Optimal Distribution Feeder Reconfiguration for Reliability Improvement Considering Uncertainty

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***Abstract*—This paper proposes a new method to improve the reliability of the distribution system using the reconfiguration strategy. In this regard, a new cost function is defined to include the cost of active power losses of the network and the customer interruption costs simultaneously. Also, in order to calculate the reliability indices of the load points, the reconfiguration technique is considered as a failure-rate reduction strategy. Regarding the reliability cost, the composite customer damage function is employed to find the customer interruption cost data. Meanwhile, a powerful stochastic framework based on a two- point estimate method is proposed to capture the uncertainty of random parameters. Also, a novel self-adaptive modification method based on the clonal selection algorithm is proposed as the optimization tool. The feasibility and satisfying performance of the proposed method are examined on the 69-bus IEEE test system.**

***Index Terms*—Clonal selection algorithm, composite customer damage function (CCDF), reconfiguration, reliability.**

I. Introduction

ACORDING to the failure statistics, the distribution networks engage the most contribution to the unavailability of supply to the users [1]. In other words, most of the failures occur in the distribution networks [2]. These statistics emphasize the necessity of reassessment of the available strategies to improve the electrical services by improving the reliability indices. Some of the most significant methods to improve the reliability of the system are [3]–[5]: network automation, adding protective devices, improving the accuracy of the available protection methods, reclosing and switching, fast fault prediction techniques, fast team to accelerate the repair process, and fewer equipment failures to avoid contingencies and reconfiguration.

The reconfiguration problem is defined as the process of changing the topology of the network using some sectionalizing switches (normally closed switches) and tie switches (normally open switches) so that all of the constraints are observed and the radial structure of the system is preserved simultaneously [6]. Based on the problem significance, in recent years, a wide range of studies has been implemented on the reconfiguration issue. Nevertheless, the main focus of most of these studies has been on some conventional objectives, such as power losses, voltage deviation, and load balance. Among these useful but conventional objective functions, most attention has been given to the active power losses. Here, new methods based on the neural network (NN) [7]; optimum flow pattern [8]; graph theory [9]; brute-force approach [10]; heuristic techniques [11]; expert systems [12]; ant colony optimization algorithm [13], [14]; and hybrid simulated annealing algorithm and tabu search (TS) [15] have been studied. Meanwhile, other objectives, such as improving load balance [16] and voltage deviation [17], have been studied.

From the reliability view in [18], a new methodology is proposed to improve the reliability of the distribution system and to reduce the total power losses of the network in a multiobjective framework. In this paper, probabilistic reliability models are used to evaluate the reliability of the load points. In [19], a new reliability-oriented reconfiguration method based on the interval analysis technique is proposed to enhance the reliability of the system. In [20], a new method is presented to compute the sensitivities of the state variables with respect to switching operations and then obtain an estimation of voltages and power flows in the network. In [21], a new model was proposed to see the effect of the reconfiguration on the reliability indices. Here, the system average interruption frequency index (SAIFI) and system average interruption duration index (SAIDI) as two significant load-oriented indices are considered to be optimized. However, neglecting the active power losses function is a major challenge in this paper. Also, neglecting the costs associated with the customer interruptions has put the algorithm far from a real operating point. In [22], a genetic-based approach is proposed to increase the reliability of the system using the reconfiguration. Here again, neglecting the real power losses objective in the evaluations has limited the research to just the reliability indices. In addition, the main deficiency with all of the aforementioned works is the investigation in the deterministic (or not fully probabilistic; that is, [18]) framework which will neglect the uncertainty effects in the evaluations.

Therefore, the main purpose of this paper is to investigate the positive role of the reconfiguration strategy on the reliability and power loss of the distribution networks. In this regard, a new cost function is proposed to include the customer interruption costs as well as the active power losses, simultaneously. In order to evaluate the customer interruption costs, the load-point reliability indices of the system in each switching scheme should be calculated individually. Here, a typical CCDF is utilized to convert the customer energy losses to the equivalent money losses. Moreover, a sufficient stochastic framework based on $2m$ point estimate method (PEM) is formulated to capture the uncertainty of forecast errors of the active and reactive

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NOMENCLATURE

Symbol	Description	Symbol	Description
$Acum_\theta$	Accumulator of θ^{th} sub-modification	C_{Ploss}	Cost coefficient factor here 168 ($/kW)
C_i	Cost of interruption of the i^{th} bus in ($/kW)	$E(S_i^k)$	k^{th} moment of i^{th} output random variable
$f(X)$	Objective function	F	Power flow equations
$fitness_i$	Fitness function of the i^{th} antibody.	$g_i(X)$	Inequality constraints of the MOP
$h_i(X)$	Equality constraints of the MOP	$\|I_{f,i}\|$	Current amplitude of the i^{th} feeder
I_i	Current of i^{th} branch	$I_{f,i}^{\max}$	Maximum current of i^{th} feeder
$Iter$	Iteration number	$L_{a(i)}$	Average load connected to i^{th} bus
L_1 and L_2	Penalty factors here are supposed as 10^{10}	Lévy	Mathematics Lévy operator
M_P	Column-wise mean value of the population	N	Antibody population size
N_{br}	Number of branches	N_{FL}	Number of main loops in the system
n_{Mod_θ}	Number of solutions chosen θ^{th}modification	$P_{ij,\max}^{Line}$	Maximum power flow between i^{th} and j^{th} buses
$\left\|P_{ij}^{Line}\right\|$	Absolute power flow in the branch ij	Prb_θ	Probability stack of θ^{th} modification method
P_i/Q_i	Net injected active/reactive power at the i^{th} bus	r_i	Repair rate of the i^{th} component
r_S	Average outage time	R_i	Resistance of i^{th} branch
$rand_i()$	Random value in the range [0,1]	S	Probabilistic solution set of output variables
T_F	A random integer equal to 1 or 2	Tie_j/Sw_k	Status of j^{th} tie /sectionalizing switch
U_S	Annual system outage time	V_i	Amplitude of the voltage at the i^{th} bus
V_{max}/V_{min}	Max/Min value of voltage magnitude	X_{Gbest}	The best solution in the algorithm population
X	Control vector	$Y_{i,j}/\Theta_{i,j}$	Magnitude/Angle of the branch admittance between the i^{th} and j^{th} buses
$z_{l,1}, z_{l,2}$	Estimated locations of random variable z_l	Z	Input set of uncertain variables
$\omega_{l,k}$	weighting factor of $z_{l,k}$	λ_i	Failure rate of the i^{th} component
λ_S	Average failure rate	δ_i	Angle of the voltage at the i^{th} bus
φ_1	Random number in the range [0,1]	μ_{z_i}	Mean value of input random variable z_l
σ_{Zl}	Standard deviation of zl	$\Upsilon_{l,3}$	Skewness coefficient of zl
$\xi_{l,k}$	Standard location of z_l	β	Clonal factor
ρ_i	Current reduction coefficient	ε	Learning factor

loads, failure rate and repair rate, and the cost coefficients (including the cost of megwatt power losses as well as the customer interruption costs), concurrently. In comparison to the Monte Carlo simulation, PEMs require very little computational burden. Since the problem investigated is a complex optimization problem, a sufficient optimization method based on clonal selection algorithm (CSA) is proposed. The proposed algorithm makes use of a self-adaptive modification mechanism to explore the problem search space globally. The feasibility and satisfying performance of the proposed method areamined on the 69-bus IEEE distribution test system.

The rest of this paper is organized as follows: In Section II, the reconfiguration problem formulation is described. In Section III, the main idea behind the use of the reconfiguration technique as a reliability reinforcement strategy is explained. Section IV explains the proposed stochastic framework based on $2m$ PEM. In Section V, the proposed optimization algorithm is described. The simulation results are shown and discussed in Section VI. Finally, Section VII shows the main conclusions and remarks about the proposed method.

II. PROBLEM FORMULATION

In this part, the objective function is investigated and the relevant constraints are described in detail.

A. Cost Objective Function (f)

This paper suggests a new cost function to include two significant system targets: 1) that is, the cost of active power losses and 2) the expected customer interruption cost. The proposed cost function will provide a good opportunity to reach a proper compromise between the active power losses (as an attractive issue to the power utilities) and the reliability of the system. It is shown in the *Simulation Results* section that the proposed cost function has a good tendency to optimize the other objective functions, such as the voltage deviation, SAIFI, SAIDI, and average energy not supplied (AENS), simultaneously. The new cost function is as follows:

$$\min f(X) = \mathrm{Cost}_{\mathrm{Ploss}} + \mathrm{Cost}_{\mathrm{Rel}}. \tag{1}$$

The first term of (1) deals with the cost of the active power losses which can be evaluated as follows:

$$\begin{aligned}\mathrm{Cost}_{\mathrm{Ploss}} &= C_{\mathrm{Ploss}} \times P_{0\mathrm{loss}}(X)\\ &= C_{\mathrm{Ploss}} \times \left(\sum_{i=1}^{N_{br}} R_i \times |I_i|^2\right)\end{aligned} \tag{2}$$

where X is the control vector including the status of the tie and sectionalizing switches of the network as follows:

$$\begin{aligned} X &= [\overline{\mathrm{Tie}}, \overline{Sw}];\\ \overline{\mathrm{Tie}} &= [\mathrm{Tie}_1, \mathrm{Tie}_2, \ldots, \mathrm{Tie}_{N_{\mathrm{tie}}}];\\ \overline{Sw} &= [Sw_1, Sw_2, \ldots, Sw_{N_{sw}}].\end{aligned} \tag{3}$$

In this paper, 0 and 1 are considered as the closed and open status, respectively. The second term of (1) deals with the reliability which is evaluated in the form of the expected customer interruption. The customer interruption costs measure the expected economic losses which are caused by the power failures in the consumption side and are considered as input data in the costs (ECOST) planning and operational issues. Evaluating the ECOST will allow the network planners to verify the adequate level of reliability for customers, provide economic justification for determining the network reinforcement and redundancy allocation, identify weak points in the system, determine appropriate maintenance scheduling, and develop appropriate operation policies [5]. In order to evaluate the ECOST function, the load-point reliability indices, including the average failure rate λ_S, the annual system outage time U_S, and the average outage time r_S should be calculated as follows:

$$\lambda_S = \sum_i \lambda_i; \quad U_S = \sum_i \lambda_i r_i \tag{4}$$

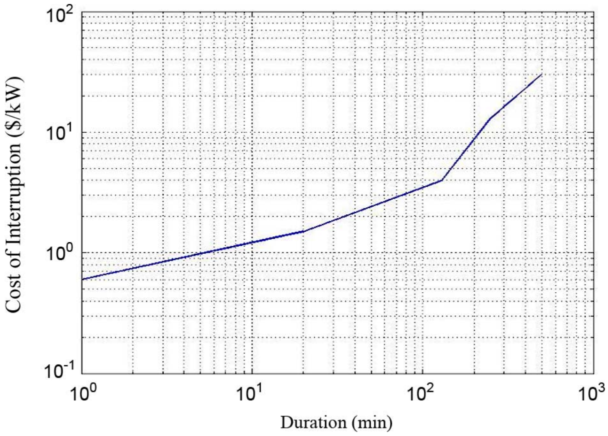

Fig. 1. Typical CCDF.

$$r_S = \frac{U_S}{\lambda_S} = \frac{\sum_i \lambda_i r_i}{\sum_i \lambda_i}. \tag{5}$$

The ECOST for the ith bus is calculated as follows [23]:

$$\text{ECOST}_i = L_a(i) C_i \lambda_i \tag{6}$$

where C_i is the cost of interruption of the ith bus in (U.S.$ per kilowatt) which is a nonlinear function of the interruption duration time. The value of C_i, corresponding to the interruption duration time, is calculated using the CCDF. Fig. 1 shows a typical CCDF [23]. Finally, the total ECOST of the network can be calculated as follows:

$$\text{Cost}_{\text{Rel}} = \sum_{i=1}^{N_{br}} \text{ECOST}_i = \sum_{i=1}^{N_{br}} L_{a(i)} C_i \lambda_i. \tag{7}$$

B. Constraints

During the optimization process, the following constraints should be accurately preserved:

- Distribution power-flow equations

$$P_i = \sum_{i=1}^{N_{bus}} V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j)$$
$$Q_i = \sum_{i=1}^{N_{\text{bus}}} V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j). \tag{8}$$

- Distribution line limits

$$|P_{ij}^{\text{Line}}| < P_{ij,\max}^{\text{Line}}. \tag{9}$$

- Bus voltage constraints

$$V_{\min} \le V_i \le V_{\max}. \tag{10}$$

- Feeder current limitation

$$\left|I_{f,i}\right| \le I_{f,i}^{\max} \;\; ; i = 1, 2, \ldots, N_{br}. \tag{11}$$

- Keeping the radiality of the network:: During the reconfiguration process, the order of feeders should be rearranged so that the radial structure of the network would be preserved. The number of main loops in the system is calculated as follows:

$$N_{FL} = N_{br} - N_{\text{bus}} + 1. \tag{12}$$

III. Reconfiguration as a Reliability Reinforcement Strategy

According to the failure statistics, a great proportion of the interruptions occurs in the voltage level of the distribution, especially as a result of overhead and underground cable failures [5]. For underground cables, the resistive losses would cause high temperature which changes proportionally to the square of the current magnitude. On the other hand, for underground cables, a maximum temperature threshold is defined which, if exceeded, will cause insulation failures [24]. Meanwhile, at high temperature, the process of moisture absorption occurs more speedily. Once moisture invades extruded dielectrics, such as cross-linked polyethylene or ethylene-propylene rubber, the voltage withstand capability of the cable is reduced and the probability of dielectric breakdown increases (failure rate of the cable is increased) [5]. In addition, high currents can cause the overhead lines to sag which will reduce the ground clearance and increase the probability of an electric break occurring [25]. Therefore, any strategy which can reduce the current magnitude in the feeders can reduce the line/cable temperature and, therefore, improve the reliability of the system. Reconfiguration strategy can reduce the current magnitude in the network feeders by changing the path/direction of the power flow. As a direct result, the feeders' temperature can be decreased sufficiently. The reconfiguration strategy can also enhance the reliability indices in another way. By decreasing the amount of power losses in the network, the maximum loadability of the network is increased which would improve the reliability of the system too. Therefore, the reconfiguration strategy can improve the reliability indices by reducing the current magnitude and, thus, can be assumed as a failure-rate reduction technique. In order to formulate the problem, it is assumed that any line i has an initial failure rate before reconfiguration called λ_i^{init}. Through the reconfiguration process, the failure rates of the feeders are changed. The best failure rate, which can be achieved through fully active/reactive current compensation, is called λ_i^{best}. So, according to the percentage of the current compensation, a new failure rate is gained as follows [4]:

$$\lambda_i^{\text{new}} = \rho_i(\lambda_i^{\text{init}} - \lambda_i^{\text{best}}) + \lambda_i^{\text{best}} \;; \rho_i = \frac{\left|I_{R-\text{new}}^i\right|}{\left|I_{R-\text{old}}^i\right|}. \tag{13}$$

In this study, this strategy is considered for lines with currents of more than 80% of their nominal capacity.

IV. Probabilistic Load Flow Based on PEM

The main feature of the $2m$ PEM is that it requires just the first few moments of the random variable, including the mean, variance, skewness, and kurtosis coefficients [26]. In order to describe the principles of the $2m$ PEM, the load-flow equations are assumed as a simple nonlinear function as follows [27]:

$$S = F(z). \tag{14}$$

According to (14), the uncertainty in the input data is transferred to the output data through the nonlinear load-flow equations. In order to model the uncertainty of the problem, for each input uncertain variable z_l, a probability function called f_{zl} is considered. Now, the $2m$ PEM will make use of two probability points to substitute f_{zl} by matching its mean, variance, and skewness coefficient as follows [28]:

$$S = F(\mu_{z1}, \mu_{z2}, ...z_{l,k}, \ldots, \mu_{zm})\ ; k = 1, 2 \tag{15}$$

where $z_{l,1}$ and $z_{l,2}$ as the new location points for the input uncertain variable z_l are calculated as follows:

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

$$\xi_{l,k} = \frac{\Upsilon_{l,3}}{2} + (-1)^{3-k}\sqrt{m - \left(\frac{\Upsilon_{l,3}^2}{2}\right)^2}\quad k = 1, 2 \tag{17}$$

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

Finally, the standard deviation value of S_i is evaluated as follows:

$$\begin{aligned}\sigma &= \sqrt{\mathrm{var}(S_i)} = \sqrt{E(S_i^2) - [E(S_i)]^2}\\ E(S_i^j) &= \sum_{l=1}^{m}\sum_{k=1}^{2}(\omega_{l,k} \times S_i^j(\mu_{z1}, \mu_{z2}, \ldots, z_{l,k}, \ldots, \mu_{zm}))\\ \omega_{l,k} &= \frac{1}{2m}.\end{aligned} \tag{19}$$

V. Solution Procedure

In this section, the proposed self-adaptive modified clonal selection algorithm is described completely.

A. Original Clonal Selection Algorithm (CSA)

The CSA is basically inspired from the clonal selection theory which specifically explains the performance of the body immune system to defend the organisms from foreign materials [29]. The most powerful aspect of CSA is its ability to search the problem space locally and globally. The local search mechanism is simulated through the affinity mutation of cloned antibodies. On the other hand, the global search mechanism is simulated by generating random antibodies and insertion to the population to escape from local optima. Similar to the other population-based optimization algorithms, the CSA starts with a random population. Now, for each antibody, the fitness function is evaluated [29]

$$\text{Affinity} = \text{fitness} = \frac{1}{1 + \text{objective function}}. \tag{20}$$

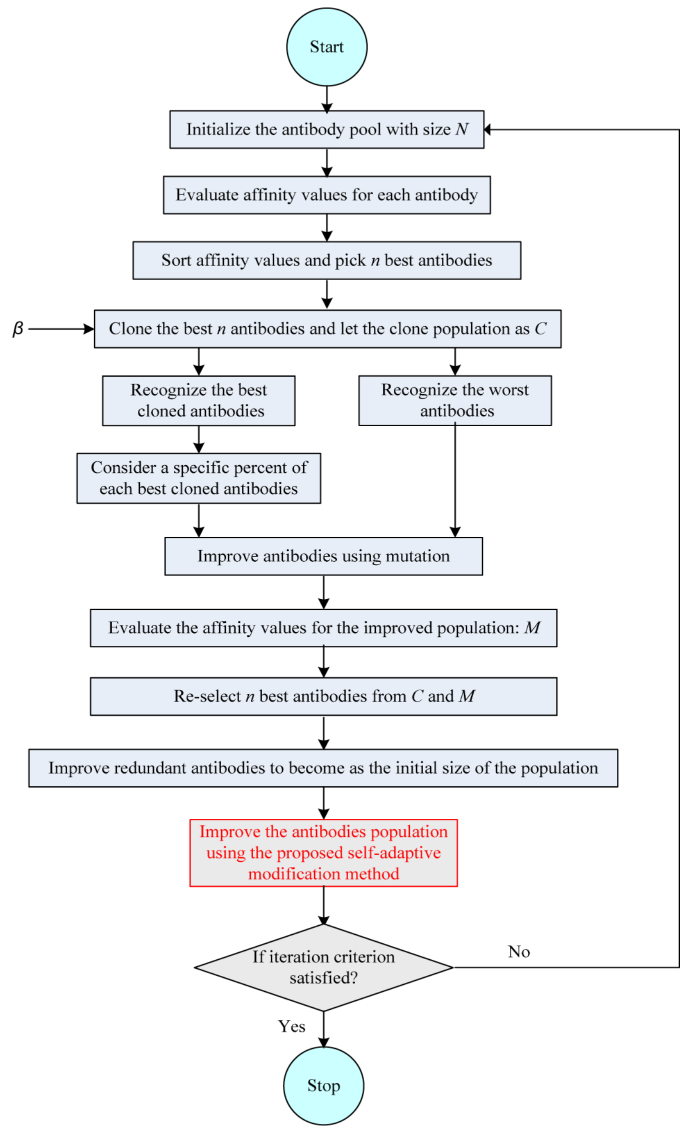

Fig. 2. Flowchart of the proposed SAMCSA.

According to the fitness function, the population is sorted. The antibodies are then cloned proportional to their affinity. In other words, the number of clones generated for an antibody with higher affinity is more than an antibody with lower affinity

$$\text{numClones} = \text{round}\left(\frac{\beta \times N}{i} + 0.5\right) \tag{21}$$

where i is the order of the antibody in the population. Here, the clones are exposed to an affinity maturation process to better encounter the antigen. In this step, the maturation degree is adjusted inversely to their parent affinity so that the greater affinity has a lower mutation degree as follows:

$$\alpha_i = \beta^{-1} \times \exp(-\text{fitness}_i). \tag{22}$$

Now, the clone is subjected to the antigen and the affinity/fitness is calculated. The flowchart of the proposed algorithm is shown in Fig. 2.

Begin:
  For i=1:N
    If $rand_m \leq Prb_1^{Iter+1}$
    Select sub-modification method 1 for the antibody i
    ElseIf $Prb_1^{Iter+1} < rand_i \leq Prb_1^{Iter+1} + Prb_2^{Iter+1}$
    Select sub-modification method 2 for the antibody i
    Else
    Select sub-modification method 3 for the antibody i
    End If
  End For ***i***
END

Fig. 3. Pseudocode for the selection of the θth submodification method by RWM.

TABLE I
CUSTOMER DATA OF THE 69-BUS TEST SYSTEM

Bus	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
No. Customers	0	0	0	0	0	10	190	350	140
Bus	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
No. Customers	110	600	580	40	40	0	180	260	280
Bus	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
No. Customers	0	4	500	25	0	120	0	70	70
Bus	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**
No. Customers	105	120	0	0	0	60	90	25	105
Bus	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**
No. Customers	125	0	115	115	5	0	30	0	160
Bus	**46**	**47**	**48**	**49**	**50**	**51**	**52**	**53**	**54**
No. Customers	160	0	365	1610	1840	180	15	20	120
Bus	**55**	**56**	**57**	**58**	**59**	**60**	**61**	**62**	**63**
No. Customers	115	0	0	0	430	0	5680	135	0
Bus	**64**	**65**	**66**	**67**	**68**	**69**	**-**	**-**	**-**
No. Customers	1080	280	80	80	120	130	-	-	-

B. *Self-Adaptive Modified CSA (SAMCSA)*

In this paper, a novel self-adaptive modification method is proposed to enhance the total search ability of the CSA as well as to avoid the premature convergence using three submodification techniques as follows.

- Submodification method 1 [30]:

$$Le'vy(\omega) \sim \tau = \mathrm{Iter}^{-\omega}\,;\ (1 < \omega \leq 3) \tag{23}$$

$$X_i^{\mathrm{new}} = X_i^{\mathrm{old}} + \varphi_1 \oplus Le'vy(\omega). \tag{24}$$

- Submodification method 2:

$$X_i^{\mathrm{new}} = X_i^{\mathrm{old}} + T_F(X_{\mathrm{Gbest}} - M_p). \tag{25}$$

- Submodification method 3: As can be seen from (21), the value of β as the clonal factor would affect the number of clones created for the relevant antibodies. Therefore, a new *dynamic tuning* formulation is proposed which will balance between the local and global search

$$\beta^{\mathrm{Iter}+1} = \left(\frac{1}{10N}\right)^{(1/10N)} \beta^{\mathrm{Iter}}. \tag{26}$$

The mechanism of the proposed self-adaptive modification method will allow each solution to choose the proper submodification technique which best fits its current situation. In order to reach this goal, a probability stack is defined for each submodification method ($prb_\theta = 0.33 \ \ \& \ \ \theta = 1,2,3$). Also, an accumulator is defined for each submodification method which is initially zero ($Acum_\theta$). In each iteration, after the population is sorted in descending order, a weighting factor is designated to each solution as follows:

$$Wgt_j = \frac{Log(N - j + 1)}{\sum_{i=1}^{n} Log(i)}; j = 1, \ldots, N. \tag{27}$$

Then, the accumulator and the probability stack of each submodification method are updated as follows:

$$\mathrm{Acum}_\theta = \mathrm{Acum}_\theta + \frac{Wgt_l}{n_{\mathrm{Mod}_\theta}} l = 1, \ldots, n_{\mathrm{Mod}_\theta} \tag{28}$$

$$Prb_\theta = (1 - \varepsilon) \times Prb_\theta + \varepsilon \times \frac{\mathrm{Acum}_\theta}{\mathrm{Iter}}, (\theta = 1,2,3). \tag{29}$$

In the last step, Prb_θ is normalized as follows:

$$Prb_\theta = \frac{Prb_\theta}{(\sum_{\theta=1}^{3} Prb_\theta)}. \tag{30}$$

In each iteration, the ith solution would select the proper submodification method using the roulette wheel mechanism (RWM) as shown in Fig. 3.

VI. SIMULATION RESULTS

In this section, the satisfying performance of the proposed method is examined on the 69-bus IEEE test system.

Assumptions

The case study is the 69-bus IEEE radial distribution test system [31]. In this paper, some assumptions are made to evaluate the reliability indices. It is assumed that there is a circuit breaker (CB) at the substation with a sectionalizer at the beginning of each section. Since the reconfiguration strategy only affects the reliability of the feeders, the other network components, such as the transformers, breakers, busbars, and sectionalizing switches, are supposed to be fully reliable. It is assumed that the failure rate of the branch with the biggest impedance is 0.4 (fr/year) and the least failure rate of 0.1 (fr/year) belongs to the branch with the least impedance. Accordingly, the failure rates of the other branches can be evaluated proportionally [5]. The switching time and repair time are supposed to be 0.5 (h) and 6 (h), respectively. The least failure rate that each feeder can achieve after fully active/reactive current compensation is supposed to be 0.85 of its initial value. The consumers statistical data are shown in Table I. The initial antigen pool size is 100, and the initial value of the clonal factor β is 0.6.

A. *Analytical Discussion*

The analysis is implemented in the stochastic and deterministic frameworks. Also, as a result of high popularity of some reliability indices in the industrial and distribution utilities, the effect of reconfiguration on two main different types of reliability indices is investigated: 1) customer-orientated indices, including SAIFI and SAIDI, and 2) load and energy-orientated indices which include the AENS index. Since the proposed SAMCSA is used in this paper for the first time to solve the reconfiguration problem at the beginning, the single objective

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

TABLE II
SINGLE-OBJECTIVE OPTIMIZATION OF THE ACTIVE POWER LOSSES (DETERMINISTIC FRAMEWORK)

Method	loss [kW]	loss cost [$]	Open switches
Initial Network	225.0	37,800.0	s11-66,s13-20,s15-69, s27-54,s39-48
Liu [32]	102.6	17,236.8	s11-66,s13-20,s14-15,s50-51,s44-45
Bi, Liu [33]	102.1	17,152.8	s11-66,s13-20,s14-15,s50-51,s47-48
Shirmoh [12]	106.63	17,914.2	s11-66,s17-18,s67-68,s21-22,s47-48
Li *et al*. [34]	99.62	16,736.2	s11-66,s13-20,s14-15,s50-51,s47-48
Yu *et al*. [35]	99.62	16,736.2	s11-66,s13-20,s14-15,s50-51,s47-48
SAMCSA	**99.62**	16,736.2	**s11-66,s13-20,s14-15,s50-51,s47-48**

TABLE III
RESULTS OF OPTIMIZING THE SAIFI, SAIDI, AND AENS FOR 25 TRAILS (DETERMINISTIC FRAMEWORK)

Case	Method	Best Solution ($\times 10^{-4}$)	Worst Solution ($\times 10^{-3}$)	Average ($\times 10^{-3}$)	Standard deviation ($\times 10^{-3}$)	CPU Time (Sec)
SAIFI	GA	14400.30	1482.58	1467.30	25.94	17.62
	PSO	14253.62	1440.02	1436.04	10.03	16.95
	CSA	14243.26	1439.40	1431.18	7.51	17.22
	SAMCSA	14197.96	1424.33	1420.02	3.53	15.44
SAIDI	GA	12811.03	12882.21	12849.33	41.00	17.28
	PSO	12730.29	12830.62	12812.04	39.79	16.62
	CSA	12762.83	12830.14	12803.46	38.11	17.52
	SAMCSA	12591.05	12642.57	12610.86	17.52	13.62
AENS	GA	28392.91	2903.28	2859.31	24.39	17.84
	PSO	28173.55	2840.77	2829.20	12.87	17.30
	CSA	28143.27	2832.85	2826.76	9.01	17.29
	SAMCSA	27973.63	2799.16	2798.14	0.67	15.23

optimization of the active power losses is implemented in the deterministic framework.

Table II shows the results of optimizing the active power-loss function. As can be seen from this table, the proposed SAMCSA has located the best optimal operating point that is found by the other well-known works in the area. It is worth noting that for these solutions, the maximum voltage deviation of the system is reduced.

In Table III, the results of single-objective optimization of SAIFI, SAIDI, and AENS by the proposed method are shown. The values of SAIFI, SAIDI, and AENS before reconfiguration are 1.719368 (fr/Cust.yr), 14.27470 (h/Cust.yr) and 3.168866 (kWh/Cust.yr), respectively. Since there is not any work available in this area, the simulation results for the genetic algorithm (GA), particle swarm optimization (PSO) algorithm, and original CSA are shown too. 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. The simulation results reveal that the proposed SAMCSA provides better results in comparison to GA, PSO, and the original CSA method in terms of robustness and CPU time. In addition, by comparing the values of SAIFI, SAIDI, and AENS indices before reconfiguration with their values after reconfiguration, the positive effect of the reconfiguration technique as a reliability reinforcement strategy can be deduced easily.

Table IV shows the results of optimizing the proposed cost function in the deterministic framework. For better comparison, some of the methods mentioned in the *Introduction* Section including NN [7], optimum flow pattern [8], ACO [13], [14], TS [15], honey bee mating optimization (HBMO) [6], GA [22]

TABLE IV
RESULTS OF OPTIMIZING THE PROPOSED COST FUNCTION (TOTAL COST) (DETERMINISTIC FRAMEWORK)

Status	Method	Power Loss	ECOST	Total Cost (f)	SAIFI	SAIDI ($\times 10^{-2}$)	AENS ($\times 10^{-2}$)
Before Reconfiguration	-	225.0	152,530.6	189,959.9	1.7193	1427.47	316.88
After Reconfiguration	NN [7]	125.1	108,410.0	129,432.5	1.4343	1288.00	286.22
	Optimum flow pattern [8]	128.2	106,619.4	128,172.1	1.4276	1279.97	284.47
	ACO [13-14]	126.0	107,459.1	128,642.1	1.4300	1287.72	286.24
	TS [15]	130.0	107,765.9	129,621.1	1.4367	1286.08	285.78
	HBMO [6]	130.3	106,728.7	128,633.7	1.4314	1274.11	283.22
	GA	130.3	106,781.8	128,688.8	1.4456	1283.01	288.35
	PSO	130.1	106,419.7	128,285.9	1.4293	1275.43	284.66
	CSA	132.8	106,110.7	128,431.5	1.4324	1277.89	285.93
	SAMCSA	128.2	106,168.3	**127,721.1**	1.4276	1273.85	283.11

and PSO are simulated to optimize the proposed cost function (single-objective optimization of the total annual cost function). The superiority of the proposed SAMCSA algorithm can be deduced from these results too. Similar conclusion about the reliability can be made from this table. According to Table IV, the reconfiguration strategy can play a significant role in improving the reliability of the system. In fact, an appropriate switching scheme can reduce the expected customer interruption costs when reducing the MW power losses concurrently. In other words, neglecting any of these effective parameters (power-loss cost function and the reliability index) can reduce the efficiency of the reconfiguration strategy by limiting its maximum potential ability. In order to see the effect of optimization of the proposed cost function on the other reliability indices, the results of SAIFI, SAIDI, and AENS are also shown in Table IV comparatively. As seen from these results, while the new values for SAIFI, SAIDI, and AENS indices are not as optimal as their values in the single-objective optimization problem (that is, Table III), they are obviously improved in comparison to the status of before reconfiguration. It should be considered that this improvement in the value of these three indices is achieved through optimizing the proposed cost function. In other words, the proposed cost function has a sufficient tendency to improve these three significant reliability indices too. From the view of the total annual cost, the proposed method has reduced the system costs by about U.S.$62 238.769. This amount of reduction is a significant savings per year.

Nevertheless, there is a nonlinear relationship between the amount of power losses and the total system cost (the proposed cost function) which can be inferred by comparing the optimal solutions which are found by PSO and CSA algorithms. As can be seen from Table IV, the PSO algorithm has found a more optimal solution (less cost value) than the GA. In comparison to the GA, this reduction in the total system cost by the PSO algorithm has resulted in a higher ECOST value but with lower active power losses. This event shows the nonlinear behavior of the active power losses and ECOST in an increasing or decreasing process. This situation emphasizes the necessity of using an appropriate formulation to reach the best compromise between these two significant objectives and was previously proposed in the form of (1).

As noted earlier in the Assumption part, in the reliability evaluations, the switching time and repair time are supposed to be

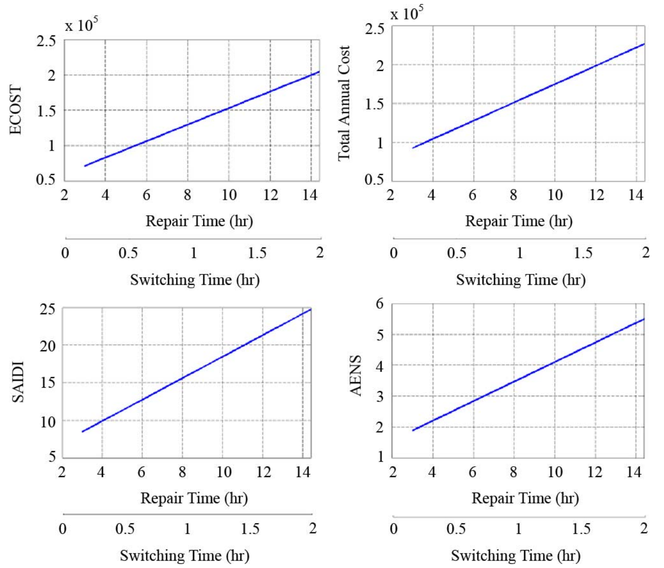

Fig. 4. Sensitivity analysis of switching time and repair time on the reliability indices.

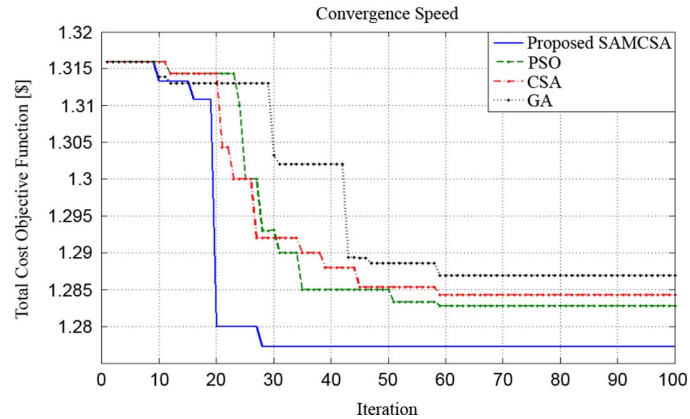

Fig. 5. Convergence graph of total cost objective function by the use of the CSA, PSO, GA, and the proposed SAMCSA.

TABLE V
RESULTS OF OPTIMIZING THE PROPOSED COST FUNCTION BY SAMCSA (STOCHASTIC FRAMEWORK)

Status	Power loss [kW]	Power loss cost [$]	ECOST [$]	Total Cost (*f*) [$]
Deterministic Framework	128.29	21,552.70	106,168.38	127,721.13
Stochastic Framework	**129.79**	**21,805.20**	**106,186.56**	**127,992.48**

TABLE VI
STANDARD DEVIATION OF THE OBJECTIVES (STOCHASTIC FRAMEWORK)

Status	Power loss ($\times 10^{-2}$) [kW]	ECOST [$]	Total Cost (*f*) [$]
Before Reconfiguration	543.61	2981.73	3378.64
After Reconfiguration	**484.09**	**2922.44**	**3351.02**

0.5 (h) and 6 (h), respectively. These values are selected according to the literature and have been found after extensive investigations [1]. Nevertheless, in this section, some sensitivity analyses are implemented to determine the impact of these two parameters on the reliability indices. Fig. 4 shows the sensitivity analyses on switching time and repair time. According to this figure, increasing these parameters will increase the values of the reliability indices proportionally. However, as can be seen, the reliability indices are more affected by changing the switching time value than the repair time value. Also, while changing the "switching time" and "repair time," the values can affect the values of the objective functions, but for the variation range considered, a similar switching scheme has been found in all cases. In other words, the values of the objective functions are changed proportionally to the values of these two parameters. As can be seen from Fig. 4, the values of power losses and SAIFI functions are not considered in these figures. The reason is that these two objective functions are not affected by the switching time and repair time values and, therefore, are not shown here. In order to observe the convergence speed of the SAMCSA, Fig. 5 shows the optimization process of all algorithms comparatively. From this figure, the proposed algorithm has successfully converged in the first place.

In this part, the stochastic framework based on $2m$ PEM is employed to capture the uncertainty associated with the forecast error of the active and reactive loads, the power-loss cost factor (C_{Ploss}), the customer interruption cost, and the failure rate and repair rate values simultaneously. In this paper, the forecast error of the uncertain parameters is modeled by a normal distribution function.

Table V shows the results of the stochastic analysis. As can be seen from Table V, including the uncertainty effects in the evaluations has resulted in the incremental costs in the objective functions. These additional costs show that the results of the deterministic framework are less dependable and more idealistic optimal solutions to operate the system. In order to reach a greater understanding of the stochastic method, Table VI shows the standard deviation values of the objectives before and after reconfiguration. As seen from this table, the standard deviation values of all the objectives are reduced after the reconfiguration. In fact, the new optimal operating point is a more reliable operating point for the system.

As mentioned before, this work considers a normal distribution function with a mean value of the base case to model the uncertainty of the random variables. For each normal PDF, a specific standard deviation value was assumed. In this section, a sensitivity analysis is implemented to see the effect of changing the standard deviation values of the random variables on the objective functions. In this regard, the standard deviation values of all random variables are changed together and the stochastic framework is run for each case individually. The values of the standard deviation parameters change from 0.5 to 4 times their initial value in the discrete steps of 0.1. The simulation results are shown in Fig. 6. In order to better understand the effect of changing the standard deviation values of the random variables on the mean value and standard deviation of the objective functions, the idea of cumulative density function is employed here. According to this figure, increasing the standard deviation value of the random variables has increased the standard deviation of the objective functions (which could be guessed before). Nevertheless, the expected values of the three targets (i.e., power losses, ECOST, and total annual cost) are affected in a different way. According to Fig. 6, increasing the standard deviation value has resulted in a U.S.$11.4682 and U.S.$11.4816

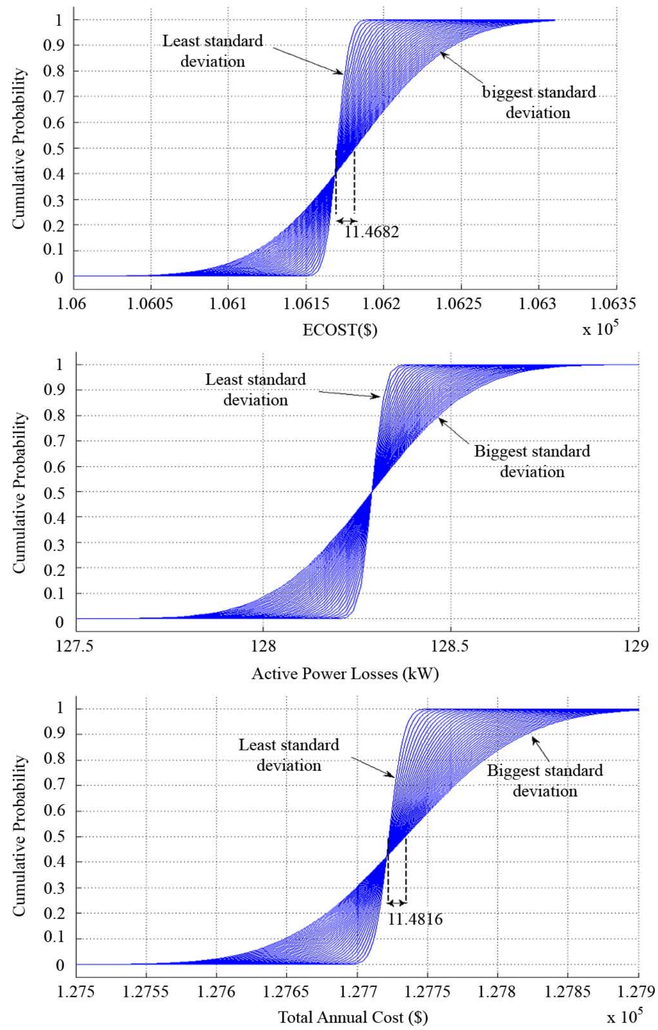

Fig. 6. Sensitivity analysis of the standard deviation value of the random variables on the three targets.

TABLE VII
MEAN AND THE STANDARD DEVIATION VALUES OF SOME BUSES

Status		V_5	V_{13}	V_{20}	V_{29}	V_{35}
Before Reconfiguration	μ ($\times 10^{-2}$)	99.90	96.58	95.79	99.98	99.89
	σ ($\times 10^{-9}$)	122.87	5228.24	8510.19	82.96	1979.02
After Reconfiguration	μ ($\times 10^{-2}$)	99.95	98.18	98.00	99.98	99.89
	σ ($\times 10^{-9}$)	10.53	4669.58	5249.69	141.36	1979.02
Status		V_{45}	V_{52}	V_{59}	V_{60}	V_{68}
Before Reconfiguration	μ ($\times 10^{-2}$)	99.83	97.87	92.50	91.99	96.86
	σ ($\times 10^{-9}$)	976.67	1887.18	5238.78	5527.88	4126.62
After Reconfiguration	μ ($\times 10^{-2}$)	99.76	99.27	94.16	93.66	98.42
	σ ($\times 10^{-9}$)	1161.09	1505.60	2716.93	3004.68	3672.29

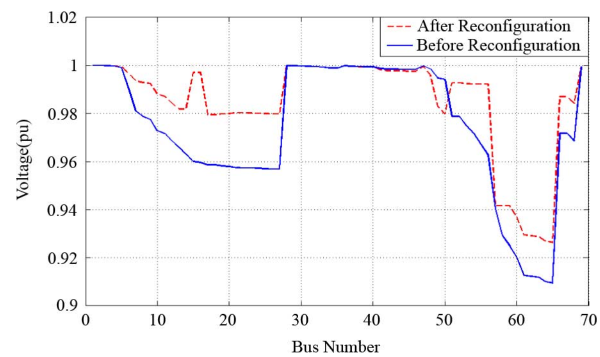

Fig. 7. Voltage profile of the system by optimizing the proposed cost function (stochastic framework).

increase in the expected values of the ECOST and the total annual cost objective functions, respectively It is clear that this amount of money is little for the length of a year. In other words, much of the uncertainty spectrum is captured by the proposed stochastic framework for small values of the standard deviation of the normal PDFs. This result is even clearer for the active power losses objective function. According to Fig. 6, changing the standard deviation of the random variables in the range of 0.5 to 4 times their initial value has very little effect on the expected value of the power losses (here, it is, 7.976027e-5 (in kilowatts), which is hard to detect from the figure). These results show the high stability of the proposed stochastic method to capture the uncertainty effects.

In order to see the effect of optimizing the proposed cost function as well as considering the uncertainty effects on the voltage of the network, Table VII shows the mean and the standard deviation values of a set of bus voltages before and after reconfiguration. It can be observed that optimal reconfiguration has provided good results for the mean and the standard deviation values. By comparing the results of mean value in this table, it is deduced that the optimal reconfiguration could improve the voltage of the system in the majority of the buses. In the buses that the voltage magnitude is not improved, the system is experiencing an appropriate voltage level and, in fact, these buses have a voltage magnitude close to 1 p.u. (like bus 29). Similarly, the standard deviation values of a great proportion of the buses are reduced.

As mentioned before, a lower standard deviation value means a more dependable operating point for the system. However, the standard deviation values of some of the buses (such as buses 29 and 45) are increased. This phenomenon can be seen in some other buses in the system too. In order to explain this event, it should be noted that the main target in this paper is the optimization of the cost objective function and, thus, any improvement in the voltages of the buses is an indirect result of the proposed stochastic framework. In this study, about 75.36231% of the buses are improved from the voltage magnitude view after reconfiguration. In the case of the standard deviation, about 76.81159% of the buses are improved and just 23.188405% of the buses have gained higher standard deviation values. These statistical reports show the high efficiency of the proposed stochastic framework to improve the voltage profile as an indirect goal. In order to see the positive effect of the reconfiguration strategy on the voltage profile of the system, Fig. 7 shows the comparative plot of the bus voltages before and after reconfiguration in the stochastic framework. According to Fig. 7, the maximum voltage deviation of the system is effectively reduced.

VII. CONCLUSION

This paper proposed a new stochastic framework based on the failure rate reduction idea to investigate the potential ability of reconfiguration as a reliability reinforcement strategy. The simulation results showed considerable savings in the network annual costs by improving the reliability of the system and reducing active power losses through optimal reconfiguration. Also, a proper balance between the reliability costs and the active power losses costs can yield the best compromised cost function. The superiority and satisfying performance of the proposed SAMCSA over the other popular optimization methods were demonstrated too. Meanwhile, a complete sensitivity analysis was implemented to show the effect of: 1) switching time and repair time on the reliability indices and 2) the standard deviation values of the normal PDFs on the expected values of the objectives. From the first analysis, it was seen that while the values of the objective functions (except SAIFI and power losses) are affected by changing the values of switching time and repair parameters, the optimal switching scheme for the network will still remain the same. From the second analysis, the high stability of the proposed stochastic framework to capture the uncertainty effects was deduced. Future research will focus on the DG effect on the system reliability and reconfiguration.

APPENDIX

In this section, a simple mathematical example is given to better understand the proposed $2m$ PEM.

Example: Assume the below two-variable function

$$y = f(z_1, z_2) = ln(z_1) + 2z_2. \tag{31}$$

The two variables z_1 and z_2 have the mean values of $\mu_{z1} = 14$ and $\mu_{z2} = 16$, respectively. The historical data show that z_1 and z_2 have random behavior that can be modeled with normal PDF with the standard deviation of $\sigma_{z1} = 0.5$and $\sigma_{z2} = 0.4$. We want to consider the uncertainty of the two parameters z_1 and z_2 using the $2m$ PEM technique. In this regard, we should find the expected value of $y(E(y))$ and its standard deviation value (σ_y) by $2m$ PEM. The below steps are required to run $2m$ PEM:

Step 1) To evaluate σ_y, both $E(y)$ and $E(y^2)$ are required:

$$\sigma_y = \sqrt{E(y^2) - [E(y)]^2}. \tag{32}$$

Step 2) Each point of $z_1 = 14$ and $z_2 = 16$ should be replaced with two concentration points as follows [(16) in the paper]:

$$z_{1,k} = \mu_{z1} + \xi_{1,k}.\sigma_{z1};\ k = 1,2 ==> \begin{cases} z_{1,1} = 14 + \xi_{1,1}.0.5 \\ z_{1,2} = 14 + \xi_{1,2}.0.5 \end{cases}$$
$$z_{2,k} = \mu_{z2} + \xi_{2,k}.\sigma_{z2};\ k = 1,2 ==> \begin{cases} z_{1,1} = 16 + \xi_{2,1}.0.4 \\ z_{1,2} = 16 + \xi_{2,2}.0.4. \end{cases} \tag{33}$$

Step 3) In (33), $\xi_{l,k}$ should be first calculated. The values of $\xi_{l,k}$ are calculated as below (17)

$$\begin{cases} \xi_{1,1} = \frac{\Upsilon_{1,3}}{2} + (-1)^2\sqrt{2 - \left(\frac{\Upsilon_{1,3}^2}{2}\right)^2} \\ \xi_{1,2} = \frac{\Upsilon_{1,3}}{2} + (-1)^1\sqrt{2 - \left(\frac{\Upsilon_{1,3}^2}{2}\right)^2} \\ \xi_{2,1} = \frac{\Upsilon_{2,3}}{2} + (-1)^2\sqrt{2 - \left(\frac{\Upsilon_{2,3}^2}{2}\right)^2} \\ \xi_{2,2} = \frac{\Upsilon_{2,3}}{2} + (-1)^1\sqrt{2 - \left(\frac{\Upsilon_{2,3}^2}{2}\right)^2}. \end{cases} \tag{34}$$

Step 4) Similarly, for evaluating $\xi_{l,k}$, the two values of $\Upsilon_{1,3}$ and $\Upsilon_{2,3}$ should be first evaluated. According to (18), for normal PDFs, $\Upsilon_{1,3} = \Upsilon_{2,3} = 0$. Therefore, the values of (34) and then (33) are evaluated as follows:

$$\begin{cases} \xi_{1,1} = \xi_{2,1} = +\sqrt{2} \\ \xi_{1,2} = \xi_{2,2} = -\sqrt{2} \end{cases}$$
$$=> \begin{cases} z_{1,1} = 14 + \sqrt{2} \times 0.5 \approx 14.7071 \\ z_{1,2} = 14 - \sqrt{2} \times 0.5 \approx 13.2928 \\ z_{2,1} = 16 + \sqrt{2} \times 0.4 \approx 16.5656 \\ z_{2,2} = 16 - \sqrt{2} \times 0.4 \approx 15.4343. \end{cases} \tag{35}$$

According to the above equations, the uncertain variable $z_1 = 4$ is replaced by two points $z_{1,1} = 14.7071$ and $z_{1,2} = 13.2928$. Similarly, $z_2 = 16$ is replaced by $z_{2,1} = 16.5656$and $z_{2,2} = 15.4343$. Now, (31) should be calculated four times to find $E(y)$. Each time that a new point $z_{l,k}$ replaces z_l in the equation, the other random variables should take their mean value as follows (note that $\omega_{l,k} = (1/2m) = 0.25(19)$):

$$\begin{aligned} E(y) &= \omega_{1,1} \times f(14.7071, \mu_{z2}) + \omega_{1,2} \\ &\quad \times f(13.2928, \mu_{z2}) \\ &\omega_{2,1} \times f(\mu_{z1}, 16.5656) \\ &\quad + \omega_{2,1} \times f(\mu_{z1}, 15.4343) = 34.6384. \end{aligned} \tag{36}$$

Similarly, $E(y^2)$ is calculated as follows:

$$\begin{aligned} E(y^2) &= \omega_{1,1} \times f^2(14.7071, \mu_{z2}) + \omega_{1,2} \\ &\quad \times f^2(13.2928, \mu_{z2}) \\ &\omega_{2,1} \times f^2(\mu_{z1}, 16.5656) \\ &\quad + \omega_{2,1} \times f^2(\mu_{z1}, 15.4343) = 1200.5. \end{aligned} \tag{37}$$

Step 5) By evaluating $E(y)$ and $E(y^2)$, σ_y is calculated

$$\sigma_y = \sqrt{\mathrm{var}(y)} = \sqrt{E(y^2) - E(y)^2} = 0.8007. \tag{38}$$

REFERENCES

[1] R. Billinton and R. N. Allan, *Reliability Evaluation of Power Systems, Plenum*, 2nd ed. New York: Springer, 1996.

[2] A. Kavousifard and H. Samet, "Consideration effect of uncertainty in power system reliability indices using radial basis function network and fuzzy logic theory," *Neurocomput.*, vol. 74, pp. 3420–3427, 2011.

[3] I. Ziari, G. Ledwich, A. Ghosh, and G. Platt, "Integrated distribution systems planning to improve reliability under load growth," *IEEE Trans. Power Del.*, vol. 27, no. 2, pp. 757–765, Apr. 2012.

[4] A. Kavousi-Fard and M. R. Akbari-Zadeh, "Reliability enhancement using optimal distribution feeder reconfiguration," *Neurocomput.*, vol. 106, pp. 1–11, 2013.

[5] A. H. Etemadi and M. Fotuhi-Firuzabad, "Distribution system reliability enhancement using optimal capacitor placement," *IET Gen. Transm. Distrib.*, vol. 2, no. 5, pp. 621–631, 2008.

[6] T. Niknam, A Kavousi-Fard, and A. Seifi, "Distribution feeder reconfiguration considering fuel cell/wind/photovoltaic power plants," *J. Renew Energy*, vol. 37, no. 1, pp. 213–225, 2012.

[7] H. Kim, Y. Ko, and K. H. Jung, "Artificial neural-network based feeder reconfiguration for loss reduction in distribution systems," *IEEE Trans. Power Del.*, vol. 8, no. 3, pp. 1356–1366, Jul. 1993.

[8] S. K. Goswami and S. K. Basu, "A new algorithm for the reconfiguration of distribution feeders for loss minimization," *IEEE Trans. Power Del.*, vol. 7, no. 3, pp. 1484–1491, Jul. 1992.

[9] E. Lopez and H. Opaso, "Online reconfiguration considering variability demand. Applications to real networks," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 549–553, Feb. 2004.

[10] A. B. Morton and I. M. Y. Mareels, "An efficient brute-force solution to the network reconfiguration problem," *IEEE Trans. Power Del.*, vol. 15, no. 3, pp. 996–1000, Jul. 2000.

[11] T. Taylor and D. Lubkeman, "Implementation of heuristic search strategies for distribution feeder reconfiguration," *IEEE Trans. Power Del,*, vol. 5, no. 3, pp. 239–245, Jul. 1990.

[12] D. Shirmohammadi and H. W. Hong, "Reconfiguration of electric distribution networks for resistive line loss reduction," *IEEE Trans. Power Syst.*, vol. 4, no. 1, pp. 1492–1498, Feb. 1989.

[13] C. T. Sua, C. F. Changb, and J. P. Chiouc, "Distribution network reconfiguration for loss reduction by ant colony search algorithm," *Elect. Power Syst. Res.*, vol. 75, no. 2–3, pp. 190–199, Aug. 2005.

[14] C. F. Chang, "Reconfiguration and capacitor placement for loss reduction of distribution systems by ant colony search algorithm," *IEEE Trans. Power Syst.*, vol. 23, no. Nov., pp. 1747–1755, May 2008.

[15] Y. J. Jeon and J. C. Kim, "Network reconfiguration in radial distribution system using simulated annealing and tabu search," in *Proc. IEEE Power Eng. Soc. Winter Meeting*, 2000, pp. 23–27.

[16] M. A. Kashem, V. Ganapathy, and G. B. Jasmon, "Network reconfiguration for load balancing in distribution networks," *Proc. Inst. Elect. Eng., Gen., Transm, Distrib.*, vol. 14, no. 6, pp. 563–567, 1999.

[17] A. Kavousi-Fard, T. Niknam, and A. Khosravi, "Multi-objective probabilistic distribution feeder reconfiguration considering wind power plants," *Int. J. Elect. Power Energy Syst.*, vol. 55, pp. 680–691, 2013.

[18] B. Amanulla, S. Chakrabarti, and S. N. Singh, "Reconfiguration of power distribution systems considering reliability and power loss," *IEEE Trans. Power Del.*, vol. 27, no. 2, pp. 918–926, Apr. 2012.

[19] P. Zhang, W. Li, and S. Wang, "Reliability-oriented distribution network reconfiguration considering uncertainties of data by interval analysis," *Elect. Power Energy Syst.*, vol. 34, no. 1, pp. 138–144, 2012.

[20] A. Gonzalez, F. M. Echavarren, L. Rouco, and T. Gomez, "A sensitivities computation method for reconfiguration of radial networks," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1294–1301, Aug. 2012.

[21] L. Tsai, "Network reconfiguration to enhance reliability of electric distribution systems," *Elect. Power Syst. Res.*, vol. 27, no. 2, pp. 135–140, 1993.

[22] Y. Bin, W. Xiu-Li, B. Zhao-Hong, and W. Xi-Fan, "Distribution network reconfiguration for reliability worth enhancement," in *Proc. Int. Conf. Power Syst. Technol.*, China, Oct. 4, 2002, pp. 2547–2550.

[23] L. Goel and R. Billinton, "Evaluation of interrupted energy assessment rates in distribution systems," *IEEE Trans. Power Del.*, vol. 6, no. 4, pp. 1876–1882, Oct. 1991.

[24] P. L. Lewin, J. E. Theed, A. E. Davies, and S. T. Larsen, "Method for rating power cables buried in surface troughs," *Proc. Inst. Elect. Eng., Gen. Transm. Distrib.*, vol. 146, no. 4, pp. 360–364, 1999.

[25] R. E. Brown, *Electric Power Distribution Reliability*. New York: Marcel Dekker, 2002.

[26] A. Baziar and A. Kavousi-Fard, "Consideration effect of uncertainty in the optimal energy management of renewable micro-grids including storage devices," *Renew. Energy*, vol. 59, pp. 158–166, 2013.

[27] T. Niknam and A. Kavousifard, "Impact of thermal recovery and hydrogen production of fuel cell power plants on distribution feeder reconfiguration," *IET Gen. Transm. Distrib.*, vol. 6, no. 9, pp. 831–843, 2012.

[28] A. Kavousi-Fard and T. Niknam, "Considering uncertainty in the multi-objective stochastic capacitor allocation problem using a novel self adaptive modification approach," *Elect. Power Syst. Res.*, vol. 103, pp. 16–27, 2013.

[29] J. Brownlee, Clonal selection theory&clonalg: The clonal selection classification algorithm (CSCA), Tech. Rep. 02, 2005.

[30] C. Brown, L. S. Liebovitch, and R. Glendon, "L′ evy flights in dobe juhoansi foraging patterns," *Human Ecol.*, vol. 35, pp. 129–138, 2007.

[31] M. A. Kashem, V. Ganapathy, and G. B. Jasmon, "A geometrical approach for network reconfiguration based loss minimization in distribution systems," *Elect. Power Energy Syst.*, vol. 23, pp. 295–304, 2001.

[32] L. Liu and X. Chen, "Reconfiguration of distribution networks based on fuzzy genetic algorithms," in *Proc. CSEE* (in Chinese), 200, vol. 20, pp. 66–69.

[33] P. Bi, J. Liu, and C. Liu, "A refined genetic algorithm for power distribution network reconfiguration," in *Autom. Elect. Power Syst.* (in Chinese), 2002, vol. 26, pp. 57–61.

[34] L. Zhenkun, C. Xingying, Y. Kun, S. Yi, and L. Haoming, "A hybrid particle swarm optimization approach for distribution network reconfiguration problem," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, 2007, pp. 1–7.

[35] Y. Jianming, Z. Fan, N. Feng, and M. Yuanshe, "Improved genetic algorithm with infeasible solution disposing of distribution network reconfiguration," in *Proc. WRI Global Congr. Intell. Syst.*, 2009, vol. 2, pp. 48–52.

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