Electric Distribution System Reconfiguration For Loss Reduction Using Genetic Algorith

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Abstract

This paper presents the solution approach for the optimal reconfiguration problem in distribution networks implementing genetic algorithm technique.

Network reconfiguration in distribution system is changing the status of sectionalizing switches to reduce the power loss in the system. The main objective of network reconfiguration is to find the network topology which have the minimum losses during any conditions exists in the network. A network configuration is a valid solution to the problem if it satisfies reliability, security and other operation constraints.

A genetic algorithm is adapted and used in this work. The primary case study system is a part of the Baghdad area distribution network. It consists of main feeder, 6 laterals feeders and 48 buses. The algorithm validity is verified first via application to standard systems. Results show that the genetic algorithm is suitable for off-line reconfiguration studies.

Keywords

Distribution system; Loss minimization; Network reconfiguration; genetic algorithm.

الخلاصة :

يقدّمُ هذا البحث طريقة لحَلَّ مسألة إعادة التشكيل المثاليةِ في شبكاتِ التوزيع الكهربائية. استخدمت تقنية الخوارزميات الجينية (genetic algorithm) لحَلَّ المسألة اعلاه.

اعادة تمثيل الشبكة في نظامِ التوزيعِ يعرف بتَغيير حالة مفاتيح الفصل (sectionalizing switches) لغرض تقليل الخسائر الكهربائيةِ في النظامِ. إنّ الهدفَ الرئيسيَ لاعادة تشكيل الشبكة هو ايجاد طوبوغرافية الشبكةَ التي سَيكونُ فيها اقل الخسائرُ أثناء أيّ ظرف عمل في الشبكةِ.

حورت الخوارزمية الجينية واستَعملتُ في هذا العملِ. استخدمت شبكة ذات مغذي رئيسي , ستة فروع و48 عمومي كجزء من شبكة بغداد- الرصافة للتوزيع. تم تصديق الخوارزميةَ أولاً عن طريق التطبيقِ على أنظمةِ قياسيةِ ومطابقة للنتائج. الاستنتاج الاساسي هو امكانية استخدام طريقة الخوارزمية الجينية لحَلَّ مسألة التشكيل الامثل لمنظومات التوزيع.

List of symbols

A	Branch incident matrix
C	Cost function
det(A)	Determinant of A
g(x)	Power flow equations
I_i	Line current in section i
L	Number of sections
P_i	Section-i send end active power
Q_i	Section-i send end reactive power
r_i	Section resistance
V_i	The voltage at bus-i
V_i^{min}	Lower limit of a quantity
V_i^{max}	Upper limit of a quantity
GA	genetic algorithm
Pc	Crossover probability
Pm	Mutation probability

1. Introduction

Network reconfiguration refers to the closing and opening of switches in a power distribution system in order to alter the network topology, and thus the flow of power from the substation to the consumers. Distribution feeders contain number of switches that are normally closed(sectionalizing switches) and switches that are normally open (tie switches).When the operating conditions change, network reconfiguration is performed by the opening / closing of the network switches under a number of constraints. These are;

i. Operating in radial configuration.

ii. All loads are served.

iii. Lines, transformers, and other equipments operate within their current capacity limits.

iv. Bus voltage within regulatory limits.

A computational efficiency branch and bound type heuristic method was proposed in [1] in order to reconfigure the distribution system for minimum loss. The implementation of the reconfiguration in a realistic short term planning was introduced in [2]. Switching index adoption based on branch voltage drops and branch constraints were used in a developed reconfiguration algorithm for loss reduction proposes presented in [3]. A fuzzy logic controlled genetic algorithm for optimal reconfiguration aiming minimum loss and radiality provision was introduced in [4]. Global optimum solution for a sample distribution system reconfiguration was obtained adopting brute-force and ant colony algorithms. Results and system data were presented in [5, 6].

In this work a genetic algorithm optimization solver is adopted and used to find the optimal network configuration. This obviously, based on satisfying many operational requirements and constraints. Primarily, the minimum loss is a target plus the radiality and voltage drop constraints.

2. The Power Loss Derivation

Consider a distribution system consists of a radial main feeder only. The one-line diagram of such a feeder comprising n branches or nodes is shown in fig. (1). [7]

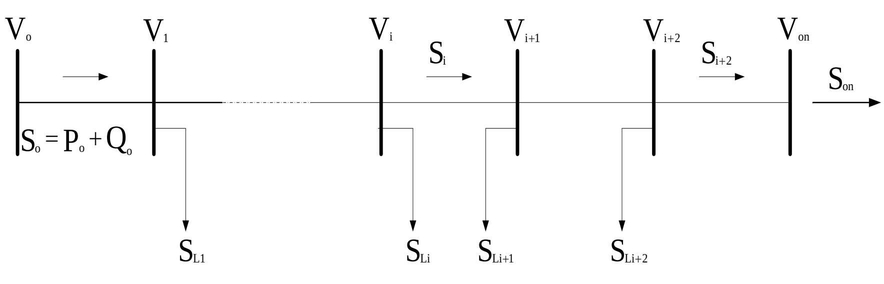

Fig. (1) One line diagram of a main distribution feeder.

Power flow equations for a radial distribution network using real power, reactive power, voltages at the sending and receiving ends of a branch are given in equations (1a, 1b, and 1c);

$$P_{i+1} = P_i - r_{i+1}\frac{P_i^2 + Q_i^2}{|V_i|^2} - P_{Li+1} \quad (1a)$$

$$Q_{i+1} = Q_i - x_i\frac{P_i^2 + Q_i^2}{|V_i|^2} - Q_{Li+1} \quad (1b)$$

$$|V_{i+1}|^2 = |V_i|^2 - 2(r_{i+1} \cdot P_i + x_{i+1} \cdot Q_i) + (r_{i+1}^2 + x_{i+1}^2)\frac{P_i^2 + Q_i^2}{|V_i|^2} \quad (1c)$$

Equations (1), are called the branch flow equations. Power flow in radial distribution network can be described by a set of recursive branch flow equations. The quadratic terms in the equations represent the losses in the branches. These terms are much smaller than the power terms P_i and Q_i, hence, they can be ignored. The set of new branch equations can be written as shown in equation (2);

$$P_{i+1} = P_i - P_{Li+1} \quad (2a)$$

$$Q_{i+1} = Q_i - Q_{Li+1} \quad (2b)$$

$$|V_{i+1}|^2 = |V_i|^2 - 2(r_{i+1} \cdot P_i + x_{i+1} \cdot Q_i) \quad (2c)$$

The power loss in a branch is calculated as given by equation (3);

$$(3) \quad \text{Loss}_i = r_i\,[(P_i^2 + Q_i^2)/V_i^2]$$

The total system loss is the sum of all the branches loss given by equation (4);

$$\text{Total Loss} = \sum_{i=1}^{n} \text{Loss}_i = \sum_i^n r_i\,[(P_i^2 + Q_i^2)/V_i^2] \quad (4)$$

3. The Optimization Problem

This section describes the formulation of the distribution system reconfiguration problem. The objective of the feeder reconfiguration is to minimize the distribution system losses with turning on / off sectionalizing switches. Mathematically, the problem can be formulated as follows [8];

Cost function:

$$\text{Min.C} = \sum_{i=1}^{L} r_i \frac{(P_i^2 + Q_i^2)}{V_i^2} \quad (5)$$

Subject to:

$$g(x) = 0 \quad (6)$$

$$V_i^{min} < V_i < V_i^{max} \quad (7)$$

$$I_i^{min} < I_i < I_i^{max} \quad (8)$$

$$\det(A) = 1 \text{ or } -1 \quad \text{radial system} \quad (9)$$

$$\det(A) = 0 \quad \text{not radial} \quad (10)$$

The check for the network reconfiguration constraints is divided into two subsets [9]:

- 'Before' the load flow, checking for the supply provision & radiality of the system, and,
- 'After' the load flow, checking for voltage drop and line capacity limits.

The above reconfiguration problem has the following constrains [10]:

(a) Radial network constraint;
Distribution network should be composed of radial structure considering operational point of view. Therefore, each section has only one up-stream section.

(b) Power source limit constraint;
The total loads of each partial network cannot exceed the capacity limit of the corresponding power source.

(c) Voltage constraint;
Voltage magnitude at each section must lie within their permissible ranges.

(d) Current constraint;
Current magnitude of each branch (switch and line) must lie within their permissible ranges.

4. Genetic Algorithm

To solve the optimization problem formulated in equation (5) a genetic algorithm (GA) is proposed, the most popular form of Evolutionary Algorithms, inspired by the principle of evolution and, in essence, consists on a population of strings transformed by three genetic operators: selection, crossover and mutation. Each string (chromosome) represents a possible solution to the problem being optimized and each part of the string (sub string) represents a value for some variable of the problem (gene).

These solutions are classified by an evaluation function, giving better values, or fitness, to better solutions. Each solution must be evaluated by the fitness function (having the role of environment) to produce a value. The pair (chromosome, fitness) represents an individual. The GA algorithm proposed in this paper has the following characteristics, [11].

A. Initialization

A random initial population is considered. Parameters of GA must be initialized such as generation size, population size, crossover probability and mutation probability for capacitor addition and feeder reconfiguration

B. Fitness Evaluation

All individual are evaluated with the same fitness function. The fitness function incorporates the objective function, i.e., the total costs associated to power losses, energy losses and capacitors equation (5) with cost penalties if an individual violates any of the constraints.

C. Genetic operators

Genetic operators are the stochastic transition rules applied to each chromosome during each generation procedure to generate a new improved population from the previous one. A genetic algorithm usually consists of reproduction, crossover and mutation operators.

1) Reproduction

Reproduction is a probabilistic process for selecting two parent strings from the population of strings on different basis. In this paper the "roulette-wheel" mechanism is used on the individual fitness values. This ensures that the probability of a string to be selected is proportional to its fitness relative to the rest of the population. Therefore, strings with higher fitness values have a higher probability of contributing offspring.

2) Crossover

The crossover operator divides a population into the pairs of individuals and performs recombination of their genes with a certain probability [12].

Crossover is performed immediately after selection and reproduction. And it is used to combine the pairs of selected strings (Parents) to create new strings that potentially have a higher fitness than either of their parents.

It is usually performed with a probability called crossover probability (Pc) usually is chosen to be near one to preserve some of the good strings found previously. Note that this operation does not change the value of bits.

There are several ways of doing the crossover. Some common crossover operations are: one-point crossover, two-point crossover, cycle crossover and uniform crossover [13,14].

i. One - point crossover:

One-point crossover is the simplest crossover operation. Two individuals are randomly selected as parents from the pool of individuals formed by the selection procedure and one position in the individual genetic code is chosen. All gene entries after that position are exchanged among individuals. The newly formed offspring created from this mating are put into the next generation [12,14].

An example of this type of crossover is shown in Fig. (2).

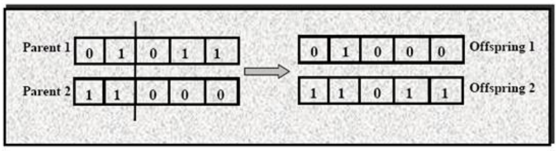

Fig.(2) One Point Crossover Example

Recombination can be done at many points (multi-point crossover), so that multiple portions of good individuals are recombined, this process is likely to create even better individuals, in which the number of crossover point for each pair of parents is chosen randomly [12].

ii. Two- point Crossover:

In this crossover type two positions in a pair of chromosome are chosen at random and the segments between them are exchanged. An example of this type of crossover is shown in Fig. (3) [15].

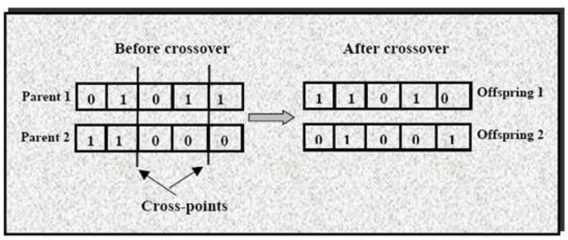

Fig.(3) Two Point Crossover Example

iii. Uniform Crossover:

The process of uniform crossover is happened at each bit position, which exchanges elements between the two selected parent strings to create new offspring string by means of a random mask [15,16].

A mask, a binary array with length equal to the length of the chromosomes, is generated randomly. Thus, uniform crossover means that every point has an equal chance of being a crossover point and all chromosomes in a population are crossed over in the same position, as shown in Fig. (4) [14,17].

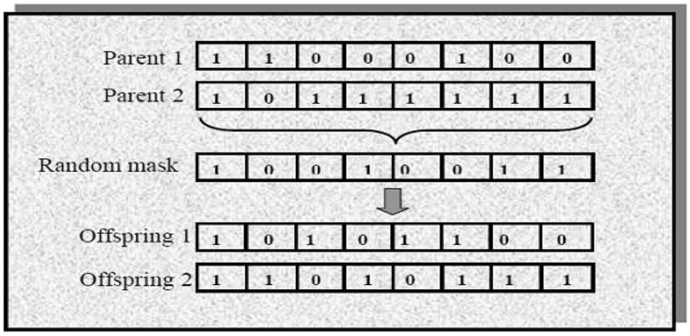

Fig.(4) Uniform Crossover Example

3. Mutation:

The mutation operator is applied to every string resulting from the crossover process. When using mutation operator a portion of the new individuals will have some of their bits flipped with a predefined probability (mutation probability P_m) usually quite low, e.g. 0.001.

The purpose of mutation is to maintain diversity within the population and prevent premature convergence. The usage of this operator allows the search of some regions of the search space, which would be otherwise unreachable.

Eventually, it helps the GA avoid premature convergence, getting trapped at local optima and find the global optimal solution. An example is given in Fig. (5) [12, 18].

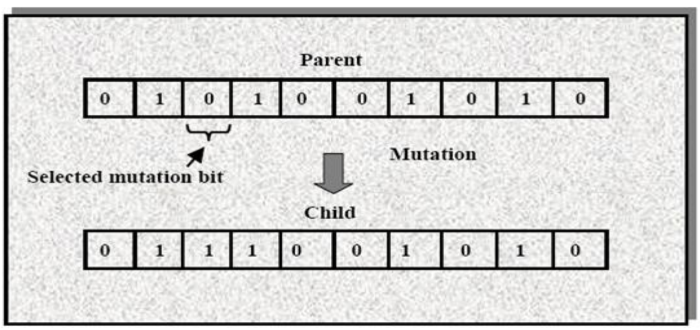

Fig.(5) Mutation Operator

D. Genetic Parameters

The following parameters are used in the present research:
Population size=2000
Number of generation=50
Crossover probability=0.75.
Mutation probability=0.095.

It is known that the choice of the crossover and mutation probabilities critically affect the behavior and the performance of the GA. In most studies these probabilities remain unchanged in the course of GA execution. Instead of using fixed crossover and mutation probabilities, GA dynamically changes these values during the optimization process and according to the genetic diversity. This feature will maintain the genetic diversity in the population and thus prevents GA to converge prematurely to local optimum. The heuristic updating principals are; using large Pc and small Pm when genetic diversity in the current generation is large. The increase of *pc* leads to rich information exchange between individuals, while the decrease of Pm avoids random search In the other case, to avoid premature convergence, Pc and Pm must be changed in such a way to introduce new genetic characteristics and to reduce the loss of genetic material. So, Pc must be reduced and Pm augmented. Accordingly to the above, the flow chart of the program is given in Fig. 6. In this paper, the program is written using MATLAB.

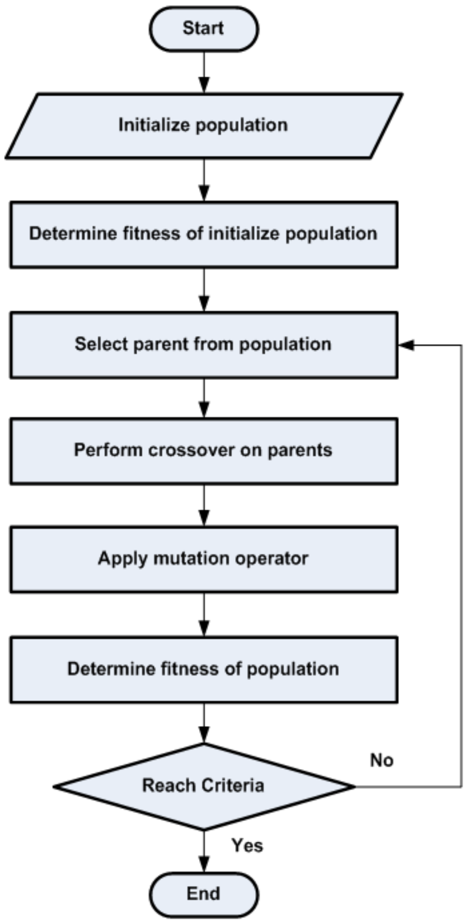

Fig. 6: Flow chart of GA

4.1 Details of GA for the Problem

4.1.1 Genetic string representation:

The only parameter, which determines the minimum loss configuration, is the position of the normally open sectionalizing switches. Note that the number of positions of open sectionalizing switches are identical to keep the system radial once the topology of the distribution system is fixed, even if the open switch positions are changed.

Therefore, to memorize the radial configuration, it is enough to number every open switch position, and to-memorize which switch is open corresponding to each open switch position number [19].

Since open loop radial distribution system can be depicted as a graph, as shown in Fig. (7), where several sectionalizing switches are located on each branch between two busbars, the open switch positions can be remembered by memorizing branch numbers [20].

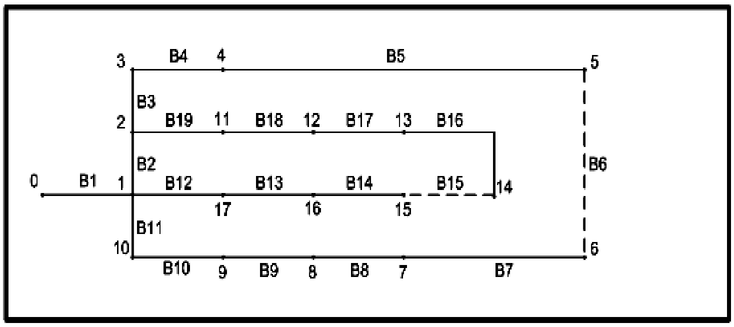

Fig.(7) Graph of distribution system model

Then, the length of a strings equals to the number of branchs. Thus, the string structure can be depicted as shown in fig. (8). In Fig. (8), " Branch State No. (i) " means the state branch number. Where i-th switch position exists. " Branch State No (i)" is expressed by a binary code as shown in Fig. (8). for '1' if the branch i is closed, or '0' if the branch i is open.

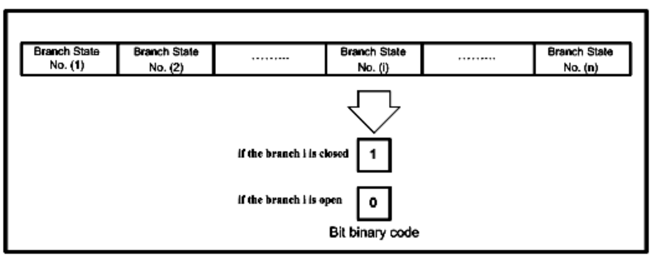

Fig.(8) String structures

In this string structure, by applying the crossover operation, it is expected that the resulting string sometimes present a loop configuration or de-energized sections. In such a case, this string is abandoned, and another mate is selected for another crossover. Using the above representation, the radial network shown in Fig. (7) can be represented by string in Fig. (9).

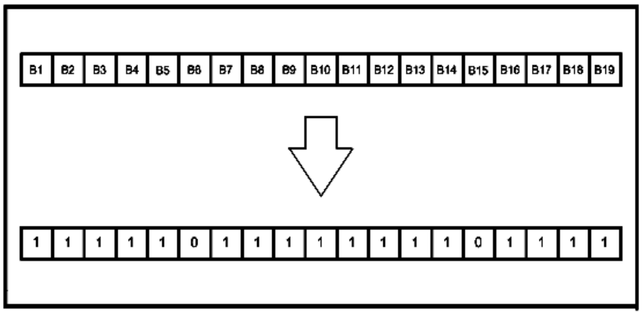

Fig.(9) The Crossover Structure and representation of the Network Topology

4.1.2. String evaluation "Fitness Function":

In a genetic algorithm, a fitness function is a mapping, which determines the fitness of each string in the population.

The GA proceeds to evolve better-fitting strings, and the fitness value is the only information available to the GA. The strings with large fitness values offer better solutions to the problem and have a higher probability of being selected [16].

Therefore, the string evaluation "fitness function" of the GA methodology for the reconfiguration problem can be obtained using the fitness described by the following equations:

$$\mathbf{Fitness} = \frac{\mathbf{1}}{\mathbf{P_{Loss}}} \qquad (11)$$

According to the above equations, the less loss in the distribution system, the higher the fitness value. Thus, we can take P_{Loss} as the fitness function in the GA.

4.1.3. String Operation:

a. Crossover

Crossover operation exchanges partial radial networks at the boundary of the section of the crossover point. The crossover operation takes two parents switch vectors (two chromosomes) and cuts at a randomly selected point. The two parents are crossed over at that point and two offspring are produced. An example of this operator is shown in fig. (10).

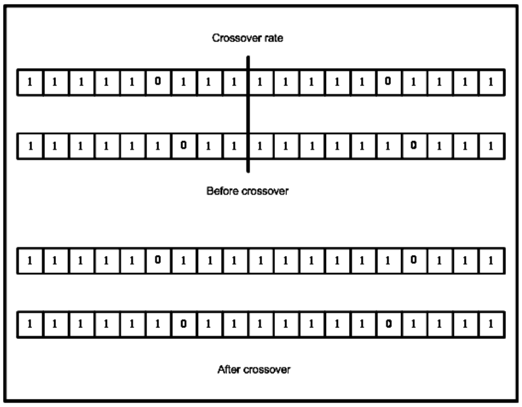

Fig.(10) The Crossover of Two -Switch Vectors

After applying the crossover operator it is expected that the resulting string sometimes violate the constraints and need be modified. The modification take place by one of the following [19,20] :

i. Change the crossover point until a string, which does not violate the constraints is generated.

ii. Modify string after the string operation.

Here, (i) is utilized as the modification of the string. Moreover, the fitness values of strings that violate power source limit, voltage, and current constraints are modified.

b. Mutation

Mutation is a bit exchange at a string position .Random alteration of genes in a string or values of a string may occur. For binary coded string, a mutation represents a simple bit change and it is provides random excursion into new parts of the search space [21].

4.1.4. Stopping criteria (Termination.):

There are many ways to terminate a GA, many of them similar to termination conditions used for conventional optimization algorithms. A iteratively performs the operations on each generation of individuals to produce new generation until some stopping criterion is satisfied [15].

The stopping criterion can be stated in either of following ways:

1. The algorithm has reached the maximum number of generations or specified fitness value.
2. When all chromosomes in a generation are identical.
3. Taking the best solution after performing a fixed number of evaluations.

Here, (1) is utilized as the termination of the GA. When the user input maximum allowable number of generation for the GA is reached, the best solution found.

4. 2 Application of GA to solve the reconfiguration problem

The main program represent optimum network reconfiguration for genetic algorithm shown in fig. (11), included two sub-program , the first sub-program to calculate power losses and given the tie line (open switch), the second sub-program to calculate crossover and mutation.

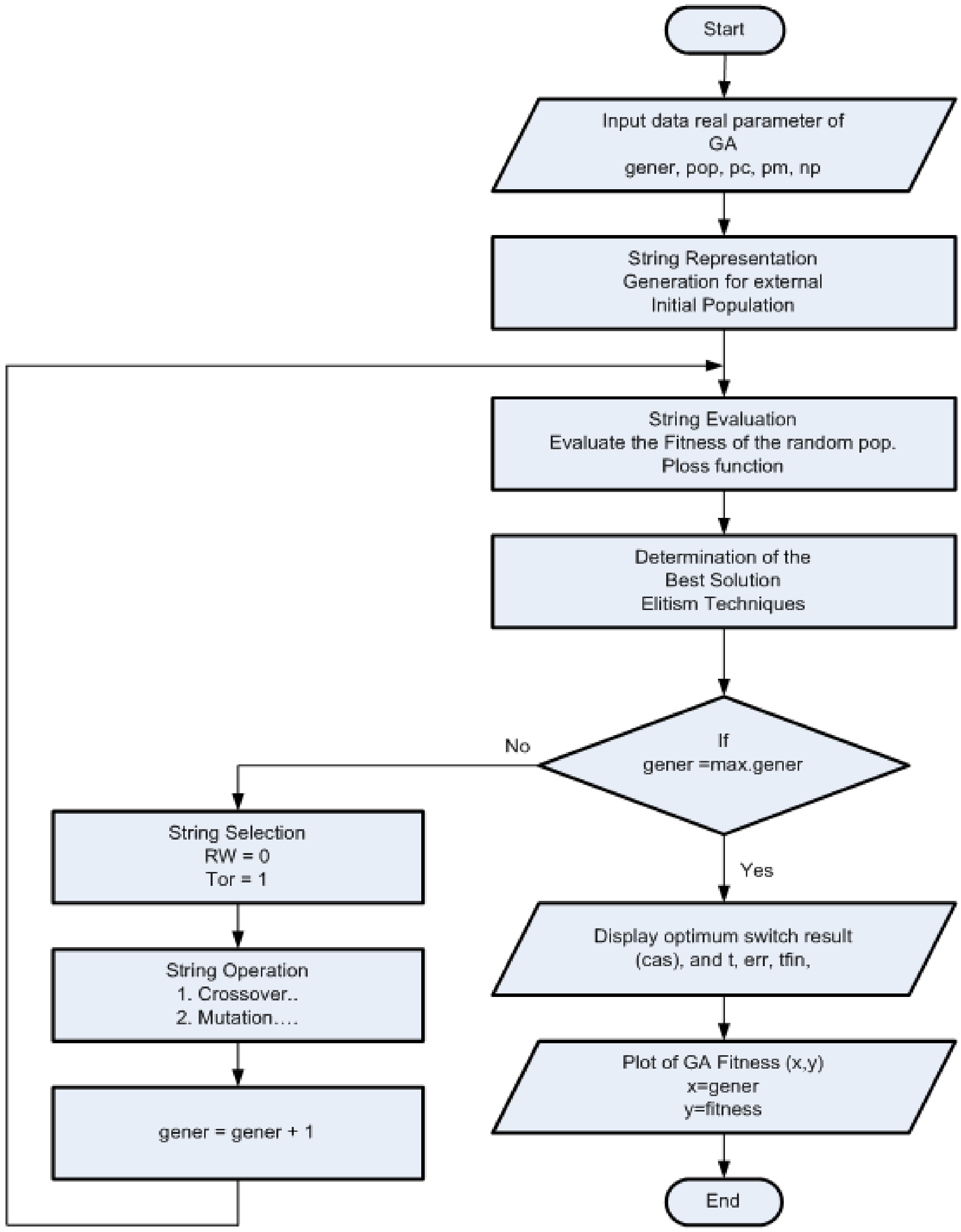

Fig. 11: Flow chart optimization program for network reconfiguration

In summary the steps of the program are as follow:-

1. Input data a real parameter of genetic algorithm, number of generation, population size, the proportion ratio rate of crossover and mutation, the size of chromosome represented number line in the distribution system with used binary number 0 or 1.

   0: represent open line.

   1: represent close line.

2. String representation generation for external initial population.

3. String evaluation, to evaluate the fitness of random population (power loss), go to sub-program to calculate fitness function power losses including fast-decoupled

Fitness: represented the maximization in genetic algorithm.

Power: represented the minimization in optimum configuration.

4. Determine the best solution in the generation with used elitism techniques.

5. String selection, in the executing start program present the massage to choice the selection method.

   0: if used roulette wheel selection method.

   1: if used tournament selection method.

6. String operation, go to sub-program to calculate the crossover and mutation.

7. If the number of generation equal maximum number:

   a. Display results optimum switch, run time, maximum fitness, minimum power loss.

   b. Plot of genetic algorithm with two dimension (x,y).

   x : represented number of generation.

   y : represented fitness maximization.

5. Algorithm Validation

The GA is first used to find the optimal feeder configuration of well documented systems. Standard systems were considered [20]. Table.1 shows the here used GA results along with those obtained in the respective references. The results of table.1 verify the validity of the GA algorithm adopted in this work.

Table. 1: (18)-bus system results using GA in comparison with other techniques

System	Losses	Tie switches
18- bus system	Before reconfiguration=112.34 kW After reconfiguration using (PSO) = 107.48 kW After reconfiguration using proposed GA=103.7 kW	[(6-10), (13-17)] Before [(6-10), (16-17)] After

6. Al - Baghdad System Case Study

The power supply to the city of Baghdad is provided basically from two main substations of 400/132 kV (Baghdad East and Baghdad west), which in turn supply many substations of 132/33 kV (or 132/33/11 kV) distributed geographically throughout the city. A schematic diagram showing the structure of this system is given in Fig. (12). These 132/33 kV substations in turn provide power supply to a very large number of 33/11 kV substations. Most of these 33/11 kV substations are equipped with two transformers of 31.5 MVA each. The 11 KV distribution feeders are supplied from the low voltage bus bars of these substations using underground cable and / or over-head line systems. Each 11 KV feeder provides the supply to a large number of 11 / 0.4 KV transformers. One such substation was selected located in Bghdad.

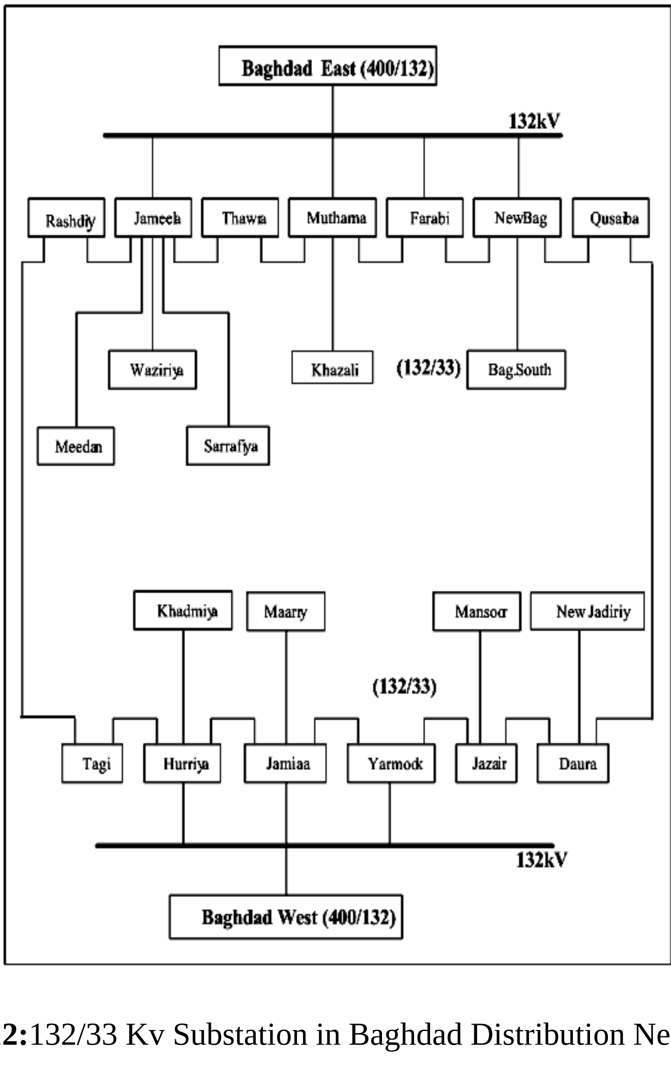

Fig. 12:132/33 Kv Substation in Baghdad Distribution Network

The test is 11 KV system with 48 buses, main feeder, 6 laterals, and 7 capacitor in buses location (9, 13, 24, 32, 36, 42 and 48), size of capacitor (100, 75, 100, 200, 200, 350 and 200 KVAR) respectively, (1, 80, 1, 2, 2, 3.7 and 2 µF) respectively. The system data with power demand information are tabulated in Appendix A. The schematic diagram of test system is shown in fig.(13). There are two looping branches (tie lines) in the system and sectionalizing switches on every branch of the system. Initial system real power loss of 10.593 kW. Applying the proposed GA, the final power loss is 8.976 kW. The results of table.2 show that the power loss after reconfiguration is reduced by 7.7 %of its initial value.

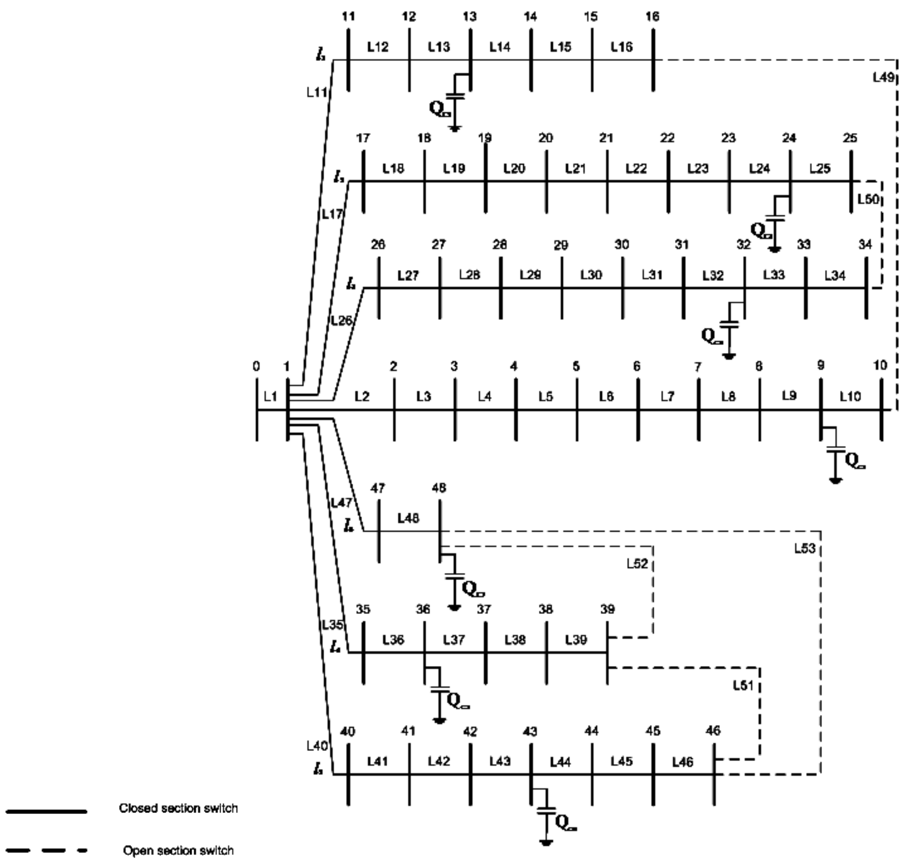

Fig.13 Initial configuration of the practical network

By implementing the program of Genetic Algorithm (GA), the global optimum configuration for loss reduction is obtained. In GA program, used two methods selection, roulette wheel method and tournament method with elitism technique, results comparison of two selections and real parameter in genetic algorithm, a one-point crossover, mutation operator is used. The result of Convergence characteristics, number of generation with fitness function of genetic method shown fig. (14)

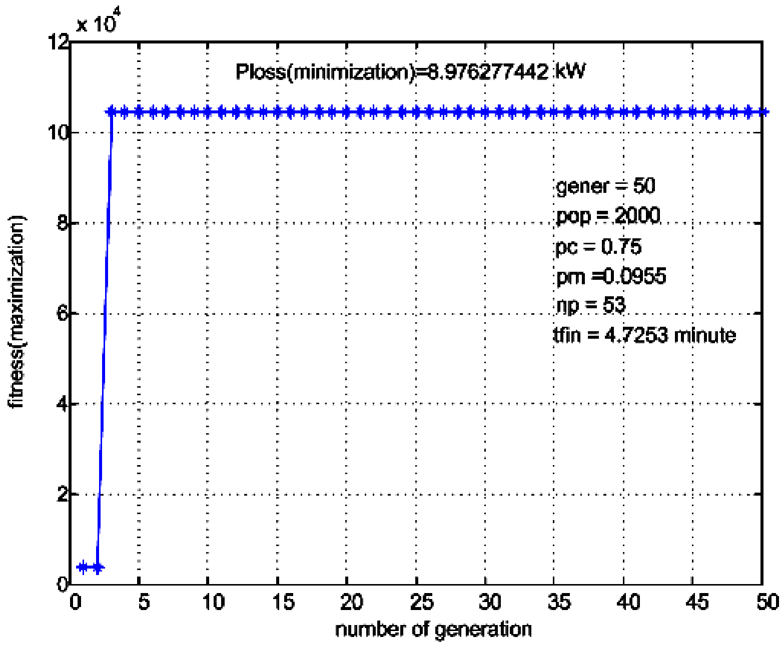

Fig. 14: Convergence characteristics of GA of the 48-bus system

Conclusions

In this work, a standard genetic algorithm method has been presented to solve the problem of optimal distribution network reconfiguration for loss reduction. The components of the proposed genetic algorithm based method, including population, crossover, mutation, function design, etc., were described. The proposed algorithm has been tested on standard systems. Results show that the proposed genetic algorithm based method is feasible, efficient and promising for distribution system reconfiguration. Extensive series of simulation studies of Palestine Street in Baghdad city.

System is performed considering different loading conditions as far as magnitude and power factor are concerned. The overall system reconfiguration pattern is almost as that of Table.2. In all the cases the four tie switches are closed and different section switch to open for different loading type and case. The general conclusion for Palestine Street in Baghdad city is “better to keep the tie switches closed all the time and open the switches shown in Table.2 for all loading conditions”. GA used successfully to reduce power loss considering balanced condition and various load characteristics. Because GAs reach quickly the region of the optimal solutions and it's accuracy for two reasons:

* GAs avoid local minima by searching in several regions (working with a population of solutions) to arrive at a global minima.

* The only information they need is some performance value that determines how good a set of switches is (no gradient information).

*The initial population represent important factor in the program genetic algorithm to arrive to the best fitness function and low time executing process of the program.

Table. 2: Baghdad system results using GA

System	Power Loss	Tie Switches
Before reconfiguration	10.593kW	(10-16), (25-34), (39-64), (39-48) , (46-48)
After Reconfiguration using GA	8.976kW	(14-15), (33-34), (37-38), (44-45), (39-48)

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Appendix A

Table A.1: Network Data for Baghdad Case at (11kV) Rated Voltage before Reconfiguration

Line No.	Line State	Send. Bus	Rec. Bus	Line Resistance (Ω)	Line Reactance (Ω)	Rec. End Bus Load		
						P (kW)	Q (kVAR)	Qc (kVAR)
1	1	0	1	0.0031	0.0022	0.00000	0.00000	0
2	1	1	2	0.0031	0.0022	969.679	469.637	0
3	1	2	3	0.7440	0.5470	401.246	194.333	0
4	1	3	4	0.8680	0.6380	100.311	48.582	0
5	1	4	5	0.4340	0.3190	401.246	194.333	0
6	1	5	6	0.1628	0.1200	1003.11	485.832	0
7	1	6	7	0.6200	0.4600	936.243	453.470	0
8	1	7	8	0.5890	0.4330	735.619	356.284	0
9	1	8	9	0.3570	0.2620	869.369	521.054	100
10	1	9	10	1.0186	1.0137	1270.61	615.388	0
11	1	1	11	0.0434	0.0319	922.058	446.572	0
12	1	11	12	1.0171	1.0125	1276.69	618.332	0
13	1	12	13	0.4340	0.3190	638.347	384.166	75
14	1	13	14	1.0403	1.0296	2908.02	1408.41	0
15	1	14	15	0.3660	0.2690	922.058	446.572	0
16	1	15	16	0.1860	0.1370	425.565	48.7060	0
17	1	1	17	0.0233	0.0171	1791.42	867.626	0
18	1	17	18	0.3880	0.2850	1264.53	612.442	0
19	1	18	19	0.2790	0.2050	948.402	459.332	0
20	1	19	20	0.5520	0.4050	421.512	204.147	0
21	1	20	21	0.3970	0.2920	1896.80	918.663	0
22	1	21	22	1.0233	1.0171	1686.04	816.590	0
23	1	22	23	0.0780	0.0570	316.134	153.110	0
24	1	23	24	0.9900	0.7300	1053.78	610.368	100
25	1	24	25	0.9900	0.7300	632.267	306.220	0
26	1	1	26	0.0160	0.0120	559.313	270.888	0
27	1	26	27	0.3720	0.2730	838.970	406.332	0
28	1	27	28	0.4400	0.3230	1258.45	609.499	0
29	1	28	29	0.3660	0.2690	1258.45	609.499	0
30	1	29	30	0.4500	0.3300	1817.77	880.386	0
31	1	30	31	0.2950	0.2160	2237.25	1083.55	0
32	1	31	32	0.2850	0.2100	1817.77	1080.38	200
33	1	32	33	0.4590	0.3370	1957.59	948.108	0
34	1	33	34	1.0217	1.0160	1957.59	948.108	0
35	1	1	35	0.0372	0.0273	607.950	294.444	0
36	1	35	36	0.2880	0.2120	1925.17	1132.40	200

37	1	36	37	0.4190	0.3080	303.975	147.221	0
38	1	37	38	0.4030	0.2960	3343.72	1619.44	0
39	1	38	39	0.8680	0.6380	222.915	1079.62	0
40	1	1	40	0.0620	0.0456	719.407	348.425	0
41	1	40	41	0.2110	0.1550	1726.57	836.220	0
42	1	41	42	0.2170	0.1600	1582.69	766.535	0
43	1	42	43	0.4190	0.3080	3597.03	2092.12	350
44	1	43	44	1.0388	1.0285	2877.63	1393.69	0
45	1	44	45	0.6360	0.4670	3884.79	1881.49	0
46	1	45	46	1.0140	0.6105	4677.46	2265.39	0
47	1	1	47	0.1023	0.0752	1491.50	722.367	0
48	1	47	48	0.0285	0.0210	1750.89	1047.99	200
49	0	10	16	0.0388	0.0285			
50	0	25	34	0.0118	0.0087			
51	0	39	46	0.0481	0.0353			
52	0	39	48	0.0837	0.0615			
53	0	46	48	0.0357	0.0262			