EFFECT OF FUZZY PENALTY ON CONVERSION OF OPTIMAL POWER FLOW USING GENETIC ALGORITHM

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ABSTRACT

The optimal power problem seeks to find an optimal profile of active and reactive power generation along with the voltage magnitudes in such a manner as to minimize the total operating cost of electric power system, while satisfying network security constraints .The Simple Genetic Algorithm with fixed penalty and variable penalty advantages finds its own utility in optimal power flow solutions .This paper presents three algorithm with an effect of variable penalty using Fuzzy Logic selection on the convergence of OPF. Fuzzy Logic variable penalty based study is provided to visualize the effect of selection of control variables on OPF convergence with solution time and improved value. Extensive study is provided on IEEE 30 bus system to draw certain important conclusions

Key words: *Optimal Power Flow ,Fuzzy Penalty ,Variable Penalty, Genetic Algorithm, contingencies*

1. INTRODUCTION

OPF is helpful in minimizing the generation cost, electricity prices to the end consumer and reduces the transmission line congestion [1][2]. OPF is used in security constraints by applying the inequality and equality constraints within the system operating constraints. These methods provide the solution to the system with large numbers of variables as compared to the conventional methods which gives better solution for minimum variable constraints condition. For getting the optimal solution the Linear Programming [LP], Non Linear Programming, Quadratic Programming [QP] and Krush-Kuhn-Tucker (KKT) Methods are useful for nonlinear equation in case of Newton based algorithm [3]-[7]. Different types of genetic algorithms are used for getting the optimal solution [10]. The operation like proportionate reproduction, simple mutation and one point cross-over in binary codes are mainly used in simple genetic algorithm [11]. In simple genetic algorithm based OPF with variable penalty uses the fuzzy base. The fuzzy based penalty is imposed in the proposed algorithm instead of fixed penalty. The fuzzy penalty is imposed through various fuzzy rules. These fuzzy rules for penalty uses various linguistic variables based on the objection functions. The objective function value is fuzzified into three linguistic variables low, medium and high. The fuzzy penalty imposed is also fuzzified into low, medium and high linguistic variables. The fuzzy membership function and multi-objective problem solved with fuzzy sets theory and max-min operator for minimizing generation cost and optimization of active power losses [12]. A fuzzy technique used to determine optimal location of thyristor controlled series capacitor (TCSC) to control active power flows and for reduction in transmission line congestion [13]. The generator selectivity based on sensitivity to the congested line and Fitness Distance Ratio PSO (FDR-PSO) fuzzy PSO helps in reducing the congestion in the transmission line [14]. Fuzzy adaptive bacterial foraging for congestion management based on optimal rescheduling of active powers of generators with generator sensitivity to the congested line [15]. The nonlinear objective function is solved with Real Genetic Algorithm (RGA). The analytical hierarchy process (AHP) with fuzzy sets is used to evaluate the RGA fitness function which helped in congestion management [16]. The uncertainties in the evaluation of load demand and wind speed for optimal power flow solution is solved with the help of fuzzy based hybrid PSO method [17]. After introduction this paper is organized as follows – Section II gives information about GA. Application of GA in OPF is explained in section III. Section IV deals with the problem definition. Case study results are discussed in section V and VI summarized the conclusion.

2. OPTIMAL POWER FLOW PROBLEM STATEMENT

The optimal power flow is the power flow solution of system in which certain control variables are adjusted to minimize an objective function while satisfying physical and operating limits on state and control variable.
The minimum fuel cost problem is stated as

$$\text{Minimize } F = \sum_{i}^{N_g} \left(a_i P_{gi}^2 + b_i P_{gi} + c \right) \quad \$/\text{h} \tag{1}$$

The above optimization function is subject to

1. Active power balance in the network

$$P_i(V,\delta) - P_{gi} + P_{di} = 0 \quad i = 1, 2 \ldots N_b \tag{2}$$

2. Reactive power balance in the network

$$Q_i(V,\delta) - Q_{gi} + Q_{di} = 0 \quad i = N_{v+1}, N_{v+2} \ldots N_b \tag{3}$$

3. Security related constraints

a. Limits on real power generation.

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad i = 1, 2 \ldots N_g \tag{4}$$

b. Limits on voltage magnitude

$$V_i^{\min} \le V_i \le V_i^{\max} \quad i = N_{v+1}, N_{v+2} \ldots N_b \tag{5}$$

c. Limits voltage angles

$$\delta_i^{\min} \le \delta_i \le \delta_i^{\max} \quad i = 1, 2 \ldots N_b \tag{6}$$

4. Functional constrain

a. Limits on reactive power

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \quad i = 1, 2 \ldots N_g \tag{7}$$

b. Limits on line flow

$$0 \le \left| P_{TL} \right| \le P_{TL}^{\max} \tag{8}$$

Limits on imaginary power flow

$$0 \le \left| Q_{TL} \right| \le Q_{TL}^{max} \tag{9}$$

The real power flow equation is

$$P_i(V,\delta) = \sum_{i=1}^{N_b} V_i V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \tag{10}$$

$$Q_i(V,\delta) = \sum_{i=1}^{N_b} V_i V_j (G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij})) \tag{11}$$

Let us assume that $g(x,u)$ be the set of equality constraints equation given by (2)-(3) can be arranged as

$$g(x,u) = 0 \tag{12}$$

And let $h(x,u)$ be the set of inequality constraints and defined as

$$h(x,u) \le 0 \tag{13}$$

Where u is control variable which define the system and govern the evolution of system from one state to another state, while x is the state variable which describes the behavior or status of the system on any stage.

Hence in optimal power flow method, the problem is to find a set control variable such that the total objective function over any stage is minimized subject to set of constraints on control and state variable.

3. BRIEF INTRODUCTION TO GENETIC ALGORITHM

It is an evolution process based on the theory of survival of the fittest. Genetic Algorithm is used for global function/control optimization with fixed penalty and with variable penalty effects. It follow a non-systematic search procedure with diversity of population is an important concern.
The genetic algorithm works on three basic operators-

- Reproduction
- Cross-over
- Mutation

The first step of any GA is to generate the initial population. A binary string of suitable length L is associated to each member (individual) of the population. This string usually represents a solution of the problem. A sampling of this initial population creates an intermediate population.
Crossover is the primary genetic operator, which explores new regions in the search space. Crossover is responsible for the structure recombination (information exchange between mating chromosomes) and is usually applied with high probability .

Mutation is used both to avoid premature convergence of the population (which may cause convergence to a local, rather than global, optimum) and to fine-tune the solutions. The mutation operator has defined by a random bit value change in a chosen string with a low probability of such change.

To minimize fitness function is equivalent to getting a maximum fitness value in the searching process. A chromosome that has lower cost function should be assigned a larger fitness value. The objective of OPF has to be changed to the maximization of fitness to be used in the simulated roulette wheel.

Fitness Function $ff = \frac{1}{1+f^2}$ (14)

Where,

$$f = f_C + P_1\left(\sum h^2(x,u)\right) + P_2\left(\sum g^2(x,u)\right) \tag{15}$$

4. PROPOSED ALGORITHMS FOR SOLUTION OF OPF :

Simple Genetic Based OPF with fuzzy penalty

In this class of algorithms, three algorithms i.e. Algo-FA, Algo-FB and Algo-FC suggested with different set of control and state variables are subjected to fuzzy based penalty on the equality and inequality constraints.

Application of the genetic algorithm with Fixed penalty to optimal power flow with voltages as control vectors posses a slow convergence problem, as GA is random population based search algorithm. In this case, the GA utilizes large generations and without guaranteed convergence. Considering, the disadvantages of it, this paper suggests, algorithms with Fuzzy based variable penalty which speeds the solution and accuracy.

Let,

$$U = \{V, \delta, P, Q\} \tag{16}$$

Where,

V be the set voltage magnitudes of buses in a power system
δ be the set angles of buses in a power system
P be set of active power

Q be the set of reactive power
Let, B is set defined as,

$$B = \{G, L, C, TL, T\} \tag{17}$$

Where,
G is set of generating buses G
L is set of load buses and
C be set of controlled buses
TL is the set of transmission lines
T is set of transformers

Let, MG Є G, is maximum generation capability bus. In this paper, it is assumed that this bus will supply the losses in power system.

The set of control variables and state variables can be chosen from these set for GA based optimal power flow. The proposed algorithms suggested for optimal power flow using the classical methods and Genetic Algorithm are illustrated below sequentially.

4.1 Optimal Power Flow :

The algorithm for solution of optimality is given below-

1. Read the system data
2. Obtain the bus admittance matrix
3. Assume the control variables

$V_i = 1.0\,pu$ and $\delta_i = 0$ i=1,2……….N_b (18)

4. Initialize the λ and α
5. Let $X = [V \quad \delta \quad \lambda \quad \alpha \quad y]^T$ (19)
6. Calculate the Jacobian and Hessian matrix elements and let

$\Delta X = [\Delta V \quad \Delta\delta \quad \Delta\lambda \quad \Delta\alpha \quad \Delta y]^T$ (20)

7. Calculate the change in

$\Delta V \quad \Delta\delta$ and $\Delta\lambda \quad \Delta\alpha \quad \Delta y$

using equation (19)

8. Check the converge of

If $\|\Delta X\| \le \varepsilon$ (21)

Go to step 11

Else go to step 9

9. $X = X + \Delta X$
10. Go to step 5and update the solution
11. Stop

4.2 GA Based Approach

4.2.1 - Algorithm (A):

Genetic algorithm is emerged as a global optimization technique for many optimization applications. The conventional algorithm of OPF suffers from disadvantage of getting trapped into local optimum; hence the GA with Fuzzy based variable penalty is used to obtain the solution of OPF. In this paper,various combination of control variables were tested extensively to find the effect of control variable on the convergence of Simple Genetic Algorithm with variable penalty. The proposed algorithms developed from the various combinations of control variable are presented below.

Algorithm (A):

The wide spread control variables used are chosen to find the optimum solution as

$$u = [V_G \quad P_G]^T \tag{22}$$

$$X = [P_{TL} \quad Q_{TL} \quad V_L \quad \delta \quad Q_G]^T \tag{23}$$

The penalty function is used to improve the convergence criterion of Simple GA in this algorithm. The fitness function which is to be minimized is given by

$$F = f_c + \sum_{i=1}^{p} P_{eq}\left[g_i(x,u)\right]^2 + \sum_{j=1}^{m} \lambda_{ineq}\left[h_j(x,u)\right]^2 \tag{24}$$

OR

$$F = f_c + P_{eq} \sum_{i=1}^{p} \left[G_i(x,u)\right]^2 + P_{ineq} \sum_{j=1}^{m} \left[H_j(x,u)\right]^2 \quad \text{Where}$$

$$\left[G_i(x,u)\right]^2 = g_i^{\,2}(x,u) \tag{25}$$

$$\left[H_j(x,u)\right]^2 = \left(\max\left[0, h_j(x,u)\right]\right)^2 \tag{26}$$

Where P_{eq} and P_{ineq} are the Penalty terms for the equality and inequality constraints.

For the assumed control variables, the state variables X of system are obtained by using fast decoupled load flow solution, by iteratively solving the equation

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} H & 0 \\ 0 & L \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} \tag{27}$$

to get the load flow solution.

The obtained load flow solution is used to obtain fitness function given in (24 OR 25). The cross-over and mutation are carried out on the population to change the search direction. In this algorithm PV-PQ switching is not allowed during the fast decoupled load flow (FDLF)calculations, as limits of reactive power capabilities of generator are considered under inequality constraints.

Equation (24 or 25) indicates that while minimizing the objective function F, a positive penalty is added whenever the constraint is violated, the penalty being proportional to square of the amount of violation.

4.2.2 - Algorithm (B):

This algorithm is similar to the algorithm (A) except for PV-PQ bus switching. In this algorithm PV-PQ bus switching is allowed during the fast decoupled load flow calculations.

4.2.3 - Algorithm (C):

In this algorithm, more practical set of control variables are chosen as-

$$\begin{aligned} u &= \left[V_{MG}\ P_G\ Q_G\ Q_C\right]^T \\ x &= \left[P_{TL}\ Q_{TL}\ V_{G\notin MG}\ V_C\ V_L\ \delta\ \right]^T \end{aligned} \tag{28}$$

Fast decoupled load flow applied to obtain the state variables using control variables considered all possibilities of power system including PV-PQ bus switching.

5. CASE STUDY

An extensive study was made to understand the effect of various combinations of control variables on the convergence of optimal power problem (OPF). The classical approach and simple genetic approach as discussed in section III are used to study the effect of widespread control variables on the OPF solution of IEEE-30 bus system. The details of IEEE-30 bus system can be obtained from reference [18]. The suggested algorithms are tested under both normal and contingent conditions. Total 41 contingencies of one transmission line each are considered during the study. Various conditions of simulations studies are listed in Table 1.

Table 1: Assumed conditions for parametric study

Parameter	Specification
Gene length	8
Maximum generation	100
Crossover probability	0.1 to 1
Mutation probability	0.1 to 1
Population size	50
Maximum runs	10
Parent selection	Roullete wheels selection
Voltage regulation	±5 %
Fuzzy based Penalty term for equality constraints and in-equality constraints	
Tolerance on constraint and functional variables	1e-10
Processor	Intel i3
CPU Speed	2.4 GHz
RAM Capacity	2 GB

All the study is carried out on the computer having specifications given in Table 2.

Table 2: CPU Specifications

Parameter	Specification
Processor	Intel i3
CPU Speed	2.4 GHz
RAM Capacity	2 GB

The cross-over and mutation probabilities are varied in the step of o.1 to 1.0. For each ordered pair of (cross-over probability, mutation probability), 10 runs were taken for each case of system conditions i.e. normal or contingency. The result obtained are analyzed and presented below.

5.1 Cost of generation:

The objective function of OPF is to provide a system conditions, where minimum objective function to be obtained. In this specific study, fuel cost is considered as objective function. The minimum fuel cost is considered as objective function. The minimum fuel cost leads to the lesser tariff rate to the end users. Average cost of generation under various contingency conditions obtained after 10 runs for each Algorithm is shown in figure (1) for ordered pair (0.7,0.5). The Algorithm-FC provides lesser cost amongst the entire Algorithm suggested. The fuel cost for cases of contingencies is shown in figure (2). During line loss (no. 36), fuel cost reduction of 0.12 $/MW is achieved by Algorithm-FC in comparison with Algorithm-FA.

The statistical comparison of fuel cost under the no contingency condition for the ordered pair of cross-over(CV) and mutation probability(μ) of (0.1, 0.1) and (0.7, 0.5) are given in Table 3.

Table 3 : Fuel cost comparison based on statistical parameters under no contingency condition (Algorithm with Fixed penalty-Algo-A,B,C & Algorithm with Fuzzy based variable penalty-Algo-FA,FB,FC).

Parameter	CV=0.1, μ=0.1			CV=0.1, μ=0.1		
	Algo-A	Algo-B	Algo-C	Algo-FA	Algo-FB	Algo-FC
Average	88.65	88.59	88.49	87.61	87.63	87.61
Minimum	88.55	88.47	88.46	87.59	87.56	87.60
Maximum	88.77	88.73	88.52	87.67	87.69	87.68
Kurtosis	2.044	1.578	1.44	2.87	3.96	2.55
Skewness	0.324	0.0514	-0.50	1.247	1.251	0.727
Std. deviation	0.081	0.1063	0.0267	0.028	0.037	0.020

Parameter	CV=0.7, μ=0.5			CV=0.7, μ=0.5		
	Algo-A	Algo-B	Algo-C	Algo-FA	Algo-FB	Algo-FC
Average	88.53	88.53	88.53	87.61	87.60	87.57
Minimum	88.47	88.48	88.45	87.58	87.58	87.54
Maximum	88.68	88.56	88.75	87.68	87.67	87.60
Kurtosis	3.195	1.267	3.08	3.468	4.206	2.541
Skewness	1.4602	0.259	1.38	1.107	1.492	0.837
Std. deviation	0.0879	0.0387	0.123	0.0306	0.0292	0.021

Algorithm-FC has the tendency to converge towards global optimum, as the spread of convergence values (standard deviation) of fuel cost found to be minimum for this algorithm than all others.The Algorithm–FC provides better estimate of average value \$ 87.61/MW for CV=0.1 and μ=0.1and \$ 87.57/MW for CV=0.7 and μ=0.5. Minimum and maximum values attained by different algorithms show that, Algorithm-FC achieves the values less than the fuel cost achieved by Algorithm-FA and Algorithm-FB. Skewness parameters shows that Algorithm-FA and Algorithm-B are skewed than Algorithm-FC.

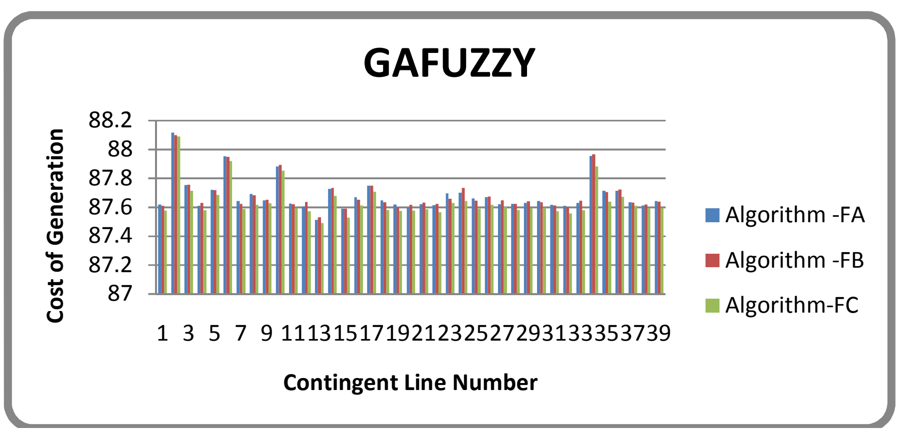

Figure (1): Fuel cost comparison for different GAFuzzy based Algorithms

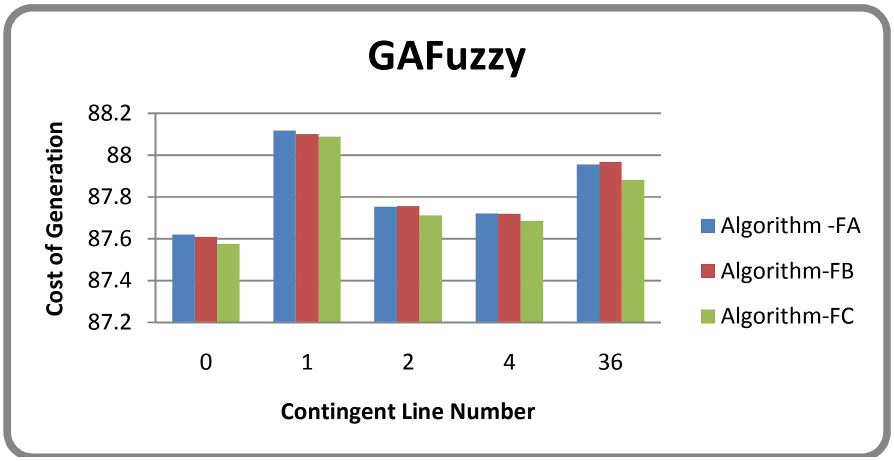

Figure (2): Fuel cost comparison for different GAFuzzy based Algorithms (Algo-F) for selected contingent conditions (derived from fig. 1)

Under contingent condition of transmission line 36, the performance of various GA Fuzzy based algorithms indicated in terms of statistical parameters is given in table (IV). Here also, Algorithm-FC provides better estimate of fuel cost in comparisons with other algorithms. The standard deviation of objective function obtained for Algorithm-FC in 10 runs is 0.050 and 0.026 under ordered pair (0.1, 0.1) and (0.7, 0.5) respectively. Under this situation kurtosis is 4.65 and 1.35 under ordered pair (0.1, 0.1) and (0.7, 0.5) respectively

Table 4 : Fuel cost comparison based on statistical parameters under contingency condition of transmission line no. 36

Parameter	CV=0.1, μ=0.1			CV=0.1, μ=0.1		
	Algo-A	Algo-B	Algo-C	Algo-FA	Algo-FB	Algo-FC
Average	88.90	88.97	88.91	87.95	87.96	88.00
Minimum	88.81	88.84	88.76	87.86	87.85	87.92
Maximum	89.07	89.15	89.10	88.03	88.14	88.03
Kurtosis	2.95	1.58	2.28	2.30	1.79	4.65
Skewness	1.20	0.13	0.51	-1.38	-0.63	0.20
Std. deviation	0.10	0.13	0.12	0.051	0.105	0.050

Parameter	CV=0.7, μ=0.5			CV=0.7, μ=0.5		
	Algo-A	Algo-B	Algo-C	Algo-FA	Algo-FB	Algo-FC
Average	89.48	89.38	88.86	87.98	87.96	87.84
Minimum	89.13	89.10	88.80	87.87	87.90	87.81
Maximum	89.76	89.54	88.89	88.05	88.03	87.87
Kurtosis	2.53	2.58	1.85	3.81	1.84	1.35
Skewness	-0.44	-0.92	-0.57	0.49	0.19	0.08
Std. deviation	0.23	0.17	0.04	0.049	0.048	0.026

Table 5 : Computational time comparison based on statistical parameters under no contingency condition (Algo-A, Algo-B, Algo-C for Fixed Penalty and Algo-FA, Algo-FB, Algo-FC are for Fuzzy based Variable Penalty)

Parameter	CV=0.1, μ=0.1			CV=0.1, μ=0.1		
	Algo-A	**Algo-B**	**Algo-C**	**Algo-FA**	**Algo-FB**	**Algo-FC**
Average	29.09	29.39	25.33	16.52	16.56	32.90
Minimum	27.83	28.18	24.57	14.17	14.46	26.71
Maximum	30.15	30.24	25.83	24.26	23.04	40.09

Parameter	CV=0.7, μ=0.5			CV=0.7, μ=0.5		
	Algo-A	**Algo-B**	**Algo-C**	**Algo-FA**	**Algo-FB**	**Algo-FC**
Average	29.85	29.70	24.49	17.28	17.43	31.13
Minimum	27.69	28.48	23.68	16.81	15.75	27.65
Maximum	32.60	32.40	25.17	18.00	19.89	42.43

Table 6 : Computational time comparison based on statistical parameters under contingent condition of line 36

Parameter	CV=0.1, μ=0.1			CV=0.7, μ=0.5		
	Algo-FA	**Algo-FB**	**Algo-FC**	**Algo-FA**	**Algo-FB**	**Algo-FC**
Average	15.38	18.10	28.19	16.11	17.43	28.54
Minimum	14.01	16.10	26.01	15.82	15.75	26.98
Maximum	19.15	20.90	31.12	16.73	20.01	30.62

From the previous section, we observe that the Algorithm-FA founds better estimate of objective functions under the contingency condition with less computational or solution time as compared to the other GA Fuzzy based algorithms. The average time for Algo-FC in both no contingency and contingency condition found higher side as compared to other algorithm.

5.2: Allocation of Real power generation:

Under the no contingency condition and contingent condition, the percentage generation allocation for each generating bus is given in table (VII) and (VIII) respectively.

From table (VII) and (VIII), it can be seen that, under normal or no contingency condition Algorithm-FC chooses the system condition which minimize the loss in the system, while under contingent condition, it chooses the system states so that loss will be minimum amongst all other algorithms. From table (VII), Algorithm-FC loads the costlier generator located at bus number 8,11,13 to its highest capacity, and still keeps the cost of generation minimum i.e. $87.57 as compared to other algorithms. While the other algorithms cater the load requirement by drawing maximum share of real power from less costly generators i.e. from bus no 1, 2, and 5 . While under contingent condition Algorithm-FC at bus number 1 ,11 loads the generator to its maximum value as compared to other bus no.2,5,8,13 .under contingent condition the % loss increases as compared to the no contingency condition , but still it keeps the cost of generation minimum to $ 87.84 in Algo-FC as compared to other algorithms.

Table 7 : Percentage share of each generator towards load under no contingency condition

Bus/Algorithm	% Share of Real Power Generation		
	AlgoA-FA	**AlgoB-FB**	**AlgoC-FC**
1	38.42 32.87	38.39 32.90	36.73 32.98
2	5.7 12.81	10.69 12.51	15.91 12.80
5	14.75 15.54	11.47 15.56	32.82 14.01
8	17.29 18.06	10.44 18.01	3.25 18.22
11	14.86 18.31	17.18 18.34	13.30 18.66
13	10.59 15.21	13.58 15.23	0.71 15.39
% Total Gen.	101.6 112.7	101.7 112.5	102.7 112.0
% Load	100	100	100
% Loss	1.61 12.70	1.75 12.55	2.71 12.06
Fuel cost	88.47 87.61	88.48 87.60	88.45 87.57

Table 8 : Percentage share of each generator towards load under contingent line number 36 conditions

Bus/Algorithm	% Share of Real Power Generation		
	AlgoA-FA	**AlgoB-FB**	**AlgoC-FC**
1	38.44 34.22	38.34 34.33	38.48 34.13
2	17.14 16.46	16.53 16.73	9.99 16.17
5	11.54 21.44	8.30 21.47	11.24 18.49
8	14.46 19.35	15.64 19.30	15.62 19.31
11	12.70 19.39	10.30 19.39	17.61 19.44
13	8.13 18.10	13.48 18.07	9.24 18.07
% Total Gen.	102.4 128.9	102.6 129.2	102.1 125.6
% Load	100.00	100.00	100.00
% Loss	2.40 28.98	2.60 29.29	2.17 25.61
Fuel Cost	89.13 87.98	89.10 87.96	88.80 87.84

Comparative charts are provided for various algorithm in figure (3) and (4) under no contingency and contingent conditions for share of costlier and cheaper generating stations.

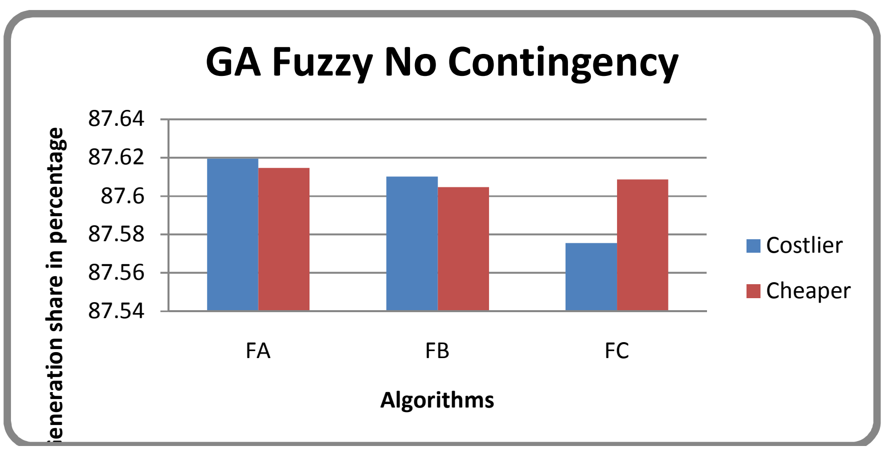

Figure (3): Comparison chart for share of generation under no contingency condition

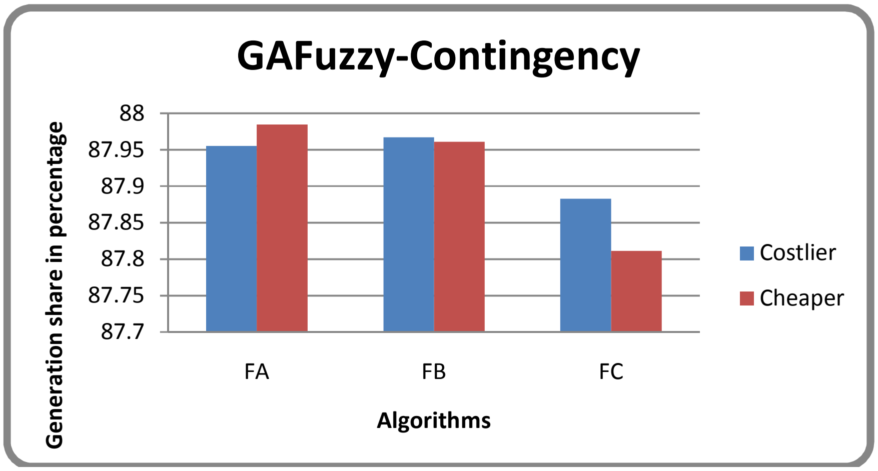

Figure (4): Comparison chart for share of generation under contingency condition

5.3: Bus Voltage Profile

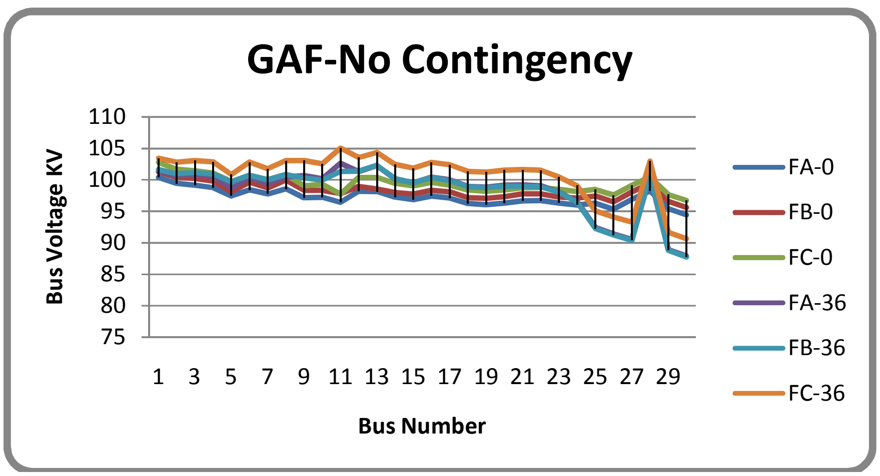

Figure (5): Comparison chart for voltage profile of buses under no contingency condition

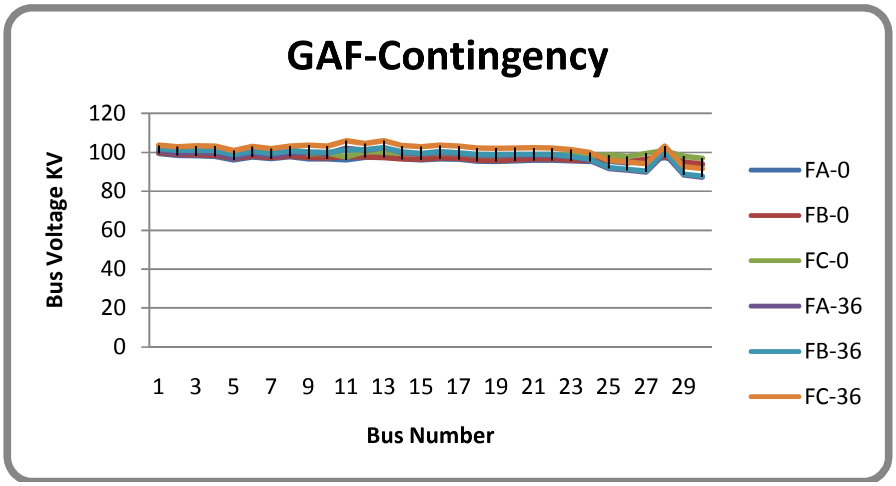

Figure (6): Comparison chart for voltage profile of buses under contingency condition

The voltage profile obtained during study are presented in figure (5) and (6) under normal and contingent conditions respectively. It can be observed that voltages achieved in Algorithm-FC during normal operating condition are slightly lower than those obtained in the Algorithm-FA and Algorithm-FB. In contingent condition, Algorithm-FC achieves the higher voltages than the Algorithm-FA and Algorithm- FB, by adjusting the reactive power within their limits at the generating buses. The reactive power share by each generating station under this contingent condition is shown in figure (7). Here, the +ve sign is considered for injection of the reactive power into bus and -ve sign is vice-versa of it.

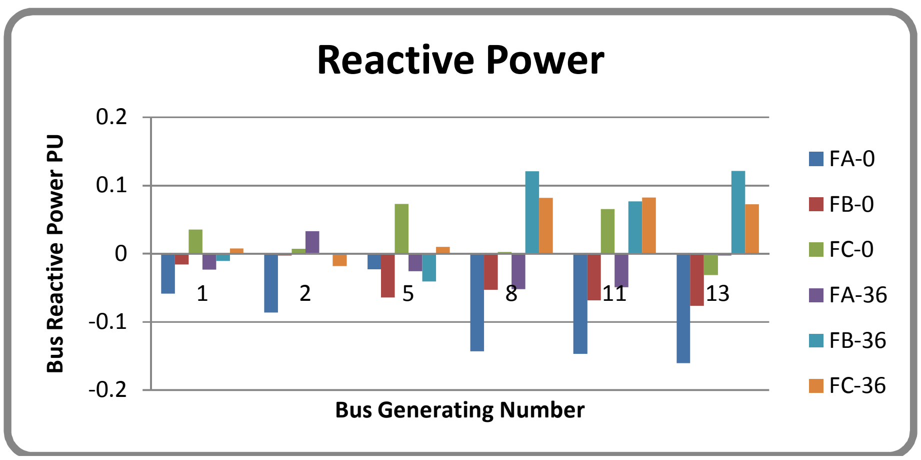

Figure (7): Comparison chart for reactive power at generating buses

6. CONCLUSION

In this paper, an extensive study was carried out to visualize the effect of Fuzzy based variable Penalty on the convergence of OPF using simple genetic algorithm. Overall this three algorithm with Fuzzy based Variable Penalty improves the performance of the algorithms over the Fixed Penalty based algorithm . This extensive study proves that Fuzzy based variable Penalty Algorithm-FC proved to be effective in obtaining global solution under normal and contingent conditions. Algorithm-FC has prove its suitability with global optimal solution and computational time. Effect of solution obtained by these Fuzzy based variable Penalty algorithms as compared to the fixed penalty based algorithms are also been analyzed for generation allocation and bus voltage profile. It is found that solution provided by Algorithm-FC is realistic. This shows that the overall performance of these algorithm improved with Fuzzy based variable penalty.

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APPENDIX-A: FUEL COST CURVE COEFFICIENTS USED

Gen. no.	1	2	5	8	11	13
a	0.14	0.2	0.14	0.2	0.2	0.2
b	20.4	19.3	20.4	19.3	19.3	19.3
c	5.00	5.00	5.00	5.00	5.00	5.00

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APPENDIX-B: FLOW CHART FOR SGA BASED ALGORITHM