Distribution System Reconfiguration Using the PC Cluster based Parallel Adaptive Evolutionary Algorithm

Kyeong-Jun Mun*, Hwa-Seok Lee**, June Ho Park†, Gi-Hyun Hwang*** and Yoo-Sool Yoon****

Abstract - This paper presents an application of the parallel Adaptive Evolutionary Algorithm (AEA) to search an optimal solution of a reconfiguration in distribution systems. The aim of the reconfiguration is to determine the appropriate switch position to be opened for loss minimization in radial distribution systems, which is a discrete optimization problem. This problem has many constraints and it is very difficult to find the optimal switch position because of its numerous local minima. In this investigation, a parallel AEA was developed for the reconfiguration of the distribution system. In parallel AEA, a genetic algorithm (GA) and an evolution strategy (ES) in an adaptive manner are used in order to combine the merits of two different evolutionary algorithms: the global search capability of GA and the local search capability of ES. In the reproduction procedure, proportions of the population by GA and ES are adaptively modulated according to the fitness. After AEA operations, the best solutions of AEA processors are transferred to the neighboring processors. For parallel computing, a PC-cluster system consisting of 8 PCs was developed. Each PC employs the 2 GHz Pentium IV CPU, and is connected with others through switch based fast Ethernet. The new developed algorithm has been tested and is compared to distribution systems in the reference paper to verify the usefulness of the proposed method. From the simulation results, it is found that the proposed algorithm is efficient and robust for distribution system reconfiguration in terms of the solution quality, speedup, efficiency, and computation time.

Keywords: Adaptive Evolutionary Algorithm, Distribution System Reconfiguration, Evolution Strategy, Genetic Algorithm, PC-cluster

1. Introduction

In recent years, to satisfy the desire of customers, effective distribution system reconfiguration, one of the important functions of the distribution systems, has been required by changing feeder configuration through remote controlled switch to reduce power losses, subject to several operational constraints such as line/transformer capacity limits and voltage drop limits. Distribution systems are radially operated by opening tie and section-nalizing switches. Therefore, in distribution system reconfiguration, by changing switch status, power losses can be reduced during normal operating conditions. However, the number of switches is very large, and there are many constraints. Therefore, it is difficult to obtain optimal reconfiguration because it is a non-linear optimization problem.

Recently, several works on the reconfiguration of distribution systems have been reported. Shirmohammadi and Hong [1] proposed the branch and bound method. To get the optimal solution, they opened the switch with the lowest current derived in the load flow while all switches were closed. Baran and Wu [2] proposed the branch exchange operation to solve the reconfiguration problem for the distribution systems. Taylor and Lubkeman [3] used the heuristic method for reconfiguration problems. Brauner and Zabel [4] implemented the expert system. However, the results of these methods are only approximates and local minima.

Therefore, algorithms with global searching capability such as simulated annealing (SA) [5], genetic algorithm (GA) [6], and tabu search (TS) [7] are proposed to solve the reconfiguration of distribution systems. Unfortunately, SA requires a great deal of time to obtain optimal solution. GA can attain near optimal solution quickly, but it takes much time to get global optimal solution due to its probabilistic searching characteristics. TS is based on heuristics and it generally finds a good solution. However,

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its performance is affected by the initial solution and it takes a significant amount of time to escape local minima by diversification operation. Therefore, recently, several hybrid algorithms by paralleling of GA, SA, and TS have been proposed to obtain better solutions, and to reduce the computation time by mixing the advantages of each algorithm [8].

In parallel computing, problems are divided into several sub problems, and allocated to each processor. This reduces computation time and enhances computation efficiency. To realize parallel algorithm, parallel computers such as the transputer were used but these computers are costly to use. Recently, PC clustering, one of the types of parallel or distributed processing systems that is composed of a collection of interconnected workstations or PCs working together as a single, integrated computing resources has been used for parallel computing [9].

Evolutionary algorithms (EA) are based on the principles of genetics and natural selection. Among EAs, GA simulates the crossover and mutation of natural systems, giving it a global search capability [10], whereas, evolution strategy (ES) simulates the evolution of an asexually reproducing organism. ES can find a global minimum, in case of combining another EA, and it could also be used as an efficient local search technique [11]. In the conventional method described above, parameter values and operator probabilities for the GA and ES are adapted to determine a solution and find it efficiently [12-15]. For GA, the population size, crossover rate, mutation rate and operation method are adaptively modified in each generation [12, 13]. To enhance the performances of ES, mutation parameters are adapted during the run in ES [14, 15].

In this paper, we propose Adaptive Evolutionary Algorithm (AEA), which is an algorithm in which the ratio of population to which GA and ES will adjust is adaptively modified in the process of reproducing in accordance to fitness. We use ES to optimize locally, while the GA optimizes globally. In other words, the resulting hybrid scheme produces improved reliability by exploiting the "global" nature of the GA as well as the "local" improvement capabilities of the ES. In this investigation, parallel AEA was developed for the reconfiguration of distribution systems. After AEA operations for each processor, the best solution of each AEA processor is transferred to the neighboring processors. For parallel computing, a PC cluster system consisting of 8 PCs was developed. Each PC employs a 2 GHz Pentium IV CPU, and is connected with others through switch based fast Ethernet.

To verify the usefulness of the proposed method, the newly developed algorithm has been tested and compared with a 32 and a 69 bus distribution system in the reference paper [5]. From the simulation results, it is found that the proposed algorithm is efficient and robust for distribution system reconfiguration in terms of the solution quality, speedup, efficiency, and computation time.

2. Reconfiguration of the Distribution System

Distribution systems deliver power to customers from distribution substations feeders. The aim of the distribution system reconfiguration is to determine the correct switch position to be opened for loss minimization in a radial distribution system. The monitoring and control functions of the distribution automation system make it possible to control remote switches relevantly according to the decision of dispatchers.

In this paper, the open switch positions are determined for reconfiguration to minimize power losses while satisfying several operational constraints such as line/transformer capacity limits, voltage drop constraints, and radial constraints. The objective function is expressed as below by Eq. (1).

$$Min\ P_{loss} = Min \sum_{i=1}^{n} \frac{P_i^2 + Q_i^2}{|V_i|^2} r_i^2 \tag{1}$$

where, P_i, Q_i : real and reactive power injected to the i-th node

V_i : node voltage of the i-th node

r_i : resistance of the i-th section

Constraints considered in this paper are line current capacity constraint, voltage drop limit constraint, and radial constraint. Constraints are described as below.

a) line current capacity constraint

$$I_k \le I_{\lim} \tag{2}$$

where, I_k : current of the k-th section

$I_{\lim}$: line current capacity

b) voltage drop limit constraint

$$V_{\min} \le V_k \le V_{\max} \tag{3}$$

where, V_k : node voltage of the k-th node

$V_{\min}$: lower bound of the node voltage

$V_{\max}$: upper bound of the node voltage

c) radial constraint: Each node should only be provided with power from one feeder.

3. Parallel Adaptive Evolutionary Algorithm Using PC Clustering

GA, one of the probabilistic optimization methods, is robust and it is able to solve complex and global optimization problems. But the disadvantage is that it can suffer from excessive computation time before providing an accurate solution because of minimally using prior knowledge and not exploiting local information [10]. ES, which simulates the evolution of an asexually reproducing organism, is efficient in its local search capabilities. However, to solve complex problems, it forms hybrid EA [15].

In this paper, to reach the global optimum accurately and reliably in a short execution time, we designed AEA by bringing together pieces of the GA and ES. In AEA, GA operators and ES operators are applied simultaneously to the individuals of the present generation to create the next generation. Individuals with higher fitness value have a higher probability of contributing one or more chromosomes to the next generation. This mechanism gives greater rewards to either the GA operation or the ES operation depending on what produces superior offspring. To enhance the global search capability, the best solutions of each AEA-based node are transferred to the corresponding AEA-based node at each specified iteration. For parallel computing, a PC-cluster system consisting of 8 PCs was developed in this investigation.

3.1 PC Cluster System

Since the mid 1980s, high performance computers have been needed according to the development of large-scale science and engineering. Since supercomputers are expensive, cluster systems were developed to replace supercomputers because of their availability of inexpensive high performance PCs, high speed networks, and development of integrated circuits.

PC cluster systems provide higher availability as well as enhanced performance by lower cost through the interconnection of several PCs or workstations. PC cluster systems are very competitive with parallel machines in terms of the ratio of cost to performance because clustering is one of the types of parallel or distributed processing systems, which is composed of a collection of interconnected low cost PCs working together as single and integrated computing resources. Also, it is easy to add nodes that construct the PC clustering. A basic construction diagram for the PC clustering is shown in Fig. 1.

The performance of the PC cluster system depends on the quality of the message passing system, libraries, and compilers for parallel programming and performance of individual nodes. Therefore, it is important to select each component described above properly to obtain superior performance. The PC cluster system implemented in this paper is composed of 8 nodes based on fast Ethernet with an Ethernet switch. For the operating system, the master node uses a Windows 2000 server, and slave nodes use Windows 2000 pro. To connect each node, fast Ethernet cards and switching hubs were used. In data communication, a MPI library was utilized, which is effective for parallel application by using the message-passing method through TCP/IP over the Internet. Symantec PC-anywhere was used for remote control of each node, and MS visual C++ 6.0 was used for compilers of parallel programming. Table 1 describes the specifications of the 8-node PC cluster system developed in this paper.

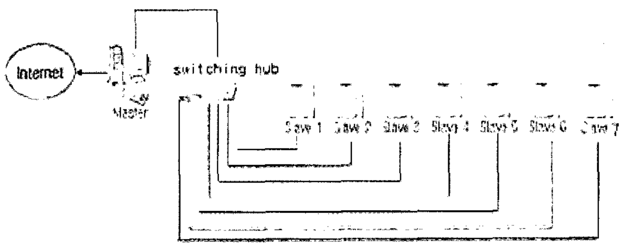


Fig. 1 Structure of PC cluster system

Table 1 Specifications of 8-node PC cluster system

CPU	Intel 2.0 GHz
Mother Board	LeoTech P4XFA
Chipset	VIA P4X266A
RAM	DDR SD RAM 256MB
HDD	Samsung 40GB 5600rpm
NIC	3Com 3CSOHO 100-TX
Network Switch	3Com 3C16465C Switch
Operating System	Window 2000 Server Window 2000 Pro
MPI Library	MPICH 1.2.5
Compiler	Visual C++ 6.0

3.2 Parallel Adaptive Evolutionary Algorithm

In AEA, the number of individuals created by the GA and ES operations is changed adaptively. An individual is represented as a real-valued chromosome, which makes it possible to hybridize GA and ES operations.

For AEA to self-adapt its use of GA and ES operators, each individual has an operator code to determine which operator to use. Suppose a '0' refers to GA, and a '1' to ES. At each generation, if it is more beneficial to use the GA, more '0's should appear at the end of individuals. If it is more beneficial to use the ES, more '1's should appear. After reproduction by roulette wheel selection according to the fitness, GA operations (crossover and mutation) are performed on the individuals that possess the operator code of '0' and the ES operation (mutation) is performed on the individuals that have an operator code of '1'. Elitism is also used. The best individual in the population reproduced both the GA population and ES population in the next generation. The major procedures of AEA are as follows:

(1) Initialization: The initial population is generated randomly. For each individual, an operator code is randomly initialized. According to the operator code, GA operations are performed on the individuals with operator code '0', while ES operation is applied where the operator code is '1'.

(2) Evaluation and Reproduction: Using the selection operator, individual chromosomes are selected in proportion to their fitness, which is evaluated using an objective function. After reproduction, GA operations (crossover and mutation) are performed on the individuals having an operator code of '0' and the ES operation (mutation) is performed on the individuals having an operator code of '1'. At every generation, the percentages of '1's and '0's in the operator code indicate the performance of the GA and ES operators.

(3) Preservation of Minimum Number of Individuals: At each generation, AEA may fall into a situation where the percentage of the offspring by one operation is nearly 100% and the offspring by other operation dies off. Therefore, it is necessary for AEA to preserve a certain amount of individuals for each EA operation. In this paper, we randomly change the operator code of the individuals with a higher percentage until the number of individuals for each EA operation becomes higher than a certain amount of individuals to be preserved. The predetermined minimum number of individuals to be preserved is set to 20% of the population size.

(4) GA and ES: The real-valued coding is used to represent a string of population. Modified simple crossover and uniform mutation are used as genetic operators. The modified simple crossover operator is defined as follows: if 2 strings, S_v^t and S_w^t are selected for the crossover operation and the crossover point is selected at the k-th component of the individual, the resulting offspring are defined as the combination of two vectors (individuals) as shown in Eq. (4)-Eq. (5).

<before crossover> < after crossover>

$$S_v^t = [v_1,\cdots, v_k,\cdots,v_N] \quad S_v^{t+1} = [v_1,\cdots, v_k', v_{k+1}',\cdots,v_N'] \quad (4)$$

$$S_w^t = [w_1,\cdots, w_k,\cdots, w_N] \quad S_w^{t+1} = [w_1,\cdots, w_k', w_{k+1}',\cdots, w_N'] \quad (5)$$

crossover point

where, $v_j' = \alpha_1 \times v_j + \alpha_2 \times w_j$

$w_j' = \alpha_1 \times w_j + \alpha_2 \times v_j$

α_1, α_2 : Random value between 0 and 1

v_j ,w_j : upper and lower bound of each variable

N : no. of variables

In uniform mutation, we select a random gene k in an individual. If an individual and the k-th component of the individual is the selected gene, the resulting individual is as follows:

$$S_v^t = [v_1,\cdots, v_k,\cdots,v_N] \quad S_v^{t+1} = [v_1,\cdots, v_k', v_{k+1},\cdots,v_N] \quad (6)$$

mutation point

where, v_k' : Random value between upper bound and lower bound of k-th variable

Mutation is performed independently on each vector element by adding a normally distributed Gaussian random variable with mean zero and standard deviation (σ), as shown in Eq. (7). After adapting the mutation operator for ES population, if the improved individuals of the past generation are fewer than the present generation, standard deviation decreases in proportion to the decrease rates of standard deviation (c_d), otherwise, the next generation standard deviation increases in proportion to increase rates of standard deviation (c_i), as shown in Eq. (8).

$$v_k^{t+1} = v_k^t + N(0, \sigma^t) \quad (7)$$

$$\sigma^{t+1} = \begin{bmatrix} c_d \times \sigma^t, & if & \phi(t) < \delta \\ c_i \times \sigma^t, & if & \phi(t) > \delta \\ \sigma^t, & if & \phi(t) = \delta \end{bmatrix} \quad (8)$$

where, $N(0, \sigma^t)$: gaussian random variable

v_k^t : k-th variable in generation t

σ^t : standard deviation of the generation t

$\phi(t)$: improved ratio of individual number after adapting mutation operator for population of ES in t generation

c_d , c_i: increase and decrease rate of the standard deviation

δ : constant range from 0 to 1

(5) Elitism: The best individual in the population is preserved to perform both GA operations and ES operations in the next generation. This mechanism not only forces GA not to deteriorate temporarily, but also forces ES to exploit information to guide subsequent local search in the most promising subspace.

The flowchart for searching optimal solutions using the proposed AEA is shown in Fig. 2. The configuration of population is shown in Fig. 3.

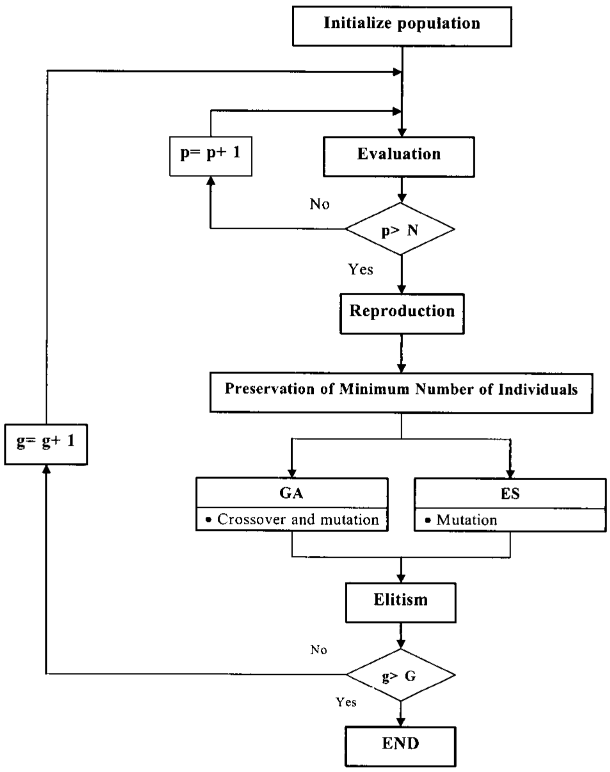


Fig. 2 Flowchart for searching optimal solution using AEA

S_1	V_{11}	•••	V_{1m}	*
S_2	V_{21}	•••	V_{2m}	*
		⋮		
S_n	V_{p1}	•••	V_{pm}	*

where, V_{ij} : The values between upper bounds and lower bounds of each variable

p : number of population

m : number of variables

* : operator code

n : number of strings

Fig. 3 String architecture in the population

The proposed AEA is paralleled by the PC cluster system to enhance both the solution quality and computation time. Fig. 4 shows the connection structure between each AEA node. In parallel AEA, AEA operators are executed for each node. Individuals of each AEA node with higher fitness value are transferred to the neighboring AEA node to enhance the search capability of AEA.

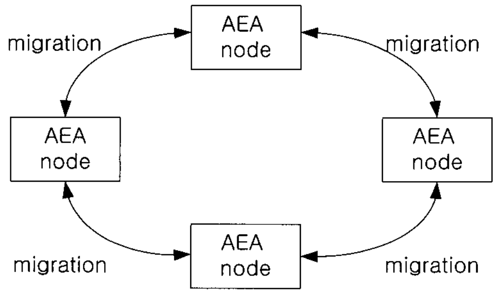


Fig. 4 Connection structure of each AEA node

3.3 Parallel AEA for the Reconfiguration of the Distribution System

To implement the proposed parallel AEA for the reconfiguration of distribution systems, we must determine several parameters of the AEA. The parameters for the reconfiguration of distribution systems are the position of the opened sectionalizing switches. Therefore, AEA encodes the open switch position of each loop for the distribution system, and generates the initial population. AEA operations, i.e., crossover, mutation and gaussian mutation operation are applied to the individuals of the present generations to create the next generation. Fig. 5 represents the string architecture of the AEA. As shown in Fig. 5, each string represents the open switch position of each loop for the distribution system.

In the evaluation procedures of AEA, the fitness of each string can be obtained by the following equations. As shown in Eq. (9), fitness is composed of power losses and several constraints such as line/transformer capacity limit, voltage drop limit, and radial constraint.

String 1	SW_{11}	SW_{12}	···	SW_{1N}
String 2	SW_{21}	SW_{22}	···	SW_{2N}
			⋮	
String p	SW_{p1}	SW_{p2}	···	SW_{pN}

where, SW_{ij} : open switch for j-th loop of i-th string
N: no. of loops in the distribution system
p: no. of population

Fig. 5 Coding method of AEA for distribution system reconfiguration

$$Fitness = \frac{\alpha}{\beta + Loss + \sum_i penalty_i} \quad (9)$$

where, $Loss$: power loss [kW]

$penalty_i$: penalty of the i-th constraint, i = 1, 2, 3

$$penalty_1 = \begin{cases} 0 & if \ I_a < I_{max} \\ \gamma_1 & otherwise \end{cases}, \quad a = 1, 2, \cdots, T$$

$$penalty_2 = \begin{cases} 0 & if \ V_a < V_{max} \\ \gamma_2 & otherwise \end{cases}, \quad a = 1, 2, \cdots, T$$

$$penalty_3 = \begin{cases} 0 & if \ radiality \ constraint \ satisfied \\ \gamma_3 & otherwise \end{cases}$$

I_a : line current of section a

V_a : voltage of section a

V_{max} : allowable maximum voltage drop

I_{max} : line current capacity

T : no. of section

$\alpha, \beta, \gamma_1, \gamma_2, \gamma_3$: constants

4. Case Studies

To demonstrate the usefulness of the proposed method, the reconfiguration of distribution systems was conducted on a 32 bus and a 69 bus system [5].

4.1 32 bus distribution system

The 32 bus distribution system has 5 loops, and sectionalizing switches are placed between load buses. Feeder voltage is set to 12.66 kV, loads are modeled as constant power, and the total loads are 3,715 kW and 2,300 kVAR, respectively. Fig. 6 presents the test system. Table 2 describes the simulation parameters of the proposed method. Fig. 7 describes the PC cluster system developed in this paper.

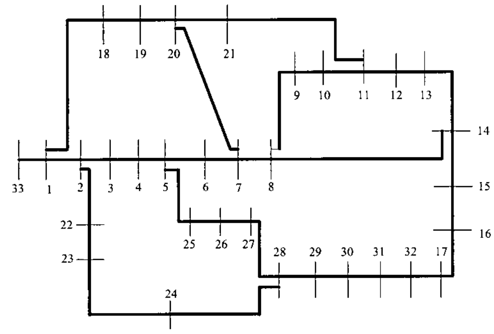


Fig. 6 Example distribution system with 32 buses

Table 2 Simulation coefficients in the parallel AEA

Coefficient	AEA	GA	ES
No. of generations	200	200	200
No. of populations	40	40	40
Crossover probability	0.8	0.8	-
Mutation probability	0.01	0.01	-
c_d	0.995	-	0.995
c_i	1.005	-	1.005
α	500	500	500
β	0	0	0

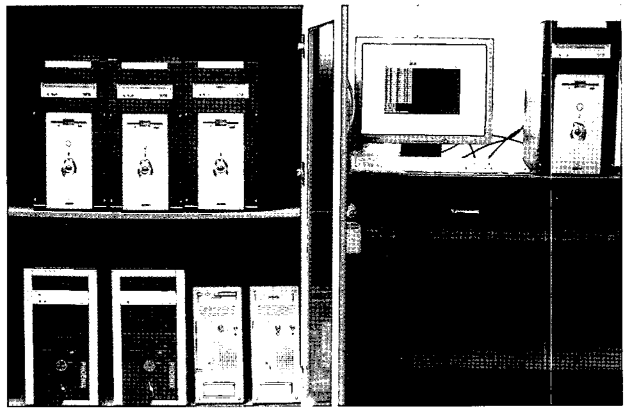


Fig. 7 PC cluster system for the proposed method

To demonstrate the usefulness of the proposed method, results of the proposed methods are compared with those of GA alone and ES alone. The optimal solution is found by GA, ES and AEA. However, more iterations are needed for GA and ES than AEA to determine the optimal solution. Fig. 8 presents the loss according to the generation. As the generation increased, the loss found in each generation decreased to 131.85 kW with switches of (6-7), (8-9), (13-14), (24-28), and (31-32) opened. As compared with the loss of 186.04 kW of the initial configuration, loss of the optimal solution reduced 29.1% and minimum voltage increased 2% from 11.69 kV to 11.89 kV.

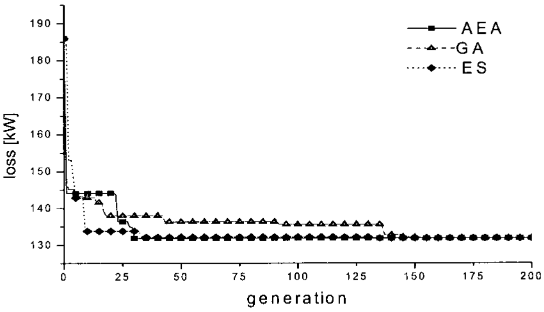


Fig. 8 Loss vs. generation curves for GA, ES, and the proposed method

Fig. 9 provides graphs of the number of individuals for GA and ES operation in AEA. As shown in Fig. 9, the percentage of individuals for GA operation is greater than that of individuals for ES operation in the initial generation. However, from generation to generation, the percentage of individuals for ES operation exceeds that of individuals for GA operation. The AEA produces improved reliability by exploiting the "global" nature of the GA initially as well as the "local" improvement capabilities of the ES from generation to generation. Table 3 describes open switch position and loss of the initial solution and optimal solution by the proposed method, respectively. Fig. 10 presents the initial and optimal configuration by the proposed method.

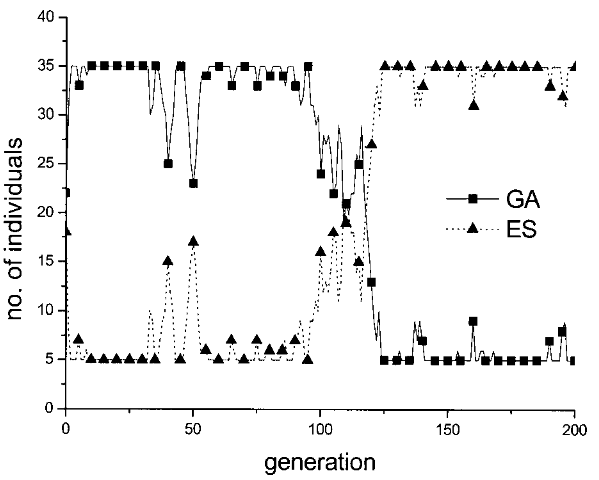


Fig. 9 Number of individuals of GA operation and ES operation

Table 3 Opened switch positions and losses for initial and optimal solutions

Initial Configuration	Open Switch Position	24 -28	7 -20	17 -32	11 -21	8 -14
	Loss	186.04[kW]				
Optimal Configuration	Open Switch Position	24 -28	6 -7	31 -32	8 -9	13 -14
	Loss	131.85[kW]				

To demonstrate the effects of the parallel characteristics by PC clustering, speedup and efficiency are evaluated. Speedup and efficiency are described below:

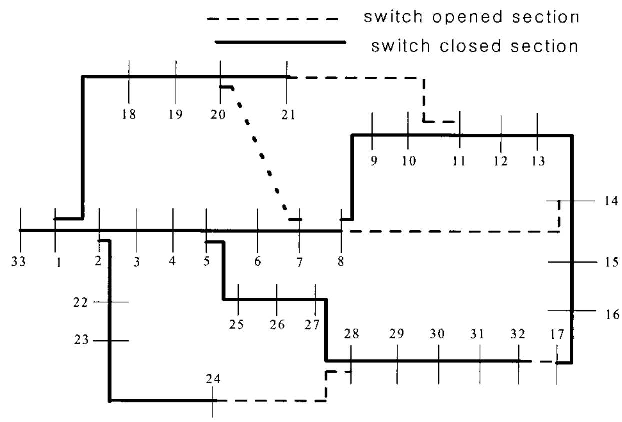
• speedup

$$S_p = \frac{T}{T_p} \tag{10}$$

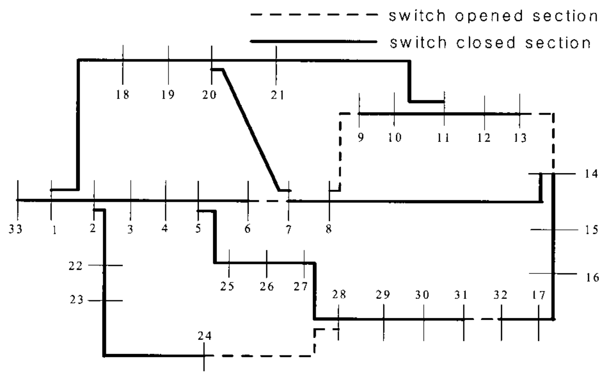
where, S_p : speedup

T : run time on one processor

T_p : run time on p processor



(a) initial configuration



(b) optimal configuration by the proposed method

Fig. 10 Initial and optimal configuration by the proposed Method

• parallel computation efficiency

$$E_p = \frac{S_p}{p} \tag{11}$$

where, E_p : parallel computation efficiency

p : no. of processors

Fig. 11 presents the speedup, efficiency, and computation time as the number of nodes increases. From Fig. 11, it is found that computation time is decreased while solution quality is maintained. Speedup increased as the number of nodes increased almost linearly, but somewhat lowered because of communication overhead when communication was executed between nodes.

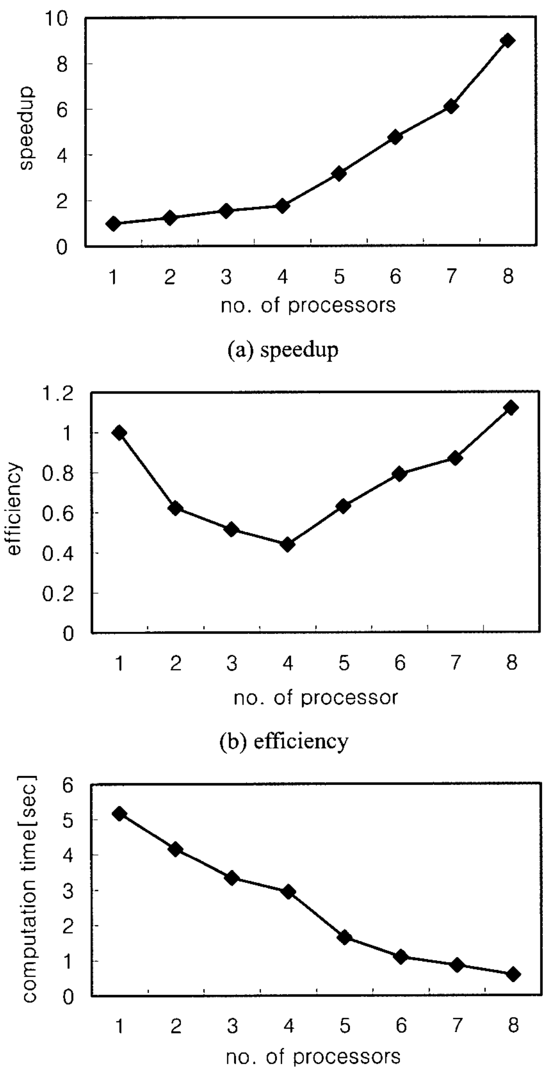


Fig. 11 Speedup, efficiency, and computation time according to the node number

4.2 69 bus distribution system

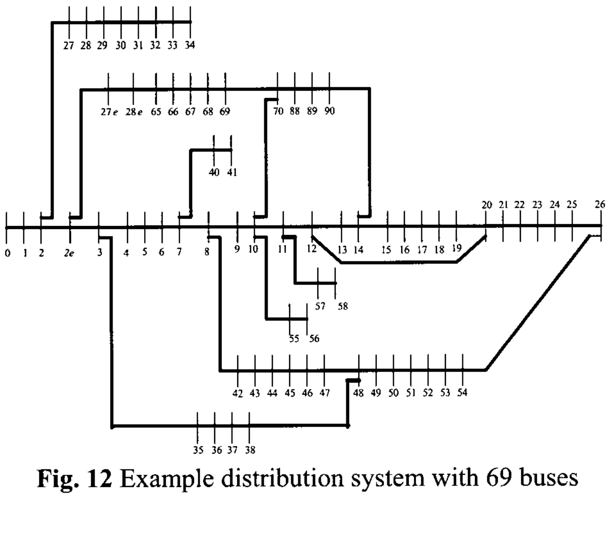


Fig. 12 Example distribution system with 69 buses

The 69 bus distribution system has 5 loops, and sectionalizing switches are placed between load buses. Feeder voltage is set to 12.66 kV, loads are modeled as constant power, and the total loads are 3,802.12 kW and 2,694.60 kVAR, respectively. Fig. 12 shows the test system. Simulation parameters of the proposed method are the same as those of the 32 bus distribution system case.

To reveal the usefulness of the proposed method, its results are compared with those of GA alone and ES alone. Fig. 13 shows the loss according to the generation. As indicated in Fig. 13, the optimal solution is found by GA, ES, and AEA. As each generation increased, the loss found in each generation decreased to 93.79 kW with switches of (10-70), (13-14), (47-48), (50-51), and (12-20) opened. As compared with the loss of 204.8 kW of the initial configuration, loss of the optimal solution reduced 54.2% and minimum voltage increased 4% from 11.56 kV to 11.98 kV.

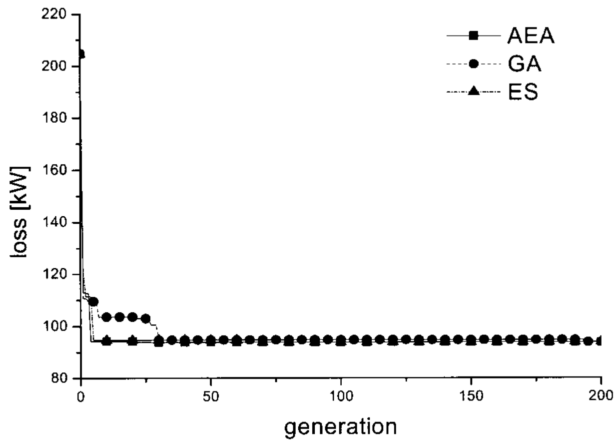


Fig. 13 Loss vs. generation curves for 69 bus system with each algorithm

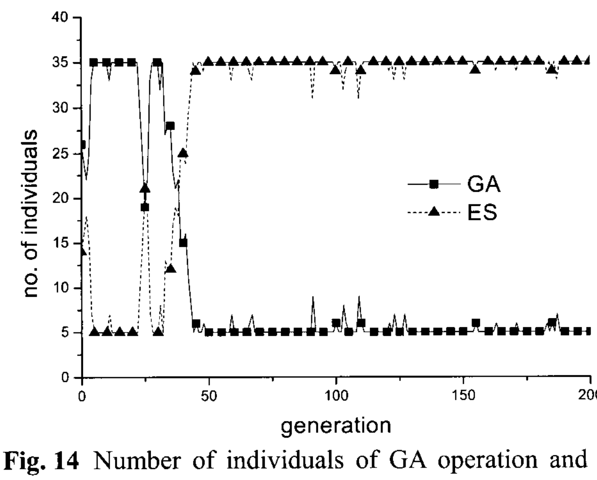


Fig. 14 Number of individuals of GA operation and ES Operation

Fig. 14 provides graphs of the number of individuals for GA and ES operation in AEA. As shown in Fig.14, the percentage of individuals for GA operation is greater than that of individuals for ES operation in the initial generation. However, from generation to generation, the percentage of individuals for ES operation exceeds that of individuals for GA operation.

Table 4 describes open switch position and loss of the initial solution and optimal solution by the proposed method, respectively. Fig. 15 presents the initial and optimal configuration by the proposed method. Fig. 16 indicates the speedup, efficiency, and computation time as the number of nodes increases. From Fig. 16, it is found that computation time is decreased while solution quality is maintained. Speedup increased as the number of nodes increased almost linearly, but somewhat lowered because of communication overhead when communication was executed between nodes.

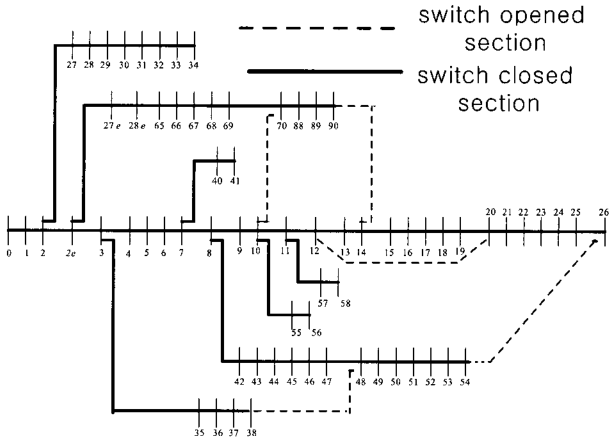
Table 4 Opened switch positions and losses for initial and optimal solutions

Initial Configuration	Open Switch Position	10 -70	14 -90	38 -48	26 -54	12 -20
	Loss	204.08[kW]				
Optimal Configuration	Open Switch Position	10 -70	13 -14	47 -48	50 -51	12 -20
	Loss	93.79[kW]				

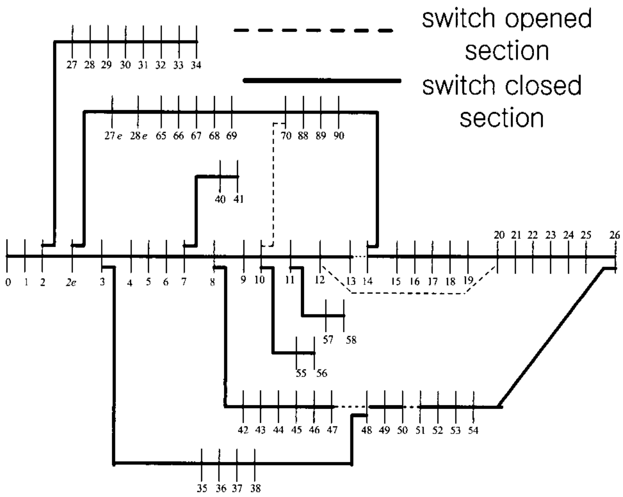
5. Conclusion

This paper presents an application of parallel AEA to search an optimal solution for reconfiguration of distribution systems. For parallel computing, a PC cluster system consisting of 8 PCs was developed. For compilers of parallel programming, MS visual C++ 6.0 was used under the Windows operating system. In parallel AEA, GA and ES are used in an adaptive manner in order to combine the merits of two different evolutionary algorithms: the global search capability of GA and the local search capability of ES. In the reproduction procedure, proportions of the population by GA and ES are adaptively modulated according to the fitness. The proposed algorithm is paralleled by the PC cluster system to enhance both the solution quality and computation time, and it is very competitive with the parallel machine in terms of cost/performance.

To indicate the usefulness of the proposed method, its results are compared with those of GA alone and ES alone. From the simulation results, it is found that the proposed algorithm is efficient and robust for distribution system reconfiguration in terms of solution quality, speedup, efficiency, and computation time.

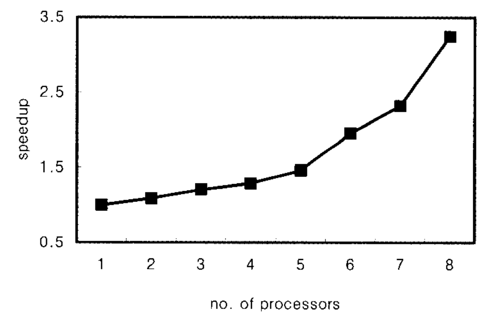


(a) Initial Configuration

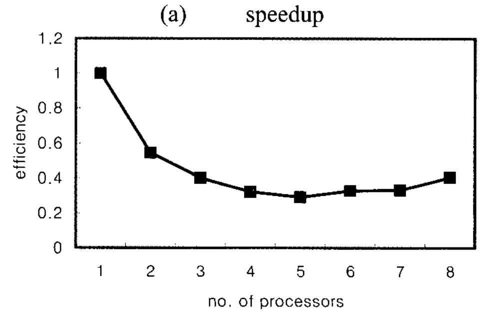


(b) optimal configuration by the proposed method

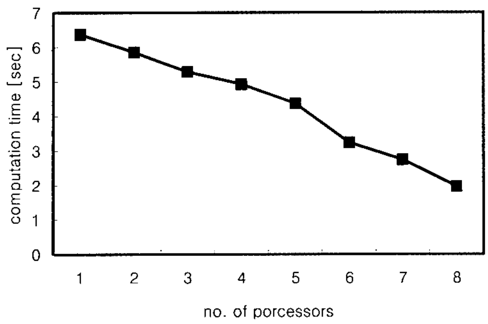
Fig. 15 Initial and optimal configuration by the proposed method



(a) speedup



(b) efficiency



(c) computation time

Fig. 16 Speedup, efficiency, and computation time according to the node number

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