OPTIMAL RECONFIGURATION OF RADIAL DISTRIBUION SYSTEM USING ARTIFICIAL INTELLIGENCE METHODS

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Abstract – Reconfiguration of radial distribution system is the significant way of altering the flow of power through lines. This altered flow changes the real power losses, reactive power losses and voltage profiles. Privatized RDS need to operate profitably with minimum operational losses and power quality. Envisaging such a prospect, this paper focuses on the aspects of loss minimization and voltage enhancement of RDS by artificial intelligence methods. A sample 33-bus system and 69-bus system are chosen for the study and the results are being compared..
Keywords - Optimization, Evolutionary programming, Genetic algorithms

I. INTRODUCTION

With the advent of computers and Supervisory Control and Data Acquisition systems, automated distribution system analysis has become a necessity. The choice of solution method for the practical application requires careful analysis of comparative merits and demerits of available methods with respect to required storage, computation speed, flexibility in load modeling, integration with other conventional methods, convergence criterion, etc. A RDS is reconfigured by opening and closing the sectionalizing and tie-switches such that powers flowing from main substation to the various loads are re-routed. Normally, network reconfiguration is obtained by closing one tie-switch and opening one sectionalizing switch to retain the basic radial topology. The reconfiguration of the system alters feeder loading and may be used to alleviate feeder overloading, reduce real/reactive power losses and improve the voltage profile.

The problem of RDS reconfiguration is a zero-one problem. It requires the determination of a combination of branches, one branch from each loop, to be switched out such that the resulting configuration of RDS has the best reliability and the best voltage profile. It is obvious that as the circuit elements are switched in and out, certain variables tracking their status or quantifying their circuit parameters assume discrete values. Another fact of this problem naturally besieging any proposed solution strategy is the discontinuous nature of solution space.

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Further, optimal reconfiguration may be required to address multiple objectives such as loss minimization and voltage profile enhancement. So, this problem of reconfiguration of RDS is addressed in this paper and the results are focused.

Numerous methods [1, 2, 4] have been tried to solve this problem. In this paper, we have chosen Evolutionary Programming (EP) and Fuzzy Mutated Genetic Algorithm (FMGA) methods for the analysis. kW and kVAR losses minimization are the main objectives while maintaining a good voltage profile. Problem formulation, description of solution methods are presented in sections II, III and IV. Conclusions and comparisons are made in section V.

II. PROBLEM FORMULATION

The optimization problem is stated as below:

Minimize: Operational Real Power Loss = PL
Minimize: Operational Reactive power Loss = QSS
Subject to the constraint on the voltage profile:
$V_{jMIN} \le V_j \le V_{jMAX} \; \forall \; j = 1 \text{ to } N$

In order to quantify the extent of violation of limits imposed on voltages at buses in a RDS, the Voltage Deviation Index (VDI) is defined as:

$$VDI = \sqrt{\sum_{i=1}^{NVB} (V_{Li} - V_{LiLIM})^2 \Big/ N}$$

where NVB is the number of buses that violate the prescribed voltage limits and V_{LiLIM} is the upper limit of the i^{th} load bus voltage if there is a upper limit violation or lower limit if there is a lower limit violation. During reconfiguration, if the state of the system has voltage limit violations, the proposed algorithm solution must try and minimize the index, VDI.

III. EVOLUTIONARY PROGRAMMING

The EP method is used to reconfigure the radial systems by power loss minimization. While solving an optimization problem, the standard EP based algorithm starts with a population of randomly generated candidate solutions and evolves towards better solutions over a number of generations or iterations.

From an existing population called parent population, a new population called offspring population is generated through a mutation operator. This operator perturbs each individual in the existing parent population by a random amount to produce new offspring individual. The degree of optimality of each new individual is measured by its fitness value, which can be expressed as a function of the objective function of the problem.

The various steps in the standard EP based algorithm are presented in Figure 1 to solve the Reconfiguration of Radial systems for Power Loss Minimization (RRPLM) problem.

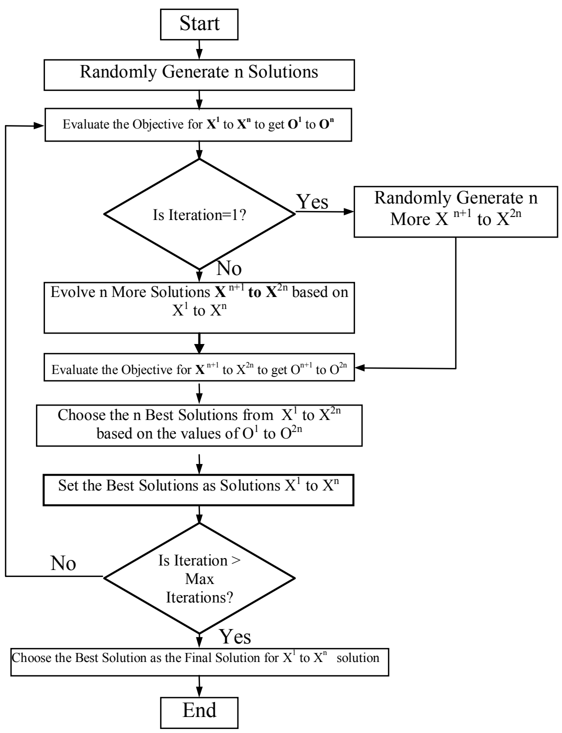

Fig. 1 Flowchart of the Evolutionary Programming-based power loss minimization method

IV. FUZZY MUTATED GENETIC ALGORITHM

Fuzzy mutated genetic algorithm [4] for RDS reconfiguration with multi-objective optimization uses all the features of genetic algorithm. It is a stochastic search mechanism. This method involves reproduction, crossover in addition to a new chromosome structure from a fuzzy controlled mutation.

In reconfiguration of RDS, a tie line, when closed, creates one loop. For preserving the radial property, one branch must be opened from the set of branches forming the loop. The number of branch selection bits is chosen based on maximum number of branches and a wrapping up approach is used to determine the branch to be opened.

Coding and Decoding

In FMGA, the chromosome consists of n substrings of binary numbers. Each tie line represents one substring. The leftmost bit of the substring is the status of the tie line. '1' is closed and '0' is opened and it is followed by the other bits (1/0) representing the branch to be opened if the status bit is '1'. The number of branch selection bits is chosen based on maximum number of branches and wrapping up approach is used to determine the branch to be opened. For multiple tie lines closing, same branch should not be selected more than once. The decoding procedure scans the chromosome from left to right. If the same branch is encountered more than once, choosing some other branch from the loop-forming branch set, the corresponding tie line ignores the later choice of the previously selected branch.

Fitness Function

The overall fitness function (f) of the multi-objective optimization problem is defined as:

$$f = \frac{1}{1 + (\eta_1 * P_{loss}) + (\eta_2 * Q_{loss}) + (\eta_3 * VDI)}$$

where η_1, η_2 and η_3 are constants that provide relative weights to the optimization functions. P_{loss} and Q_{loss} are the real and reactive power losses respectively. VDI is the voltage deviation index.

Reproduction and Crossover

The population size affects parallel search. A large population does not necessarily lead to good convergence. It should not be very small or very large. In FMGA, reproduction and crossover are similar to SGA. The selection mechanism uses roulette wheel. The crossover recombines an individual with another individual split at the same crossover sites based on the pre-selected crossover probability. Single point crossover is used. Since, crossover is the dominant operator that exploits the already available knowledge to generate better solutions; the crossover probability should be high.

Fuzzy Mutation

The mutation randomly alternates a bit in the individual according to mutation probability. An efficient search can be achieved with a diverse population. The diversity and convergence characteristics of population can be seen from incremental changes in standard deviation of fitness distribution ($\Delta\sigma$) and average fitness (Δf_{av}) of population.

A fuzzy rule has two inputs ($\Delta\sigma$ and Δf_{av}) and mutation probability as the output as designed in Table 1. Triangular membership function shown in Figure 1 is used for both inputs of fuzzy system. The fuzzy sets for the inputs are LN (Large Negative), SN (Small Negative), ZR (near Zero), SP (Small Positive) and LP (Large Positive).

Table I Fuzzy rule base for mutation probability

Δf_{av} ↓ / $\Delta\sigma$ →	LN	SN	ZR	SP	LP
LN	VL	VL	L	L	M
SN	VL	L	M	M	M
ZR	L	M	M	S	S
SP	L	M	S	S	VS
LP	M	M	S	VS	VS

The output of the fuzzy system uses five fuzzy labels i.e., VS (Very Small), S (Small), M (Medium), L(Large) and VL(Very Large) . The rule base is evaluated using max-min rule for inference mechanism and centroid defuzzification.

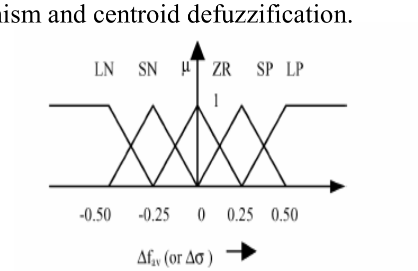

Fig. 2 Membership functions for both inputs of fuzzy systems

V. RESULTS OF SYSTEM STUDY

In this section, Fuzzy Mutated Genetic Algorithm and EP techniques have been applied on 33-bus and 69-bus RDS and the results are presented. In FMGA, the population size and crossover probability are chosen as 30 and 0.9 respectively.

33-Bus Test System

EP

Table II. EP results for 33-bus RDS

State	Lines switched out	kW loss	kVAR loss	VDI
Base case	33-34-35-36-37	207.92	105.99	0.0249
Optimal case	07-14-09-32-37	129.70	101.86	0.0034

From Table II, it can be seen that the real power loss, reactive power loss and VDI are reduced from 207.92 kW to 129.70 kW, 105.99 kVAR to 101.86 kVAR and 0.0249 to 0.0034 respectively. The execution time is 0.734 seconds with Intel Pentium IV Processor.

FMGA

Table III. FMGA results for 33-bus RDS

State	Lines switched out	kW loss	kVAR loss	VDI
Base case	33-34-35-36-37	207.92	105.99	0.0249
Optimal case	07-14-09-33-37	129.76	101.86	0.0034

From Table III, it can be seen that the real power loss, reactive power loss and VDI are reduced from 207.92 kW to 128.15 kW, 105.99 kVAR to 101.86 kVAR and 0.0249 to 0.0034 respectively. The execution time is 0.453 seconds with Intel Pentium IV processor.

69-Bus Test System

EP

Table IV. EP results for 69-bus RDS

State	Lines switched out	kW loss	kVAR loss	VDI
Base case	69-70-71-72-73	226.92	104.02	0.01194
Optimal case	72-23-13-50-60	137.66	59.83	0.0024

From Table IV, it can be seen that the total kW loss in the lines of RDS reduces from 226.92 KW to 137.66 kW and the total kVAR losses reduce from 104.02 kVAR to 59.85 kVAR. It is also observed that the VDI improves from 0.01194 to 0.0024. The execution time is 4.203 seconds with Intel Pentium IV Processor.

FMGA

Table V. FMGA results for 69-bus RDS

State	Lines switched out	kW loss	kVAR loss	VDI
Base case	69-70-71-72-73	226.92	104.92	0.01194
Optimal case	72-26-70-65-60	136.23	59.38	0.0025

The results are presented in Table V and it is observed that the total kW loss in the lines of RDS reduces from 226.92 KW to 136.28 kW, the total kVAR losses reduce from 104.02 kVAR to 59.38 kVAR. It is also observed that the VDI improves from 0.01194 to 0.0025. The execution time is 4.281 seconds with Intel Pentium IV Processor.

VI. CONCLUSION

In this paper, two algorithms namely FMGA and EP are used to reconfigure the RDS by minimizing the real and reactive power losses and at the same time improving the power quality. The comparison of results with both the algorithms shows that FMGA is able to find potentially good switching options. EP has good solution but it takes a longer time to converge. In FMGA, more potential solutions that are found quickly and crossover exploits these new candidate solutions to find the best solution quickly.

APPENDIX

See Figs. A1 and A2 and Tables A1 – A4.

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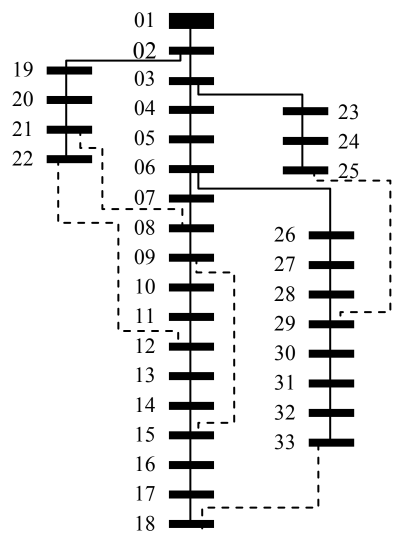

Fig. A1 Single Line diagram of 33-bus radial System

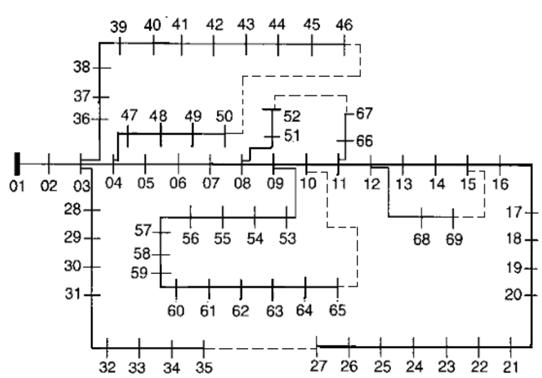

Fig. A2 Single Line diagram of 69-bus radial system

Table A1.1 Data for 33-bus test system

Line Number	From Bus	To Bus	R (Ω)	X (Ω)	Load at Receiving End Bus	
					Real Power Load (kW)	Reactive Power Load (kVAR)
1	Main SS	2	0.0922	0.0477	100.0	60.0
2	2	3	0.4930	0.2511	90.0	40.0
3	3	4	0.3660	0.1864	120.0	80.0
4	4	5	0.3811	0.1941	60.0	30.0
5	5	6	0.8190	0.7070	60.0	20.0
6	6	7	0.1872	0.6188	200.0	100.0
7	7	8	1.7114	1.2351	200.0	100.0
8	8	9	1.0300	0.7400	60.0	20.0
9	9	10	1.0400	0.7400	60.0	20.0
10	10	11	0.1966	0.0650	45.0	30.0
11	11	12	0.3744	0.1238	60.0	35.0
12	12	13	1.4680	1.1550	60.0	35.0
13	13	14	0.5416	0.7129	120.0	80.0
14	14	15	0.5910	0.5260	60.0	10.0
15	15	16	0.7463	0.5450	60.0	20.0
16	16	17	1.2890	1.7210	60.0	20.0
17	17	18	0.7320	0.5740	90.0	40.0
18	2	19	0.1640	0.1565	90.0	40.0
19	19	20	1.5042	1.3554	90.0	40.0
20	20	21	0.4095	0.4784	90.0	40.0
21	21	22	0.7089	0.9373	90.0	40.0
22	3	23	0.4512	0.3083	90.0	50.0
23	23	24	0.8980	0.7091	420.0	200.0
24	24	25	0.8960	0.7011	420.0	200.0
25	6	26	0.2030	0.1034	60.0	25.0
26	26	27	0.2842	0.1447	60.0	25.0
27	27	28	1.0590	0.9337	60.0	20.0
28	28	29	0.8042	0.7006	120.0	70.0
29	29	30	0.5075	0.2585	200.0	600.0
30	30	31	0.9744	0.9630	150.0	70.0
31	31	32	0.3105	0.3619	210.0	100.0
32	32	33	0.3410	0.5302	60.0	40.0
33*	21	8	0.0000	2.0000		
34*	9	15	0.0000	2.0000		
35*	12	22	0.0000	2.0000		
36*	18	33	0.0000	2.0000		
37*	25	29	0.0000	2.0000		

Table A1.2 Data for 69-bus test systems

S.No	From Bus	To Bus	R (Ω)	X (Ω)	Load at Receiving End Bus	
					Real power load (kW)	Reactive Power load (kVAR)
1	1	2	0.0005	0.0012	0.0	0.0
2	2	3	0.0005	0.0012	0.0	0.0
3	3	4	0.0015	0.0036	0.0	0.0
4	4	5	0.0251	0.0294	0.0	0.0
5	5	6	0.3660	0.1864	2.60	2.20
6	6	7	0.3811	0.1941	40.40	30.00
7	7	8	0.0922	0.0470	75.0	54.0
8	8	9	0.0493	0.0251	30.0	22.0
9	9	10	0.8190	0.2707	28.0	19.0
10	10	11	0.1872	0.0619	145.00	104.00
11	11	12	0.7114	0.235	145.0	104.0
12	12	13	1.0300	0.3400	8.0	5.0
13	13	14	1.0440	0.3450	8.0	5.50
14	14	15	1.0580	0.3496	0.0	0.0
15	15	16	0.1966	0.0650	45.5	30.0
16	16	17	0.3744	0.1238	60.0	35.0
17	17	18	0.0047	0.0016	60.0	35.0
18	18	19	0.3276	0.1083	0.0	0.0
19	19	20	0.2106	0.0690	1.00	0.60
20	20	21	0.3416	0.1129	114.0	81.0
21	21	22	0.0140	0.0046	5.00	3.50
22	22	23	0.1591	0.0526	0.0	0.0
23	23	24	0.3463	0.1145	28.0	20.0
24	24	25	0.7488	0.2475	0.0	0.0
25	25	26	0.3089	0.1021	14.0	10.0
26	26	27	0.1732	0.0572	14.0	10.0
27	27	28	0.0044	0.0108	26.0	18.60
28	28	29	0.0640	0.1565	26.0	18.60
29	29	30	0.3978	0.1315	0.0	0.0
30	30	31	0.0702	0.0232	0.0	0.0
31	31	32	0.3510	0.1160	0.0	0.0
32	32	33	0.8390	0.2816	14.0	10.0
33	33	34	1.7080	0.5646	9.5	14.0
34	34	35	1.4740	0.4873	6.0	4.0
35	35	6	0.0044	0.0108	26.0	18.55
36	36	37	0.0640	0.1565	26.0	18.55
37	37	38	0.1053	0.1230	0.0	0.0
38	38	39	0.0304	0.0355	24.0	17.0
39	39	40	0.0018	0.0021	24.0	17.0
40	40	41	0.7283	0.8509	1.20	1.0
41	41	42	0.3100	0.3623	0.0	0.0
42	42	43	0.0410	0.0478	6.0	4.30
43	43	44	0.0092	0.0116	0.0	0.0
44	44	45	0.1089	0.1373	39.22	26.30
45	45	46	0.0009	0.0012	39.22	26.30

Table A2 (Continued)

S. No	From Bus	To Bus	R (Ω)	X (Ω)	Load at Receiving End Bus	
					Real power load (kW)	Reactive Power load (kVAR)
46	4	47	0.0034	0.0084	0.0	0.0
47	47	48	0.0851	0.2083	79.0	56.40
48	48	49	0.2898	0.7091	384.70	274.50
49	49	50	0.0822	0.2011	384.70	274.50
50	8	51	0.0928	0.0473	40.50	28.30
51	51	52	0.3319	0.1114	3.60	2.70
52	9	53	0.1740	0.0886	4.35	3.50
53	53	54	0.2030	0.1034	26.40	19.00
54	54	55	0.2842	0.1447	24.0	17.20
55	55	56	0.2813	0.1433	0.0	0.0
56	56	57	1.5900	0.5337	0.0	0.0
57	57	58	0.7837	0.2630	0.0	0.0
58	58	59	0.3042	0.1006	100.0	72.0
59	59	60	0.3861	0.1172	0.0	0.0
60	60	61	0.5075	0.2585	1244.0	888.0
61	61	62	0.0974	0.0496	32.0	23.0
62	62	63	0.1450	0.0738	0.0	0.0
63	63	64	0.7105	0.3619	227.0	162.
64	64	65	1.0410	0.5302	59.0	42.0
65	11	66	0.2012	0.0611	18.0	13.0
66	66	67	0.0047	0.0014	18.0	13.0
67	12	68	0.7394	0.2444	28.0	20.0
68	68	69	0.0047	0.0016	28.0	20.0
69*	52	67	0.0047	0.0016		
70*	15	69	0.0047	0.0016		
71*	10	65	0.0047	0.0016		
72*	46	50	0.0047	0.0016		
73*	35	27	0.0047	0.0016		

Table A3 Loop details for 33-bus radial system

	Line Numbers					
Loop1	33	18	19	20	06	07
Loop2	34	12	13	14		
Loop3	35	08	11	10	09	21
Loop4	36	32	17	16	15	
Loop5	37	24	23	22	28	

Table A4 Loop details for 69-bus radial system

	Line Numbers								
Loop1	40	41	42	43	44	45	72	49	48
Loop2	32	33	34	73	26	25	24	23	
Loop3	12	13	14	70	68	67			
Loop4	50	51	69	66	65				
Loop5	71	60	61	62	63	64			