 797, whereas the PSO reaches to its final overall fitness of 0.6585 at iteration

892. This implies that the ICA offers a more optimal solution than the PSO with a faster execution time.

6. Conclusions

A multi-objective approach to the distribution system network reconfiguration issue is presented in this research. Reliability indices of SAIFI, SAIDI, ASUI, and AENS, as well as power loss minimisation, are objective functions. The suggested issue is resolved by implementing the effective ICA inside a fuzzy framework. Here we review and compare the findings from our tests of the suggested reconfiguration issue on the 33-bus and 69-bus test systems with those from other studies. In this paper, we test the ICA method in a variety of single-and multi-objective settings. The findings show that the suggested ICA algorithm outperforms the state-of-the-art while requiring less time to run. The updated ICA can really find its best answer in the first few cycles. Hence, compared to other approaches, the ICA provides a superior optimum solution with overall fuzzy fit-ness.

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