Multi-stage Reconfiguration of Distribution Network for Loss Reduction and Reliability Improvement

Zhang Zhu-Hui
College of Equipment Engineering
Engineering University of Armed Police Force
Xi'An, China
e-mail:Zhang_zhuhui@sina.com

Duan Dong-Li
College of Equipment Engineering
Engineering University of Armed Police Force
Xi'An, China
e-mail: mineduan@163.com

Abstract—Electrical distribution network reconfiguration is a complex combinatorial optimization process aimed at finding a radial operating structure that minimizes the system power loss or maximizes the system reliability while satisfying operating constraints. It has been traditionally performed assuming that loads of buses are constant values, but in real systems the values always change with time. To ensure the system operate safely and economically, decision makers have to reconfigure the distribution feeder dynamically with time according to the changing loads. In this paper, a multi-stage reconfiguration method is presented for both the indices of power loss reduction and reliability improvement with a load curve model. An enhanced genetic optimization algorithm is used to handle the reconfiguration problem so as to determine the number of stages and switch operation schemes in each stage. The effectiveness of the proposed method is demonstrated on 33-bus radial distribution system and a practical system.

Keywords- distribution system; reconfiguration; reliability evaluation; power loss; genetic algorithm

I. INTRODUCTION

Network reconfiguration of distribution feeders, as one of the most important content in distribution automation research, is a process that alters feeder topological structure, changing the open/close status of sectionalizing switches and tie switches in the system. It is performed to improve the system's operating conditions and reduce the system cost.

There are two fundamental challenges in the problem of distribution systems reconfiguration. The first challenge is related to the high number of switching elements and the nonlinear characteristics of the electrical behavior constraints. Changing the switches status yields a very large number of network topologies that need to check the radial nature while seeking the optimal configuration. Each feasible topology has to satisfy the constraints including branches thermal limit, voltage level at buses, and substations' power capacity. Hence, the reconfiguration problem is a highly complex combinatorial and constrained nonlinear mixed integer optimization problem. The second challenge is related to customer's changing power demand with time. Customers power demand changes significantly over time, and consequently, an operating topology obtained for a certain regime may no longer be optimal under new operating conditions. Clearly, a single-time optimization is not an effective solution to the problem. In a long run, power system decision makers have to reconfigure the distribution feeder dynamically in real time according to the changing loads to ensure the system operate safely and economically. Naturally, it will be a dynamic optimization problem to alter the system structure timely.

To find an appropriate solution for the static case, meta-heuristic methods are frequently used and they have been clearly demonstrated to be both feasible and advantageous[1-11]. This review is focused on some contributions related to GAs, as GA or enhanced GA can efficiently identify the optimal or near optimal network configurations.

Moreover, it has been found using GA to resolve the planning problem of large-scale power distribution networks is more suitable and efficient than several other methods[12,13]. In spite of that, its main drawback is the slow convergence velocity and the required running time.

Therefore, an enhanced GA optimization technique is used to solve the problem of distribution reconfiguration with time-varying power loads, which yields the minimum power loss or the maximum system reliability. The coding strategy uses the open switch number representation. An approach based on the information of a single loop caused by closing a normally open switch is to perform the GA operators.

This paper is organized as follows: Section II give a mathematical model for the distribution network reconfiguration problem. A description of the enhanced Genetic Algorithm (EGA) is presented in Section III. Simulation results of test case and practical case are presented in Section IV, and Section V concludes this paper.

II. PROBLEM FORMULATION

A. Mathematical model for distribution network reconfiguration

1) Static mathematical model with constant loads

Traditionally, network reconfiguration has been performed assuming that loads of buses are constant values. In this case, the reconfiguration problem for loss reduction or reliability improvement is always treated as a static planning problem.

Thus, the problem can be formulated as follows:

$$MinF_c = w_1 P_{Tloss}(k) + w_2 Re(k) \quad (1)$$

Here, k is the feasible solution of the network. P_{Tloss} and Re represent the power loss and the reliability indices respectively.

The purpose of distribution network reconfiguration in static case is to find a radial operating structure that minimizes the system power loss and maximizes the system reliability while satisfying operating constraints. From a practical point of view, the simulation result is a trade-off between the power loss and the reliability indices.

Subject to:

a) Radial network constraint:

The distribution system can not deviate from the radial structure.

$$\phi(k) = 0 \quad (2)$$

b) Voltage constraints:

Voltage magnitude at each node must lie with their permissible ranges to maintain power quality.

$$V_{i,\min} \le |V_i| \le V_{i,\max}, i \in [1,2,...,N_b] \quad (3)$$

Where, $V_{i,\min}$ and $V_{i,\max}$ are the minimum and maximum voltage limits of bus i.

c) Current constraints:

Current magnitude of each branch (feeder, laterals, and switches) must lie with their permissible ranges.

$$k_i I_i \le I_{i,\max}, i \in [1,2,....,N_l] \quad (4)$$

Where, $I_{i,\max}$ is the maximum current limit of branch i.

d) Kirchhoff's current and voltage laws:

$$\begin{aligned} g_i(I,k) &= 0 \\ g_v(V,k) &= 0 \end{aligned} \quad (5)$$

2) Dynamic mathematical model with time-varying loads

In real systems, the load values always change with time. To ensure the systems operate safely and economically, decision makers have to reconfigure the distribution feeder dynamically in real time according to the changing loads. Naturally, it will be a dynamic optimization problem. Here, EENS is picked as reliability indices to exemplify the objective function in $(T = t_1 - t_0)$ as follows:

$$MinFc = \int_{t_0}^{t_1} w_1 P_{Loss}(k(t))dt + \int_{t_0}^{t_1} w_2 EENS(k(t))dg(t) \quad (6)$$

Here, w_1 and w_2 represent the weights of power loss and reliability, $k(t)$ is the optimization variables of structure at time t, EENS is calculated by year, then $g(t)$ is the function of t as year. The first term on the right-hand side is the power loss in time T, while the second term describes the expected energy not supplied in T. In this case, (2)-(5) remain valid.

It is a dynamic optimization problem, which is to generate a discrete objective function so as to get the optimal solutions by stage. The time interval of $[t_0, t_1]$ can be divided into N short intervals, the time duration of j_{th} interval is ΔT_j, which is so-called stage. With this discrete way, the term of (6) can be

$$MinFc = \sum_{j=1}^{N} (w_1 P_{Loss}(k_j)\Delta T_j + w_2 EENS(k_j) g(\Delta T_j)) \quad (7)$$

Here, k_j is the feasible solution of the network at the j_{th} stage.

Now that the dynamic reconfiguration problem with time-varying loads is simplified as the combination of several simple static optimization problems, it should be noted the global optimal solution is not a simple addition of several local optimum in each stage. The reason is that the reconfiguration in next stage depends on the operation structure in this stage.

B. Time-varying load model

Considering the time-varying feature of loads, the mean load value $\overline{L(t)}$ at t can be written as

$$\overline{L(t)} = P_{e,k}(t) \times L_{\max} \quad (8)$$

Here, $L_{\max}$ is a constant value, representing the maximum load of the load point in one year. $P_{e,k}(t)$ $(0 \le P_{e,k}(t) \le 1)$ is the ratio of load value at t to the value of $L_{\max}$, $P_{e,k}(t)$ is a time sequence, which is mainly affected by the variation of the load type of k.

Load forecasting is often inaccurate affected by many factors. Since the actual load value is bounded function, we suppose the prediction error is normally distributed, then the prediction error also has an upper bound $N_{\max}$ and a lower bound $N_{\min}$. The analog value of the load $L(t)$ at time t can be obtained by correction as follows.

$$L(t) = \overline{L_k(t)} + N(0,\sigma), N(0,\sigma) \in [N_{\min}, N_{\max}] \quad (9)$$

Here, $N(0,\sigma)$ is a truncated normal distribution variable in $[N_{\min}, N_{\max}]$ with mean $\mu = 0$ and standard deviation σ.

C. Power loss of radial distribution network

The power flows are calculated by the following set of recursive equations derived from the single-line diagram in Fig .1.

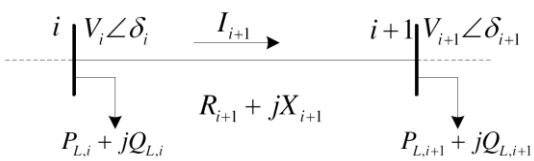

Figure 1. Single-line diagram for power flow calculation

From Fig.1, the current flowing through branch between nodes i and $i+1$ is

$$\tilde{I}_{i+1} = \frac{V_i\angle\delta_i - V_{i+1}\angle\delta_{i+1}}{R_{i+1} + jX_{i+1}} \quad (10)$$

Load power consumption is given by

$$P_{i+1} - jQ_{i+1} = V_{i+1} * \tilde{I}_{i+1} \quad (11)$$

From (10) and (11), the voltage magnitude at node $i+1$ is given by

$$V_{i+1} = \{[(P_{i+1}R_{i+1} + Q_{i+1}X_{i+1} - \frac{|V_i|^2}{2})^2 - (R_{i+1}^2 + X_{i+1}^2)(P_{i+1}^2 + Q_{i+1}^2)]^{1/2} - (P_{i+1}R_{i+1} + Q_{i+1}X_{i+1} - \frac{|V_i|^2}{2})\}^{1/2} \quad (12)$$

Here, P_{i+1} and Q_{i+1} are total real and reactive power loads through node $i+1$. They are

$$P_{i+1} = \sum_{j=i+1}^{N_b-1} P_{L,j} + \sum_{j=i+1}^{N_b-1} P_{loss,j}$$
$$Q_{i+1} = \sum_{j=i+1}^{N_b-1} Q_{L,j} + \sum_{j=i+1}^{N_b-1} Q_{loss,j} \quad (13)$$

Where, N_b is the number of nodes in the system, $P_{loss,i}$ and $Q_{loss,i}$ are the real and reactive power loss in branch i respectively.

$$P_{loss,i} = \frac{R_i(P_i^2+Q_i^2)}{|V_i|^2}$$
$$Q_{loss,i} = \frac{X_i(P_i^2+Q_i^2)}{|V_i|^2} \quad (14)$$

By summing up the loss of all branches of the feeder, total power loss of the feeder can be determined as

$$P_{Tloss} = \sum_{i=1}^{N_l} k_i P_{loss,i} \quad (15)$$

Here, N_l is the total number of branches in the radial distribution system, k_i is a binary variable that represents the topological status of the branches.

In this paper, the system average interruption frequency index (SAIFI), the system average interruption duration index (SAIDI), the average interruption unavailability index (SAIUI), and the expected energy not supplied (EENS) are used as the typical quantities to evaluate distribution network reliability[14].

III. ENHANCED GA FOR RECONFIGURATION

GA is an artificial intelligence method simulating natural evolution, which uses 3 main operators selection, crossover, and mutation to produce individuals with better fitness. The main point of the algorithm we used in this paper can be summarized as follows.

1) Codification and Feasible Population: In this paper, the individuals are represented by a string of integer numbers (chromosome) whose dimension is the total number of switches to be disconnected from the network. Consequently, the length of the string is equal to the number of the system loops.

2) Crossover: The traditional crossover process randomly selects two parents (chromosomes) for a gene exchange with a given crossover rate. For the reconfiguration problem, it means one or several edges are exchanged between two spanning trees for a given distribution network graph. The exchange property of spanning trees has been proven by Kruskal.

Denote T_1 and T_2 as two feasible radial structure of the distribution system, if

$$\mathbf{e} = E(T_1) \setminus E(T_2) = \{e_1, e_2, e_3, ..., e_t\}$$
$$\mathbf{f} = E(T_2) \setminus E(T_1) = \{f_1, f_2, f_3, ..., f_t\}$$

there exists a sequence $f_{j1}, f_{j2}, f_{j3}, ..., f_{jt}$ of $\mathbf{f}$, such that $T_2 + e_i - f_{ji}$ is also a feasible radial structure of the distribution system. It is shown in Fig .2.

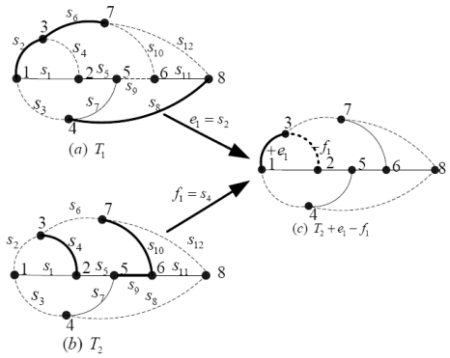

Figure 2. Branch exchange between two spanning trees for crossover operation of GAs

Let $loop(T_i, S_j)$ represent the single loop formed by closing the open switch S_j in tree T_i . It can easily be known that $loop(T_1, f_i)$ or $loop(T_2, e_i)$ is always a single loop, where $f_i \in \mathbf{f}$ and $e_i \in \mathbf{e}$.

For a given graph, to list the fundamental loops could be much more complex, but if there is only a single loop in the graph, to find it would be rather easy according to the graph theory. Based on the Kruskal theorem and the information of the single loop, the crossover operator for the distribution network reconfiguration problem is shown in Fig .3.

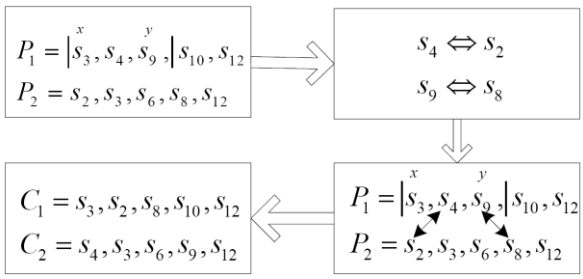

Figure 3. Crossover process based on the information of a single loop

3) Mutation: Mutation operator allows GA to avoid local optima and to explore new research area as it introduces new information into the knowledge base. Select one or multiple genes in the chosen parent randomly, one single loop is formed by closing the branch in the corresponding tree. With a depth-first graph search algorithm, the single loop can be determined. A new gene is randomly chosen in this loop to replace the first selected. The above mutation process is shown in Fig .4.

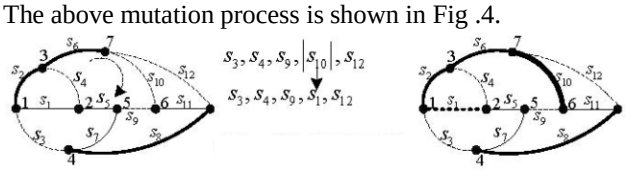

Figure 4. Mutation process based on the information of a single loop

4) Crossover rate and mutation rate

To ensure the convergence speed, crossover rate and mutation rate are established by sort-based adaptive algorithm.

$$P_c = \begin{cases} P_{c1} - \frac{2(P_{c1}-P_{c2})}{Pop}(\frac{Pop}{2} - r'(C) + 1), & r'(C) \le \frac{Pop}{2} \\ P_{c1}, & r'(C) > \frac{Pop}{2} \end{cases} \quad (16)$$

$$P_m = \begin{cases} P_{m1} - \frac{2(P_{m1}-P_{m2})}{Pop}(\frac{Pop}{2} - r(C) + 1), & r(C) \le \frac{Pop}{2} \\ P_{m1}, & r(C) > \frac{Pop}{2} \end{cases} \quad (17)$$

Here, Pop represents the population size; $r(C)$ represents the sequence number of individual C in population; $r'(C)$ represents the one with low sequence number in the crossover individuals; P_{c1} and P_{m1} are crossover rate and mutation rate of the individuals whose fitness value is below average value respectively; P_{c2} and P_{m2} crossover rate and mutation rate of the individuals who have the top fitness value.

At the end of the process, the generated individuals are evaluated using the power loss function or the reliability function, taking into account the operational constraints. Their aptitudes are compared with the results of their parents. Naturally, the individual with the best aptitude is selected.

IV. EXPERIMETN AND ANALYSIS

In order to ascertain the effectiveness of the proposed algorithm, results for 33-bus system has been obtained. For the system, the substation voltage is considered as 1 p.u. and all the tie and sectionalizing switches are considered as candidate switches for reconfiguration problem.

The proposed methodology of distribution system reconfiguration for maximizing the reliability at the load points and minimizing the system power loss is first applied to the modified 33-bus, 12.66kV, radial distribution system. It consists of 5 normally open switches and 32 normally closed switches. The normally open switches are s33, s34, s35, s36, and s37, the normally closed switches are s1 to s32. The line data and load data of this system are given in [15], the total real and reactive power loads on the system are 3715 kW and 2300 kVar, respectively. The initial power loss of this system are 210.99 kW and 143.02 kVar.

A. *Static case*

The simulation results for Baran system are shown in Table I. It shows the results of reconfiguration for maximum reliability, for minimum power loss, and for maximum reliability and minimum power loss with varying weights.

In Table I, the units of SAIUI, SAIFI, EENS and power loss are respectively hours/year, times/year, mwhr and kw. The best operation schemes are to open the switches s10, s13, s16, s28, and s33, when the single objective function is minimization of SAIUI, SAIFI and EENS respectively. In this case, SAIF=2.158, SAIUI=1.047, EENS=3.302, and P_{Tloss} =164.41. When the value of w1 and w2 are 0.5X1000 and.5X8760, we get the best solution of multi-objective optimization. The operation schemes are s7, s9, s14, s32, s37, and the system indices are SAIFI =2.467, SAIUI=1.259, EENS=3.867, and P_{Tloss} =139.55.

TABLE I. OPTIMAL SOLUTION OF BARAN SYSTEM FOR STATIC CASE

Item	Initial case	Min SAIUI	Min SAIFI	Min EENS	Min Loss	$w1*$EENS $+w2*$Loss
Solution	33,34, 35, 36,37	10,13, 16, 28,33	10,13, 16, 28,33	10,13, 16, 28,33	7,9, 14, 32,37	7,9, 14, 32,37
Loss	210.99	164.41	164.41	164.41	139.55	139.55
SAIUI	1.247	1.047	1.047	1.047	1.259	1.259
SAIFI	2.445	2.158	2.158	2.158	2.467	2.467
EENS	3.846	3.302	3.302	3.302	3.867	3.867

In order to show the efficiency of the described method, a basic GA with real number coding strategy has been initially implemented and applied to the system.

The convergence results of various system indices for GA and EGA are shown in Fig.5. It can be seen from Fig.5, the Enhanced GAs converge to optimum solution more quickly with better accuracy compared to traditional GA, while the best solution can be generally obtained in 10 iterations with various objective functions. The reason lies in that all resulting individuals after proposed GA operators are radial structures, which decreases the search space considerably.

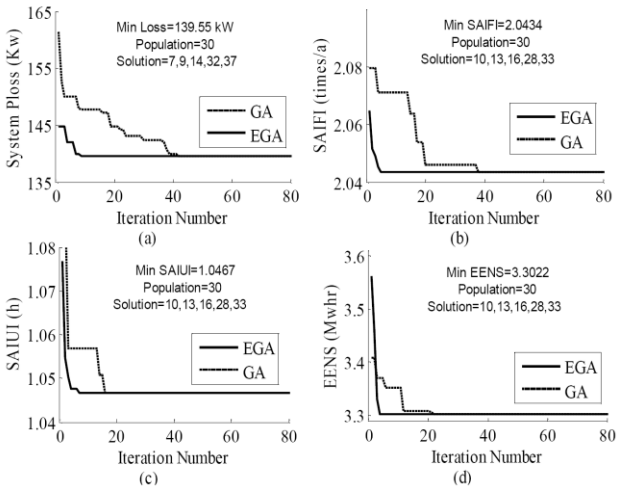

Figure 5. Convergence results s for GA and EGA

B. *Time-varying load demand case*

Suppose the studied systems have 3 different loads, load 2 -- load 12 are industry customers, load 13 -- load 22 are commerce customers, and load 23 -- load 32 are resident customers. The same type customers have the same load curve, and the maximum load of each load point in one year is refereed in [15]. In dynamic case, the load data at any time can be generated by the terms of (8)-(9) according to the load type of k and the time t.

To reconfigure the system with above data and the proposed GA technique, the optimal operation schemes in each stage and its indices of power loss and reliability are shown in Table II. The initial opened switches set is s7,s9,s14,s32,s37, which is the optimal schemes when the

system operates with peak load. From Table II, the system should adjust its operate structure 4 times in considered mission time, namely the dynamic reconfiguration would be divided into 4 stages. The reconfigure strategy is to open s28, s31 and close s32, s37 at the 1_{th} hour, then to open s32 and close 31 at the 4_{th} hour, then to open s37 and close s28 at the 19_{th} hour, at last to open s28 and close s37 at the 22_{th} hour. With this strategy, the power loss and EENS are respectively 2471kw and 8.10kwh, compared to the indices respectively 2504kw and 8.29kwh under the optimal schemes with peak load.

TABLE II. OPTIMAL SOLUTION OF BARAN SYSTEM FOR TIME-VARYING LOAD DEMAND CASE

phase	interval	switch scheme	$P_t(loss)$ in each phase(kw)				EENS in each phase(kwh)			
			1	2	3	4	1	2	3	4
1	[0,24]	7,9,14,28,31	2533.83	-	-	-	8.51	-	-	-
2	[0,3,24]	7,9,14,28,32	213.2	2259.3	-	-	0.72	7.21	-	-
3	[0,3,18,24]	7,9,14,32,37	213.2	1542.0	720.0	-	0.72	4.99	2.35	-
4	[0,3,18,21,24]	7,9,14,28,32	213.2	1542.0	391.0	325.8	0.72	4.99	1.25	1.04

V. CONCLUSIONS

In this paper, a multi-stage reconfiguration method is presented for both the indices of power loss reduction and reliability improvement with a load curve model. An enhanced GA is used to handle the reconfiguration problem to determine the number of stages and switch operation schemes in each stage. The effectiveness of the proposed method is demonstrated on Baran system and a practical system. The main contribution is to reconfigure the distribution feeder dynamically in real time according to the changing loads. As customers power demand changes significantly over time in real system, and consequently, an operating topology obtained for a certain regime may no longer be optimal under new operating conditions. We present a mathematical model for the dynamic distribution network reconfiguration problem and use the enhanced GA to solve this problem. The reconfiguration results not only recommend a stage division method, they but also present the optimal switch schemes in each stage. Other major contribution of this paper is to incorporate reliability evaluation methods into the distribution system reconfiguration problem. The simulation result is a trade-off between the power loss and the reliability indices. It means that the proposed approach can recommend a small set of possible solutions for decision makers in order to select the most suitable radial topology from them.

ACKNOWLEDGMENT

This work was supported in part by the National Natural Science Foundation of China under Grant no. 71401178 and in part by the open funding program of joint laboratory of flight vehicle ocean-based measurement and control under Grant No. FOM2014OF016.

REFERENCES

[1] E. Naderi, H. Seifi, and M. S. Sepasian, “A dynamic approach for distribution system planning considering distributed generation,” IEEE Trans. Power Del., vol. 27, no. 3, pp. 1313–1322, 2012.

[2] E. M. Carreno, R. Romero, and A. Padilha-Feltrin, “An efficient codification to solve distribution network reconfiguration for loss reduction problem,” IEEE Trans. Power Syst., vol. 23, no. 4, pp. 1542–1551, Nov. 2008.

[3] V. Farahani, B. Vahidi, and H. A. Abyaneh, “Reconfiguration and capacitor placement simultaneously for energy loss reduction based on an improved reconfiguration method,” IEEE Trans.Power Syst., vol. 27, no. 2, pp. 587–595, 2012.

[4] V. Parada, J. A. Ferland, M. Arias, and K. Daniels, “Optimization of electrical distribution feeders using simulated annealing,” IEEE Trans. Power Del., vol. 19, no. 3, pp. 1135–1141, 2004.

[5] H. Yann-Chang, Y. Hong-Tzer, and H. Ching-Lien, “Solving the capacitor placement problem in a radial distribution system using tabu search approach,” IEEE Trans.Power Syst., vol. 11, no. 4, pp. 1868–1873, 1996.

[6] Y.-J. Jeon and J.-C. Kim, “Application of simulated annealing and tabu search for loss minimization in distribution systems,” Int. J. Elect. Power Energy Syst.,, vol. 26, no. 1, pp. 9–18, 2004.

[7] 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, 2012.

[8] W. Wu-Chang and T. Men-Shen, “Application of enhanced integer coded particle swarm optimization for distribution system feeder reconfiguration,” IEEE Trans.Power Syst., vol. 26, no. 3, pp. 1591–1599, 2011.

[9] A. Y. Abdelaziz, R. A. Osama, and S. M. El-Khodary, “Reconfiguration of distribution systems for loss reduction using the hyper-cube ant colony optimisation algorithm,” Generation, Transmission Distribution, IET, vol. 6, no. 2, pp. 176–187, 2012.

[10] S. Ching-Tzong and L. Chu-Sheng, “Network reconfiguration of distribution systems using improved mixed-integer hybrid differential evolution,” IEEE Trans. Power Del., vol. 18, no. 3, pp. 1022–1027, 2003.

[11] Y.-z. Yu, J.-d. Huang, and J. Ren, “Reconfiguration of distribution network based on improved plant growth simulation algorithm,” in Second International Conference on Intelligent Computation Technology and Automation, vol. 1, 2009, pp. 387–391.

[12] V. Miranda, J. V. Ranito, and L. M. Proenca, “Genetic algorithms in optimal multistage distribution network planning,” IEEE Trans.Power Syst., vol. 9, no. 4, pp. 1927–1933, Nov.1994.

[13] Y. C. Huang, “Enhanced genetic algorithm-based fuzzy multi-objective approach to distribution network reconfiguration,” Proc. Inst. Elect. Eng., Gen. Transm. Distrib, vol. 149, no. 5, pp. 615–620, 2002.

[14] J. E. Mendoza, M. E. Lopez, C. A. C. Coello, and E. A. Lopez, “Microgenetic multiobjective reconfiguration algorithm considering power losses and reliability indices for medium voltage distribution network,” Generation, Transmission Distribution, IET, vol. 3, no. 9, pp. 825–840, 2009.

[15] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Trans. Power Del.,vol. 4, no. 2, pp. 1401–1407, Aug. 1989.