MINIMIZING POWER LOSS THROUGH NETWORK RECONFIGURATION USING THE PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract—This study aims to minimize power loss through network reconfiguration in traditional distribution networks and microgrids. To address this problem, an algorithm composed of an objective function and operation constraints is proposed. Network connection matrices based on graph theory and the backward/forward sweep method is used to analyze power flow. A minimizing power loss approach is developed for network reconfiguration, and the particle swarm optimization algorithm is adopted to solve this optimal combination problem. The proposed approach is tested on the IEEE 33-bus test system and the first outdoor microgrid test bed established by the Institute of Nuclear Energy Research in Taiwan. Simulation results demonstrate that the proposed approach can be applied in networkreconfiguration to minimize power loss.

Index Terms—Microgrid, Network Reconfiguration, PSO, Connection Matrices, Power Loss.

I. INTRODUCTION

The function of traditional distribution networks is to distribute electrical power to customers because voltage level in such networks is relatively lower and their total length is longer compared with transmission networks. Thus, reducing power loss in distribution networks is vital. At present, many distribution energy resources (DERs) are connected to distribution networks. Distribution networks have become active networks called microgrids. Microgrids consist of DERs and loads. DERs include renewable and nonrenewable generation units, as well as storage devices, such as photovoltaic systems, wind turbines, fuel cells, microturbines, diesel engines, battery banks, and supercapacitors, among other. [1]–[2]. Microgrids can be operated under grid-tied and islanding modes through a static switch at the common coupling point between the main power grid and the microgrid. In the grid-tied operation mode, the microgrid may act as a load or source at any time in terms of the main power grid. The islanding operation mode must be operated autonomously based on the power balance principle to maintain constant voltage and frequency. Numerous renewable energy units are used in microgrids. Thus, CO_2 emissions are reduced and global warming is prevented. Constructing microgrids in industrial parks, campuses, shopping malls, off-shore islands, and remote districts is worthwhile because of the aforementioned advantages.

Planning, designing, operating, and controlling microgrids are more complex compared with traditional distribution systems. Consequently, an energy management system (EMS) is essential in the system operation stage in microgrids. To increase operating efficiency, the network reconfiguration approach, which is one of the functions in EMS, has been adopted to minimize power loss and improve voltage quality.A. Merlin and H. Back [3]used the spanning tree structure to model a distribution system. The obtained solution results were independent from the initial status of the switches; however, their algorithm was very time-consuming. S. Civanlar et al. [4]proposed the branch-exchange method to minimize the number of switching operations; however, this approach is not systematic and can only reduce power loss. Y. J. Jeon et al. [5] presented the simulated annealing algorithm for network reconfiguration; this algorithm was easy to code but required considerable computation time in large-scale systems. B. Venkatesh and R. Ranjan[6] proposed an approach that used a fuzzy adaptation of evolutionary programming as a solution technique; however, as a system grew large, this method became increasingly complex.H. Hamdoui et al. [7] used the ant colony approach algorithm to identify the optimal combination of feeders with different parameters for a new topology design. This method is highly efficient and convergence definitely occurs; however, the length of time required to achieve convergence remains uncertain.

In the present study, a population-based stochastic optimization technique that adopts the particle swarm optimization (PSO) algorithm is used to search for the optimal network reconfiguration problem. This paper is divided into four sections. Section 1 presents the introduction. Section 2 reviews network reconfiguration algorithms and describes the network reconfiguration problem and its formulation. Section 3 demonstrates and discusses the simulation results.

Section 4 concludes the paper.

II. PROBLEM FORMULATION

A. Description of the Network

Most distribution networks exhibit a radial configuration from the distribution substation to the customers. Sectionalizing switches and tie switches are installed in these systems to consider normal and abnormal operations. Under normal conditions, the sectionalizing switches are typically closed and the tie switches are generally open. Nevertheless, the network can be changed by performing switching actions for the best network topology to increase system performance. This process is called reconfiguration. Through network reconfiguration, power loss is reduced, load distribution becomes uniform, and overloading is avoided. System reliability is enhanced after a fault occurs.

A combinatorial problem arises because of switching actions. Therefore, when the number of switches is high, the possibility of reconfiguration increases. The most common approaches to solve this problem in network reconfiguration can be classified as follows:

1. Mathematical optimization methods,
2. Heuristic methods, and
3. Artificial intelligence methods.

These methods have advantages and disadvantages. Based on literature reviews, these techniques can effectively address network reconfiguration problems. Solving anetwork reconfiguration problem involves two components: (1) the objective function and the system operating constraints and (2) the power flow algorithm. The common objective function is power loss minimization, and the constraints are the upper and lower limits of bus voltages, the ampere capacity of the conductor, and feasible network topology. The power flow algorithms must suit the characteristics of distribution networks with high X/R ratio, short distance between two connected buses, and unbalanced load distributions and system structure.

B. Objective Function

The objective function used in this study minimizes power loss.This objective function can be expressed as

$$\min f = \sum_{i=1}^{L} \left| I_j \right|^2 R_j \,, \quad (1)$$

which is subject to

$$P_{i+1} = P_i - r_i I_i^2 - P_{Li+1} \,, \quad (2)$$

$$Q_{i+1} = Q_i - x_i I_i^2 - Q_{Li+1} \,, \quad (3)$$

$$V_{Li} \le V_i \le V_{Ui} \,, \quad (4)$$

$$g \in G \,. \quad (5)$$

In (1), L represents the number of lines and I_j denotes the current of the j^{th} line. Meanwhile, in (2) and (3), P_i and Q_i denote the real and reactive power flow out of bus i, respectively; $r_i$and x_i are the resistance and reactance between bus $i$and i+1; Li represents the line current between bus i and i+1; V_i, V_{Ui}, and V_{Li}denote the voltage at bus i and its upper and lower limits, respectively; g is the network topology; and G represents the sets of radial topologies, which cannot be closed-loop and islanding topologies.

C. Power Flow Algorithm

Graph theory and the backward/forward sweep method [8]–[9] were applied in the proposed power flow algorithm. Graph theory is a systematic approach to build incidence matrices that correspond to network topologies. The incidence matrices used in the proposed algorithm is the A matrix, which is the element–bus incidence matrix, and the K matrix, which is branch–path incidence matrix. Based on these matrices, the bus-injection to branch-current (BIBC) matrix and the branch-current to bus-voltage (BCBV) matrix can be established according to various system structures. Furthermore, BIBC and BCBV matrices are adopted in the power flow algorithm. The power flow solution procedure is described as follows.

Step 1：Build the A matrix. The K matrix can be derived using (6). Establish the BIBC matrix using (7), as follows:

$$K = [A^{-1}]^t \,, \quad (6)$$

$$[BIBC] = -K \,. \quad (7)$$

Step 2：Transpose the BIBC matrix and add the primitive line impedance into the corresponding non-zero element position to derive the BCBV matrix.

Step 3：Compute the equivalent bus injection current at each bus connected to the source or load using (8) as follows:

$$I_i^k = \left(\frac{P_i + Q_i}{V_i^k}\right)^* \,. \quad (8)$$

Step 4：Calculate the voltage derivation of each bus using (9):

$$[\Delta V^k] = [BIBC][BCBV][I^k] \,. \quad (9)$$

Step 5：Update the bus voltage using (10), where V_{no_load} is the no-load voltage at each bus, that is,

$$[V^{k+1}] = [V_{no\_load}][\Delta V^k] \,. \quad (10)$$

Step 6：Check whether convergence is achieved using (9). If convergence is achieved, then proceed to step 3; otherwise, end the solution procedure. ε is the maximum toleration, that is,

$$max_i \left(\left| I_i^{k+1} \right| - \left| I_i^k \right| \right) > \varepsilon \,. \quad (11)$$

(3)

D. PSO Algorithm

(5)PSO was introduced by J. Kennedy and R.C. Eberhart [10]-[11] in 1995. This algorithm is a population-based optimal search techniqueattributed to the social behavior of certain animals, such as fish schooling or bird flocking. PSO simulates the population behavior that combines the cognition-only model and the social-only model, as shown in (12) and (13), respectively. The cognition-only model searches for the individual best solutions as the local best (pbest) and changes particle position and velocity to move in a multi-dimensional space until the position does not change or the computational limits are reached. In the social-only model, the pbest and global best (gbest) are compared to update the gbest and change particle position and velocity. The combination of pbest and gbest in PSO allowsthe particle to adjust rapidly and correctly, which results in fast convergence using (14)–(16).

$$V_n^{k+1} = V_n^k + c_1 \times rand_1 \times (pbest_n^k - s_n^k), \tag{12}$$

$$V_n^{k+1} = V_n^k + c_2 \times rand_2 \times (gbest^k - s_n^k), \tag{13}$$

$$V_n^{k+1} = w \times V_n^k + c_1 \times rand_1 \times (pbest_n^k - s_n^k) + c_2 \times rand_2 \times (gbest^k - s_n^k), \tag{14}$$

$$s_n^{k+1} = s_n^k + v_n^{k+1}, \tag{15}$$

$$w = w_{\max} - (w_{\max} - w_{\min}) \times \frac{k}{k_{\max}}, \tag{16}$$

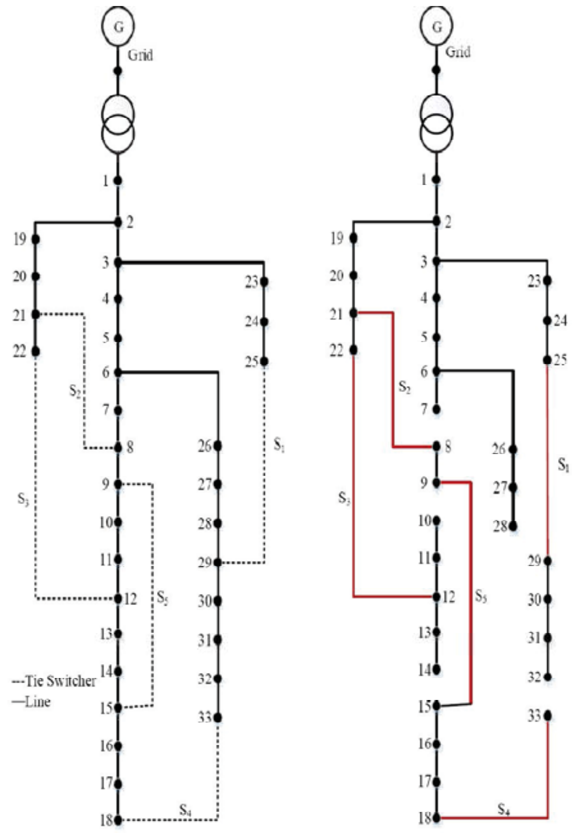
where k_{max} is the maximum iteration, n is the particle number, V_n^k is the velocity ofparticle n at the k^{th} iteration, s_n^k is the k^{th} position of particle n, c_1 and c_2 are learning factors, $rand_1$ and $rand_2$ are random numbers between 0 and 1, $pbest_n^k$ is the best value of particle n at the k^{th} iteration, and $gbest^k$ is the global best value at the k^{th} iteration. w, w_{max}, and $w_{min}$are acceleration coefficients, maximum weighting values, and minimum weighting values, respectively. In this study, the related parameters of PSO are set to $n = 500$, $w_{max} = 0.9$, $w_{min} = 0.2$, $c_1 = 2$, and $c_2 = 2$. Moreover, the maximum iteration number is 200.

III. NUMERICAL RESULTS

In this section, the IEEE 33-bus test system and the microgrid of the Institute of Nuclear Energy Research (INER) in Taiwan were used as sample systems to verify the effectiveness of the proposed approach. The IEEE 33-bus test system is a traditional distribution system. It is a three-phase balance passive network that is only connected with loads. The INER microgrid is an active network with both DERs and loads. The simulation results are discussed in the following sections.

A. IEEE 33-Bus Test System

Figure 1(a) shows the IEEE 33-bus test system with five tie switchers and 32 sectionalizing switchers. The simulation result of the optimal network topology that uses the proposed approach for network reconfiguration is illustrated in Fig. 1(b). In the figure, five tie switchers are closed and five sectionalizing switchers between buses 7 and 8, 9 and 10, 14 and 15, 29 and 30, and 32 and 33 are opened. The convergence characteristics of the proposed method are shown inFig. 2, the power loss from initial value (144.75 kW) to the globaloptimum (140.74kW) at the 24^{th}iteration.Figure 3 indicates the simulation result of the bus voltage profile. The lowest bus voltage was 0.9131 p.u. at bus 18 before reconfiguration and 0.9413 p.u. at bus 32 after reconfiguration. Thus, the voltage profile before reconfiguration was better than that after reconfiguration. In addition, the simulation results of power loss before and after reconfigurationshown in Fig. 4 indicated that the power loss in each line section varied because the line flow was changed and the total power loss was 202.68 kW and 140.74 kW, respectively. Evidently, power loss was reduced after reconfiguration. Based on these numerical results, the proposed network reconfiguration algorithm effectively improved voltage profile, reduced power loss, and increased operation efficiency under normal operating conditions.



(a)Before reconfiguration (b)After reconfiguration

Fig. 1 IEEE 33-bus test system

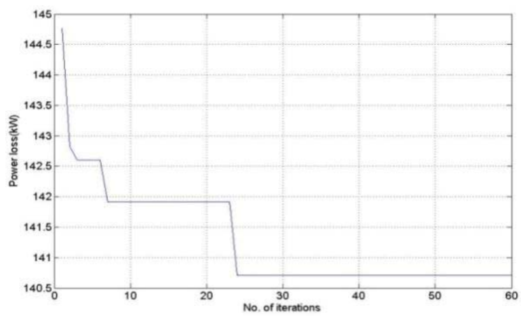


Fig. 2 Convergence characteristics of proposed methodof the IEEE 33-bus test system

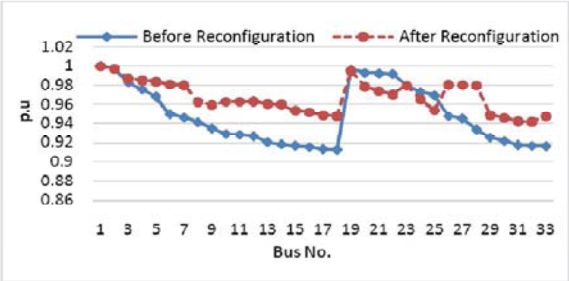


Fig. 3 Simulation result of the bus voltage of the IEEE 33-bus test system

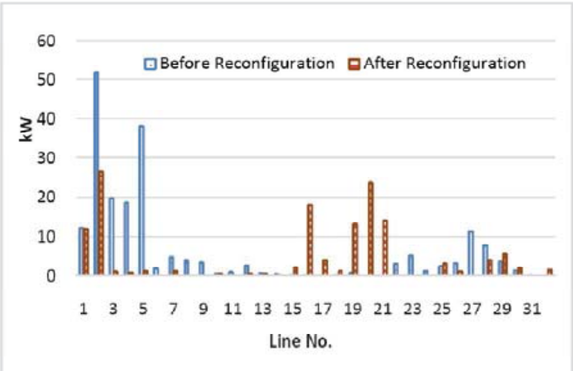


Fig. 4 Simulation result of the power loss of the IEEE 33-bus test system

B. INER Microgrid

The first outdoor microgrid test bed was developed by INER in Taiwan. This system consists of three zones with DERs and loads and includes a tie switcher and 11 sectionalizing switchers, as shown in Fig. 5. For example, zone 1 comprises 21 units of 1.5 kW high concentrator photovoltaic, 1 unit of 65 kW microturbine, a 60 kWh battery bank, and a lumped load in an office building (Building 048). The bus and line data of the INER microgrid for simulation are provided in Tables 1 and 2 in the Appendix. Although this is a sample network topology, the solution can be derived via a brute force search. Our proposed algorithm is a systematic approach that can be applied in a complex network topology. Thus, the effectiveness of the proposed approach can be verified using this sample system by comparing the results of the proposed approach with that of the brute force search method.

The simulation result indicated that the tie switcher was closed and a sectionalizing switcher between buses 3 and 7 was opened. This outcome is the same as that in the brute force search method. The convergence characteristics of the proposed method are shown inFig. 6, the power loss reducedto the globaloptimum at the 18^{th}iteration.Figure 7 depicts the simulation result of the bus voltage profile. The lowest bus voltage was 0.9745 p.u. at bus 10 before reconfiguration and 0.9774 p.u. at bus 12 after reconfiguration. Similarly, the voltage profile was improved after reconfiguration. Figure8 demonstrates that the simulation result of power loss has changed after reconfiguration. The total power loss was 2.18 kW before reconfiguration, which was reduced to 1.65 kW after reconfiguration. Based on the numerical results, the proposed algorithm was proven to be a feasible approach to improve voltage quality, reduce power loss, and increase efficiency under normal operating conditions.

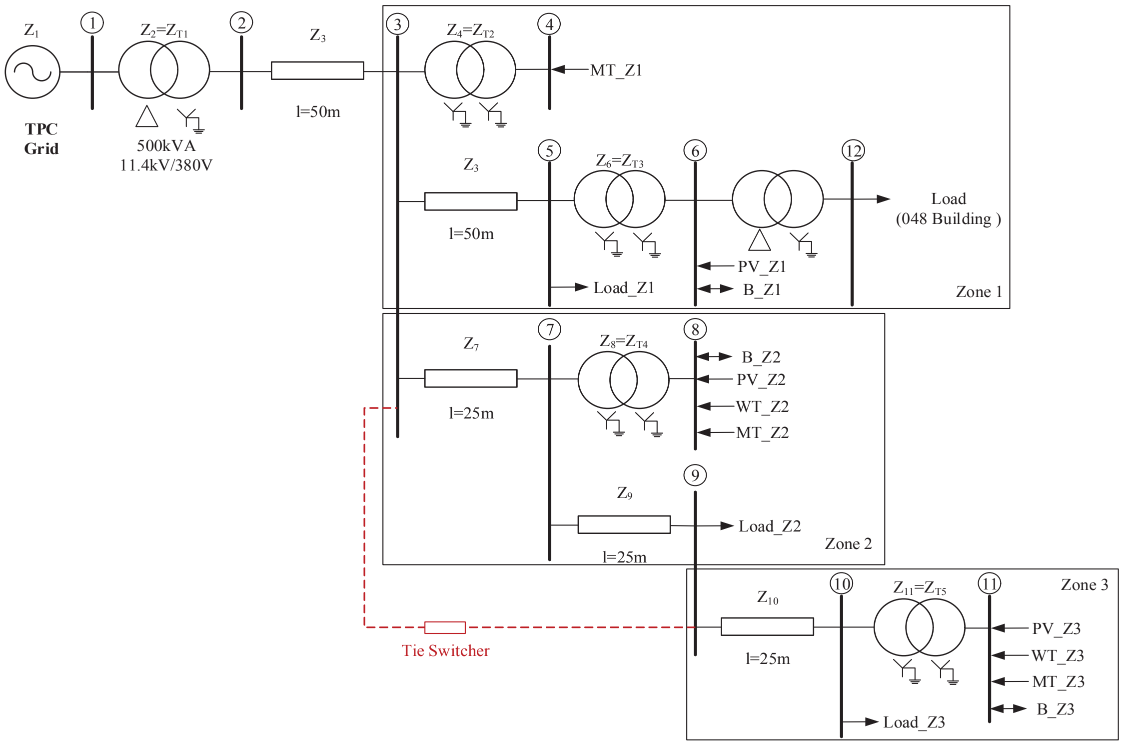


Fig. 5Single line diagram of the INER microgrid

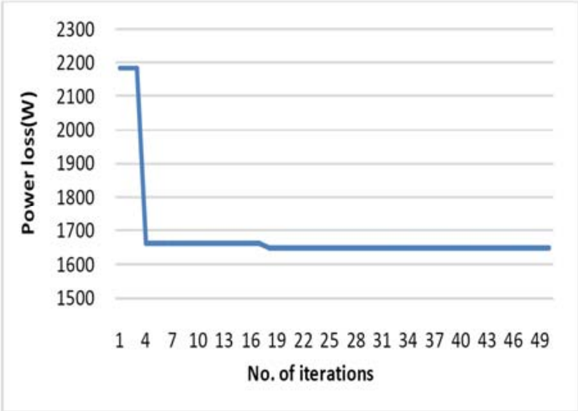


Fig. 6 Convergence characteristics of proposed methodof the INER microgrid

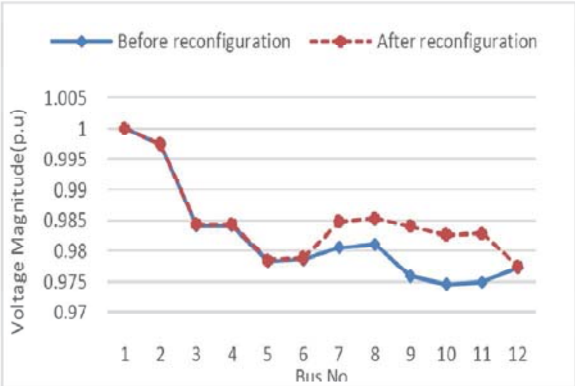


Fig. 7 Simulation result of the bus voltage of the INER microgrid

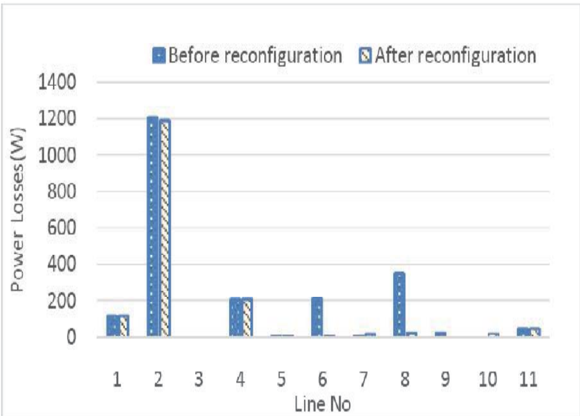


Fig. 8 Simulation result of the power loss of the INER microgrid

CONCLUSION

A network reconfiguration algorithm that applies a graph theory-based power flow solution technique has been developed in this study. PSO exhibits self-learning capability to obtain the most optimal solution, and the graph theory-based power flow algorithm can easily establish network topology using incidence matrices according to different system structures. The IEEE 33-bus system and the INER microgrid have been used as sample systems to verify the effectiveness of the proposed approach. The numerical results demonstrate that this approach can improve voltage profile, reduce total power loss, and increase efficiency under normal operating conditions. The developed algorithm can be applied in traditional distribution networks with or without DERs and microgrids to improve system operation performance.

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APPENDIX

Table 1 Bus data of the INER microgrid

Bus No.	Base kV	P load(kW)	Q load(kvar)
1	11.4	0	0
2	0.38	1.6027	0.9317
3	0.38	0.20835	0.1213
4	0.48	0	0
5	0.38	60	10
6	0.38	-55.694	0.2795
7	0.38	1.2822	0.74539
8	0.38	-19.6	0
9	0.38	60	0
10	0.38	30.481	5.2795
11	0.38	-9.8	0
12	0.208	38.2663	0.2795

Table 2 Line data of of the INER microgrid

Form Bus	To Bus	Line R(pu)	Line X(pu)	Z%	Distance (m)	Transformer Rating(kV)	Transformer Capacity (kVA)	X/R
1	2	-	-	3.85	-	11.4/0.38	500	8.02
2	3	0.2918	0.354	-	50	-	-	-
3	4	-	-	2	-	0.38/0.48	100	8
3	5	0.2918	0.354	-	50	-	-	-
5	6	-	-	4	-	0.38/0.38	150	8
3	7	0.2918	0.354	-	25	-	-	-
7	8	-	-	8	-	0.38/0.38	400	8
7	9	0.2918	0.354	-	25	-	-	-
9	10	0.2918	0.354	-	25	-	-	-
10	11	-	-	-	-	0.38/0.38	150	8
3	9	0.2918	0.354	-	25	0	-	-
6	12	-	-	4	-	0.38/0.208	150	8

★★★