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Research article

Multi-objective optimal operation of smart reconfigurable distribution grids

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Abstract: Reconfiguration is a valuable technique that can support the distribution grid from different aspects such as operation cost and loss reduction, reliability improvement, and voltage stability enhancement. An intelligent and efficient optimization framework, however, is required to reach the desired efficiency through the reconfiguration strategy. This paper proposes a new multi-objective optimization model to make use of the reconfiguration strategy for minimizing the power losses, improving the voltage profile, and enhancing the load balance in distribution grids. The proposed model employs the min-max fuzzy approach to find the most satisfying solution from a set of nondominated solutions in the problem space. Due to the high complexity and the discrete nature of the proposed model, a new optimization method based on harmony search (HS) algorithm is further proposed. Moreover, a new modification method is suggested to increase the harmony memory diversity in the improvisation stage and increase the convergence ability of the algorithm. The feasibility and satisfying performance of the proposed model are examined on the IEEE 32-bus distribution system.

Keywords: reconfiguration strategy; fuzzy interactive method; modified harmony search

Nomenclature

Indices

e	Index for scenario
g	Index for an element of a scenario
k	Index for feeder
i,j	Index for bus
s	Index for scenario

z	Index for uncertain parameter
m,l	Index for solution in harmony memory
n	Index for an element of the solution vector
t	Index for iteration number
w	Index for objective function

Sets

B	Set of buses
C	Set of feeders
W	Set of objectives
Ω	Set of solutions in problem search space
ξ_s	Set of scenarios

Parameters

bw	Arbitrary distance bandwidth
bw^{max} & bw^{min}	Maximum and minimum values of the bandwidth
DT	Distance between scenarios.
d	Length of the control vector
R	Resistance of feeder
I^{rate}	Nominal current
$f(.)$	Objective function
$f^{min/max}$	Minimum/Maximum value of objective
$g(.)/h(.)$	Equality/Inequality constraints
L	Number of objective functions
$HMCR$	Harmony memory considering rate in the range of (0,1)
PAR	Pitch adjusting rate in the range of (0,1)
PAR_{max} & PAR_{min}	Maximum and minimum values of PAR
V^{min}/ V^{max}	Minimum/maximum bus voltage
Y/θ	Line admittance magnitude/phase angle
Z	Number of uncertain parameters
$\rho_1, \ldots, \rho_6$	Constant value in the range (0,1]
N_s	Initial number of scenarios
N_{sr}	Number of scenarios after reduction
NI	Maximum number of iterations
μ^{ref}	Satisfying degree of the objective function
μ	Fuzzy membership function value

Variables

dev	Voltage deviation function
I	Commitment state of the dispatchable unit
n_{rand}	Random integer
P/Q	Active/reactive power injections
PL	Power flow in the feeder/line
PL^{max}	Maximum power flow in the feeder/line
P_{loss}	Active power losses

pr^{norm}	Normalized probability value of each scenario
pr	Probability of an element in a scenario.
S	A possible scenario of the problem.
Tie	Tie switch
SW	Sectionalizing Switch
V/δ	Bus voltage magnitude/phase angle
U	Scenario set
U	Probability level in the scenario U
X	Control vector/solution
X^{best}	Best solution in HM
x^{rand}	Random element in the control vector X
B	Random number in the range [0,1]

1. Introduction

The electricity distribution system is the final link in the delivery of electric energy from the transmission system to end-use consumers. Distribution systems supply a large number of consumers and play a critical role in the power quality and reliability of the electrical services. The statistical reports show that more than 80 percent of electricity interruptions occur at the distribution voltage level [1]. These reports emphasize on the significance of reinforcing the structure and quality of the distribution system for reducing the overall system costs; either the cost of the power supply or the cost of interruptions. One of the most viable methods for enhancing the quality of the distribution electrical services is the reconfiguration strategy. By definition, reconfiguration is the process of changing the topology of the distribution grid for achieving pre-determined targets using some normally closed and open switches [2]. Generally, distribution systems are constructed with radial topology so that the system protection is preserved in acceptable level and at the same time the power losses are preserved low. Moreover, the radial topology is significantly less expensive than the mesh topology to build. In comparison to the other available reinforcement strategies of the distribution system such as capacitor placement, shunt reactor allocation, rewiring of the network, and the installation of the distributed generation, the reconfiguration strategy does not impose any capital investments to system planners. In addition, this strategy can be utilized in different scheduling time horizons, from hourly to daily to monthly, and therefore is extremely useful for system operators [3].

Extensive research has been conducted in recent years to investigate various aspects of the reconfiguration strategy, in which the main focus has been the power loss reduction, conceivably due to significant power losses at the distribution system and its impact on the total system operation cost. Some of the well-investigated methods that have assessed the role of the reconfiguration on the optimization of the power losses are brute-force approach [4], neural network [5], optimum flow pattern [6], heuristic techniques [7], graph theory [8], ant colony algorithm [9,10], expert systems [11], and hybrid simulated annealing algorithm and Tabu search [12]. In the area of voltage drop correction, the role of the reconfiguration in reducing the maximum bus voltage deviations from their nominal value is discussed in [13]. The main idea is to change the topology of the network in a way that the voltage drop is reduced in buses and the radial structure as well as the thermal limitations of the feeders are preserved. In [14,15,16], the positive effect of the reconfiguration in improving the reliability of the network is investigated. Also, it is shown in [16] that reconfiguration strategy can be considered as a failure rate reduction methodology by rerouting the power flow in distribution feeders. In that work, the system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), and average energy not supplied are considered as the reliability targets. The load balance increment and service restoration abilities of the reconfiguration strategy by changing the supply path of the consumers are addressed in [17]. This research shows the precious role of reconfiguration in the case of emergency situation and fault clearance in the network.

The existing work clearly show the viable role of the reconfiguration strategy in smart distribution systems for increasing the overall efficiency of the electricity supply and delivery. However, the challenging issue is that each of these targets can show a conflicting behavior with respect to other operation targets. In order to solve this issue, the application of an appropriate multi-objective optimization framework seems inevitable. Moreover, the main deficiency with majority of the existing work is the deterministic analysis framework. Neglecting the uncertainty can result in idealistic and less-reliable solutions that can jeopardize the network's reliable operation. Therefore, this paper proposes a multi-objective optimization framework based on fuzzy theory to simultaneously minimize the total active power losses, bus voltage deviations, and load imbalances. The proposed framework employs the min-max fuzzy satisfying approach to choose the best compromised solution from the non-inferior solution set in the problem search space. Since the optimal operation and management of the reconfiguration is a discrete nonlinear constrained optimization problem, a powerful optimization algorithm is required to search the problem space globally. Therefore, a new modified optimization method based on harmony search (HS) is proposed that can optimally solve the problem. In addition, a new modification method is proposed that can help increase the diversity of the harmony memory (HM) and thus reduce the possibility of trapping in local optima. This can further increase the convergence ability of the algorithm by avoiding premature convergence. The proposed problem is solved in a stochastic framework based on scenario generation to model the uncertainties of the active and reactive loads. The feasibility and satisfying performance of the proposed method are examined on a standard test system.

The rest of this paper is organized as follows: Section 2 describes the problem formulation including the objective function and constraints. Section 3 explains the stochastic framework based on scenario generation. The proposed modified HS (MHS) algorithm is described in section 4. The proposed multi-objective framework is explained in Section 5. The simulation results on the test system are discussed in section 6. Finally, the concepts and conclusions are summarized in section 7.

2. Problem Formulation

In this section, the problem formulation, including the objective functions and constraints, are explained.

2.1. Objective functions

As mentioned above, the problem considers a multi-objective formulation optimizing 1) active power losses, 2) maximum bus voltage deviation and 3) feeder load balance. These objectives are described as following:

$$f_1(X) = P_{loss}(X) = \sum_k R_k I_k^2(X) \qquad k \in C \tag{1}$$

$$f_2(X) = dev(X) = \max[\left|1 - V^{\min}(X)\right|, \left|1 - V^{max}(X)\right|] \tag{2}$$

$$f_3(X) = Balance(X) = -\min_k \left| \frac{I_k^{rate} - I_k(X)}{I_k^{rate}} \right| \qquad k \in Q \tag{3}$$

$$X = [Tie_1, Tie_2, .., Tie_{N_{Tie}}, SW_1, SW_2, .., SW_{N_{sw}}] \tag{4}$$

The objective function (1) represents total active power losses in network feeders, (2) represents the voltage deviation function which improves the voltage profile of the network by minimizing the maximum bus voltage deviations, and (3) represents the load balance function for improving the feeders load balance. To calculate these targets, the power flow is run for each switching scheme during the optimization process. A complete description on the power flow methods can be found in [18,19]. The problem control vector incorporates the optimal status of the tie and sectionalizing switches as shown in (4).

2.2. Constraints

The problem is subject to the following constraints:

$$PL_k \le PL_k^{\max} \qquad k \in C \tag{5}$$

$$P_i = \sum_j V_i V_j Y_{ij} Cos(\theta_{ij} - \delta_i + \delta_j) \qquad i \in B \tag{6}$$

$$Q_i = \sum_j V_i V_j Y_{ij} Sin(\theta_{ij} - \delta_i + \delta_j) \qquad i \in B \tag{7}$$

$$I_k \le I_k^{\max} \qquad k \in C \tag{8}$$

In above equations, (5) shows the distribution lines constraint, (6) and (7) represent the nodal power balance equations in the polar form of the AC power flow which ensure the equality of load and generation at each bus. The polar form is associated with the choice of voltage magnitude and voltage phase angle as state variables. It is worth noting that there are some papers that use other forms of the AC power flow such as the rectangular form. Eq. (8) shows the feeder power flow constraint due to the thermal limits. It should be noted that the radial topology of the grid should be preserved before and after the reconfiguration. In this way, each time a tie switch is closed a sectionalizing switch in the formed loop is opened to make the network radial.

3. Stochastic Method

Due to volatility of the distribution system consumers' load profiles, the forecast results of active and reactive loads commonly represent a certain level of error. In fact, even the most accurate methods do not guarantee a one hundred percent accurate results. In order to model these uncertainties, this paper employs a scenario-based approach to generate deterministic problem of the stochastic problem. In this regard, the first step is to consider a probability density function (PDF) for the uncertain parameters. This PDF is then split into several probability levels as shown in Fig. 1. Each of these probability levels shows the existence of some error in the value of the uncertain parameter. In order to generate a complete scenario, the roulette wheel mechanism (RWM) is employed. Fig. 2 shows the structure of RWM oriented with the seven-level PDF shown in Fig. 1. Suppose that there is z number of uncertain parameters in the problem. For each scenario s and for each uncertain parameter, a random number β is generated uniformly in the range of [0,1].

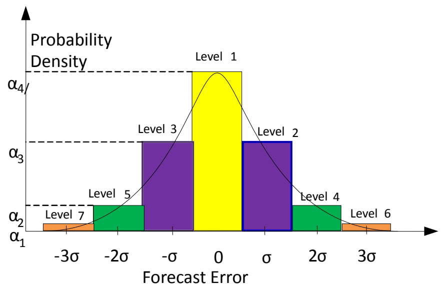

Figure 1. PDF used to model the uncertainty associated with active and reactive loads.

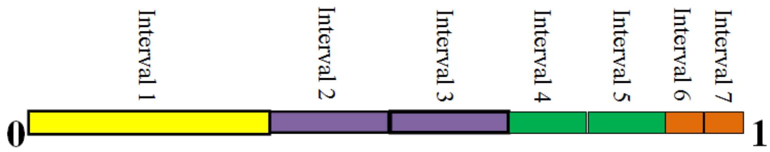

Figure 2. The Roulette Wheel Mechanism (RWM).

The length of the RWM is 1 in which each slice has a specific length which shows its specific value. According to its value, β drops in one of the slices of the RWM. This slice refers to one of the probability levels in the PDF of the relevant uncertain parameter in Fig. 1. It is clear that a slice in RWM with wider area refers to an interval in its PDF (here Fig. 1) with higher probability. Each probability level indicates the possibility of some forecast error in the uncertain parameter. This process is repeated z times to generate a complete scenario.

$$U_s = [u_{s1}, u_{s2}, u_{s3} ...., u_{sz}] \tag{9}$$

By repeating this procedure, N_s initial scenarios are produced:

$$S = \begin{bmatrix} U_1 \\ U_2 \\ ... \\ U_{Ns} \end{bmatrix} = \begin{bmatrix} u_{11}, u_{12}, u_{13} ...., u_{1z} \\ u_{21}, u_{22}, u_{23} ...., u_{2z} \\ ... \\ u_{N_s 1}, u_{N_s 2}, u_{N_s 3} ...., u_{N_s z} \end{bmatrix} \tag{10}$$

Each of these scenarios has a specific probability value. Initially, a large number of scenarios is generated. In order to reduce computation requirements, the number of scenarios should be reduced. The idea for scenario reduction is based on two main tasks: 1) deleting scenarios with the lowest probability and 2) deleting similar scenarios. The following steps are employed to reduce the scenarios:

Step 1: Assume ξ_s as the initial set of the scenarios. Also assume *DS* as the set of scenarios that are kept after scenario reduction. It is clear that this set is empty at the beginning. Evaluate the distance between any two scenarios as follows:

$$DT_{ee'} = DT\left(S_e, S_{e'}\right) = \sqrt{\sum_{g=1}^{w}\left(s_{eg} - s_{e'g}\right)^2} \quad e, e' = 1, 2, \ldots, N_S \tag{11}$$

Step 2: For each scenario R_e, calculate the least distance with other scenarios as follows:

$$DT_{el} = \min DT_{ee'} \quad e, e' \in N_s; e' \neq e \tag{12}$$

where l holds the number of scenarios with the least distance from scenario s.

Step 3: Multiply the probability of each scenario pr_e with the least distance from other scenarios:

$$PD_{e'l} = pr_l \times DT_{e'l} \quad e' \in N_s \tag{13}$$

Step 4: The d^{th} scenario with the lowest value of the below criterion is omitted from the initial scenarios set ξ_s:

$$PD_d = \min PD_e \quad e \in N_s \tag{14}$$

$$\xi = \xi - \{d\}, \; DS = DS + \{d\}, \; pr_l = pr_l + pr_d \tag{15}$$

Step 5: Repeat Steps 2 to 4 until finding the desired number of scenarios.

By the use of this procedure, N_{sr} final scenarios are remained. Therefore, by solving the stochastic problem for all scenarios, there will be N_{sr} final optimal solutions. But, it is generally expected that a stochastic problem would finally has one single optimal solution than a set of optimal solutions as follows:

$$f = \sum_{s=1}^{N_{sr}} pr_s^{norm} \times f_s \tag{16}$$

It is worth noting that due to the discrete nature of the proposed optimization problem, it is not possible to solve the problem for each scenario and then aggregate them to reach a final solution. In fact, the proposed stochastic optimization problem is solved just one time and all scenarios are applied when calculating the objective functions. In other words, each time that a new solution is created during the optimization process, all N_{sr} scenarios are applied to the problem and the objective functions are calculated N_{sr} times. Therefore, for the single feasible solution X_i, N_{sr} scenarios generate N_{sr} values for the objective functions with different probabilities. The aggregation process is done for these N_{sr} objective function values to reach a final aggregated value for the objective functions. This aggregated value belongs to the feasible solution X_i.

The initial number of scenarios considered here is 1000 which is reduced to 20 scenarios after scenario reduction. This process shows a filtering ratio of 1000/20 = 50 for the proposed problem. This value of filtering ratio is chosen to reduce computational burden. It is clear that a larger number of scenarios would result in a better covering of uncertainty spectrum but with the cost of higher computational burden. The filtering ratio can be reduced to capture much uncertainty spectrum of the problem. Therefore an appropriate filtering ratio as scenario reduction should be utilized to reduce the cost of computational effort while keeping a good approximation of the system uncertainties.

4. Modified Harmony Search Algorithm

4.1. Original harmony search algorithm

HS algorithm was first introduced by Geem et al. in 2001 [20] to mimic the behavior of musicians for playing a note with the most harmony. This algorithm is categorized in the group of metaheuristic optimization methods that search the problem space with an initial random start. In comparison with other optimization methods, HS is constructed such that it can handle both discrete and continuous optimization problems without requiring the differential gradients. It does not need an initial setting of the variables and is free from divergence. It is further shown that HS overcomes the main shortcoming of genetic algorithm in the building block theory and thus does not depend on the formation of the chromosomes during the improvisation stage. In order to solve the problem, HS algorithm constructs an initial random matrix called harmony memory (HM). Each row of HM shows a note that is played by a musician and should be improved to reach the most harmony with other notes. In this way, the improvisation stage is implemented based on three main ideas: 1) memory consideration 2) pitch adjustment and 3) random research. In the memory consideration part, the HM is improved by mixing the available solutions in HM to generate a new solution using the HM considering rate (HMCR) constant as follows:

$$
\begin{aligned}
& x_{mn}^{new} = \begin{cases} x_{mn}^{HM} & for \quad rand < HMCR \\ x_{mn}^{rand} & for \quad else \end{cases} \\
& X_m^{HM} = [x_{m1}^{HM}, \ldots, x_{md}^{HM}] \\
& X_m^{rand} = [x_{m1}^{rand}, \ldots, x_{md}^{rand}]
\end{aligned}
\tag{17}
$$

According to the above formulation, as the value of HMCR parameter becomes larger, the new solution is more likely to be selected from the HM solutions.

The second improvisation stage happens by pitch adjustment of the solutions. Each component that comes out of the memory consideration stage is checked to see whether it should be pitch-adjusted or not. Here the pitch adjusting rate (PAR) is employed to fix the new solutions as follows:

$$
x_{mn}^{new} = \begin{cases} x_{mn}^{rand} \pm rand \times bw & for \quad rand < PAR \\ x_{mn}^{rand} & for \quad else \end{cases}
\tag{18}
$$

In the original HS algorithm, *bw* is constant. Nevertheless, it is demonstrated in the literature that HS performance is improved by updating the value of *bw* as follows [21]:

$$bw_t = bw^{\max}\exp(\theta \times t)$$
$$\theta = \frac{Ln(\frac{bw^{\min}}{bw^{\max}})}{NI} \tag{19}$$

Similarly, it is shown that by updating the value of PAR, the total performance of the HS can be improved effectively [21]:

$$PAR_t = PAR^{\min} + t \times \frac{(PAR^{\max} - PAR^{\min})}{NI} \tag{20}$$

By applying the above steps, HM is updated. Then, the termination criterion is checked. In the case that the termination criterion is not satisfied, the above steps are repeated.

4.2. Modification method based on HS

HS algorithm is a powerful optimization tool that has shown great success in solving the discrete optimization problems. This paper, however, proposes a new modification method to increase the diversity of the HM and avoiding the premature convergence. During the optimization process, each solution in the HM is improved by these modification methods to find a more optimal position.

- *Modification strategy* 1

The first modification method employs the crossover and mutation operators from the genetic algorithm to generate new solutions out of the HM. For each solution X_m, three random solutions X_{m1}, X_{m2}, X_{m3} are chosen such that $m_1 \neq m_2 \neq m_3 \neq m$. Now, by using the mutation operator, these three solutions are mixed to generate a random solution:

$$X^{ut} = X_{m_1}^{HM} + \rho_1 \times (X_{m_2}^{HM} - X_{m_3}^{HM}) \tag{21}$$

Considering X^{best} as the best solution in HM, three new solutions are generated as below:

$$x_{1n}^{new} = \begin{cases} x_n^{mut} & \text{if } \rho_2 \leq \rho_3 \\ x_n^{best} & else \end{cases}$$
$$x_{2n}^{new} = \begin{cases} x_n^{mut} & \text{if } \rho_3 \leq \rho_4 \\ x_n & else \end{cases} \tag{22}$$
$$X_3^{new} = \rho_5 \times X^{best} + \rho_6 \times (X^{best} - HM(n_{rand}))$$

- *Modification strategy* 2

The second modification method shows a consultation among the players for reaching the most harmony among them. Therefore, for each two players/solutions X_m and X_l, the interaction practice can be interpreted by the following mathematical formulation:

$$\begin{aligned}&\text{If } f(X_m) < f(X_l)\\ &X_m^{new} = X_m + \rho_7 (X_m - X_l)\\ &\text{Elseif } f(X_m) > f(X_l)\\ &X_m^{new} = X_m + \rho_7 (X_l - X_m)\end{aligned} \tag{23}$$

- *Modification strategy* 3

The third modification method is a dynamic formulation to update the HMCR value. As mentioned before, a larger HMCR will let more similarity appear between the new solutions with those in the HM and vice versa. Nevertheless, it is more practical to have a larger HMCR at the beginning of the optimization to motivate the algorithm for using HM. This simulates a more local search at the beginning of the optimization. On the other hand, at the end of the optimization a smaller HMCR will let the algorithm explore the unknown search space with more random movements. This idea shows a global search when HM has reached to a saturated status to yield any additional optima. Therefore, the following dynamic formulation is chosen for updating the HMCR value based on running the algorithm for several times:

$$HMCR_{t+1} = \left(\frac{1}{2NI}\right)^{\left(\frac{1}{NI}\right)} \times HMCR_t \tag{24}$$

5. Interactive Fuzzy Satisfying Method

The proposed problem is a multi-objective optimization problem with conflicting targets which requires an appropriate managing framework to be solved optimally. Technically, a multi-objective optimization problem can be shown as below:

$$\begin{aligned}&\min F = [f_1(X), f_2(X), ..., f_L(X)]^T\\ &s.t.\\ &h(X) < 0\\ &g(X) = 0\end{aligned} \tag{25}$$

In order to solve the above formulation, this paper suggests an interactive fuzzy satisfying approach. This method let the operator determine the satisfying degree of each objective. In fact, this formulation would choose the most optimal solution from the non-inferior solution set such that the operators' preferences are satisfied:

$$F(X) = \min_{x \in \Omega} \left\{ \max_{w \in W} \left| \mu_w^{ref} - \mu_w^f(X) \right| \right\} \tag{26}$$

In the above equation, the parameter μ^{ref} shows the satisfying degree of the relevant objective which is determined by the operator in the range [0,1]. Also, μ_w^f is the membership function value of w^{th} objective which is calculated using the trapezoidal fuzzy membership as follows:

$$\mu_w^f(X) = \begin{cases} 1 & for \ \ f_w(X) \le f_w^{\min} \\ \dfrac{f_w^{\max} - f_w(X)}{f_w^{\max} - f_w^{\min}} & for \ \ f_w^{\min} \le f_w(X) \le f_w^{\max} \\ 0 & for \ \ f_w(X) \ge f_w^{\max} \end{cases} \tag{27}$$

6. Simulation Results

This section investigates the performance of the proposed method in solving the reconfiguration problem for the IEEE 32-bus test system [18]. Fig. 3 shows the one-line diagram of the test system, which includes 32 buses, 5 tie switches (shown by dotted lines) and 32 sectionalizing switches (shown by solid lines). The system nominal voltage level is 12.66 kV. Regarding the optimization algorithm, 30 random solutions are generated in the HM and the termination criterion is 200 iterations. The single objective optimization (Case 1) is done in the deterministic framework to highlight the performance (Case 2).

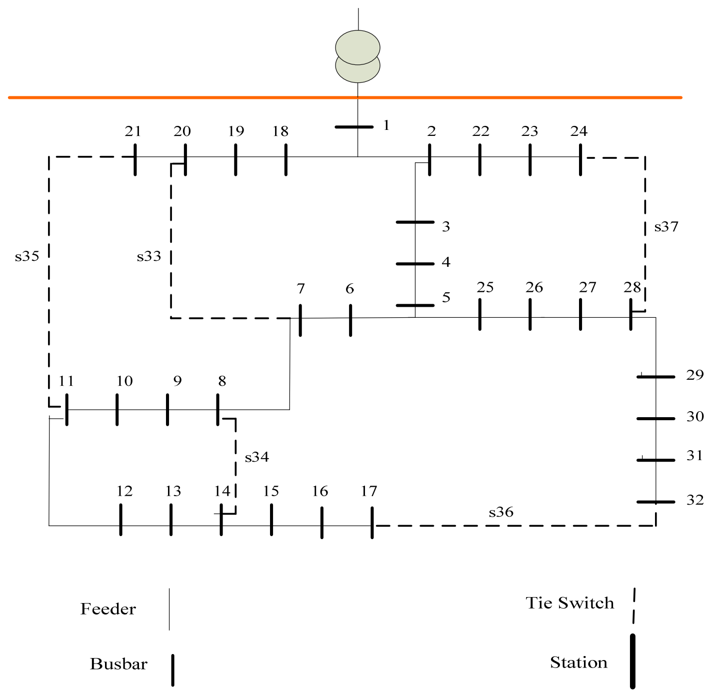

Figure 3. The one-line diagram of the 32-bus test system.

Case 1: First, the analysis is performed on the single-objective optimization structure. The main purpose is to show the positive role of the reconfiguration strategy on different objectives. Table 1 shows the results of the optimization on the network active power losses. It is worth noting that the initial network power loss is 202.67 kW which is reduced to 139.53 kW after the reconfiguration. For better comparison, the results of some of existing methods are provided in the table. According to these results, the proposed MHS algorithm could reach the global solution also found by other methods.

Table 1. Single objective optimization of power losses target (Deterministic Framework).

Method	Power loss [kW]	Open switches
DPSO [22]	139.53	s7,s9,s14,s32,s37
DPSO–ACO [23]	139.53	s7,s9,s14,s32,s37
HBMO [13]	139.53	s7,s9,s14,s32,s37
Shirmohammadi [11]	140.26	s7, s10, s14, s32,s37
DPSO–HBMO [22]	139.53	s7,s9,s14,s32,s37
MHBMO [13]	139.53	s7,s9,s14,s32,s37
McDermott et al. [13]	139.53	s7,s9,s14,s32,s37
The proposed MHS	**139.53**	**s7, s9, s14, s32, s37**

Table 2 shows the results of the optimization of the voltage deviation function. According to these results, the voltage deviation of the system is reduced from the initial value of 0.087 pu to 0.061 pu after the reconfiguration. Note that the improvement is achieved without any capital investments and only by switching actions in the network. Similarly, the proposed MHS algorithm could reach the global optimal solution that is found by other methods for this network.

Table 2. Single objective optimization of voltage deviation target (Deterministic Framework).

Method	Voltage deviation[p.u]	Minimum voltage	Open switches
DPSO [22]	0.06120031	0.93879681	s7,s9,s14,s32,s37
PSO–ACO [23]	0.06120031	0.93879681	s7,s9,s14,s32,s37
DPSO–HBMO [22]	0.06120031	0.93879681	s7,s9,s14,s32,s37
DPSO–ACO [23]	0.06120031	0.93879681	s7,s9,s14,s32,s37
GA [13]	0.06218097	0.93781902	s7,s10,s14,s32,s37
HBMO [13]	0.06120031	0.93879681	s7,s9,s14,s32,s37
The proposed MHS	**0.06120031**	**0.93879681**	**s7,s9,s14,s32,s37**

The simulation results of optimizing the load balance objective are shown in Table 3. In order to analyze this objective, the feeders' maximum current capacities are assumed as the following: feeders 1 and 2 can carry up to 1200 A, feeders 3, 4, and 5 can carry up to 426 A and the other feeders can carry up to 307 A. The initial value of the load balance objective function before the reconfiguration is 0.5413235. The simulations are done by genetic algorithm, original HS, and the proposed MHS algorithm. According to the simulation results, the proposed MHS could reduce the load balance target value from 0.541 to the optimal value of 0.344 after the reconfiguration. In comparison to other algorithms, the proposed MHS could reach a better solution than the other algorithms. According to the last column of Table 3, the proposed MHS could reach the optimal solution in less time which shows the higher search ability of this algorithm. Being equipped with powerful searching mechanisms, the proposed MHS could find the optimal solution in the first few iterations.

Table 3. Single objective optimization of load balance target (Deterministic Framework).

Method	Load Balance	Open switches	CPU Time (s)
Genetic Algorithm	0.344162601	s7,s11,s14,s36,s37	13.54
Harmony Search Algorithm	0.343929465	s7,s10,s14,s36,s37	11.75
The proposed MHS	0.343774159	**s7,s9,s14,s36,s37**	**8.37**

Case 2: In order to simultaneously optimize all objective functions, the problem is solved using the discussed min-max fuzzy structure. Table 4 shows the results of multi-objective optimization framework. It is worth noting that this paper assumes similar significance for all objectives and thus consider $\mu_{ref} = 1$ for the three objectives. It is clear that the satisfying degree of objectives can change according to the preferences and requirements. The simulation results show that the proposed MHS algorithm could optimize all objectives properly. In addition, while each of the objective functions has attained higher value than the single-objective optimization results, they are all optimized and reduced to appropriate value with regard to the initial network situation. In other words, the proposed multi-objective framework could reach a proper balance in optimizing the three objectives. From the computational burden point of view, the proposed MHS algorithm shows superior performance than the other algorithms. In order to better understand the positive role of the reconfiguration on the voltage profile, Fig. 4 shows the network buses voltage profiles before and after the reconfiguration. The voltage levels of most of the buses are improved after the optimal switching.

Table 4. Multi-objective optimization using interactive fuzzy satisfying method (Stochastic Framework).

Method	Power loss [kW]	Voltage deviation [p.u]	Load Balance	Open switches	CPU Time (s)
Genetic Algorithm	143.761969	0.06266643	0.40372161	s6,s9,s14,s36,s37	264.38
Harmony Search Algorithm	142.7391667	0.062183436	0.37531157	s7,34,s11,s32,s37	221.06
Proposed MHS	**141.261544**	**0.06218097**	**0.37731568**	s7,s10,s14,s32,s37	153.78

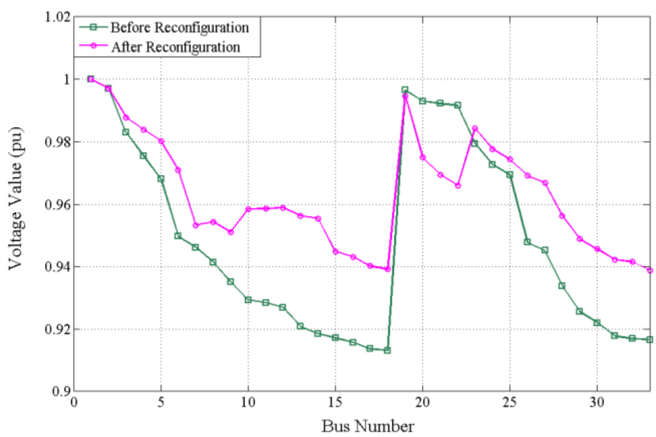

Figure 4. Voltage profile improvement after the reconfiguration.

In order to assess the effect of considering uncertainty on the problem, the simulation results for two cases of deterministic and stochastic frameworks are provided in Table 5. According to these results, considering the uncertainty effects in the simulations has increased the optimal values of all objective functions. While the objective function values in the stochastic framework seem to be far from their optimal values in the deterministic framework, but the new values are more realistic and reliable. In other words, this increase in the objective functions is the cost of reaching more reliable and practical values compatible with the likely forecast errors in uncertain parameters.

Table 5. Comparison of objective function values in the deterministic and stochastic framework.

Method	Power loss [kW]	Voltage deviation [p.u]	Load Balance
Deterministic Framework	140.327481	0.06184041	0.36440572
Stochastic Framework	141.261544	0.06218097	0.37731568

Finally, Table 6 shows the results of multi-objective optimization problem considering different weighting factors for the objective functions. The main purpose is to show the capability of the fuzzy min-max framework for handling different targets during the optimization. According to the results in Table 6, there is a proper control on satisfying each objective function by adjusting the reference membership function μ_w^{ref} for w^{th} target. In other words, in each scenario, the proposed multi-objective framework was successful to find the most compromised solution from the set of non-inferior solutions properly.

Table 6. Objective function values in with different weighting factors.

Scenario No.	Importance			Load Balance	Voltage deviation [p.u]	Power loss [kW]
	μ_1^{ref}	μ_2^{ref}	μ_3^{ref}			
Scenario 1	1	1	1	0.3773	0.062180	141.2615
Scenario 2	0.9	1	1	0.3884	0.061969	140.4725
Scenario 3	1	0.9	1	0.3507	0.062763	140.7365
Scenario 4	1	1	0.9	0.3638	0.061846	142.8311
Scenario 5	0.8	1	1	0.4022	0.061794	140.3472
Scenario 6	1	0.8	1	0.3396	0.063710	140.0648
Scenario 7	1	1	0.8	0.3473	0.061547	143.0507

7. Conclusion

This paper proposed a stochastic multi-objective optimization framework to solve the reconfiguration problem in the radial smart distribution networks. The proposed problem minimizes active power losses, voltage deviations, and load imbalance using a min-max fuzzy satisfying structure. Also, a new modification method based on MHS algorithm was devised to solve the problem optimally. In addition, a scenario based stochastic method was employed to model the uncertainty of the forecast error in active and reactive loads. Simulations on an IEEE standard distribution test system showed the considerable capability of the reconfiguration strategy in improving the considered objective functions through the optimal switching. In addition, it was seen that the proposed multi-objective framework can manage the desired objectives by providing an appropriate tradeoff in objective optimization. From the optimization point of view, the proposed MHS algorithm outperformed some of the well-known methods in the area.

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Conflict of Interest

The authors declare that there are no conflicts of interest related to this study.

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