Network Reconfiguration of Distribution Systems Using Improved Mixed-Integer Hybrid Differential Evolution

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***Abstract*—This study proposes an effective method of network reconfiguration to reduce power loss and enhance the voltage profile by the improved mixed-integer hybrid differential evolution (MIHDE) method for distribution systems. This research aims to recognize beneficial load transfers so that the objective function composed of power losses is minimized and the prescribed voltage limits are satisfied. The proposed method determines the proper system topology that reduces the power loss according to a load pattern. Mathematically, the problem of this research is a mixed-integer combinatorial optimization problem well suited to the application of MIHDE.**

***Index Terms*—Mixed-integer hybrid differential evolution, network reconfiguration, power loss reduction, switching operation.**

I. Introduction

DISTRIBUTION systems consist of groups of interconnected radial circuits. The configuration may be varied via switching operations to transfer loads among the feeders. Two types of switches are used in primary distribution systems. They are normally closed switches (sectionalizing switches) or normally open switches (tie switches). Both types are designed for both protection and configuration management. Network reconfiguration is the process of changing the topology of distribution systems by altering the open/closed status of switches.

Civanlar *et al.* [1] conducted the early work on feeder reconfiguration for loss reduction. In [2], Baran *et al.* defined the problem of loss reduction and load balancing as an integer-programming problem. Nara *et al.* [3] presented an implementation that used a genetic algorithm to look for the minimum loss configuration. In [4]–[6], the authors suggested the use of the power flow method based on a heuristic algorithm to determine the minimum loss configuration of radial distribution networks. In [7]–[9], the authors proposed a solution procedure that employed simulated annealing (SA) to search for an acceptable noninferior solution. The authors of [10] outlined and validated a methodology for optimizing the operation of megavolt (MV) distribution networks. The authors of [11] considered time varying load analysis to reduce loss. The authors of [12] approached bidirectional feeder models to simplify the calculations for distribution systems. In [13], fuzzy theory and evolutionary programming were employed to solve the feeder reconfiguration of distribution systems.

Manuscript received August 15, 2001; revised April 2, 2002.

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Digital Object Identifier 10.1109/TPWRD.2003.813641

Network reconfiguration is a complicated combinatorial, nondifferentiable, constrained optimization problem because the distribution system involves many candidate-switching combinations. Although this problem has been solved by the above methods, either optimality is not guaranteed or much computation time is required. Differential evolution (DE), developed by Stron and Price [14]–[16], is one of the best evolution algorithms (EAs). DE is a simple method that is based on stochastic searches, in which function parameters are encoded as floating-point variables. This method has been verified as a promising candidate for solving real-valued optimization problems. However, it may be likely to reach a local optimum or result in premature convergence. This shortcoming could be overcome by employing a larger population, but to do so requires much computation time. A hybrid version of DE (called HDE) has been proposed [17], to avoid the need for employing a large population. The hybrid version embeds two additional operations—acceleration phase and migration phase. The migration operation allows the HDE to upgrade the exploration of the search space and increase the likelihood of success of a global search. The best fitness may not descend continually from generation to generation. An acceleration operation can be applied to improve the fitness. However, a general mixed-integer nonlinear programming (MINLP) problem includes continuous and discrete variables, and the MIHDE [18], [19] can be applied to handle this problem.

II. Problem Description and Formulation

This paper seeks to minimize the system power loss, subject to operating constraints, under a certain load pattern. The objective function of the problem is

$$\min f = \min(P_{T,\,Loss}) \tag{1}$$

where $P_{T,\,Loss}$ is the total real power loss of the system.

The voltage magnitude at each bus must be maintained within limits. The current in each branch must satisfy the branch's capacity. These constraints are expressed as follows:

$$V_{\min} \le |V_i| \le V_{\max} \tag{2}$$

$$|I_i| \le I_{i,\,\max} \tag{3}$$

where

$\lvert V_i\rvert$	voltage magnitude of bus i;
$V_{\min}, V_{\max}$	bus minimum and maximum voltage limits;
$\lvert I_i\rvert, I_{i,\,\max}$	current magnitude and maximum current limit of branch i.

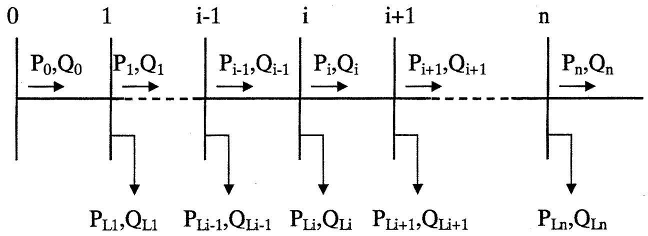

Fig. 1. Single-line diagram of a main feeder.

A set of feeder-line flow formulations is employed. Considering the single-line diagram in Fig. 1, the following set of recursive equations is used to compute power flow [2]

$$P_{i+1} = P_i - P_{Li+1} - R_{i,\,i+1}\left[(P_i^2+Q_i^2)/|V_i|^2\right] \quad (4)$$

$$Q_{i+1} = Q_i - Q_{Li+1} - X_{i,\,i+1}\left[(P_i^2+Q_i^2)/|V_i|^2\right] \quad (5)$$

$$|V_{i+1}|^2 = |V_i|^2 - 2(R_{i,\,i+1}P_i + X_{i,\,i+1}Q_i) + (R_{i,\,i+1}^2 + X_{i,\,i+1}^2)\frac{(P_i^2+Q_i^2)}{|V_i|^2} \quad (6)$$

where P_i and Q_i are the real and reactive powers that flow out of bus i, and P_{Li} and Q_{Li} are the real and reactive load powers in bus i. The resistance and reactance of the line section between buses i and $i+1$ are denoted by $R_{i,\,i+1}$ and $X_{i,\,i+1}$, respectively. The power loss of the line section that connects buses i and $i+1$ is

$$P_{Loss}(i,\,i+1) = R_{i,\,i+1}\,\frac{P_i^2+Q_i^2}{|V_i|^2}. \quad (7)$$

The power loss of the feeder $P_{F,\,Loss}$ may then be determined by summing the losses of all line sections of the feeder, given by

$$P_{F,\,Loss} = \sum_{i=0}^{n-1} P_{Loss}(i,\,i+1). \quad (8)$$

The total system power loss $P_{T,\,Loss}$ is the sum of power losses of all feeders in the system.

III. Improved Mixed-Integer Hybrid Differential Evolution

Details of the algorithms of DE [14]–[16], HDE [17], and MIHDE [18], [19] can be found in the references. The method proposed here is briefly described.

Step 1. Initialization: Initial populations are chosen randomly and attempt to cover the entire parameter space uniformly. A uniform probability distribution for all random variables is assumed

$$(X_i^0,\,Y_i^0) = (X_{\min},\,Y_{\min}) + \rho_i\,(X_{\max}-X_{\min}) + round\,(\rho_i\,(Y_{\max}-Y_{\min})) \quad (9)$$

where $\rho_i \in [0,\,1]$ is a random number, and *round(b)* represents the nearest integer to the real number b. The initial process can randomly produce N_p individuals $(X,\,Y)$.

Step 2. Mutation: A mutant vector is then generated based on the present individual $(X_i^G,\,Y_i^G)$ as follows:

$$\left(U_i^{G+1},\,V_i^{G+1}\right) = \left(X_i^G,\,Y_i^G\right) + \rho_m\left(X_j^G - X_k^G\right) + round\left(\rho_m\left(Y_j^G - Y_k^G\right)\right) \quad (10)$$

where ρ_m is the mutation rate and $\rho_m \in (-1,\,1)$; subscripts i, $j,k \in \{1,\,2,\,\ldots,\,N_p\}$; i, j, and k are all different, and j and k are randomly selected.

Step 3. Crossover: The perturbed individual $(U_i^{G+1},\,V_i^{G+1}) = (U_{1i}^{G+1},\,U_{2i}^{G+1},\,\ldots,\,U_{n_ci}^{G+1},\,V_{1i}^{G+1},\,V_{2i}^{G+1},\,\ldots,\,V_{n_di}^{G+1})$ and the present individual $(X_i^G,\,Y_i^G) = (X_{1i}^G,\,X_{2i}^G,\,\ldots,\,X_{n_ci}^G,\,Y_{1i}^G,\,Y_{2i}^G,\,\ldots,\,Y_{n_di}^G)$ are chosen according to a binomial distribution, to implement the crossover operation, and thus, generate the offspring to diversify the individuals of the next generation

$$U_{hi}^{G+1} = \begin{cases} X_{hi}^G, & \text{if the generated random number} > C_r \\ U_{hi}^{G+1}, & \text{otherwise} \end{cases} \quad (11)$$

$$V_{gi}^{G+1} = \begin{cases} Y_{gi}^G, & \text{if the generated random number} > C_r \\ V_{gi}^{G+1}, & \text{otherwise} \end{cases} \quad (12)$$

where $i = 1,\,\ldots,\,N_p$; $h = 1,\,\ldots,\,n_c$; $g = 1,\,\ldots,\,n_d$, and the crossover factor $C_r \in [0,\,1]$ is selected by the user.

Step 4. Estimation and Selection: The parent is replaced by its offspring if the fitness of the offspring exceeds that of its parent. The parent is retained in the next generation if the fitness of the offspring is worse than that of its parent

$$\left(X_i^{G+1},\,Y_i^{G+1}\right) = \arg\min\left\{f\left(X_i^G,\,Y_i^G\right),\,f\left(U_i^{G+1},\,V_i^{G+1}\right)\right\} \quad (13)$$

$$\left(X_b^{G+1},\,Y_b^{G+1}\right) = \arg\min\left\{f\left(X_i^{G+1},\,Y_i^{G+1}\right)\right\} \quad (14)$$

where $\arg\min$ means the argument of the minimum.

Step 5. Accelerated Operation if Necessary: If the best fitness at the present generation is not further improved by the mutation and crossover operations, then the present best individual is pushed toward a better point. Thus, the accelerated phase is represented as follows:

$$\left(X_b^N,\,Y_b^{G+1}\right) = \begin{cases} \left(X_b^{G+1},\,Y_b^{G+1}\right), & \text{if } f\left(X_b^{G+1},\,Y_b^{G+1}\right) < f\left(X_b^N,\,Y_b^{G+1}\right) \\ \left(X_b^{G+1},\,Y_b^{G+1}\right) - \rho_a\nabla_X f(X,\,Y)\Big|_{(X_b^{G+1},\,Y_b^{G+1})}, & \text{otherwise} \end{cases} \quad (15)$$

where $(X_b^N,\,Y_b^{G+1})$ is the now best solution. The gradient of the objective function $\nabla_X f(X,\,Y)$ can be calculated with finite variation. The step size $\rho_a \in [0,\,1]$ is determined according to the descent property. If the descent property is satisfied, that is

$$f\left(X_b^N,\,Y_b^{G+1}\right) < f\left(X_b^{G+1},\,Y_b^{G+1}\right) \quad (16)$$

then $(X_b^N,\,Y_b^{G+1})$ becomes a candidate in the next generation for addition into this population to replace the weakest individual. However, if the descent property is not satisfied, then the step size is lowered a little. The descent method is repeated to search (X_b^N, Y_b^{G+1}) until $f(X_b^N, Y_b^{G+1})$ is sufficiently small or a specified number of iterations is performed.

Step 6. Migration Operation if Necessary: A migration phase is introduced to regenerate a newly diverse population of individuals to enhance the investigation over the search space, and thus, reduce the pressure of selection from a small population. The new populations are obtained based on the best individual (X_b^{G+1}, Y_b^{G+1}). The hth or gth gene of the ith individual is as follows:

$$X_{hi}^{G+1} = \begin{cases} X_{hi}^{G+1} + \rho_1 \left(X_{h\min} - X_{hb}^{G+1}\right), \\ \qquad \text{if } \rho_3 < \dfrac{X_{hi}^{G+1} - X_{h\min}}{X_{h\max} - X_{h\min}} \\ X_{hi}^{G+1} + \rho_1 \left(X_{h\max} - X_{hb}^{G+1}\right), \\ \qquad \text{otherwise} \end{cases} \tag{17}$$

$$Y_{gi}^{G+1} = \begin{cases} Y_{gb}^{G+1} + round\left(\rho_2 \left(Y_{g\min} - Y_{gb}^{G+1}\right)\right), \\ \qquad \text{if } \rho_3 < \dfrac{Y_{gb}^{G+1} - Y_{g\min}}{Y_{g\max} - Y_{g\min}} \\ Y_{gb}^{G+1} + round\left(\rho_2 \left(Y_{g\max} - Y_{gb}^{G+1}\right)\right), \\ \qquad \text{otherwise} \end{cases} \tag{18}$$

where ρ_1, ρ_2, and ρ_3 are randomly generated numbers uniformly distributed in the range [0, 1]; $i = 1, \ldots, N_p$; $h = 1, \ldots, n_c$; and $g = 1, \ldots, n_d$.

The migration operation in MIHDE [19] is performed only if the population diversity ρ is smaller than the desired tolerance of population diversity ε_1

$$\rho = \left\{ \sum_{\substack{i=1 \\ i \neq b}}^{N_p} \left(\sum_{h=1}^{N_c} \eta_X + \sum_{g=1}^{N_d} \eta_Y \right) \right\} \Big/ (N_c + N_d)(N_p - 1) < \varepsilon_1 \tag{19}$$

where

$$\eta_X = \begin{cases} 1, & \text{if } \left|(X_{ji} - X_{jb})/X_{jb}\right| > \varepsilon_2 \\ 0, & \text{otherwise} \end{cases} \tag{20}$$

$$\eta_Y = \begin{cases} 0, & \text{if } Y_{gi}^{G+1} = Y_{bi}^{G+1} \\ 1, & \text{otherwise.} \end{cases} \tag{21}$$

Parameter ε_2 expresses the gene diversity with respect to the best individual. η_X and η_Y are the scale indices.

Equation (20) will not converge when the iteration processes meet $X_{jb} = 0$. Thus, (20) does not perfectly achieve the optimum solution. This research suggests an improvement that depends on the 2-norm concept. The migration operation of MIHDE can be improved as follows:

$$\eta_X = \begin{cases} 0, & \text{if } \displaystyle\sum_{h=1}^{N_c} (X_{hi} - X_{hb})^2 < \varepsilon_2 \\ 1, & \text{otherwise.} \end{cases} \tag{22}$$

Step 7: Steps 2 to 6 are repeated until the maximum number of iterations or the desired fitness is obtained.

IV. Calculation Procedures

Implementation of the problem begins with encoding parameters. A tie switch (TS) and some sectionalizing switches with the feeders form a loop. A particular switch of each loop is selected to open to make the loop radial such that the selected switch naturally becomes a tie switch. The network reconfiguration problem is identical to the problem of selecting an appropriate tie switch for each loop to minimize the power loss. A coding scheme that recognizes the positions of the tie switch is proposed. The total number of tie switches is kept constant, regardless of any change in the system's topology or the tie switches' positions. Fig. 2 shows an individual that is composed of TS positions. Different switches from a loop are selected for cutting to become a tie switch. The fitness value associated with this proposed configuration is determined, and a feasible solution (radial configuration) with minimum loss is obtained as well.

The fitness function to be minimized is as follows:

$$\min f = \min P_{T,\,Loss} = \min \sum_{k=1}^{M} \left(\sum_{i=0}^{n_k - 1} P_{Loss}(i,\, i+1) \right) \tag{23}$$

where M is the total number of feeders of the system and n_k is the total number of sections of feeder k. Fig. 3 shows a flowchart of the main computational procedures. The proposed method mainly involves power loss computation, bus voltage determination, and MIHDE application. The computation finds config-

TS No.(1)	TS No.(2)	...	TS No.(n)

Fig. 2. Individual composing of n tie switches.

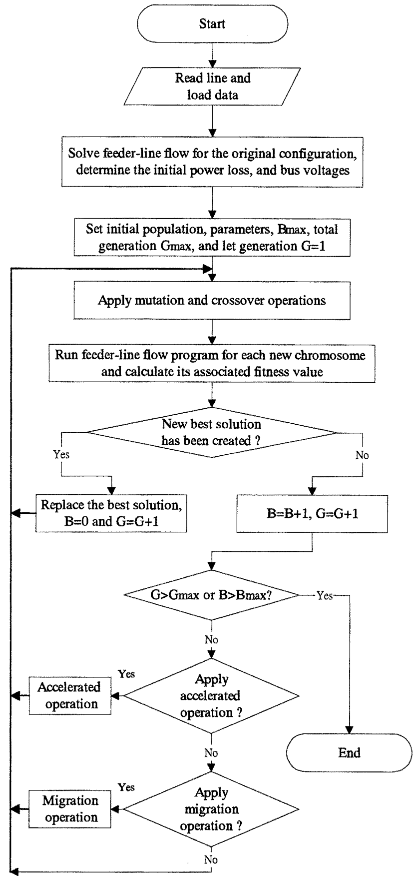

Fig. 3. Main computational procedures.

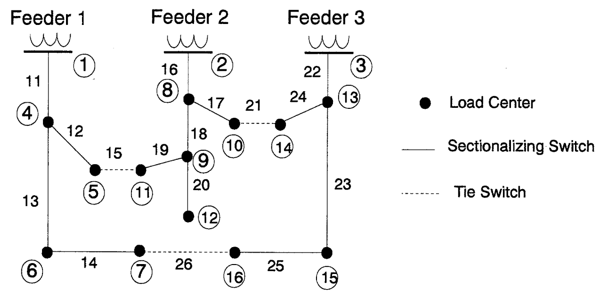

Fig. 4. Three-feeder distribution system for example 1.

TABLE I
INPUT DATA FOR EXAMPLE 1

Bus to bus	Section resistance (P.U.)	Section reactance (P.U.)	End bus real load (MW)	End bus reactive load (MVAR)	End bus fixed capacitor (MVAR)
1-4	0.075	0.1	2.0	1.6	
4-5	0.08	0.11	3.0	1.5	1.1
4-6	0.09	0.18	2.0	0.8	1.2
6-7	0.04	0.04	1.5	1.2	
2-8	0.11	0.11	4.0	2.7	
8-9	0.08	0.11	5.0	3.0	1.2
8-10	0.11	0.11	1.0	0.9	
9-11	0.11	0.11	0.6	0.1	0.6
9-12	0.08	0.11	4.5	2.0	3.7
3-13	0.11	0.11	1.0	0.9	
13-14	0.09	0.12	1.0	0.7	1.8
13-15	0.08	0.11	1.0	0.9	
15-16	0.04	0.04	2.1	1.0	1.8
5-11	0.04	0.04			
10-14	0.04	0.04			
7-16	0.12	0.12			

urations of switches in various states so that the value of the objective function is successively reduced.

V. APPLICATION EXAMPLES

The proposed method was implemented using MATLAB and run on a Pentium II-266-MHz computer. Two illustrative examples are discussed.

Example 1: The first example is a three-feeder distribution system [1], as shown in Fig. 4. Table I shows the input data for this example. The system consists of three feeders, 13 normally closed switches, and three normally open switches. The system load is assumed to be constant and $S_{base} = 100$ MVA. MIHDE is applied by setting the parameters $N_p = 5$, $G_{\max} = 50$, $B_{\max} = 40$, $\rho_m = 0.1$, $C_r = 0.5$, $\varepsilon_1 = 0.3$, and $\varepsilon_2 = 3$. Table II summarizes the computational results obtained by applying the proposed method (MIHDE). Computational results obtained by applying SA [7] are also listed in the table for comparison. SA is applied by setting the initial temperature $T_0 = 100$, final temperature $T_f = 25$, cooling rate $\alpha = 0.95$, and maximum iteration $G_{\max} = 10$. Obviously, results obtained from these two methods are nearly the same, except that the proposed method required slightly less computation time than the SA method does.

TABLE II
NUMERICAL RESULTS OF EXAMPLE 1

Main items	Original configuration	The proposed method	SA [7]
Tie switches	15, 21, 26	19, 17, 26	19, 17, 26
Power loss (kW)	511.4	466.1	466.1
Voltage Magnitude (p.u.)	V_{max}=1.0000 (Bus 1,2,3)	V_{max}=1.0000 (Bus 1,2,3)	V_{max}=1.0000 (Bus 1,2,3)
	V_{min}=0.9693 (Bus 12)	V_{min}=0.9716 (Bus 12)	V_{min}=0.9716 (Bus 12)
Number of tie switches changed	-	2	2
Loss reduction	-	8.86%	8.86%
CPU time (second)	-	7.70	8.30

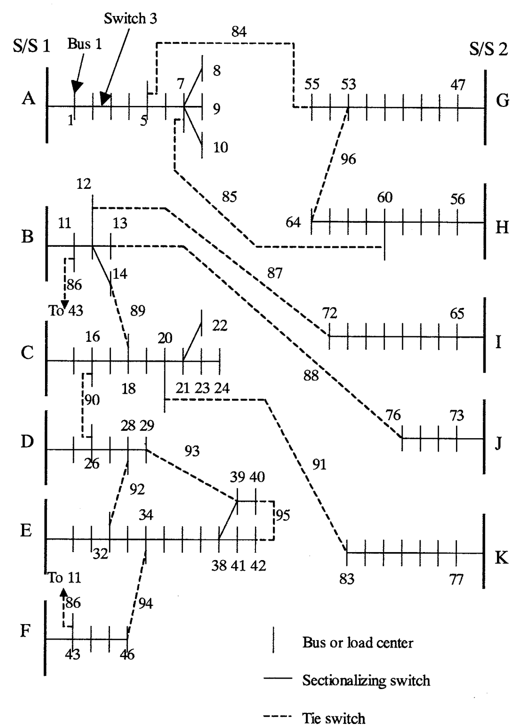

Fig. 5. Distribution system of Taiwan Power Company for example 2.

Example 2: The second example is a practical distribution network of the Taiwan Power Company (TPC). Its conductors mainly employ overhead lines ACSR 477 KCM and underground copper conductor 500 KCM. Fig. 5 shows the system and Table III shows related data. The system is 3-phase and 11.4 kV. It consists of 11 feeders, 83 normally closed switches, and 13 normally open switches. Three-phase balance and constant load are assumed. The parameters for the improved MIHDE application are $G_{\max} = 1000$, $B_{\max} = 1000$, $N_p = 5$, $\rho_m = 0.1$, $C_r = 0.5$, $\varepsilon_1 = 0.3$, and $\varepsilon_2 = 5$. The voltage constraints are $V_{\max} = 11.4 * 1.05 = 11.97$ kV and $V_{\min} = 11.4 * 0.95 = 10.83$ kV. The initial voltage at buses 4 through 10, 71, 72, and 83 is below $V_{\min}$. After network reconfiguration, these bus voltages satisfy the voltage constraints. Table IV shows the computational results. Before network reconfiguration, feeder A has a heavy load and the

TABLE III
THREE-PHASE LOAD AND LINE DATA OF EXAMPLE 2

Bus to bus	Section resistance (Ω)	Section reactance (Ω)	End bus real load (kW)	End bus reactive load (kvar)
A-1	0.1944	0.6624	0	0
1-2	0.2096	0.4304	100	50
2-3	0.2358	0.4842	300	200
3-4	0.0917	0.1883	350	250
4-5	0.2096	0.4304	220	100
5-6	0.0393	0.0807	1100	800
6-7	0.0405	0.1380	400	320
7-8	0.1048	0.2152	300	200
7-9	0.2358	0.4842	300	230
7-10	0.1048	0.2152	300	260
B-11	0.0786	0.1614	0	0
11-12	0.3406	0.6944	1200	800
12-13	0.0262	0.0538	800	600
12-14	0.0786	0.1614	700	500
C-15	0.1134	0.3864	0	0
15-16	0.0524	0.1076	300	150
16-17	0.0524	0.1076	500	350
17-18	0.1572	0.3228	700	400
18-19	0.0393	0.0807	1200	1000
19-20	0.1703	0.3497	300	300
20-21	0.2358	0.4842	400	350
21-22	0.1572	0.3228	50	20
21-23	0.1965	0.4035	50	20
23-24	0.1310	0.2690	50	10
D-25	0.0567	0.1932	50	30
25-26	0.1048	0.2152	100	60
26-27	0.2489	0.5111	100	70
27-28	0.0486	0.1656	1800	1300
28-29	0.1310	0.2690	200	120
E-30	0.1965	0.3960	0	0
30-31	0.1310	0.2690	1800	1600
31-32	0.1310	0.2690	200	150
32-33	0.0262	0.0538	200	100
33-34	0.1703	0.3497	800	600
34-35	0.0524	0.1076	100	60
35-36	0.4978	1.0222	100	60
36-37	0.0393	0.0807	20	10
37-38	0.0393	0.0807	20	10
38-39	0.0786	0.1614	20	10
39-40	0.2096	0.4304	20	10
38-41	0.1965	0.4035	200	160
41-42	0.2096	0.4304	50	30
F-43	0.0486	0.1656	0	0
43-44	0.0393	0.0807	30	20
44-45	0.1310	0.2690	800	700
45-46	0.2358	0.4842	200	150
G-47	0.2430	0.8280	0	0
47-48	0.0655	0.1345	0	0
48-49	0.0655	0.1345	0	0
49-50	0.0393	0.0807	200	160
50-51	0.0786	0.1614	800	600
51-52	0.0393	0.0807	500	300
52-53	0.0786	0.1614	500	350
53-54	0.0524	0.1076	500	300
54-55	0.1310	0.2690	200	80
H-56	0.2268	0.7728	0	0
56-57	0.5371	1.1029	30	20
57-58	0.0524	0.1076	600	420
58-59	0.0405	0.1380	0	0
59-60	0.0393	0.0807	20	10
60-61	0.0262	0.0538	20	10
61-62	0.1048	0.2152	200	130
62-63	0.2358	0.4842	300	240
63-64	0.0243	0.0828	300	200
I-65	0.0486	0.1656	0	0
65-66	0.1703	0.3497	50	30
66-67	0.1215	0.4140	0	0
67-68	0.2187	0.7452	400	360
68-69	0.0486	0.1656	0	0
69-70	0.0729	0.2484	0	0
70-71	0.0567	0.1932	2000	1500
71-72	0.0262	0.0528	200	150
J-73	0.3240	1.1040	0	0
73-74	0.0324	0.1104	0	0
74-75	0.0567	0.1932	1200	950
75-76	0.0486	0.1656	300	180
K-77	0.2511	0.8556	0	0
77-78	0.1296	0.4416	400	360
78-79	0.0486	0.1656	2000	1300
79-80	0.1310	0.2640	200	140
80-81	0.1310	0.2640	500	360
81-82	0.0917	0.1883	100	30
82-83	0.3144	0.6456	400	360
5-55	0.1310	0.2690	-	-
7-60	0.1310	0.2690	-	-
11-43	0.1310	0.2690	-	-
12-72	0.3406	0.6994	-	-
13-76	0.4585	0.9415	-	-
14-18	0.5371	1.0824	-	-
16-26	0.0917	0.1883	-	-
20-83	0.0786	0.1614	-	-
28-32	0.0524	0.1076	-	-
29-39	0.0786	0.1614	-	-
34-46	0.0262	0.0538	-	-
40-42	0.1965	0.4035	-	-
53-64	0.0393	0.0807	-	-

TABLE IV
NUMERICAL RESULTS OF EXAMPLE 2

Main items		Original configuration	The proposed method	SA [7]
Tie switches		84, 85, 86, 87, 88,89, 90, 91, 92, 93,94, 95, 96	55, 7, 86, 72, 13,89, 90, 83, 92, 39,34, 41, 62	55, 7, 86, 72, 13,89, 90, 83, 92, 39,34, 41, 62
Power loss (kW)		531.99	469.88	469.88
Bus voltages violated the voltage constraints (kV)	substation	11.400	11.400	11.400
	V_4	10.773	11.019	11.019
	V_5	10.643	10.951	10.951
	V_6	10.620	10.942	10.942
	V_7	10.602	10.912	10.912
	V_8	10.595	10.905	10.905
	V_9	10.585	10.895	10.895
	V_{10}	10.594	10.904	10.904
	V_{71}	10.818	10.866	10.866
	V_{72}	10.816	11.195	11.195
	V_{83}	10.806	10.958	10.958
System $V_{\min}$ (kV)		10.585 (bus 9)	10.866 (bus 71)	10.866 (bus 71)
Number of tie switches changed		-	9	9
Loss reduction		-	11.68%	11.68%
CPU time (second)		-	36.15	195.21

voltages of some buses are less than their voltage limits as shown in Table IV. After reconfiguration, the system displays an obvious loss reduction, and all violated buses were improved to have their voltage magnitude being within the voltage limits. For comparison, this example was also resolved by the SA with parameters $T_0 = 100$, $T_f = 25$, $\alpha = 0.95$, and $G_{\max} = 1000$. From Table IV, it can be seen that the two methods almost have the same results, except that the proposed method spent much less computation time than the SA method.

VI. CONCLUSIONS

A useful network reconfiguration approach that applies an improved MIHDE for loss reduction in distribution systems is proposed. A solution algorithm was developed based on the improved MIHDE for application to the network reconfiguration problem. The application examples lead to some important observations.

1) Power losses of distribution systems can be effectively reduced by proper feeder reconfiguration.
2) The voltage profile can be improved over that of the initial system, via feeder reconfiguration.
3) The migration operation of the MIHDE was improved. By applying acceleration and migration, the MIHDE method has the merit of requiring a smaller population for the solution search. This fact is especially useful for large-scale network applications.
4) Example applications support that the proposed method requires relatively less computation burden than the SA method in large network reconfiguration applications.

This method is helpful for operating an existing system and planning a future system. Reactive power compensation and network reconfiguration should be considered simultaneously to yield greater reduction in power loss and improvement in voltage.

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