Study of Reconfiguration for the Distribution System With Distributed Generators

Yuan-Kang Wu, *Member, IEEE*, Ching-Yin Lee, Le-Chang Liu, and Shao-Hong Tsai

***Abstract*—This paper proposes a reconfiguration methodology based on an Ant Colony Algorithm (ACA) that aims at achieving the minimum power loss and increment load balance factor of radial distribution networks with distributed generators. A 33-bus distribution system and a Tai-Power 11.4-kV distribution system were selected for optimizing the configuration and to demonstrate the effectiveness of the proposed methodology for solving the optimal switching operation of distribution systems. The simulation results have shown that lower system loss and better load balancing will be attained at a distribution system with distributed generation (DG) compared to a system without DG. Furthermore, the simulation results also satisfy and suitability reference merits of the proposal method.**

***Index Terms*—Ant colony algorithm, ant system, distributed generation, distribution system, feeder reconfiguration.**

I. Introduction

MOST of electrical distribution systems operate in radial configuration; two types of switches are used in distribution systems: sectionalizing-switches that remain normally closed, and tie-switches that remain normally open. There are several operational schemes in electrical distribution systems; one of them is "distribution feeder reconfiguration", which can bring nearly minimization of real loss, improvement in voltage profile, and relieving of overloads in the network. Moreover, distributed generation (DG) is playing an important role in electrical systems. The accepted connection of high number of DG units to electrical power systems may cause some problems in power system operation and planning. The conventional power distribution systems have radial networks with unidirectional power flows. With the advent of DGs, however, power distribution systems would have locally looped networks with bidirectional power flows. The problems of power system operations and planning schemes will be arising due to the increase of distribution generation units to the distribution power systems.

Many recent researches on network reconfiguration have focused on the minimum losses configuration problem. Various methods have been proposed to solve for the minimum loss configuration in acceptable time, and each method has different advantages and disadvantages. For example, the distribution system reconfiguration for loss reduction was first proposed by Merlin *et al.* [1]. They employed a blend of optimization techniques and heuristics to determine the minimal loss operation configuration. Since then, many techniques have been proposed: Baran and Wu's method [2] on feeder reconfigurations for loss reduction was based on branch exchange. This approach starts with a feasible configuration of the network; then one of the switches is closed and others are opened based on heuristics and approximate formulas for change in losses. Nahman *et al.* [3] presented another heuristic approach; but this search technique also does not necessarily guarantee global optimization.

A genetic algorithm (GA) is more likely to obtain the global optimal solution than heuristic search methods and takes less time than the exhaustive search [4]–[7]. The GA has the main advantage of using representation of objects (strings) instead of manipulating the objects themselves, but its main problem is the coding of the objects into strings. B. Venkatesh *et al.* [8] proposed a new optimal reconfiguration method for radial distribution systems. The proposed method is based upon a maximum loadability index and uses fuzzy modeling methods to model two objectives of loadability margin maximization and obtain the best voltage profile. In [9], [10], simulated annealing (SA) is particularly well suited for solving combinatorial optimization problems. The SA has the ability of escaping local minima by incorporating a probability function in accepted or rejected new solutions. In [11], the artificial intelligent Petri nets were applied to find the optimal switching operation for service restoration and feeder loading balance for distribution systems. After the fault location has been identified and isolated for a system fault contingency, the Petri nets model with inference mechanism is derived and applied to solve the optimal load transfer among distribution feeders. In [12], the variable scaling hybrid differential evolution (VSHDE) for solving network reconfiguration of distribution systems is a combination of genetic algorithm and a power flow method based on the heuristic algorithm for determining the minimum loss configuration of radial distribution networks.

Many optimization problems in powers systems are combinatorial optimization ones. They are difficult to solve by traditional linear or nonlinear programming methods. Therefore, the Ant Colony Search (ACS) algorithm has been utilized in this paper to try to find a near-optimum solution. The characteristics of the ACS algorithm include positive feedback, distributed computation, and a constructive greedy heuristics. Positive feedback makes sure of a rapid search for a global solution; distributed

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computation avoids premature convergence, and constructive greedy heuristics help find acceptable solution as soon as possible. These properties are counterbalanced by the fact that, for some applications, the ACS can outperform other heuristics.

The main advantage of this paper is to propose a novel feeder reconfiguration technology based on the ACS algorithm with DG. In general, the ACS algorithm is a useful evolutionary algorithm with strong global search ability. Its positive feedback would account for rapid discovery of good solutions in comparison to GA algorithm. Therefore, the proposed method in this paper can provide another useful algorithm for the feeder reconfiguration work.

II. Problem Formulation

Feeder reconfiguration is a very important function of automated distribution systems to reduce distribution feeder losses, load balancing and improve system security. Loads can be transferred from feeder to feeder by changing the open and close states of the feeder switches. In this paper, network reconfiguration for loss minimization can be formulated as follows:

$$\min LP_{\text{loss}} = \sum_{i=1}^{n_b} r_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{1}$$

where P_i and Q_i are, respectively, the real and reactive line powers flowing out of bus i, n_b is the number of branch, r_i and V_i is the resistance and voltage magnitude at bus i, respectively, subject to the following.

(a) Voltage constraint: voltage magnitude of each branch (feeders, laterals, switches) must lie within their permissible ranges to maintain power quality.
(b) Current constraint: current magnitude of each branch must lie within their permission ranges.
(c) Power source limit constraint: total loads of a certain partial network can not exceed the capacity limit of the corresponding power source.
(d) Isolation constraint: all of nodes are energized.
(e) Radial network constraint: distribution networks should be composed of radial structure operation.

In our research, a 33-bus test system and a practical distribution network of Taiwan Power Company (TPC) have been utilized as our test systems. The 33-bus test system has been widely used as a typical circuit on the feeder reconfiguration research work, and the proposed TPC network is a common representative distribution circuit in Taiwan, which is also suitable as our demonstration network. The details for these system topologies and parameters will be represented in Section V and the Tables XI and XII, respectively.

For load balancing, we use a load balancing index in the 33-bus test system for the whole system as the sum of these measures

$$LB_i = \sum_{i=1}^{n_b} \left(\frac{S_i}{S_i^{\max}} \right)^2 = \sum_{i=1}^{n_b} \frac{P_i^2 + Q_i^2}{S_i^{\max 2}} \tag{2}$$

where S_i is the complex power at the sending end of branch i; $S_i^{\max}$ is used as a measure of how much the branch i is loaded. The branch can be a transformer, a tie line with a sectionalizing switch, or simply a line section. The constraint of load balancing is the same as (1).

In the TPC distribution network, the object of algorithm is to make distribution network reach the load balancing after the reconfiguration and to satisfy the load level of transformer and feeder line. It may be computed as follows:

$$B(T) = \sum_{T_i} FN_{T_i} \times \left(\frac{I_{T_i}}{I_{T,avg}} \right)^2 \tag{3}$$

$$B(F) = \sum_{F_j} \left(\frac{I_{F_j}}{I_{F_{j,avg}}} \right)^2 \tag{4}$$

$$I_{T,avg} = \frac{1}{nt} \sum_{i=1}^{nt} I_{T_i} \tag{5}$$

$$I_{F_{j,avg}} = \frac{1}{nf} \sum_{j=1}^{nf} I_{F_j} \tag{6}$$

where $B(T)$ is the main transformer load balancing index; $B(F)$ is the feeder line load balancing index; FN_{Ti} is the feeder line number through main transformer T_i; I_{Ti} is the total current of feeder line F_j; nt is the total main transformer number; nf is the total feeder line number; the entire optimization model of load balancing is the combination of (3) and (4), which is denoted as follows:

$$\min \text{OPT} = W_T \cdot B(T) + W_F \cdot B(F) \tag{7}$$

where W_T and W_F is the load balancing weight of main transformer and feeder line, respectively. The objective function can take different importance of overload balancing weights into account, and the constraint of (7) is the same as (1).

III. Ant Colony Search

The ACS is based on the behavior of the ants while searching for food. Each ant leaves a pheromone trail on the path from nest to food. The pheromone evaporates with time, so that the other ants can reach the food by following the "shortest" paths marked with strong pheromone quantities [13]–[16]. Some ACS applications recently proposed in the distribution system area concern feeder restoration and optimum switch adjustments for distribution system planning. In Fig. 1(a), ants are moving in a straight line that connects a food source and their home colony. Once an obstacle appears in the straight line as shown in Fig. 1(b), the environment will change and the ants that are just in the front cannot continue following the pheromone trail. Therefore those ants will choose the paths randomly, which means that the ants will choose the path to point C or D with the same probability. Later on, those ants that choose the shorter path around the obstacle will move faster than the ants that choose the longer path. The pheromones on the shorter path will be reconstructed more rapidly and this will cause more ants to choose the shorter path. After all, all ants will choose the same path due to the positive feedback. The full procedures of the ACS algorithm can be summarized as follows.

Step 1) Each ant is placed on a starting state. Then ant will build a full path, from the beginning to the end state,

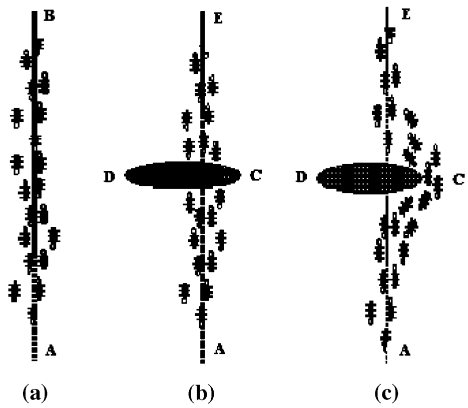

Fig. 1. Behavior of ants.

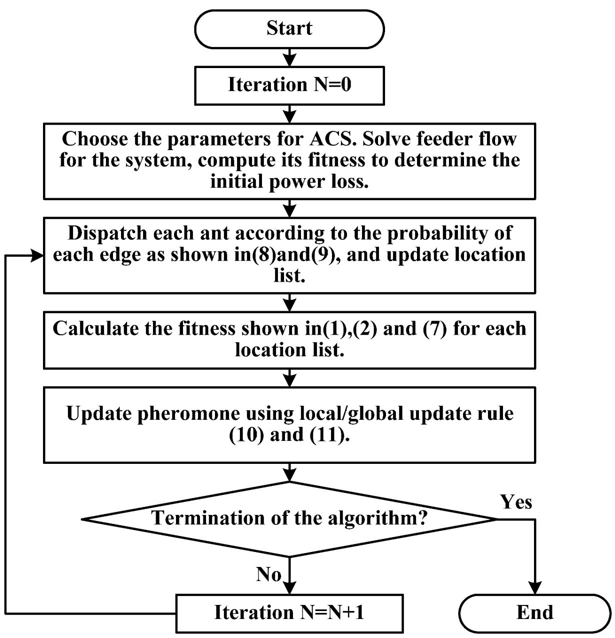

Fig. 2. Computation procedure of the proposed ACS method.

through the repetitive application of state transition rule as follows:

$$P_{ij}^{k} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}\cdot[\eta_{ij}]^{\beta}}{\sum\limits_{u\in J_k(i)}[\tau_{iu}]^{\alpha}\cdot[\eta_{iu}]^{\beta}}, & \text{if } j \in J_k(i) \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

$$j = \begin{cases} \arg\max_{u\in J_k(i)} \left\{[\tau_{iu}]^{\alpha}\cdot[\eta_{iu}]^{\beta}\right\}, & \text{if } q \le q_o \\ S, & \text{otherwise} \end{cases} \tag{9}$$

where τ is the pheromone which deposited on the edge between node i and j; η is the inverse of the edge distance; $J_k(i)$ is the set of nodes that remain to be visited by ant k positioned on node i; α and β are parameters that control the relative importance of trail versus visibility; q is a random number uniformly distributed in $[0\ldots1]$; q_0 is a parameter $(0 \le q_0 \le 1)$, and S is a random variable selected according to the probability distribution given in (8). The state transition rule resulting from (9) and (8) is called pseudorandom-proportional rule. The state transition rule (9) favors transitions towards nodes connected by short edges and with a large amount of pheromone. The parameter q_0 determines the relative importance of exploitation versus exploration. Every time an ant in city i has to choose a city j to move to, which samples a random number $0 \le q_0 \le 1$. If $q \le q_0$, then the best edge [according to (9)] is chosen (exploitation).

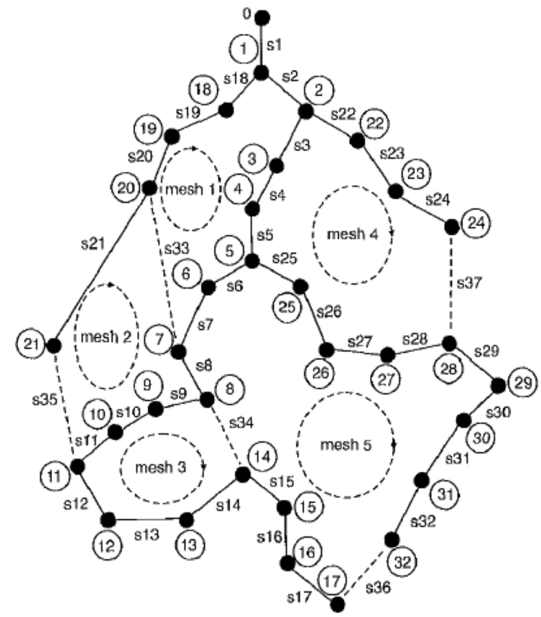

Fig. 3. 33-bus distribution system.

TABLE I
INSTALLATION NODE AND CAPACITY OF DG

Node #	Capacity (kW/p.f.)
3	50/0.8
6	100/0.9
24	200/0.9
29	100/1

Step 2) While constructing its tour, an ant also modifies the amount of pheromone on the visited path by applying the local updating rule

$$\tau_{ij} = (1-\rho)\cdot\tau_{ij} \tag{10}$$

where ρ is a heuristically defined parameter. The local updating rule is intended to shuffle the search process. Therefore, the desirability of paths can be dynamically changed. The nodes visited earlier by a certain ant can be also explored later by other ants. The search space can be therefore extended. Furthermore, ants will make a better use of pheromone information. Without local updating rules, all ants would search in a narrow neighborhood of the best previous tour.

Step 3) Once all ants have terminated their tour, the amount of pheromone on the edge is modified again through the global updating rule. In other words, the pheromone updating rules, shown as follows in (11) and (12), are designed so that they tend to give

TABLE II
33-BUS SYSTEM WITHOUT DG

	Open Switch	P loss (kW)	Reduction (%)
Initial	s33,s34,s35,s36,s37	199.3	-
GA	s7,s9,s14,s28,s32	137	31.259
AS	s6,s9,s14,s26,s31	153.18	30.108
ACS	s7,s9,s14,s28,s32	137	31.259

TABLE III
33-BUS SYSTEM WITH DG

	Open Switch	P loss (kW)	Reduction (%)
Initial	s33,s34,s35,s36,s37	164	17.711
GA	s7,s9,s14,s28,s32	112	43.803
AS	s6,s9,s14,s26,s31	129.5	35.022
ACS	s6,s10,s14,s17,s28	110.26	44.626

TABLE IV
LOAD BALANCING INDEX WITHOUT DG

	Open Switch	Balancing index	Reduction (%)
Initial	s33,s34,s35,s36,s37,s38	148.1634	-
AS	s6,s11,s31,s34,s37	111.0251	25.065
ACS	s7,s10,s14,s28,s32	105.8324	28.57

TABLE V
LOAD BALANCING INDEX WITH DG

	Open Switch	Balancing index	Reduction (%)
Initial	s33,s34,s35,s36,s37,s38	118.9525	-
AS	S6,s9,s12,s28,s31	89.9104	24.4148
ACS	s7,s11,s14,s28,s32	83.8635	29.4938

more pheromone to paths that should be visited by ants:

$$\tau_{ij} = (1-\sigma)\cdot\tau_{ij} + \sigma\cdot\Delta\tau_{ij} \tag{11}$$

$$\Delta\tau_{ij} = \begin{cases} \frac{Q}{L_{best}}, & \text{if } route(i,j) \text{ is global best path} \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where σ is the pheromone decay parameter and $\Delta\tau_{ij}$ is the distance of the globally best tour from the beginning of the trial. This rule is intended to make the search more directed; therefore, the capability of finding the optimal solution can be enhanced through this rule in the problem solving process.

IV. Computational Procedure of the Proposed Method

The solution process begins by closing all the switches in the distribution system, sectionalizing as well as tie, and therefore the system is divided into a number of loops. The network reconfiguration problem is identical to the problem of selecting an appropriate tie switch for each loop to make the loop radial. The total number of tie switches is kept constant, regardless of any change in the systems topology or the tie switch positions. Different switches from a loop are selected for cutting the loop circuit; after each loop is made radial, a configuration is proposed. The flowchart of the proposed ACS method applied to the feeder reconfiguration work is shown in Fig. 2.

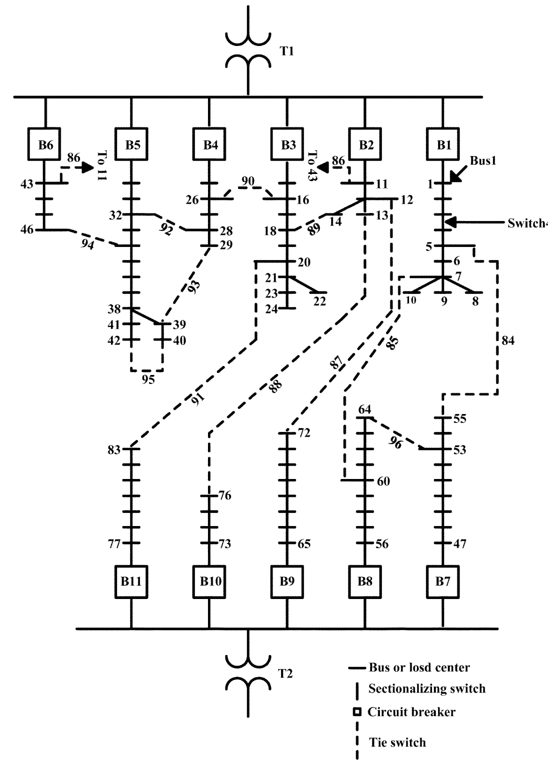

Fig. 4. Typical Taiwan Power Company distribution system topology.

TABLE VI
INSTALLATION NODE AND CAPACITY OF DG

Bus	Capacity (kW/p.f.)
7	250/0.8
12	450/0.9
19	500/0.8
28	400/0.9
34	500/0.85
71	500/1
75	400/0.85
79	400/0.9

V. Test Case

Example 1: The first example is a 33-bus distribution system, as shown in Fig. 3. Table I shows the DG installation nodes with associated capacity for the 33-bus test system. The system consists of one source transformer, 32 bus-bars, and 5 tie switches. The total active and reactive power for the whole system loads are 5048.26 kW and 2547.32 kVAR, respectively. In Fig. 3, The number in circle and number with 's' indicate the node and the line switch, respectively. In addition, the dashed line s33, s34, s35, s36, and s37 signify the original normal open tie switches. For comparison with [4], four cases are considered in our study; i.e., the initial network without DG/with DG and the optimum network without DG/with DG. The proposed method has been implemented by using MATLAB programs and run on a Pentium IV-3.4 GHz personal computer.

Tables II and III show the comparison with [4]. The Ant Search (AS) and ACS algorithms were utilized respectively to

TABLE VII
LOSS MINIMIZATION WITHOUT DG

	Switch Open	P loss (kW)	Reduction (%)
Initial	s84,s85,s86,s87,s88 ,s89,s90,s91,s92, s93,s94,s95,s96	531.99	-
GA	s7,s33,s55,s61 s72, s83, s86, s88,s89,s90,s92,s93,s95	471.5095	11.369
AS	s7,s13,s33,s39,s54, s61,s71,s86,s89, s90,s91,s92,s95	519.2076	2.403
ACS	s7,s13,s34,s39,s41, s55,s62,s72,s83, s86,s89,s90,s92	471.0776	11.449

TABLE VIII
LOSS MINIMIZATION WITH DG

	Switch Open	P loss (kW)	Reduction (%)
Initial	s84,s85,s86,s87,s88,s89,s90,s91,s92, s93,s94,s95,s96	425.1312	-
GA	s7, s33, s55, s61, s72, s83, s86, s88, s89, s90, s92, s93, s95	384.6308	9.527
AS	s6,s13,s34,s55,s61,s72,s86,s89,s90,s 91,s92,s93,s95	414.3321	2.540
ACS	s7,s13,s34,s39,s41, s55,s62,s72,s83, s86,s89,s90,s92	383.5245	9.787

TABLE IX
TPC SYSTEM WITHOUT DG

Main Tr.	Feeder	Weight	Load current after switch operation (A)				
		Initial current	WT=1 WF=0	WT=0.75 WF=0.25	WT=0.5 WF=0.5	WT=0.25 WF=0.75	WT=0 WF=1
T1		985	837	866	888	938	913
	F1	194	66	120	130	156	156
	F2	160	113	112	124	124	124
	F3	213	238	213	213	238	213
	F4	134	151	151	139	151	151
	F5	218	130	141	141	130	118
	F6	66	139	129	141	139	151
T2		706	851	827	806	755	780
	F7	157	139	156	146	136	136
	F8	87	146	162	162	146	146
	F9	159	221	159	148	148	148
	F10	92	159	139	139	139	139
	F11	211	139	211	211	186	211
Balancing index			10.98	11.13	11.25	11.31	11.37
Switch operation			s6,s13,s33, s39,s41,s55, s83,s86,s87, s89,s90,s92, s96	s7,s13,s34, s39,s41,s61, s84,s86,s87, s89,s90,s91, s92	s7,s13,s34, s39,s42,s55, s72,s86,s89, s90,s91,s92, s96	S7,s13,s33, s39,s41,s83, s54,s64,s86, s89,s72,s90, s92	s7,s13,s32, s33,s39,s42, s54,s64,s91, s90,s89,s72, s86

compare the performance with the GA algorithm. In comparison with the AS algorithm, the ACS algorithm modifies its state transition and global updating rules. In addition, the local updating rule is applied into the ACS algorithm. The details about the difference between the AS and ACS can be referred to [13] and [14].

From the result of our case study, it can be seen from the 33-bus test system that DG has the effects of loss reduction improvement over feeders in this particular case, and the topological structures of optimum network without DG are different from those with DG. Based on the 33-bus system with DG, the proposed ACS method in this paper has lower loss reduction than the method proposed in [4].

TABLE X
TPC SYSTEM WITH DG

Main Tr.	Feeder	Weight	Load current after switch operation (A)				
		Initial current	WT=1 WF=0	WT=0.75 WF=0.25	WT=0.5 WF=0.5	WT=0.25 WF=0.75	WT=0 WF=1
T1		866	750	769	749	768	795
	F1	180	107	116	107	116	143
	F2	135	87	99	87	99	99
	F3	181	182	181	182	181	181
	F4	111	117	130	114	136	128
	F5	193	141	118	130	118	118
	F6	66	116	125	129	118	126
T2		643	764	752	764	743	715
	F7	157	191	173	191	164	136
	F8	87	129	146	129	146	146
	F9	140	139	128	139	128	128
	F10	70	117	117	117	117	117
	F11	189	188	188	188	188	188
Balancing index			10.98	11.13	11.30	11.34	11.37
Switch operation			s7,s13,s32, s33,s39,s42 s54,s64,s91, s90,s89,s72, s86	s7,s13,s32, s38,s42,s54, s64,s72,s86, s89,s90,s91, s92	s7,s13,s33, s39,s63,s84, s86,s87,s89, s90,s91,s92, s95	S7,s13,s32,34 s39,s55,s64, s72,s86,s89, s90,s91,s95	s7,s13,s32, s33,s39,s42, s54,s64,s91, s90,s89,s72, s86

TABLE XI
SYSTEM DATA AND PARAMETERS FOR A 33-BUS DISTRIBUTION NETWORK

Line no.	Node i	Node j	Resistance R (Ω)	Reactance X (Ω)	Receiving node P (MW)	Receiving node Q (MVAr)
1	1	2	0.0922	0.0470	100.0	60.0
2	2	3	0.4930	0.2512	90.0	40.0
3	3	4	0.3661	0.1864	120.0	80.0
4	4	5	0.3811	0.1941	60.0	30.0
5	5	6	0.8190	0.7070	60.0	20.0
6	6	7	0.1872	0.6188	200.0	100.0
7	7	8	0.7115	0.2351	200.0	100.0
8	8	9	1.0299	0.7400	60.0	20.0
9	9	10	1.0440	0.7400	60.0	20.0
10	10	11	0.1967	0.0651	45.0	30.0
11	11	12	0.3744	0.1298	60.0	35.0
12	12	13	1.4680	1.1549	60.0	35.0
13	13	14	0.5416	0.7129	120.0	80.0
14	14	15	0.5909	0.5260	60.0	10.0
15	15	16	0.7462	0.5449	60.0	20.0
16	16	17	1.2889	1.7210	60.0	20.0
17	17	18	0.7320	0.5739	90.0	40.0
18	2	19	0.1640	0.1565	90.0	40.0
19	19	20	1.5042	1.3555	90.0	40.0
20	20	21	0.4095	0.4784	90.0	40.0
21	21	22	0.7089	0.9373	90.0	40.0
22	3	23	0.4512	0.3084	90.0	50.0
23	23	24	0.8980	0.7091	420.0	200.0
24	24	25	0.8959	0.7071	420.0	200.0
25	6	26	0.2031	0.1034	60.0	25.0
26	26	27	0.2842	0.1447	60.0	25.0
27	27	28	1.0589	0.9338	60.0	20.0
28	28	29	0.8043	0.7006	120.0	70.0
29	29	30	0.5074	0.2585	200.0	100.0
30	30	31	0.9745	0.9629	150.0	70.0
31	31	32	0.3105	0.3619	210.0	100.0
32	32	33	0.3411	0.5302	60.0	40.0
34	8	21	2.0000	2.0000		
36	9	15	2.0000	2.0000		
35	12	22	2.0000	2.0000		
37	18	33	0.5000	0.5000		
33	25	29	0.5000	0.5000		

Table IV and Table V show the results of load balancing index with and without DG, respectively, using (2) in the 33-bus test system. From the results of our case study, it can be seen from the 33-bus test system that DG has the effects of improving load balancing index over feeders in this particular case, and the topological structures of optimum network without DG are different from those with DG.

Example 2: The second example is a practical distribution network of Taiwan Power Company (TPC). Its conductors mainly consist of both overhead lines ACSR 477 KCM and

TABLE XII
SYSTEM DATA AND PARAMETERS FOR A TYPICAL TPC DISTRIBUTION NETWORK

Section bus to bus	Section resistance (Ω)	Section reactance (Ω)	End bus real load (kW)	End bus reactive load (kVAR)
B1– 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
B2– 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
B3– 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
B4– 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
B5– 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

TABLE XII *(Continued)*
SYSTEM DATA AND PARAMETERS FOR A TYPICAL TPC DISTRIBUTION NETWORK

Section bus to bus	Section resistance (Ω)	Section reactance (Ω)	End bus real load (kW)	End bus reactive load (kVAR)
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
B6– 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
B7– 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
B8– 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
B9– 65	0.0486	0.1656	0	0
65– 66	0.1703	0.3497	50	30
66– 67	0.1215	0.4140	0	0

underground lines with copper conductors 500 KCM. The three-phase 11.4-kV system is shown in Fig. 4, which consists of two transformers, 11 feeders, 83 normally closed sectionalizing switches, and 13 normally open tie switches. In our analysis, three-phase balancing and constant load are assumed. Table VI shows the DG installation nodes with associated capacity for this TPC distribution system. Some of these distributed generators were located on the feeder ends in order to compensate the voltage drop.

In example 2, the results for loss minimization without and with DG are shown in Table VII and Table VIII, respectively.

From the results based on the TPC system simulation, it can be seen that the DG has the effects of improving loss reduction over feeders, and the topological structures of optimum network without DG are different from those with DG.

In order to compare the ACS and GA techniques in a different case, the authors have applied the GA algorithm to search the loss-minimization network for the TPC 11.4-kV distribution system. The simulation results by using the GA algorithm have been also concluded in Table VII and Table VIII. Based on our simulation results, the difference on the loss reduction between the GA and ACS methods is very small. It is reasonable because the feeder reconfiguration is not an infinite optimal search problem. Therefore, the GA and ACS methods could obtain a nearly optimal solution as long as the iteration number is large enough. However, based on our research experience, the ACS method would be more suitable to the feeder reconfiguration work because it can avoid a number of incorrect feeder configuration candidates caused by the GA's random crossover and mutation operations, which would improve the performance on calculation speed.

Based on the TPC system without and with DG, The load balancing index using five different types of weights are calculated and shown in Table IX and Table X, respectively. Comparing with Table IX and Table X, through five different weights, the TPC system with and without DG can decrease the current of main transformer and avoid the overload and load difference among the feeders.

VI. CONCLUSION

In this paper, the ACS algorithm has been proposed to reduce distribution system losses. The effectiveness of ACS has been demonstrated by a 33-bus test system and a TPC distribution system respectively. The merits of the ACS are parallel search and optimization capabilities, and this method was inspired by observation of the behaviors of ant colonies. The ACS applies the state transition rule repetitively to favor transitions toward nodes connected by shorter edges. Then it applies the local updating rule to shuffle the search process to extend the search space. Finally, it applies the global updating rule to make the search more directed and to enhance the capability of finding

TABLE XII *(Continued)*
SYSTEM DATA AND PARAMETERS FOR A TYPICAL TPC DISTRIBUTION NETWORK

Section bus to bus	Section resistance (Ω)	Section reactance (Ω)	End bus real load (kW)	End bus reactive load (kVAR)
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
B10– 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
B11– 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	–	–

the optimal solution in the problem solving process. The three rules make the ACS become an extremely powerful method for optimization problems. From the results of this paper, it can be seen that DG has the improvement effects on loss reduction and can increase the system balancing index. The computational results of the 33-bus system show that the ACS method is better than the GA one. It can be observed that a 44.626% of average loss reduction can be achieved by the ACS comparing with a 43.803% by the GA when distributed generators are installed in the system; the results are shown in Table III. For a large scale system like a TPC distribution system, through five different weights, it can decrease the current of main transformer and avoid the overload and load difference among the feeders no matter whether the system is with or without DG; the results have been shown in Table IX and Table X. The case study in this paper shows that the ACS method is suitable in distribution network reconfiguration.

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