The Third AFSS(1998), 625-628

Optimal Configuration of Distribution Network using Genetic Algorithms

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ABSTRACT

This paper presents an application of genetic algorithms (GAs) for optimal configuration of distribution network. Three problems have been used to show how genetic algorithms are modified and applied. Solutions to the problems are found by minimizing the cost function which is directly related with balancing the loads. Simulation results show that genetic algorithms are technically feasible if they are tailored to meet the needs of real problem.

Keywords: genetic algorithms, load balancing, optimal network reconfiguration.

I. INTRODUCTION

One of the major issues in distribution automation is to maintain optimal configuration of distribution networks. The configuration is determined by the status of switches in the distribution network. Traditional optimal configurations are obtained by minimizing power losses and recent efforts have been made along this direction[1-2]. Network reconfiguration is required in various conditions such as abrupt changes of loads including occurrence of a fault in the network. The network reconfiguration should be conducted in a timely and effective manner so as to minimize interruptions to customers. In this paper we like to achieve optimal network configuration from the viewpoint of balancing loads instead of loss minimization.

Determining the positions of open switches is a discrete optimization problem. In order to address the problem, we present an optimization method using genetic algorithms (GAs). A genetic algorithm[3] is a process mimics the way biological evolution works. The population of individuals represents a set of potential solutions to a given problem. As the generation evolves, a new population is formed by the principle of "survival of the fittest" and the overall quality of solutions is enhanced through the process. It is expected that the optimal solution having the largest fitness is found in a relatively small number of iterations compared to other search methods.

In this paper we present the application of GAs to the problem of optimal configuration of a radial distribution network to examine the feasibility of GAs to achieve the objective.

In section II, problem statements and assumptions in solving the problems are described. In section III, we present a brief review of GAs as well as the modified GAs to resolve the problems. In section IV, numerical examples are given to show that our proposed method based on GAs works properly. Lastly, conclusion including further research is mentioned in section V.

II. PROBLEM STATEMENTS

Fig. 1 shows the configuration of a distribution feeder system adopted from [1] where terms like switch, zone, arc and node are defined. The number in Fig. 1 represents a position of a switch. In this paper, we like to solve the following problems using GA:

[problem 1: load balancing] Find the positions of open switches so as to minimize the variance of power delivered by each feeder.

[problem 2: reconfiguration] Reconfigure the system if a fault occurs in a certain point in the network.

[problem 3: search] Find the set of open switches satisfying the condition that the amount of power

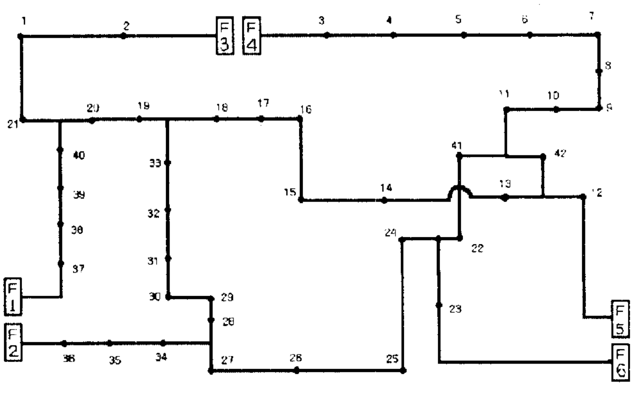

Fig. 1 Typical distribution feeder configuration[1]

each feeder supplies is always greater than that of the load connected to the corresponding feeder consumes. Since we have set the supply and the demand very closely, there is the one and only points in search space which meets the condition.

Three assumptions are made in this paper. The first one is the Concentrated Load Model(CLM) is used for analysis of the distribution system. It means power consumption occurs in the middle of the zone. Secondly, the amount of load in each zone is randomly chosen from a set of {1, 2, 3, 4}. Finally we assume that the capacities of feeders are the same in solving the power balancing and reconfiguration problems. That is not the case with the search problem.

In order to apply GAs, we need to express the problems in the mathematical formulation. The solutions of the problem 1 and 2 are obtained by locating the open switches which minimize the following cost function

$$\cos t = \sqrt{\sum_i \alpha_i \times (F_i - MF)^2 / N} \tag{1}$$

where α, F_i, MF, and N are a weight coefficient, the amount of power consumed from the feeder i, average value of F and the number of feeder, respectively. The weight coefficient is determined by the ratio of supply(S_i in Eq. (2)) to demand in the network connected to the feeder i. If the ratio is less than one, then α is given by one. Otherwise 1.2 is assigned in the simulation in this paper. Therefore an ideal case is that the loads connected to the each feeder consume the same amount of power (*cost* =0).

Problem 3 finds the location of open switches satisfying the condition that the supply are slightly greater than or closed to the demand. The corresponding cost function differs from Eq. (1) and can be obtained from

$$\cos t = \beta \times \sqrt{\sum_i (S_i - F_i)^2 / N} \tag{2}$$

where S_i is the supply from the i-th feeder. The weight coefficient β is given by $1+ 0.15 \times n$, where n is the number of feeder of which S_i (supply) is smaller than F_i (demand). To reduce the cost of Eq. (2), it is desirable to make (S_i - F_i) positive small. That means the supply from each feeder is slightly for the demand.

III. APPLICATION OF GAs

Genetic algorithms(GAs) are procedures for optimization, search and adaptation by imitating natural selection and biological evolution. They are fairly efficient compared to many other search methods and are much more efficient than exhaustive search.

Let us provide a brief procedure for simple GA. The initial population consists of randomly generated solution (individual) for a given problem. Each solution is known as chromosome in GA. We evaluate each solution by giving a fitness which reflects how well the solution solves the task in hand. A new population (offspring) is generated by interaction between selected individuals in the parent generation. The selected individual is chosen according to its fitness and the interaction which is made by genetic operators such as crossover and mutation. The last procedure is repeated until certain conditions are met. In each generation, the individual which has the best fitness may be a candidate solution to the problem.

The following is the pseudo code for a simple GA(SGA):

```
set time counter t=0
initialize population P(t);
evaluate P(t)
while (termination conditions are not met) do
        t = t+1;
        P'(t) = select parents P(t);
        crossover P'(t);
        mutate P'(t);
        P(t)=P'(t);
        evaluate P(t);
end
```

In this paper, each solution (individual or chromosome) is represented as an array of 42 (number of switches) components. Each component indicates the status of switch (1 for closed and 0 for open). For example, 1101101.... means that the third and the sixth switches are open. To produce new generation (population), the elite selection method is employed and only mutation is applied to the individual. The reason for omitting crossover, a standard operator in GA, is that it leads to an ineffective global search. Mutation evokes a small change which is regarded as a local search and it is applied to a chromosome. The result of mutation is to change the location of open switch.

Fitness should be calculated before selecting the parents from which offspring is generated. There are infinitely many ways to define fitness and let choose one of them as

$$Fitness = \frac{1}{\cos t} \tag{3}$$

where cost is already defined in Eqs. (1) and (2). It is easy to accept that fitness is inversely proportional to the cost function. However if F_i is greater than the feeder can supply, then α is 1.2 and otherwise α is 1 in this paper. The value of α is heuristically determined from a number of experiment. The same is true with the value of β in Eq. (2). It is obvious that the denominator of *Fitness* should be smaller for a better individual and therefore, assigning α to be 1.2 is punishment for a certain individual which may not survive to the next generation.

IV EXAMPLES

The first example deals with the optimization of power balancing problem in which the power delivered from the feeders is desired to be uniformly distributed. The objective can be found from the cost function of Eq. (1).

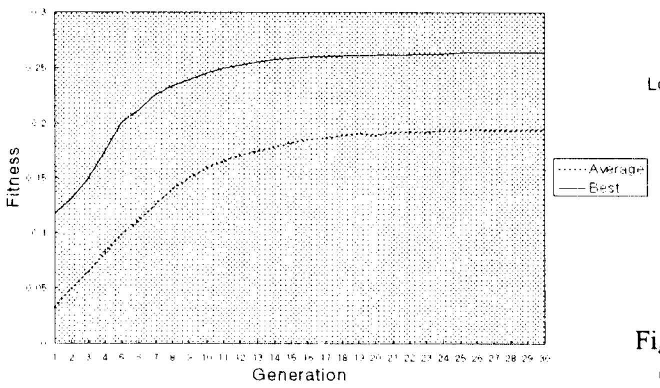

Fig. 2 Simulation result of load balancing problem

Fig. 2 shows the simulation results of 100 trials. Average fitness is obtained by averaging fitness from 100 trials. The best fitness means the best one in every generation and the optimal point is reached in less than 30 generations. The result shows that the optimal set of open switches is {11,18,27,32,40,42} and the amount of the load required from each feeder is {10, 20, 22, 17, 19, 17} where the first number indicates the amount of load taken from feeder 1 and so on. In this problem, the capacity of each feeder is given by 25.5. The time to find optimal point depends on the mutation rate and therefore it requires caution to choose the rate.

In the second example, we try to find the new position of open switches when a reconfiguration is required due to an abrupt disconnection. In Fig. 1, we assume that a fault occurs at the point of switch 4 , then the loads disconnected need to be supplied from other feeder. A new assignment of feeder by changing the position of open switches is a reconfiguration process. The evolution of solutions can be observed in Fig. 3 where the amount of load supplied by each feeder is changed so that initially small feeder becomes large and vice versa. The result represents minimization of Eq.(1) and the position of open switches in the reconfigured system is {4,18,24,31,40,42}.

The last example demonstrates the capability of GAs to find the one and only optimal point in the search space consisting of any combination of 6 different numbers in [1, 42]. We assigned the position of open switches beforehand, then set the capacity of each feeder tightly meet the given loads so that there exists the one and only optimal solution. Running GAs with the cost given by Eq. (2), we found the optimal point at the ninth generation as shown in Table 1.

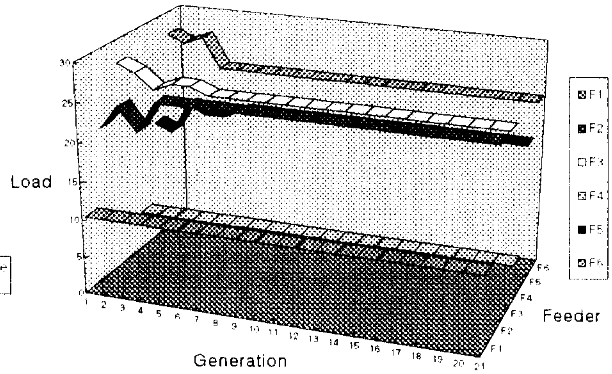

Fig. 3 Simulation result of reconfiguration: a new set of open switches is {4, 18, 24, 31, 40, 42} where disconnect switch 4 triggered the reconfiguration

V. CONCLUSION

In this paper, we demonstrate the feasibility of genetic algorithms to the optimal configuration of distribution networks problem. Three examples tested are classified as power balancing, reconfiguration and search problems which require optimization.

We use mutation exclusively, because crossover hardly yields a better result during experiment. But we believe that it is necessary to examine how to use the crossover operator for taking advantages of GAs. Of particular importance is the method of coding chromosome (individual, solution) to use the crossover in the above examples.

From the result of examples, it doesn't require much modification to use the GA procedure outlined in the paper. However a further research may include a proper use of the crossover operator and a simulation with real data from distribution network.

Table 1(a) Simulation result of search problem: the first column indicates the n-th generation and the capacity of each feeder is given by {10.5, 23.5, 31.5, 14.5, 15.5, 12.5}.

	F1	F2	F3	F4	F5	F6	Fitness
0	13	13	7	14	49	9	0.047442
1	10	16	31	10	16	22	0.157725
2	7	22	25	17	24	10	0.171598
3	6	22	27	17	23	10	0.193312
4	7	23	28	16	16	15	0.325484
5	7	26	28	16	16	12	0.325519
6	10	22	30	14	19	10	0.459276
7	10	22	34	14	15	10	0.565575
8	10	22	34	14	15	10	0.565575
9	10	23	31	14	15	12	1.994128

Table 1(b) Simulation result of search problem: the second to seventh columns show the positions of open switches.

	Switch					
0	21	20	28	25	41	9
1	40	30	26	16	6	42
2	39	32	26	18	41	11
3	38	32	26	17	41	11
4	39	32	25	16	10	42
5	39	32	24	16	10	42
6	40	32	26	14	41	9
7	40	32	26	13	41	9
8	40	32	26	13	41	9
9	40	33	27	13	41	9

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