A GENETIC ALGORITHM FOR OPTIMIZING SWITCHING SEQUENCE OF SERVICE RESTORATION

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Abstract - This paper proposes a genetic algorithm (GA) for a minimization problem of energy not supplied (ENS) during restoration process in local power systems or distribution systems. The solution of the problem provides an effective service restoration strategy that improves system reliability. The proposed optimization algorithm for the problem is a two-step genetic algorithm. The outer step creates radial network configurations and the inner step searches for an optimal sequence of switching operations that minimizes ENS for each configuration. The inner step is embedded into the outer step and calculates the fitness of the whole. The numerical results with a test power system show the validity of the proposed formulation for the service restoration problem and demonstrate the performance of the proposed solution method.

Keywords - Service Restoration, Switching Sequence, Distribution Systems, Genetic Algorithm

1 INTRODUCTION

WHEN a fault occurs, in order to ensure minimal reduction in system reliability, the areas isolated by the fault should be supplied with power. This procedure is called *service restoration.* The main objective of service restoration is to restore as many loads as possible by transferring loads in the out-of-service areas to other distribution feeders without violating constraints via network reconfigurations. Distribution systems are usually operated in a radial topology, but they have a kind of meshed structure that allows for several operating configurations. This means that normally open lines between neighboring parts of the network are generally provided in large distribution systems. Restoration of supply through alternate routes thus basically entails finding a sequence of connections and disconnections of line sections (closing and opening switches) so that all areas of the network are fed.

Because an effective service restoration strategy plays a key role in improving system reliability, there has been considerable research efforts focused on this problem. The problem has been addressed with methods such as integer programming, knowledge-based expert systems, artificial neural network, fuzzy reasoning, and heuristic search. Although these approaches can solve the problem with rather less computational burden, the results are only approximations and local optima. Moreover, it is difficult to find global optimum in a real system that would have a large number of switches.

In recent years, some meta-heuristic approaches have been used for service restoration in distribution systems; simulated annealing [1, 2, 3], tabu search [4, 5], and genetic algorithm [6, 7, 8] are used. Moreover, comparative studies for meta-heuristic approaches to service restoration have also been reported [9]. However, as far as the authors know, many studies with these meta-heuristic techniques have been made on the network reconfiguration and the loss minimization problem, but the application of these techniques to the scheduling of switching operations is limited. In the service restoration problem, it is not only concern to find a new network configuration that minimizes losses. It is also important to find an optimal sequence of switching operations. Although the multi-objective service restoration problem including the minimization of the number of necessary switching operations has been proposed (e.g., [5, 10]), it is insufficient from the perspective of optimizing the whole restoration process. In order to ensure minimal reduction in system reliability, not only the number of switching operations but energy not supplied (ENS) should be minimized.

In this paper, we propose a genetic algorithm for the minimization problem of ENS during restoration process in distribution systems. The solution of the problem provides an effective service restoration strategy that improves system reliability. The proposed optimization algorithm for the problem is a *two-step genetic algorithm*. The outer step creates radial network configurations and the inner step searches for an optimal sequence of switching operations that minimizes ENS for each configuration. The inner step is embedded into the outer step and calculates the fitness of the whole.

The remainder of this paper is organized as follows. In the following section, a problem formulation of minimizing ENS for service restoration is presented. The essence of the two-step genetic algorithm is presented in Section 3, and the details of each step are also presented in Section 4 and 5, respectively. In Section 6, numerical results are shown to demonstrate the performance of the proposed method, and conclusions are drawn in Section 7.

2 PROBLEM FORMULATION

In this section, we formulate the service restoration problem to minimize ENS in conjunction with network operating constraints.

2.1 ENS Minimization Problem

Service restoration in distribution systems involves operating the line switches to restore as many loads as possible for the out-of-service area after faults. Figure 1 shows a simple example of service restoration. A fault of the line switch 1 (LS1) is assumed to be occurred. In order to restore as many loads as possible, the distribution network is reconfigured by changing states of (line) switches, LS2, LS3 and LS4.

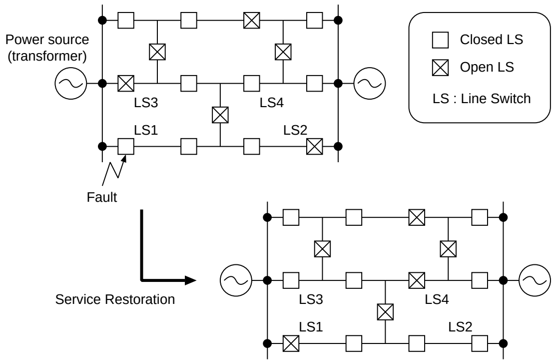

Figure 1: A simple example of service restoration

As mentioned above, not only the final network configuration but also the sequence of switching operations is important in service restoration because the sequence of operations has a considerable influence on system reliability. Moreover, the switching operations must be sequentially performed by technical limitations. Although the problems that minimize the number of necessary switching operations or duration not supplied (DNS) are already proposed, from the perspective of optimizing the whole restoration process, ENS should be minimized.

2.2 *Constraints*

Not every configuration is a valid solution to the restoration problem. Therefore, it is necessary to specify which configurations are feasible or not. The constraints that should be considered are as follows:

1. *Radial network constraint*
   Distribution system must retain radial topology.
2. *Power source constraint*
   The total loads of each sub-system must not exceed the capacity of the corresponding power source.
3. *Line capacity constraint*
   The line currents must not exceed the maximal values related to the line sections.

The first constraint addresses the admissibility of a candidate solution, and the last two constraints provide a measure of its quality or fitness. Only those networks corresponding to admissible candidates need to be evaluated for the presence of overloaded components. In addition to the constraints listed above, the following additional requirements should be satisfied in the problem. If these requirements cannot be met, a certain value will be added as a penalty to the objective function.

4. Power not supplied should decrease monotonically.
5. All de-energized loads should be restored after completing restoration.

2.3 *Objective Function*

Let h_k be power not supplied (PNS) after the k-th switching operation, and t_k be a time interval needed for the $(k+1)$-th operation. ENS to be minimized in this problem is defined as

$$\mathrm{ENS} = \sum_{k=0}^{K-1} (h_k \times t_k), \qquad (1)$$

where K is the number of switching operations. For convenience, the fault occurrence is defined as the 0-th switching operation. The relationship between PNS and ENS is shown in Figure 2. PNS just after a fault is h_0 and the time needed for the first switching operation is t_0. PNS after the first operation is h_1 and the time needed for the second operation is t_1, and so on.

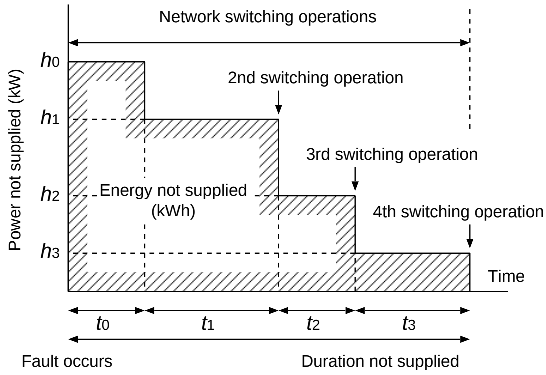

Figure 2: Energy not supplied (ENS)

3 PROPOSED SOLUTION METHOD

In this section, an optimization method based on genetic algorithm, we call a two-step genetic algorithm, is proposed for the service restoration problem defined in the previous section. The genetic algorithm (GA) is a method for search and optimization that imitates the process of natural selection and evolution. Due to their ability to find global optimal solutions for large-scale combinatorial optimization problems, GAs have been found to be efficient methods for power system problems, including the service restoration problem [7, 8]. The proposed method uses GA as an optimization procedure in each step. The outer step creates radial network configurations and the inner step searches for an optimal sequence of switching operations that minimizes ENS for each configuration.

The flowchart of the proposed algorithm is shown in Figure 3. The candidates for final configuration are created in the outer step and passed to the inner step. Then the inner step evaluates them by finding an optimal sequence of switching operations and returns their fitness to the outer step.

One of the most important factors which affect a GA's performance is the interaction of its coding of candidate solutions with the operators it applies to them. In particular, all chromosomes should represent feasible solutions. In order to improve the performance of the proposed method, we adopt the *edge-set representation* [11] for a radial network and the *random keys representation* [12] for a sequence of switching operations. By using these representations, all chromosomes generated by initialization, crossover and mutation can represent feasible solutions. The details of chromosome representations adopted in each step are described in the following sections.

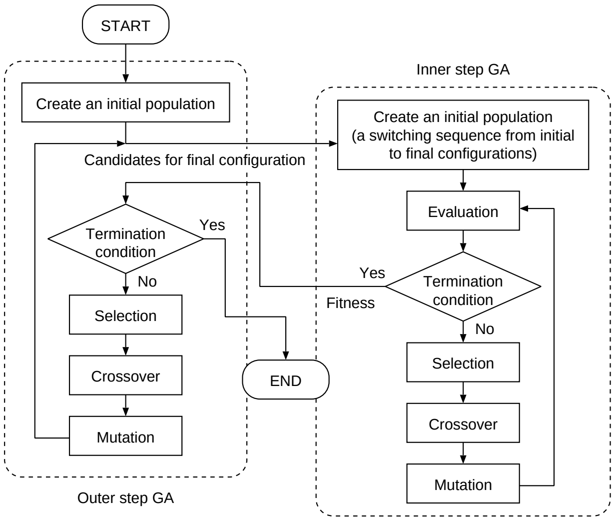

Figure 3: Two-step genetic algorithm for service restoration

4 OPTIMIZING NETWORK CONFIGURATION

In the outer step of the two-step genetic algorithm, radial network configurations as the candidates for final configuration are created. As the fitness of each configuration is evaluated by the inner step, the outer step only searches optimal radial network configurations. Hence, the problem dealt in the outer step is the conventional network reconfiguration.

4.1 Representing Radial Network

The radial network configuration can be roughly modeled as an undirected graph, where

- the edges (branches) represent line switches, and
- the nodes represent collections of power systems equipment containing feeder segments and power sources.

The network configuration problem is therefore regarded as finding an optimal spanning tree that satisfies the constraints on the corresponding graph.

Much work has been done on representing spanning trees for evolutionary search (e.g., [13]). Recent studies have indicated the general usefulness of representing spanning trees directly as lists of their edges and applying operators that always yield feasible trees [11]. In this paper, we adopt the edge-set representation and unique operators that are based on random spanning tree algorithms. These operators offer strong locality, heritability and computational efficiency.

4.2 Initialization

Kruskal's algorithm builds a minimum spanning tree (MST) on a weighted graph G by examining G's edges in order of increasing weight. It incrementally adds the edges that connect previously disconnected components. If the algorithm instead examines G's edges in random order, it returns a random spanning tree on G. This algorithm is called KruskalRST [11]. Besides KruskalRST, algorithms based on Prim's MST algorithms (PrimRST) and on random walks (RandWalkRST) are also proposed. However, Julstrom et al. indicates that the choice of initialization operator does not affect the algorithm's performance on the One-Max-Tree problem [14]. In this paper, initialization of the population is based on KruskalRST.

4.3 Crossover Operator

In GA, offspring should represent solutions that combine substructures of their parental solutions. To provide this *heritability*, a crossover operator must build a spanning tree that consists mostly of edges found in the parents. It is also beneficial to favor edges that are common to both parents [11]. This can be done by applying any of the random spanning tree algorithms to the graph $G' = (V, T_1 \cup T_2)$, where V is the set of vertices and T_1 and T_2 are the edge sets of the parental trees. Figure 4 illustrates a sketch of this crossover operation.

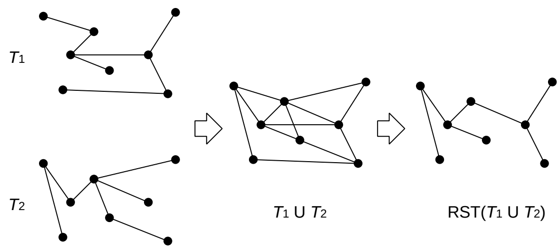

Figure 4: Crossover operation

4.4 Mutation Operator

A mutated chromosome should usually represent a solution similar to that of its parent. To provide this *locality*, a mutation operator must make a small change in a parent solution. This means that a mutated chromosome should represent a tree that consists mostly of edges also found in its parent. This can be done by deleting a random edge from T and replacing it with a random new edge that reconnects the tree. This replacement is also based on random spanning tree algorithms. Figure 5 shows this operation.

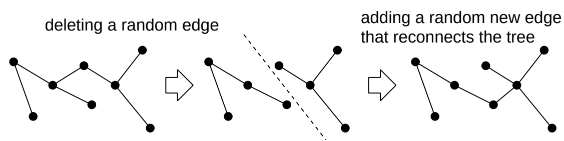

Figure 5: Mutation operator

5 SCHEDULING OF SWITCHING OPERATIONS

The inner step of the proposed method searches for an optimal sequence of switching operations that minimized

ENS for each configuration created in the outer step. The optimal values obtained in this step are regarded as the fitness values of configurations.

5.1 Determination of Operation Switches

Each switch is assumed to be operated only at most once. Under this assumption, the switches to be operated can be determined as the ones whose state changes from open to closed, and vice versa. Let T_0 and T_K be the edge set of the initial and the candidate for final configuration, respectively. The edge set E^d corresponding to the switches to be operated is determined as the symmetric difference of the two sets T_0 and T_K.

$$E^d = (T_0 \cup T_K) \setminus (T_0 \cap T_K). \tag{2}$$

Figure 6 illustrates how to identify E^d from T_0 and T_K. The fault point is assumed to be included in E^d, and the edge sets E_0^d and E_1^d are defined as follows:

$$E_0^d = E^d \cap T_0, \quad E_1^d = E^d \cap T_K. \tag{3}$$

E_0^d is the edge set corresponding to the switches whose state changes from closed to open, and E_1^d is from open to closed.

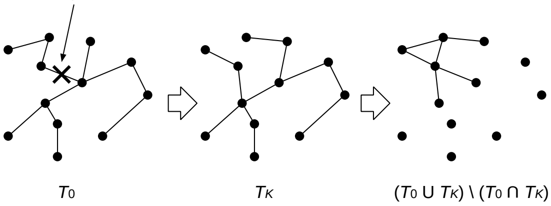

Figure 6: Determination of operation switches

5.2 Representing Sequence of Switching Operations

As mentioned above, the solution for service restoration is a sequence of operations that specify which switches need to change their state. Such a sequence is represented in the form of a string where each element of the string is the label of a switch. The first element of the string is interpreted as the switch that needs to be closed, the next element is taken as representing the switch to be open, and so on. In this paper, we assume that the distribution system must retain radial topology even during restoration process. To meet this requirement, a switching operation must be performed in the pair of *closing* and *opening*, such as (closing, opening).

For example, let $E_0^d = \{e_0, e_1, e_2\}$ and $E_1^d = \{e_3, e_4, e_5\}$. The fault occurrence is assumed to be e_0. An example of valid switching operations is as follows:

$$(e_0, e_4, e_5, e_2, e_3, e_1).$$

The fault e_0 must be located at the first position of switching operations and e_4 is located at the second position to restore the system back to a radial topology. The pairs (e_5, e_2) and (e_3, e_1) are in the form of (closing, opening).

Although the edges in E_1^d can be arbitrarily ordered, the edge in E_0^d must be chosen among edges in a loop for retaining radial network configuration. In the inner step, a sequence of switching operations is represented as a permutation of only the edges in E_1^d, and the edges in E_0^d are not included in a chromosome. In determining the order of opening operations, we adopt a method based on the perturbation mechanism [2] that is suitable for the network reconfiguration problem.

5.3 Random Keys Representation

As stated above, the problem dealt by the inner step is regarded as finding an optimal permutation of the edges (switches) in E_1^d. We adopt the random keys [12] for permutation representation. The random keys representation encodes a permutation with uniform $(0, 1)$ random numbers. These values are used as *sort keys* to decode the permutation. One of the important features of random keys is that all offspring formed by genetic operators are feasible solutions.

An example of the random keys encoding for permutation is shown below.

$$(0.46, 0.91, 0.33, 0.75, 0.51).$$

From this chromosome, we get the sequence,

$$3 \to 1 \to 5 \to 4 \to 2.$$

The inner step uses the random keys for representing a sequence of switching operations. Random keys can use every traditional crossover operators. We use a one-point crossover in the inner step. The mutation operator replaces the value of a gene by a uniform $(0, 1)$ random number.

5.4 Fitness Evaluation

Power not supplied (PNS) can be calculated as the difference between the sum of loads and the maximum flow. The maximum flow for a distribution system is defined as the sum of power flows from each power source. Let ℓ_i be a capacity (demand) of the load node i, L be the number of load nodes, and $f_k^{\max}$ be a maximum flow after the k-th switching operation. PNS after the k-th operation is calculated using the following equation:

$$h_k = \sum_{i=1}^{L} \ell_i - f_k^{\max}, \quad \forall k = 1, 2, \ldots, K. \tag{4}$$

From the equations (1) and (4), we can obtain ENS for a candidate for final configuration. Moreover, if additional requirements in Section 2 cannot be met, a value P will be added as a penalty to the objective function, as given by equation (5):

$$P = w_1 \sum_{k=1}^{K} \max\{h_k - h_{k-1}, 0\} + w_2 \max\{h_K, 0\}. \tag{5}$$

In this paper, the fitness function is formulated as the inverse of the objective function.

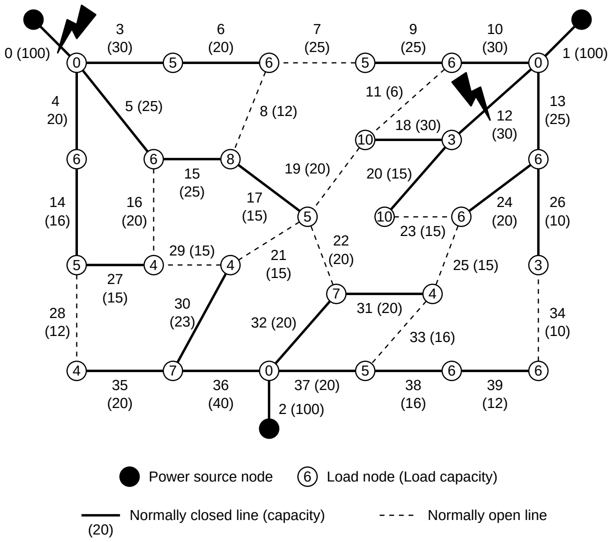

Figure 7: Test distribution system (30 nodes, 40 lines)

6 NUMERICAL RESULTS

The distribution system used in our experiments includes 3 transformers, 27 load nodes and 40 edges. Figure 7 illustrates the network structure of the system. The number in a circle shows the load capacity (demand), the number next to an edge shows the edge number, and the number in parenthesis shows the capacity of the edge. The sum of the load capacity is 124. In order to demonstrate the performance of the proposed method, two simulation cases were investigated.

- Case 1: A fault occurs on switch 12.
- Case 2: A fault occurs on switch 0.

We used a kind of steady state GA in the experiments. Initially, a certain number (*pop*) of parent individuals are set up in the population, and the same number of offspring are created from the parents. Then, the *pop* best individuals are selected as the new population from the union of parents and offspring. Roulette wheel selection was used to select pairs for reproduction. All numerical experiments were performed on AMD Athlon processor 1.5GHz. The proposed method was coded in C and we compiled the code with gcc 2.95.4 -O3.

6.1 Parameters Setting

Parameters used in the experiments are listed below.

- Time interval: $t_k = 1.0, \ \forall k = 1, 2, \ldots, K$
- Penalty function: $w_1 = 10, w_2 = 10$
- The outer step GA:
  - population size: $pop = 20$
  - prob. of crossover: $p_c = 0.4, 0.6, 0.8, 1.0$
  - prob. of mutation: $p_m = 0.03, 0.06, 0.10$
  - maximum generation: $g_{\max} = 50$
- The inner step GA:

$$pop = 8, p_c = 0.8, p_m = 0.10, g_{\max} = 5$$

6.2 Case 1

In this case, the optimal value (and the minimum ENS) is 46 and the optimal sequence of switching operations is shown in Figure 8. PNS just after a fault is 23. PNS monotonically decreases and then all de-energized loads are finally restored.

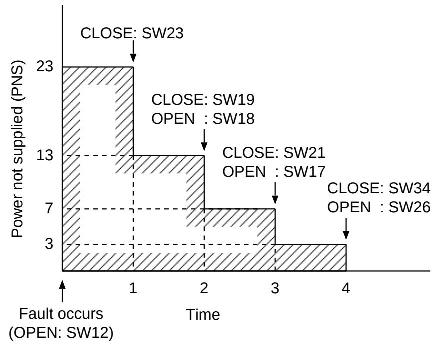

Figure 8: Optimal sequence of switching operations (Case 1)

Table 1 shows the average number of generations (in the outer step) required to obtain the optimal solution for 10 runs of the proposed method, and also shows the number of success runs in parenthesis. The proposed method can always find the optimal solution when $p_m \geq 0.06$.

	p_m		
p_c	0.03	0.06	0.10
0.4	31.2 (8)	26.6 (10)	24.6 (10)
0.6	23.1 (9)	20.6 (10)	26.2 (10)
0.8	24.7 (9)	16.3 (10)	21.4 (10)
1.0	21.1 (10)	19.7 (10)	22.8 (10)

Table 1: Average Number of Generations For 10 Runs (Case 1)

An example of convergence behavior is depicted in Figure 9. From the results of Table 1, the values of parameters p_c and p_m were set to 0.8 and 0.06, respectively. The term 'Best' in Figure 9 represents the best value within the iteration, we call *iteration-best*. This figure shows that the average and the iteration-best values gradually converge to the optimal value as the search progresses.

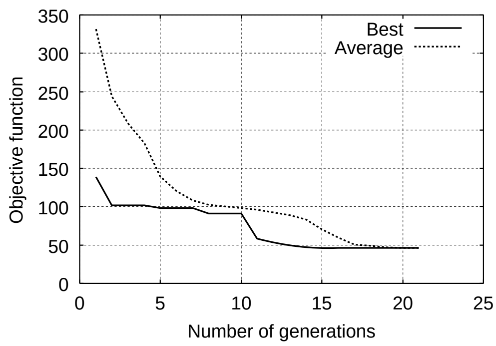

Figure 9: Convergence behavior of the proposed method (Case 1)

In order to verify the validity of the new problem formulation that minimizing ENS and the proposed solution method, the optimal solution and the near optimal solutions were searched using exact method. Among the solutions satisfying all the constraints and the requirements, the optimal and near optimal solutions are listed in Table 2. The edge number 12 in parenthesis at the first position of the sequence is the faulty edge.

#	ENS	Sequence of switching operations
1	46	(12) 23 19 18 21 17 34 26
2	47	(12) 23 19 18 34 26 21 17
3	49	(12) 23 19 18 21 17 7 3 34 26
4	49	(12) 23 19 18 21 17 7 6 34 26
5	49	(12) 23 19 18 21 17 7 9 34 26
6	49	(12) 23 19 18 21 17 7 10 34 26
7	49	(12) 23 19 18 21 17 8 3 34 26
8	49	(12) 23 19 18 21 17 8 6 34 26
9	49	(12) 23 19 18 21 17 8 15 34 26
10	49	(12) 23 19 18 21 17 16 14 34 26

Table 2: Optimal and Near-optimal Solutions (Case 1)

6.3 *Case 2*

In this case, the optimal value (and the minimum ENS) is 86 and the optimal sequence of switching operations is shown in Figure 10. PNS just after a fault is 45. PNS monotonically decreases and then all de-energized loads are finally restored.

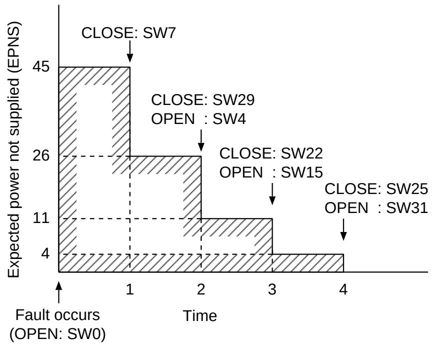

Figure 10: Optimal sequence of switching operations (Case 2)

Table 3 shows the average number of generations (in the outer step) required to obtain the optimal solution for 10 runs of the proposed solution method, and also shows the number of success runs in parenthesis. Compared with case 1, more generations are required to obtain the optimal solution and the proposed method cannot always find the optimal solution. The reason why the performance of case 2 was worse than case 1 is that the switch 0 is an important one directly connecting the power source to the network. If the switch 0 has a fault, the whole loads must be supplied with only two power sources and therefore the service restoration becomes more complicated.

	p_m		
p_c	0.03	0.06	0.10
0.4	45.2 (4)	34.6 (7)	44.5 (4)
0.6	42.4 (5)	41.6 (7)	44.1 (5)
0.8	32.1 (8)	34.2 (6)	45.9 (3)
1.0	39.5 (7)	44.4 (4)	43.4 (6)

Table 3: Average Number of Generations for 10 Runs (Case 2)

In the same way as case 1, the optimal solution and the near optimal solutions were searched using exact method. Among the solutions satisfying all the constraints and the requirements, the optimal and near optimal solutions whose ENS is not more than 90 are listed in Table 5. The edge number 0 in parenthesis at the first position of the sequence is the faulty edge. From the results in Table 5, we can find that the operation switches of the solution #1 and #13 are equivalent, but that of the solution #3 is different. Hence, if the problem formulation is not the ENS minimization problem but the multiobjective problem minimizing the final PNS and the number of switching operations, the solution #3 can be an optimal solution because the final PNS is 0 and the number of operations is 8. However, as shown in Table 5, the solution #3 cannot be an optimal solution from the perspective of optimizing the whole restoration process.

6.4 *Time Performance*

Table 4 shows the average, minimum, and maximum time required to obtain the optimal solution for 100 runs ($p_c = 0.8$, $p_m = 0.06$). Although the average time is less than 30 seconds for each cases, one difficulty is encountered when applied to large real-world problems. For improving the performance of the proposed method, it seems to be promising to be combined with some local search procedures (e.g., branch exchange [15]) or some efficient maximum flow algorithms on radial networks.

	avg.	min.	max.
Case 1	17.30	4.77	43.19
Case 2	28.73	5.63	45.99

Table 4: Time Performance (seconds) for 100 Runs

7 CONCLUSIONS

In this paper, we proposed a genetic algorithm for the minimization problem of ENS during restoration process in distribution systems. The proposed optimization algorithm for the problem is a *two-step genetic algorithm*. The outer step creates radial network configurations and the inner step searches for an optimal sequence of switching operations that minimizes ENS for each configuration. The numerical results show the validity of the proposed formulation for the service restoration problem and demonstrate the performance of the proposed solution method.

However, it is very difficult to conclude what would be the right combination of genetic parameters. There have been many research projects for *self-adaptive* GA because such adaption can tune the parameters while solving a given problem. Nevertheless, it is a very time-consuming task to design an optimal GA in an adaptive way because we have to perform computation many times by trial and error. Adaptive parameter control is one of the most important areas of research in GA for ensuring robustness of algorithms. For improving the performance of the proposed method, adaptive control mechanisms need to be explored further.

#	ENS	Sequence of switching operations															
1	86	(0)	7	29	4	22	15	25	31								
2	87	(0)	7	29	4	22	15	33	31	34	39						
3	88	(0)	7	29	4	19	15	23	20								
4	88	(0)	7	29	4	22	15	33	31	28	27	34	39				
5	89	(0)	7	29	4	22	15	33	31	28	27	16	3	34	39		
6	89	(0)	7	29	4	22	15	33	31	28	27	16	5	34	39		
7	90	(0)	7	29	4	22	15	33	31	28	27	16	3	8	17	34	39
8	90	(0)	7	29	4	22	15	33	31	28	27	16	5	8	17	34	39
9	90	(0)	7	29	4	22	15	28	27	25	31						
10	90	(0)	7	29	4	22	15	34	26	25	31						
11	90	(0)	7	29	4	22	15	34	39	25	31						
12	90	(0)	7	29	4	22	15	34	39	33	31						
13	90	(0)	29	7	4	22	15	25	31								

Table 5: Optimal and Near-optimal Solutions (Case 2)

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