An application of Genetic Algorithm with Fuzzy Inference to Real Scale Distribution System for Loss Minimization Re-configuration Problem

SHUICHI NONAKA, SHUTA MURAKAMI
Department of Electrical, Electronic and Computer Engineering
Kyushu Institute of Technology
Sensui-cho1-1, Tobata, Kitakyushu 804-8550
JAPAN

Abstract: - This paper deals with a loss minimum re-configuration problem of real scale distribution system. The problem is one of the complex integer programming problems. Since the genetic algorithm(GA) is suitable to solve combinatorial optimization problems, it can be already applied successfully to loss minimum problems in such distribution systems. Nevertheless, it is very difficult to apply a loss minimum re-configuration problem of real scale distribution system, as it stands.

In this paper, we propose a GA method with fuzzy inference, and apply it to a electric distribution networks system. From the application, the validity and effectiveness of the proposed method are shown.

Key-Words: - Power Distribution System, Genetic Algorithm, Loss Minimization, Fuzzy Inference, Re-configuration Problem, Integer Programming Problem
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1 Introduction

Most of the electric distribution networks are spreading radially. Nevertheless, there are usually available several interconnecting tie switches. Configuration adjustment may be performed by changes of the network switches state, in such a way that radiality is always reestablished after the end of the manipulations.

The optimal operating condition of the distribution networks is usually considered to be obtained when line losses are minimized, without any violations of branches loading and voltage limits. Other service quality criteria can be also used, like service continuity or voltage stability.

The loss minimization problem was formerly faced as a part of distribution networks planning studies.

Recent advances in distribution automation technology have substantially improved control and network management capabilities. Consequently, the general loss minimization problem has greater effect on distribution operation decisions.

Since the problem can be formulated as a mathematical programming model, an approximate mathematical programming solution algorithm is one of the direct type solution methods [1]-[3]. The so-called branch-exchange algorithm seems to be the most efficient approximate solution method, and many improved methods have been proposed [4],[5]. A heuristic approach is an another alternative [6],[7]. The expert system has been introduced to this area for implementing the heuristic rules [8]-[10].

Although the above mentioned algorithms can solve the problem with rather less computational burden, the calculation results are only approximate or are only local optimums. To find an approximate global optimal, the simulated annealing method is employed [11],[12]. However, the computational burden is too great to get a satisfactory solution. Recently, to get the approximate global optimum with less computational burden, the genetic algorithm(GA) method is proposed [13]. And an improved method have been proposed [14]-[16].

GA is a search algorithm based on the mechanics of natural selection and natural genetics. It combines the adaptive nature of the natural genetics or the evolution procedures of organs with functional optimizations. By simulating the survival of the fittest among string structures, the optimal string (solution) is searched by randomized information exchange. In every generation, a new set of artificial strings is created using bits and pieces of the fittest of the old ones. It efficiently exploits historical information to speculate on a new search point with expected improved performance.

Since GA utilizes the coded discrete information of the artificial strings, it can be applied to illstructured discrete optimization problems as well as continuous optimization one. Moreover, it searches from a population of points, not a single point, and the possibility of finding a near optimum in an early generation is very high.

The genetic algorithm was successfully applied to the loss minimum re-configuration problem[15]. In the proposed algorithm, the coded strings consist of sectionalized switch status or radial configurations, and the fitness function consists of the total system losses and penalty values of voltage drop and current capacity violations.

In this paper, we improve this method more usefully, and propose a new method with an automatic adjustment function of genetic parameters by some fuzzy reasoning rules.

2 Problem Formulation

2.1 Composition of distribution system

In the open loop radial distribution system, each radial feeder is divided into load sections with sectionalized switches and has connections to other feeders via several open cut switches.

Fig.1 shows such a distribution system.

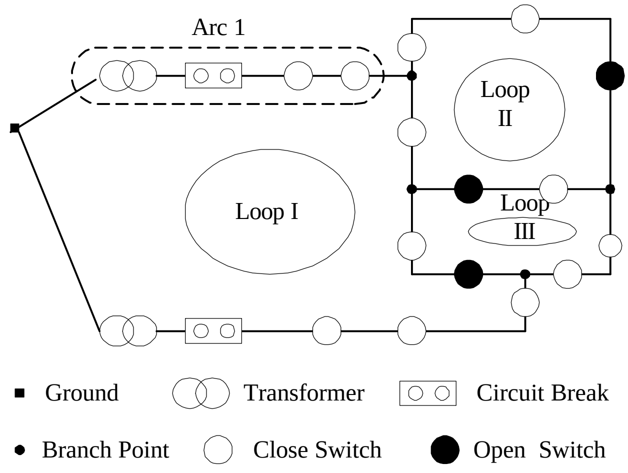

Fig.1 Basic composition of distribution system

The distribution systems loss minimum re-configuration problem is to decide the position of open sectionalized switches, which minimize distribution losses under the current capacity and voltage drop limit constraints. The system consists of transformers, sectionalized switches, branch points and ground shown in Fig.1. As to this problem, 'Section' is treated as a part from circuit break to the first sectionalized switch or from a sectionalized switch to branch point, 'Feeder' is treated as a part from transformer to the first load section, and 'Arc' is treated a part from branch point to branch point.

2.2 Formulation of a loss minimum problem

This problem can be formulated as a 0-1 integer programming problem as follows.

[Objective function]

Min $L(x_{ij})$

$$= \sum_t \sum_i \sum_j \{I_{jt1}^2 + I_{jt1} I_{jt} + I_{jt}^2\} r_j x_{ij} / 3 \qquad (1)$$

[Subject to]

(Line capacity constraint)

$$\sum_{j \in J_{ik}} I_{jt} x_{ij} \le b_{ik} \qquad (2)$$

$$(i = 1,2,\cdots,I,\ t = 1,2,\cdots,T,\ k = 1,2,\cdots,K)$$

(Trans. capacity constraint)

$$\sum_{j \in I_r} \sum_{J_i} I_{jt} x_{ij} \le b_r \qquad (3)$$

$$(r = 1,2,\cdots,r,\ \ t = 1,2,\cdots,T)$$

(Voltage drop constraint)

$$\sum_{m \in T_{il}} \Big(\sum_{q \in J_{il}} u_{qt} x_{iq} \Big) z_m \le v_{il} \qquad (4)$$

$$(i = 1,2,\cdots,I,\ \ l = 1,2,\cdots,S_i,\ \ t = 1,2,\cdots,T)$$

(Power supply constraint)

$$\sum_i x_{ij} = 1 \qquad (j = 1,2,\cdots,J) \qquad (5)$$

where,

L : the sum of distribution loss,

x_{ij} : =1 , if load section *j* belongs to feeder *i*;

: =0 , otherwise; 0-1 variable,

r_j : resistance at section *j*,

I_{jt} : load of section *j* at time *t*,

I_{jt1} : current flow through section *j* at time *t*,

b_{ik} : line capacity of the *k*-th supervising point of feeder *i* ,

b_r : capacity of *r*-th trans. ,

z_l : impedance of section *l*,

u_{qt} : $u_{qt} = I_{qt}(q \ne l), \quad u_{qt} = I_{qt}/2 \ \ (q = l)$,

v_{il} : voltage drop limit of section *l* of feeder *i* ,

S_i : number of supervising points of feeder *i* ,

J_{ik} : set of sections which exist between section *k* and the end point of feeder *i* ,

I_r : set of feeders connected to *r*-th trans. ,

J_i : set of all load sections of feeder *i*,

T_{il} : set of sections which exist on the path from the root to section *l* of feeder *i*,

In the above formulation, the followings are assumed.

(i) section load is uniformly distributed balanced constant current load.
(ii) power factor of section load is 1.0.
(iii) current phase shift caused by line impedance is negligibly small.
(iv) the maximum voltage drop occurs at the end point of the feeder because no capacitors ordinarily are facilitated in urban distribution systems.
(v) the line capacity violations are observed only at the roots of the branches where the diameters of the wire change.

2.3 Necessary conditions

The feasible solution of distribution system must satisfy eq.(5). Namely the following four necessary conditions must be satisfied.

[Condition-1]

The number of open sectionalized switches is,

$$p = b - a + 1 \quad (6)$$

where,
a: the number of branch points
b: the number of branches

[Condition-2]

In the same Arc, the number of the open sectionalized switch is one or zero.

[Condition-3]

In an Arc connecting the branch points, the Arc including the open sectionalized switch need.

[Condition-4]

In each basic loop, the open sectionalized switch more than one need.

3 Solution Algorithm by Genetic Algorithm

In this paper, we use a method for distribution system loss minimization re-configuration by the improved GA controlling the incidence of lethal gene[16].

3.1 Coding

To implement the genetic algorithm to the solution procedure for the loss minimum problem formulated in section 2, we must determine a string structure , for easily giving the decision to satisfy the conditions.

At first, all sectionalized switches in this system are corresponded to genes for coding. The value of a gene takes 0 or 1. If the switch is on, the value is 1. If off, the value is 0. So, the length of a chromosome is as many as a number of sectionalized switches. Therefore we can decide to satisfy the Condition-1 by getting a number of 0.

It is the arc units that order switches to put together in an individual, and the switches line up with small arc number.Consequently, we can decide to satisfy the Condition-2 by getting a number of 0. Still more, we can decide to satisfy the Condition-3, 4 by getting a information of arc concerning its diverging point which formed arc, or its basic loop which includes arcs.

In this way, we can easily decide to get satisfied individual and reduce calculation time compared with pass search method.

3.2 Flowchart of GA

The flowchart of GA in this paper is summarized as shown in Fig.2.

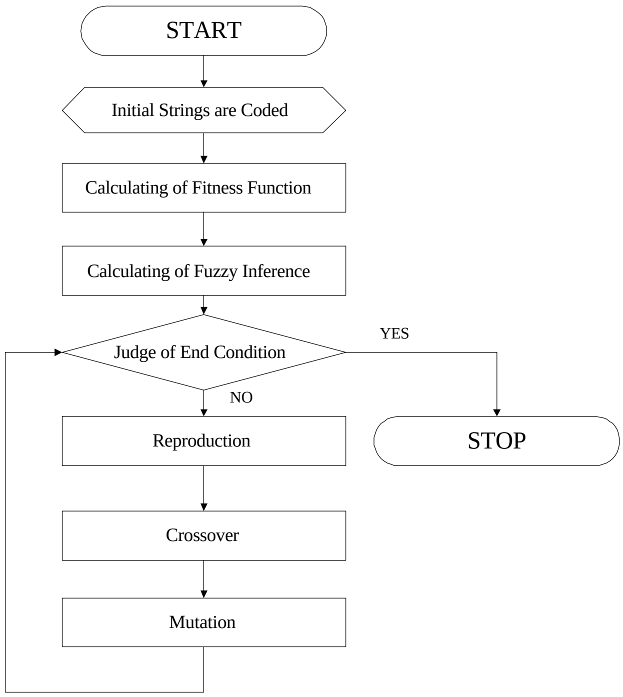

Fig 2. Flowchart of the algorithm

In Fig.2, firstly, initial strings are coded. Reproduction makes new copied strings for mating pool of the next generation. For all of the strings in mating pool, crossover and mutation are carried out according to the crossover rate and the mutation rate respectively. After these operations, reproduction to the next generation is evaluated again. These operations are repeated until the generation reaches set up terminative number.

3.3 Fitness Function

The fitness function is decided as follows, such that a distribution loss L is minimum and the subjection of eq.(2)(3)(4) are satisfied.

$$f = \frac{a}{L + \{b(g_1 + g_2) + g(g_3)\}} \tag{7}$$

where,

a : a constant coefficient for scaling

b, g : constant weights for penalty

L : the sum of loss

g_1 : penalty for eq.(2)

$$g_1 = \max\{0, (\sum_{j \in j_{ik}} I_{jt} x_{ij} - b_{ik})\} \tag{8}$$

g_2 : penalty for eq.(3)

$$g_2 = \max\{0, (\sum_{i \in I_r} \sum_{j} I_{jt} x_{ij} - b_r)\} \tag{9}$$

g_3: penalty for eq.(4)

$$g_3 = \max[0, \{\sum_{l \in T_{il}} (\sum_{q \in J_{il}} u_q x_{iq}) z_l - v_{il}\}] \tag{10}$$

3.4 Fuzzy Inference

Generally, in basic genetic algorithm method, much time need for searching of the solution. Accordingly, we propose a method with the adjustment of genetic parameters by fuzzy inference rules.

3.4.1 Fuzzy Inference Rules

The procedures to design the fuzzy logic are as follows.

Input variable of antecedent part of rules is O(t), this means population's occupation rate at generation t. That is, the rate of individuals sets, which large fitness value at generation t.

For example, the membership function of O(t) is shown in Fig.3.

And output variable of consequent part of rules are 3 genetic parameters, S(t), M(t) and P(t). where,

S(t): selection rate at generation t, the membership function is shown in Fig.4. ,

M(t): mutation rate at generation t, the membership function is shown in Fig.5 ,

P(t): population size at generation t, then membership function as shown in Fig.6.

The fuzzy rules are explained as follows.

[R1-1] If O(t) is Low then S(t) is High.
[R1-2] If O(t) is Middle then S(t) is Middle.
[R1-3] If O(t) is High then S(t) is Low.
[R2-1] If O(t) is Low then M(t) is Low.
[R2-2] If O(t) is Middle then M(t) is Middle.
[R2-3] If O(t) is High then M(t) is High.
[R3-1] If O(t) is Low then P(t) is High.
[R3-2] If O(t) is Middle then P(t) is Middle.
[R3-3] If O(t) is High then P(t) is Low.

And the membership functions take triangular distributions as shown in Fig 3,4,5,6.

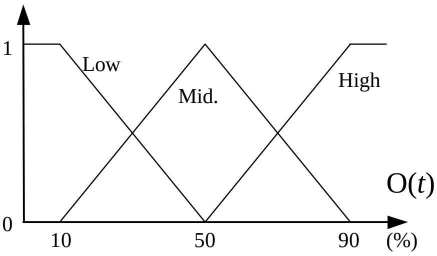

Fig. 3. Membership functions for Population's occupation rate of max fitness in current generation

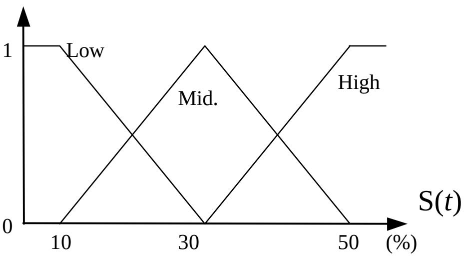

Fig. 4. Membership functions for Selection rate in current generation

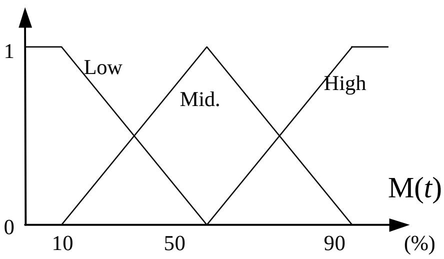

Fig. 5. Membership functions for Mutation rate in current generation

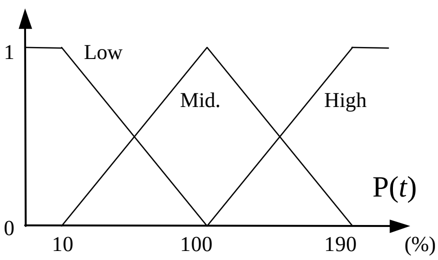

Fig. 6. Membership function for Population size in current generation

After that the outputs are computed based on the center of gravity, as shown in Fig.7. As mentioned above, each genetic parameters are adjusted on every generation for these fuzzy inference rules.

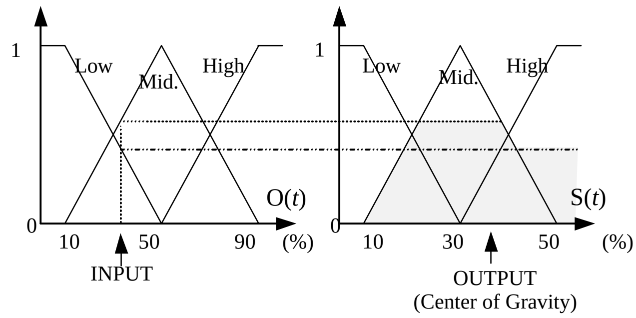

Fig. 7. A example of inference result

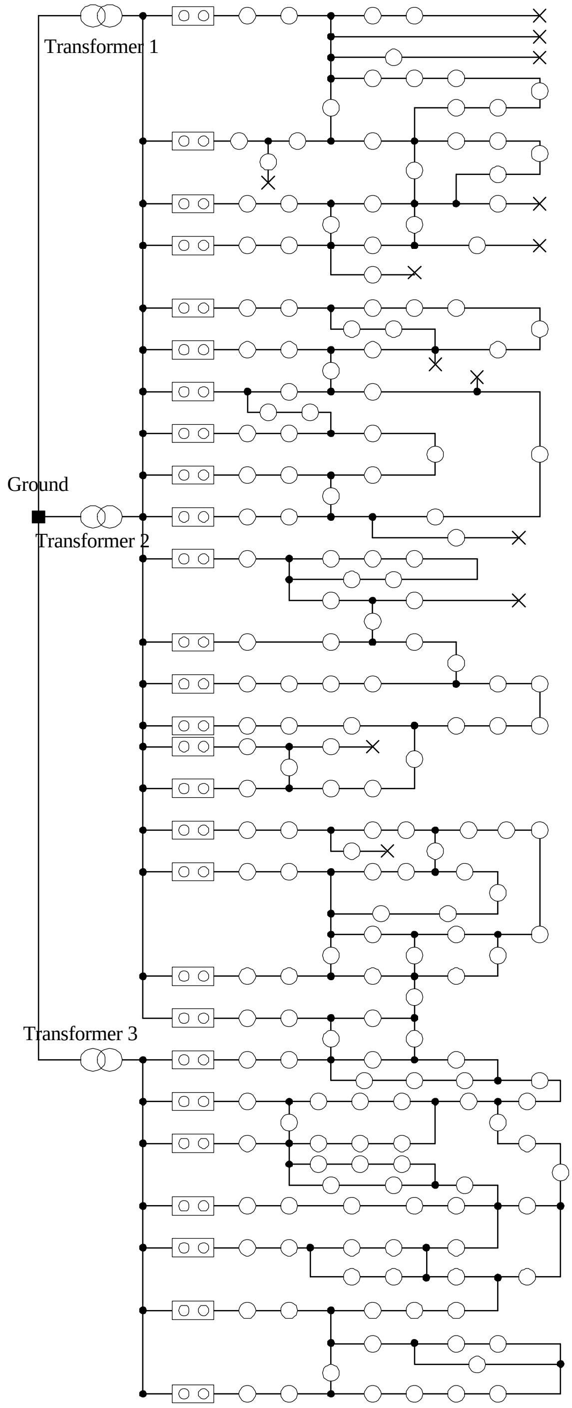

Fig.8 Practical scale system

4 Numerical Results

The proposed application is tested by the 189 sectionalized switches, 3 transformers, and 306 sections system [16] (real scale system) as shown in Fig.8 and Table 1.

In this simulation, we set up each parameters as shown in Table 2 and 10 times test changing initial strings. The results for above system are presented in Table 3.

Table 3(a) is the results of parameter fixed GA(former method). And Table(b) is the results of parameter adjusting GA with fuzzy inference.

Both results show optimum solution(Max Fitness: 520, loss of GA: 960.01[KW]). Nevertheless the proposed method is 20% faster than former method for convergence.

The mentioned above, the proposed method is effectiveness to real scale distribution system for loss minimization re-configuration problem.

Table 1 Specification of Model System

Specification	Numerical Value (PU)
Capacity of Trans.	1.5
Load of each Section	0.1
Voltage Drop Limitation on Feeder	0.1
Current Capacity of String on Feeder	1.5
Resistance of each Section	0.01

Table 2 Parameters on Simulation

Initial Population Size	100
Initial Crossover Rate	50%
Initial Mutation Rate	20%
Constant a of Fitness Function	5×10^3
Constant b of Fitness Function	100
Constant g of Fitness Function	10
Close Number of Generation	350

5 Conclusion

In this paper, an application of genetic algorithm with fuzzy inference to real scale distribution systems for loss minimum re-configuration is proposed. GA is able to produce a near optimal solution by simulating the adaptive nature of natural genetics, moreover it can be found an approximate global optimum faster than 20% by this application. This result demonstrates the validity and effectiveness of the proposed methodology. It is expected that this application may be efficiently applicable to many kinds of illconditioned problems in power system planning and operation.

Table 3. Experimental result

(a) Parameter fixed (Former method)

Case	Max Fitness	Gained Generation of the Optimal Solution	Minimal Loss of the initial String (KW)	Resulting Loss of GA (KW)
1	520	274	3446.65	960.01
2	520	249	3304.26	960.01
3	520	151	2251.84	960.01
4	520	428	2800.72	960.01
5	520	281	3276.73	960.01
6	520	160	2166.02	960.01
7	520	221	2630.24	960.01
8	520	207	2166.02	960.01
9	520	216	3446.65	960.01
10	520	230	2788.67	960.01
Average	520	241.7	2827.78	960.01

(b) Parameter adjusting method

Case	Max Fitness	Gained Generation of the Optimal Solution	Minimal Loss of the Initial String (KW)	Resulting Loss of GA (KW)
1	520	254	3276.73	960.01
2	520	167	3446.65	960.01
3	520	151	2251.84	960.01
4	520	250	2800.45	960.01
5	520	311	3304.26	960.01
6	520	173	2927.41	960.01
7	520	138	2788.67	960.01
8	520	146	2166.02	960.01
9	520	126	2380.44	960.01
10	520	230	2680.55	960.01
Average	520	194.6	2802.30	960.01

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