International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:2, No:5, 2008

Enhanced GA-Fuzzy OPF under both Normal and Contingent Operation States

Ashish Saini and A.K. Saxena

Abstract**—**The genetic algorithm (GA) based solution techniques are found suitable for optimization because of their ability of simultaneous multidimensional search. Many GA-variants have been tried in the past to solve optimal power flow (OPF), one of the nonlinear problems of electric power system. The issues like convergence speed and accuracy of the optimal solution obtained after number of generations using GA techniques and handling system constraints in OPF are subjects of discussion. The results obtained for GA-Fuzzy OPF on various power systems have shown faster convergence and lesser generation costs as compared to other approaches. This paper presents an enhanced GA-Fuzzy OPF (EGA-OPF) using penalty factors to handle line flow constraints and load bus voltage limits for both normal network and contingency case with congestion. In addition to crossover and mutation rate adaptation scheme that adapts crossover and mutation probabilities for each generation based on fitness values of previous generations, a block swap operator is also incorporated in proposed EGA-OPF. The line flow limits and load bus voltage magnitude limits are handled by incorporating line overflow and load voltage penalty factors respectively in each chromosome fitness function. The effects of different penalty factors settings are also analyzed under contingent state.

Keywords**—**Contingent operation state, Fuzzy rule base, Genetic Algorithms, Optimal Power Flow.

I. Introduction

GENETIC algorithm [1] (GA) is a general purpose search theorem which belongs to a class of biologically inspired optimization approaches. Genetic algorithms are used in a wide variety of applications in electric power system. The GA and its variants have been applied to solve unit commitment problem [2], optimal power flow [3-8,19] and for economic load dispatch [9-13]. The objective of OPF is to minimize the fuel cost and keep a secure system in both the normal and contingent states. Conventional calculus-based optimization algorithms have been used in OPF for years. The conventional optimization methods are based on successive linearizations and use the first and second derivatives of objective functions and their constraint equations as the search directions. The conventional optimization methods usually converge to a local minimum. The references [9,13] has demonstrated the superiority of GA methods in handling non-differentiable objective and references [2,7] show their ability to handle discrete variables. For better results and faster convergence, conventional GA models have been modified by including new operators such as elitism, shuffle in reproduction, multi-point or uniform crossover and creep mutation.

This paper proposes an application of adaptive EGA-Fuzzy approach with penalty factors to OPF. In EGA-Fuzzy OPF, two important parameters namely, crossover probability (P_c) and mutation probability (P_m) are varied dynamically during the execution of the program according to a fuzzy knowledge base. A new Block Swap Operator (BSO) is included to increase convergence speed and the quality of solutions. The usage of penalty factors to handle line constraints and load bus voltage limits under normal and contingent states of power system are other two significant features of EGA-Fuzzy OPF. Three sets of different penalty factors using EGA-Fuzzy OPF are analyzed for 6 bus system under normal state. The proposed OPF method is also tried for two cases, normal and contingent operation states of IEEE 30 bus system. In the contingent state, the circuit outage of one branch causes a power overflow in the parallel branch and lower voltage limit violations in nearby load buses. The EGA-Fuzzy approach always finds the best results and eliminates operational and insecure violations.

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II. Optimal Power Flow problem formulation

The operation of an electric system is complex due to its nonlinear and computational difficulties. One task of operating a power system economically and securely is optimal scheduling, commonly referred to as the optimal power flow problem. The OPF solution gives the optimal active power generation schedule to minimize fuel cost and optimal settings of all-controllable variables e.g. outputs of compensating devices, transformer tap settings and bus voltage levels. Computationally, this is a very demanding nonlinear programming problem due to a large number and type of limit constraints imposed on the power system by engineering design limits.

The objective function of active power dispatch is expressed as follows:

$$\min \quad f_p = \sum_{i \in N_g} (a_i + b_i P_{gi} + c_i P_{gi}^2) \tag{1}$$

where a_i, b_i and c_i = cost coefficients of generating unit
P_{gi} = real power generation of i^{th} unit
N_g = total number of generation units and i = 1,2,…. N_g

subject to equality and inequality constraints.
the equality constraints are:

$$P_{gi} - P_{di} - \sum_{j \varepsilon N_B} |V_i|\ |V_j|\ |Y_{ij}|\ cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{2}$$

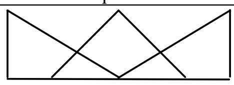
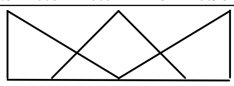
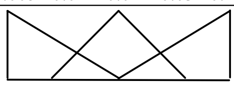
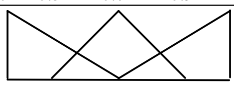
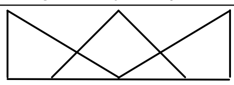
$$Q_{gi} - Q_{di} - \sum_{j \varepsilon N_B} |V_i|\ |V_j|\ |Y_{ij}|\ sin(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{3}$$

and the inequality constraints are:

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \qquad i\ \varepsilon\ N_g \tag{4}$$
$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max} \qquad i\ \varepsilon\ N_g \tag{5}$$
$$V_{gi}^{min} \le V_{gi} \le V_{gi}^{max} \qquad i\ \varepsilon\ N_B \tag{6}$$
$$\delta_{gi}^{min} \le \delta_{gi} \le \delta_{gi}^{max} \qquad i\ \varepsilon\ N_B \tag{7}$$
$$Line\text{-}MVA_l^{\ min} \le Line\text{-}MVA_l \le Line\text{-}MVA_l^{\ max} \qquad i\ \varepsilon\ n_l \tag{8}$$

where,
P_{gi} and Q_{gi} = real and reactive power generation at bus i
P_{di} and Q_{di} = real and reactive power demands at bus i
$|V_i|$ and $|V_j|$ = voltage magnitudes at bus i and j respectively
$|Y_{ij}|$ = admittance matrix
N_B = Total number of buses (Slack, generator and load buses)
n_l = total number of lines in system
l = 1 to n_l

TABLE I
MEMBERSHIP FUNCTIONS AND RANGE OF VARIABLES

Variable	Linguistic Terms	Membership Functions
Crossover Probability (P_c)	Low Medium High	 0.5 0.6 0.7 8 0.95
Mutation Probability (P_m)	Low Medium High	 0.005 0.01 0.02 0.03 0.1
Best Fitness (*BF*)	Low Medium High	 0 0.5 0.7 0.9 1
Number of generations for unchanged BF (*UN*)	Low Medium High	 0 3 6 9 12
Variance of Fitness (*VF*)	Low Medium High	 0 0.1 0.12 0.14 0.2

III. ENHANCED GA-FUZZY (EGA-FUZZY) APPROACH FOR OPF SOLUTION

After few finite numbers of generations, the fitness value of each chromosome vector becomes almost same (around 0.9). The effect of crossover is insignificant due to very small variation in the chromosome vectors. Therefore, at later stage, increasing the mutation rate of the chromosomes to inculcate new characteristics in the existing population can diversify the population. A GA-Fuzzy approach is used in proposed method in which ranges of GA parameters- crossover probability (P_c) and mutation probability (P_m) have been divided into LOW, MEDIUM and HIGH membership functions and each is given some membership values as shown in Table I.

The GA parameters (P_c and P_m) are varied based on the fitness function values as per following logic:

i) The value of best fitness for each generation *(BF)* is expected to change over a number of generations, but if it does not change significantly over a number of generations *(UN)* then this information is considered to cause changes in both P_c and P_m.

ii) The diversity of a population is one of the factors, which influences the search for a true optimum. The variance of the fitness values of objective function *(VF)* of a population is a measure of its diversity. Hence, it is also considered as another factor on which both P_c and P_m may be changed.

The membership functions and membership values for these three variables *(BF, UN* and *VF)* are selected after several trials to get optimum results. The GA parameters in proposed algorithm are varied based on fuzzy rules base [19] for the solution of OPF.

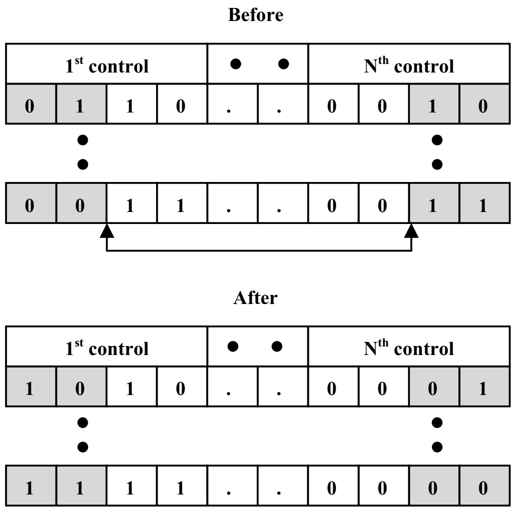


Fig. 1 Application of Block Swap Operator in EGA-Fuzzy OPF

In EGA-Fuzzy OPF, a new block swap operator as shown in fig.1 is applied to introduce random modifications to all chromosomes. It randomly selects out number of columns in a population (blocks) to be swapped. After swapping if the modified chromosome proves to have better fitness, it replaces the original one in the new population. Otherwise, the original chromosome is retained in the new population. It is applied with a probability of 0.3.

Fig.2 is a diagrammatic representation of an approach to incorporate fuzzy logic to find GA based OPF solution. Therefore, approach may be divided broadly in two parts namely EGA-OPF and Fuzzy Rule Base (for controlling the GA parameters P_c and P_m dynamically during execution). EGA-OPF part deals with encoding (of randomly generated chromosomes representing power generation of different generation units, transformer tap settings and shunt capacitor values), running load flow for each set of new generating patterns to determine all line flows, slack bus generation, bus voltages and phase angles, fitness function evaluation and application of GA operators (Reproduction, Crossover and Mutation) and new block swap operator for each generation.

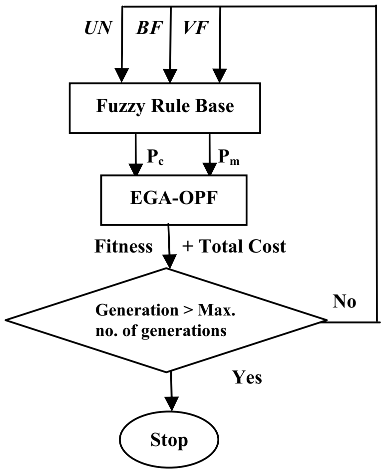


Fig. 2 EGA-Fuzzy approach for OPF problem solving

Load flow using Newton–Raphson method is run for each set of patterns corresponding to active power generations, transformer tap and shunt capacitor settings. It determines slack bus generation, bus voltage magnitudes and phase angles at all the buses. The violations of inequality functional constraints represented by equations (4)-(7) are checked.

GAs are usually designed so to maximize the fitness function (*FF*), which is a measure of quality of each candidate solution. The objective of the OPF problem is to minimize the total generation cost including power flow constraint for each line i.e. (8) and other equality and inequality constraints stated above. In proposed GA-Fuzzy approach, penalty index (pen_index_i) for each generated chromosome is calculated for lines having power overflows ($over\_flow_l$) and load bus voltage magnitude violations *(load bus voltage magnitude violation$_{lb}$)*, based on respective penalty factors (p_l) as

$$pen\_index_i = \sum_{l=1}^{n_l}(p_l \times overflow_l) + \sum_{lb=1}^{nload}(p_{lb} \times load\ bus\ voltage\ magnitude\ violation_{lb}) \quad (9)$$

and fitness function is modified to keep line flows and load bus voltage magnitude under limits as

$$FF_i = \left(\frac{A}{1+cost_i}\right) \times e^{-(k \times pen\_index_i)} \quad (10)$$

whereas, i = 1 to population size
n_l = total number of lines in system
nload = total number of load buses
l = 1 to n_l
lb = 1 to nload
p_l= penalty factor for overflow in l^{th} line
$over\_flow_l$ = overflow in l^{th} line, if any otherwise zero
p_{lb}= penalty factor for lb^{th} load bus
load bus voltage violation$_{lb}$ = load bus voltage violation in lb^{th} load bus, if any otherwise zero
pen_index_i = penalty index for i^{th} chromosome
A and k = large numerical constant
$cost_i$ = generation cost corresponding to i^{th} chromosome
FF_i = fitness value of function for i^{th} chromosome.

IV. Experiments and Results

The proposed GA-Fuzzy algorithm for solution of the OPF has been implemented on 6 bus [14] and IEEE 30 bus system [17]. The test examples have been run on 1.7 GHz Celeron with 128 MB RAM PC.

A. For 6 bus

Table II depict the values of EGA-Fuzzy parameters used for the test system.

TABLE II
EGA-Fuzzy parameters for 6 bus system

Crossover probability	Mutation probability	Selection operator	Population size	Maximum number of generations
0.9 (Initial)	0.01 (Initial)	Stochastic Remainder	50	200

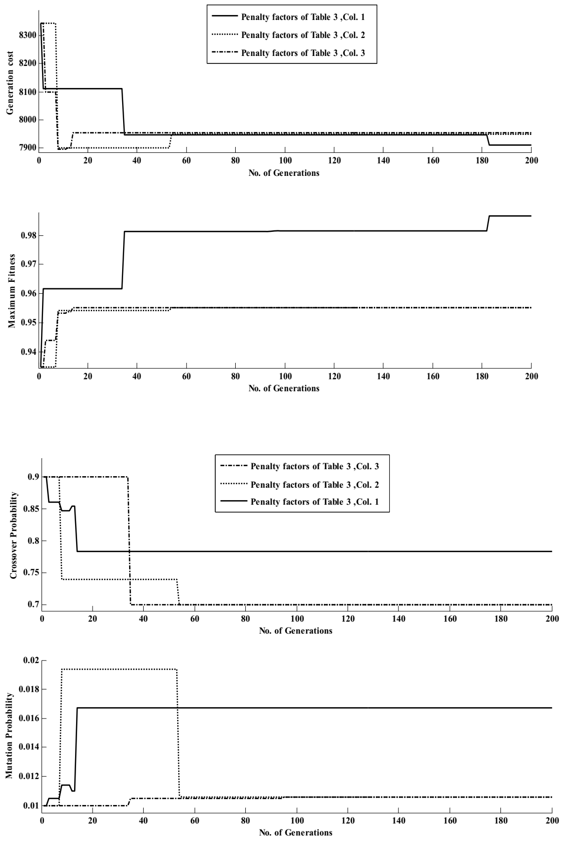


Fig. 3 Convergence of generation cost, maximum fitness, crossover and mutation probabilities for different penalty factors settings for 6 bus system using EGA-Fuzzy OPF

TABLE III

LINEFLOWS, LOAD BUS VOLTAGES, OVERFLOW LINE AND LOAD VOLTAGE PENALTY FACTORS, LOADFLOW SOLUTIONS AND GENERATION COSTS FOR DIFFERENT OVERFLOW LINE PENALTY FACTORS SETTINGS USING EGA-FUZZY OPF FOR 6 BUS SYSTEM

From bus no.	To bus no.	Line flows limits (MVA)	EGA-Fuzzy OPF **Column-1**		EGA-Fuzzy OPF **Column-2**		EGA-Fuzzy OPF **Column-3**	
			Overflow line penalty factors	Line flows (MVA)	Overflow line penalty factors	Line flows (MVA)	Overflow line penalty factors	Line flows (MVA)
1	2	100	1	30.936	1	33.744	1	33.547
1	5	100	1	74.224	1	63.610	1	63.826
2	4	100	1	56.719	1	57.428	1	57.629
3	5	100	1	53.317	1	40.396	1	40.428
3	6	100	1	31.562	1	35.631	1	35.659
4	5	50	1	49.136	20	41.698	25	41.556
4	6	100	5	87.922	10	74.194	10	74.138

Load Bus voltage (in p.u.) $V_{load}^{max} = 1.06$ p.u. $V_{load}^{min} = 0.94$ p.u.

Load bus	EGA Fuzzy OPF **Column-1**		EGA Fuzzy OPF **Column-2**		EGA Fuzzy OPF **Column-3**	
	Load voltage penalty factors	Bus voltage (in p.u.)	Load voltage penalty factors	Bus voltage (in p.u.)	Load voltage penalty factors	Bus voltage (in p.u.)
5	1	0.977		0.977	1	0.977
6	1	0.981		0.981	1	0.981

Active Power generation $P_g^{max} = 250$ MW $P_g^{min} = 50$ MW

Generator bus voltage $V_g^{max} = 1.06$ p.u. $V_g^{min} = 0.94$ p.u.

	Bus 1		Bus 2		Bus 3		Bus 4		Generation Cost (in $/hr)
	Gen. (in p.u.)	Volt. (in p.u.)	Gen. (in p.u.)	Volt. (in p.u.)	Gen. (in p.u.)	Volt. (in p.u.)	Gen. (in p.u.)	Volt. (in p.u.)	
EGA Fuzzy OPF **Column-1**	1.43729	1.001	1.86852	1.017	0.98680	1.010	1.80205	1.000	7910.2065
EGA Fuzzy OPF **Column-2**	1.30182	1.001	1.90762	1.017	1.27810	1.010	1.58700	1.000	7948.6284
EGA Fuzzy OPF **Column-3**	1.30582	1.001	1.90762	1.017	1.27810	1.010	1.58309	1.000	7954.6801

TABLE IV

LINE FLOWS FOR PENALTY FACTORS SETTINGS (TABLE 3, COLUMN 2 AND COLUMN 3) DURING 10^{TH} GENERATION FOR 6-BUS SYSTEM

From bus no.	To bus no.	For penalty factors in Table III Column 2 during 10^{th} generation	For penalty factors in Table III Column 3 during 10^{th} generation
1	2	29.77	33.076
1	5	83.822	85.357
2	4	58.131	62.424
3	5	65.958	68.788
3	6	27.537	28.507
4	5	59.259 (overflow)	60.673 (overflow)
4	6	101.883 (overflow)	104.229 (overflow)
Generation Cost		7900.4	7897.0
Max. fitness		0.9542	0.9532

TABLE V

COMPARISON OF GENERATION COST WITH OTHER METHODS FOR 6-BUS SYSTEM

OPF method	Weber [14]	OPFSA [15]	M-COGA [16]	EGA-Fuzzy OPF Column-1
Generation Cost ($/h)	8062	7938	7987.1764	7910.2065

International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:2, No:5, 2008

Three cases using different overflow line penalty factors settings named as EGA-Fuzzy OPF Column-1, EGA-Fuzzy OPF Column-2 and EGA-Fuzzy OPF Column-3 (as listed in Table III) are tried under normal state.

The load voltage penalty factors are kept same because lower limits of load bus voltage magnitudes are not violated in normal state operation. The convergence curves for generation cost and maximum fitness and variations in crossover and mutation probabilities are shown in fig. 3.The lineflows, load bus voltages, penalty factor settings, loadflow solutions and generation costs for three cases are tabulated in Table III. For EGA-Fuzzy OPF Column-1, generation cost is lowest and maximum fitness has maximum value among all the cases, though line flow is just under control at line 4-5. If higher values of penalty factors (EGA-Fuzzy OPF Column-2 and Column-3 of Table III) are chosen overcautiously, then line flows will be under control but with suboptimal generation costs.

Another major observation made in fig. 3 is that lower generation costs with lower maximum fitness values are obtained from generation number 10th to 56th generation (for EGA-Fuzzy OPF Coloumn-2 penalty factors) and from 10th to 17th generation (for EGA-Fuzzy OPF Coloumn-3 penalty factors). The results tabulated in Table IV indicate that during 10th generation overflows are resulted at lines 4-5 and 4-6 with lower generation costs and lower maximum fitness values. Although comparatively higher generation costs and higher maximum fitness values with no line overflows are obtained during later stages/generations of optimization. The reason being that during earlier generations, fitness function defined by (10) with exponentially decaying terms for line overflows and lower load bus voltage limits, gives lower maximum fitness values due to line overflows resulted by generation schedule.

The proposed EGA-Fuzzy OPF method has minimum generation cost with no line overflows and load voltage magnitude limits violation among other OPF methods listed in Table V.

B. *For IEEE 30-bus*

The IEEE 30-bus system consists of six generators, four transformers, 41 lines and nine shunt capacitors. The variable limits and generator cost parameters are listed in Table VI.

Two cases are studied. Case-1 is the normal operation case and the Case-2 is the contingent case, in which a circuit outage is simulated in branch (6,28) thus causing a power flow violation in branch (8,28) and violation of some load bus voltage magnitude limits. The GA parameters of EGA-Fuzzy OPF and optimal results for Case-1 are given in Table VII and Table VIII respectively. All power and voltage quantities are in per unit values. The base power is 100 MVA.

The convergence to final values of generation cost and maximum fitness along with crossover and mutation probabilities variations for Case-1 using EGA-OPF are shown in fig. 4.

TABLE VI
VARIABLE LIMITS AND GENERATOR COST PARAMETERS OF IEEE 30-BUS SYSTEM

Power generation limits and fuel cost parameters (S_B = 100 MVA)						
Bus	1	2	5	8	11	13
P_g^{max}	2	0.8	0.5	0.35	0.3	0.4
P_g^{min}	0.5	0.2	0.15	0.1	0.1	0.12
Q_g^{max}	2	1	0.8	0.6	0.5	0.6
Q_g^{min}	- 0.2	- 0.2	- 0.15	- 0.15	- 0.1	-0.15
a	0	0	0	0	0	0
b	200	175	100	325	300	300
c	37.5	175	625	83.4	250	250
Bus voltage limits (in p.u.)				Branch apparent power limit S_k^{max} (in MVA) Branch (8, 28)		
V_g^{max}	V_g^{min}	V_{load}^{max}	V_{load}^{min}			
1.1	0.95	1.05	0.95	12		

TABLE VII
EGA-FUZZY PARAMETERS FOR IEEE 30 BUS

Crossover probability	Mutation probability	Selection operator	Population size
0.95 (Initial)	0.01 (Initial)	Stochastic Remainder	50

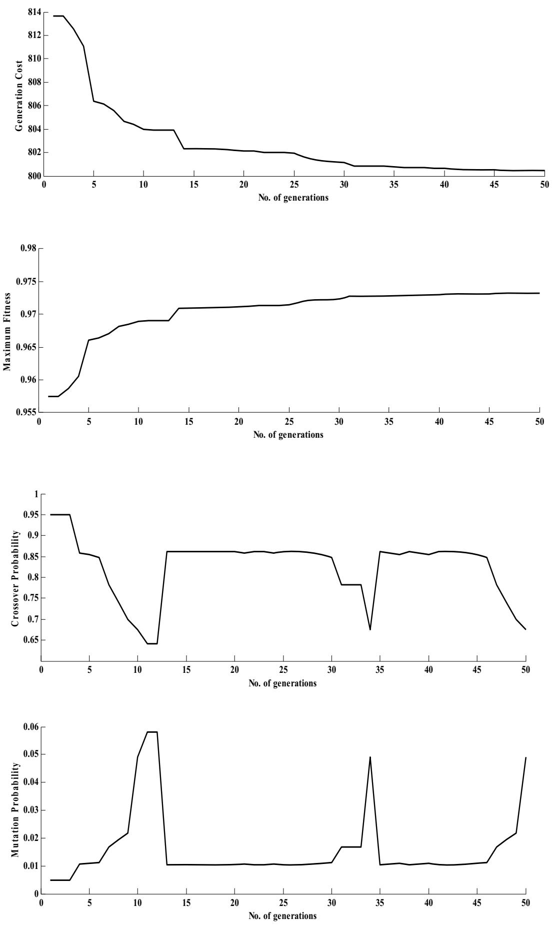


Fig. 4 Convergence of generation cost, maximum fitness, crossover and mutation probabilities using EGA-Fuzzy OPF for Case-1 of IEEE 30-bus

TABLE VIII
LINEFLOWS, LOAD BUS VOLTAGES, OVERFLOW LINE AND LOAD VOLTAGE PENALTY FACTORS, LOADFLOW SOLUTION, AND GENERATION COST FOR CASE-1 (NORMAL STATE) OF IEEE 30 BUS USING EGA-FUZZY OPF

From bus no.	To bus no.	Line flows limits (MVA)	EGA-Fuzzy OPF		At load bus	EGA-Fuzzy OPF	
			Overflow line penalty factors	Line flows (MVA)		Load voltage penalty factors	Bus voltage (in p.u.)
1	2	130	1	117.0092	3	1	1.05
1	3	130	1	58.3399	4	1	1.043
2	4	65	1	33.8512	6	1	1.038
2	5	130	1	63.6081	7	1	1.027
2	6	65	1	44.859	9	1	1.062
3	4	130	1	54.2265	10	1	1.054
4	6	90	1	48.829	12	1	1.057
4	12	65	1	30.6851	14	1	1.047
5	7	70	1	14.1992	15	1	1.047
6	7	130	1	34.697	16	1	1.05
6	8	32	1	11.1877	17	1	1.05
6	9	65	1	19.9662	18	1	1.04
6	10	32	1	13.188	19	1	1.04
6	28	32	1	16.2027	20	1	1.045
8	28	12	1	3.3171	21	1	1.045
9	11	65	1	20.8172	22	1	1.045
9	10	65	1	32.64054	23	1	1.045
10	20	32	1	9.4703	24	1	1.039
10	17	32	1	6.3406	25	1	1.043
10	21	32	1	16.5742	26	1	1.026
10	22	32	1	7.8564	27	1	1.054
12	13	65	1	15.6675	28	1	1.034
12	14	32	1	7.4018	29	1	1.041
12	15	32	1	17.485	30	1	1.027
12	16	32	1	6.6516			
14	15	16	1	1.6794			
15	18	16	1	5.5863			
15	23	16	1	4.8064			
16	17	16	1	3.3993			
18	19	16	1	2.3973			
19	20	32	1	8.1734			
21	22	32	1	2.6539			
22	24	16	1	5.7204			
23	24	16	1	2.1442			
24	25	16	1	1.6587			
25	26	16	1	4.2584			
25	27	16	1	5.8553			
27	29	16	1	6.1908			
27	30	16	1	7.145			
28	27	65	1	19.1927			
29	30	16	1	3.8992			

	Transformer tap settings			
Branch	(6,9)	(6,10)	(4,12)	(28,27)
	0.9903	0.9839	0.9903	0.9645

	Shunt capacitor (in p.u.)								
Bus	10	12	15	17	20	21	23	24	29
	0.03982	0.0002	0.04149	0.0499	0.04432	0.04354	0.0454	0.04687	0.02097

	Active power generations (in p.u.)						
Bus	1	2	5	8	11	13	
Gen. (in p.u.)	1.74886	0.48941	0.21176	0.22647	0.12588	0.12	Generation Cost (in \$/hr)
Volt. (in p.u.)	1.081	1.063	1.031	1.039	1.095	1.070	800.442

As the results listed in Table VIII for Case-1, with unity penalty factors settings for line flow constraints and load bus voltage magnitude, all generator units are scheduled for minimum generation cost 800.442$/hr without any operational and insecure violations.

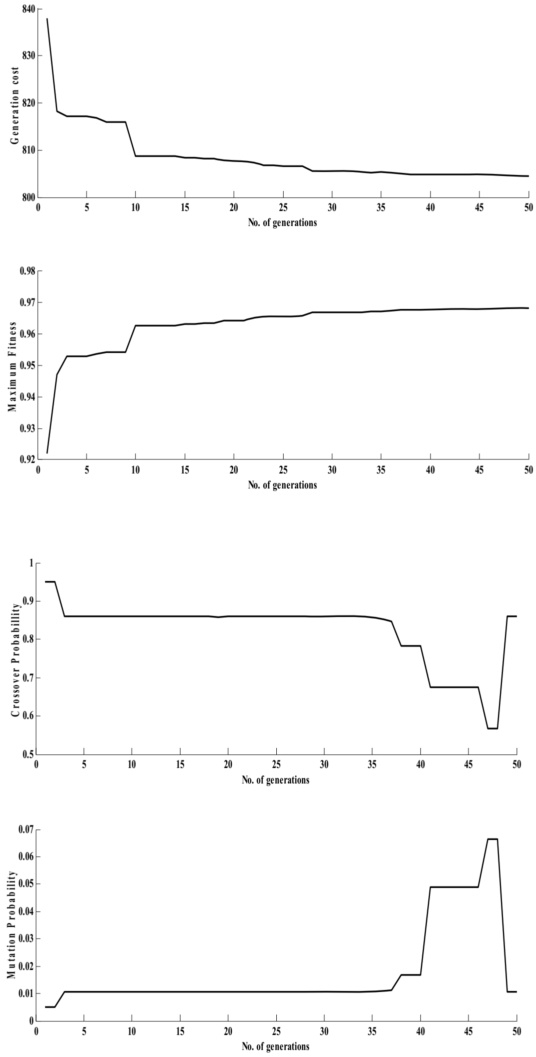


Fig. 4 Convergence of generation cost, maximum fitness, crossover and mutation probabilities for EGA-Fuzzy OPF for Case-2, Solution-1 of IEEE 30-bus

For same system settings but circuit outage of branch (6,28), power flow in branch (8,28) exceeds the maximum limit along with voltage magnitude drop at load buses 25, 26, 27, 29 and 30. In Case-2 (contingent state with congestion state), Solution-1 and Solution-2 are obtained using EGA-Fuzzy OPF with same penalty factors for line flows but different penalty factors for load bus voltage magnitude. Fig. 4 and 5 show convergence and variations in crossover and mutation probabilities for Case-2, Solution-1 and Case-2, Solution-2 respectively.

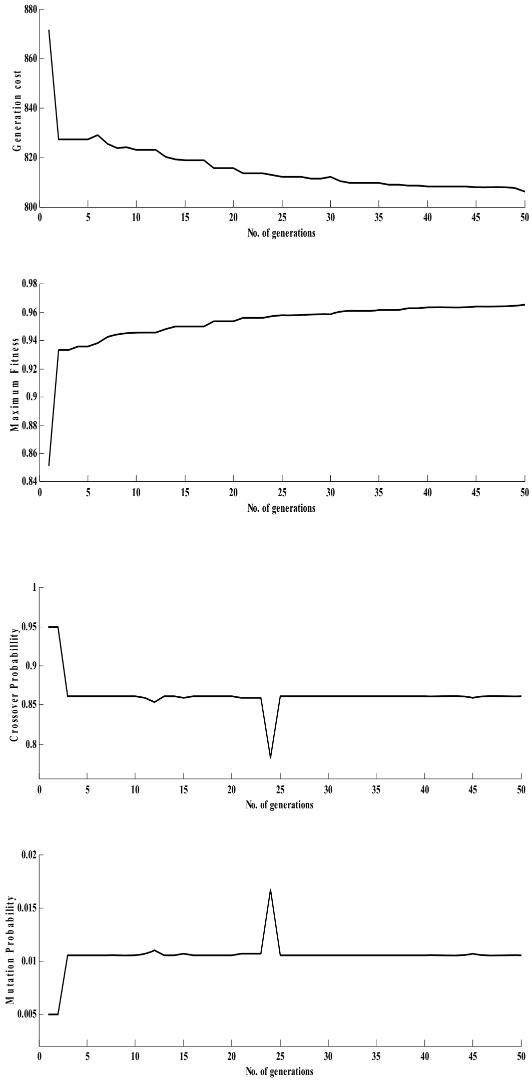


Fig. 5 Convergence of generation cost, maximum fitness, crossover and mutation probabilities using EGA-Fuzzy OPF for Case-2, Solution-2 of IEEE 30-bus

It is clear from results listed in Table IX, the line flows and load bus voltage magnitudes are under limits for penalty factors values used in Case-2, Solution-1. The line flows are well under control but with scanty violation of load bus voltage magnitude at bus 30 (≈ 0.945) in Case-2, Solution-2 due to selecting unity penalty factor settings for load buses.

Table X shows the comparison of the cost of generation for IEEE 30-bus system for both the cases with other available methods and shows it’s superiority over others.

International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:2, No:5, 2008

TABLE IX
LINEFLOWS, LOAD BUS VOLTAGES, OVERFLOW FLOW LINE AND LOAD VOLTAGE PENALTY FACTORS, LOADFLOW SOLUTION, AND GENERATION COST FOR CASE-2 (CONTINGENCY STATE) OF IEEE 30 BUS USING EGA-FUZZY OPF

From bus no.	To bus no.	Line flows limits (MVA)	EGA-Fuzzy OPF **Solution-1** Overflow line penalty factors	EGA-Fuzzy OPF **Solution-1** Line flows (MVA)	EGA-Fuzzy OPF **Solution-2** Overflow line penalty factors	EGA-Fuzzy OPF **Solution-2** Line flows (MVA)	At load bus	EGA-Fuzzy OPF **Solution-1** Load voltage penalty factors	EGA-Fuzzy OPF **Solution-1** Bus voltage (in p.u.)	EGA-Fuzzy OPF **Solution-2** Load voltage penalty factors	EGA-Fuzzy OPF **Solution-2** Bus voltage (in p.u.)
1	2	130	1	117.0941	1	122.3225	3	5	1.058	1	1.029
1	3	130	1	58.0893	1	58.7672	4	5	1.051	1	1.022
2	4	65	1	35.2645	1	35.5066	6	5	1.046	1	1.016
2	5	130	1	65.2592	1	64.8939	7	5	1.048	1	1.000
2	6	65	1	45.8348	1	46.1278	9	5	1.098	1	1.089
3	4	130	1	53.9314	1	54.578	10	5	1.088	1	1.066
4	6	90	1	47.2856	1	47.441	12	5	1.09	1	1.078
4	12	65	1	32.7012	1	32.9166	14	5	1.078	1	1.063
5	7	70	1	27.0514	1	11.7813	15	5	1.075	1	1.057
6	7	130	1	35.194	1	35.7528	16	5	1.084	1	1.067
6	8	32	1	29.7604	1	32.0634	17	5	1.083	1	1.064
6	9	65	1	30.9893	1	26.2947	18	5	1.07	1	1.051
6	10	32	1	22.0905	1	13.8451	19	5	1.07	1	1.05
8	28	12	50	11.7912	50	11.9848	20	5	1.075	1	1.055
9	11	65	1	16.6787	1	17.1137	21	5	1.074	1	1.051
9	10	65	1	35.587	1	41.9316	22	5	1.073	1	1.05
10	20	32	1	9.8212	1	9.4945	23	5	1.058	1	1.041
10	17	32	1	6.9061	1	5.5112	24	5	1.045	1	1.024
10	21	32	1	22.56	1	23.014	25	5	1.001	1	0.987
10	22	32	1	11.6946	1	11.775	26	5	0.983	1	0.969
12	13	65	1	15.0569	1	21.6305	27	5	0.983	1	0.974
12	14	32	1	8.1769	1	8.5667	28	5	1.051	1	1.022
12	15	32	1	19.5271	1	20.5364	29	5	0.962	1	0.96
12	16	32	1	7.132	1	7.5278	30	5	0.95	1	0.945
14	15	16	1	1.7774	1	2.0485					
15	18	16	1	5.559	1	5.6891					
15	23	16	1	8.7343	1	8.694					
16	17	16	1	3.8799	1	3.6635					
18	19	16	1	2.679	1	2.534					
19	20	32	1	8.6167	1	8.137					
21	22	32	1	4.0246	1	2.6012					
22	24	16	1	14.9637	1	13.952					
23	24	16	1	5.1721	1	6.1589					
24	25	16	1	12.0123	1	9.8722					
25	26	16	1	4.2647	1	4.2669					
25	27	16	1	7.9349	1	5.7534					
27	29	16	1	6.4275	1	6.2131					
27	30	16	1	7.3044	1	7.1688					
28	27	65	1	11.7875	1	11.9811					
29	30	16	1	3.7575	1	3.9264					

Transformer tap settings

Branch	(6,9)	(6,10)	(4,12)	(28,27)
Solution-1	0.9194	0.9	0.9581	1.0871
Solution-2	0.9065	0.9452	0.9452	1.0678

Shunt capacitor (in p.u.)

Bus	10	12	15	17	20	21	23	24	29
Solution-1	0.04824	0.03826	0.04413	0.03102	0.03121	0.03268	0.0009	0.04002	0.00000
Solution-2	0.02681	0.01429	0.00577	0.04286	0.03307	0.00685	0.01526	0.01517	0.02258

	Bus	1	2	5	8	11	13	Generation Cost (in $/hr)	
Solution-1	Gen. (in p.u.)	1.73494	0.52471	0.21589	0.20098	0.12589	0.13098	**Solution-1**	804.581
	Volt. (in p.u.)	1.09	1.081	1.071	1.052	1.077	1.100		
Solution-2	Gen. (in p.u.)	1.78197	0.45882	0.22412	0.18039	0.16117	0.13098	**Solution-2**	806.184
	Volt. (in p.u.)	1.061	1.055	0.998	1.023	1.100	1.100		

TABLE X
COMPARISON OF THE GENERATION COST FOR IEEE-30 BUS SYSTEM FOR NORMAL AND CONTINGENT CASES

OPF Method	Generation Cost (in $/hr) Case-1	Generation Cost (in $/hr) Case-2
Gradient projection method [17]	804.583	-
Improved genetic algorithm [18]	800.81	812.33
Enhanced genetic algorithm [5]	802.06	-
EGA-Fuzzy	800.442	804.581

V. Conclusion

In present paper an OPF method developed on adaptive EGA-Fuzzy approach is tried on 6 bus system and IEEE 30-bus system. Line flow constraints and lower voltage limits for load buses are successfully met under both normal and contingent states by employing penalty factors in determining fitness function. The proposed method shows superiority over other optimization methods, however the judicious selection of penalty factor settings is important as higher values of penalty factors may give suboptimal results. The proposed method can be generalized and easily extended to large-scale systems.

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