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Optimal Power Flow Using Genetic Algorithm: Parametric Studies for Selection of Control and State Variables

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Authors' contributions

This work was carried out in collaboration between both authors. Author CMW designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript and managed literature searches. Author APV performed the statistical analysis and manuscript and managed literature searches. Both authors read and approved the final manuscript.

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ABSTRACT

The load flow solution using optimal power flow algorithm is gaining the importance in open market for operating the electrical network in optimal way. The optimal power flow is a power flow problem in which certain controllable variables are adjusted to minimize the objective function while satisfying the constraints on the physical state variables and operating limits. Many attempts were made through various algorithmic steps to obtain the global solution quickly using conventional and evolutionary methods. Evolutionary methods like Genetic Algorithm with its own advantages finds its own utility in optimal power flow solutions. Genetic Algorithm is simple to implement but has global convergence difficulties with slow convergence rate for optimal power flow problems. This paper presents three algorithms with an effect of selection of control variables on the convergence of OPF. Different sets of control variables are used to detect their usefulness in the OPF solutions. Statistical parameter based study is also 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.

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Keywords: OPF; power flow; genetic algorithm; control variables; state variables; contingencies.

1. INTRODUCTION

OPTIMAL POWER FLOW (OPF) is the optimal procedure which minimizes the generating cost or power loss as a objective function considering the operating constraints of the system. OPF is helpful for improvement in electrical systems to reduce the electricity prices to the end consumer and in congestion management [1,2]. Optimal power flow algorithms are basically categories in two parts i) DC OPF and ii) AC OPF or Security constrained OPF. In DC OPF the transmission loss is assumed to be zero with the voltages magnitude of buses tied to 1.0 pu, which in turn linearised the power system load flow equations.

While, security based OPF is complex and detailed mathematical formulation of power flow, in which the objective function is minimized under the equality and inequality constraints i.e. security constraints. Considering non-linear nature of power system equations many algorithms were often used to solve the security based optimal power flow problem.

In solving the OPF problem, method's categorization is mainly on the objective function used and search direction used for optimal solution. The mathematical programming are used such as a Linear programming (LP) [3], nonlinear programming (NLP) [4,5] and the quadratic programming (QP) [6]. To solve the equality-constrained optimization problems, the Karush–Kuhn–Tucker (KKT) used a set of nonlinear equations, for solving a Newton-type algorithm. In Newton OPF [7], the inequality constraints are added as quadratic penalty terms to the problem objective, multiplied by appropriate penalty multipliers. Interior point (IP) methods [8] the nonnegative slack variables are used to convert the inequality constraints to equality. To get the solution which gradually reduces towards the zero, a logarithmic barrier function of the slack variables is added to the objective function [9].

To solve OPF problem researcher used GA in many approaches such as GA OPF, real coded GA, Modified Cataclysmic GA, GA Mat power OPF, Simple GA, Hybrid GA. A real-coded GA chromosome consists of four regions, one for each subset of control variables. Those subsets are generator-bus voltage magnitudes and angles, synchronous condensers reactive powers, transformer tap settings, and shunt admittances and then calculate complex voltages at load-buses. With these voltages, directly Calculate injected power at each of the generator-buses, regardless of the number of generators at the bus. The non uniform mutation parameter is used and set to very high at beginning and low at ending of process [10]. The modified cataclysmic genetic Algorithm (MCGA) overcomes the traditional genetic algorithm (GA) shortcomings such as long computational time and easily converge into global solution and has the optimization process is short. Dynamic node number optimization method, which reduces every power flow calculation time, thus speeding up the calculation speed of whole optimization process [11]. A simple genetic algorithm can give a best result using only simple genetic operations such as proportionate reproduction, simple mutation, and one-point crossover in binary codes are used [12]. GA Mat power means Hybrid GA is divided into two parts GA is applied in first part to obtain a near global solution and in second part Mat power is applied by using the solution from GA as an initial point and search using gradient information to obtain a solution which is closer to the global solution The method employs advantage of the GAs which can provide a near global solution at the beginning. Then Mat powers which can tune the control Variables to obtain the global solution are applied [13]. Hybrid genetic algorithm (GA) based approach, continuous variables are designed using real-coded GA and discrete variables are processed as binary coded GA. Binary coded GAs decision variables are coded in finite length strings and exchanging portions of two parent strings easier to implement and visualize. Whereas Real Coded GA has real parameters can be used intact and crossover and mutation operators are applied directly to real parameter values. Since the selection operator works with the fitness value, any selection operator used with binary coded GAs can also be used in real parameter GAs [14]. In mixed – integer GA the chromosome is the real-coded representation that contains a mixture of continuous and discrete control variables. Considering the generation power and bus voltage as continuous variable and desecrate variables as transformer tap setting and shunt admittance, the length of individuals short, the computational time can be reduced significantly. Dynamic programming, non-linear programming, and interior point method are not effective approach to obtain the optimal solution, because these techniques cannot offer great freedom in objective functions or the types of constraints that may be used [15]. For fast convergence of algorithm in case of Evolutionary programming OPF (EP-OPF) the steepest descent method is used of determining the global optimum solution to the OPF for a range of constraints and objective functions. The approach used in the EP-OPF is to handle the reactive power limits on all PV nodes other than the slack node by the conventional method of switching, which is applied within the load flow stage. When a PV node has been switched to a PQ node, it is no longer possible to control the voltage at that bus and as a result the algorithm does not adjust the voltage of a switched PV node [16]. In Enhanced GA (EGA) [17] the control variables and constraints included in the OPF and switchable shunt devices and transformer taps are modeled as discrete control variables. Variable binary string length is used for different types of control variables, keeping the size of GA chromosome short for minimization of computational time.

After introduction this paper is organized as follows – Section II gives information about GA. In section III Application of GA in OPF is explained, Section IV deals to the problem definition, in Section V result of case study is discussed and Section VI summarizes 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

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

The above optimization function is subject to

1. Active power balance in the network

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

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.

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

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. Evolutionary Programming seeks the optimal solution by evolving a population of candidate solutions over a number of *generations* or iterations. Genetic Algorithm is used for global function/control optimization. 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 (0.5 – 0.9).

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.

The process of genetic algorithm is summarized below.

1. Initialization: Randomly generate a population of chromosomes and evaluate the fitness of each.
2. Selection: Select chromosomes from population for Re-production based on fitness values.
3. Crossover: Produce offspring from parents using crossover technique.

4. Mutation: Perform mutation on offspring.
5. New generation: Replace current population with offspring and evaluate fitness of each chromosome.

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.

$$\text{Fitness Function} \quad ff = \frac{1}{1+f^2} \tag{14}$$

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

Generally, solution of optimal power flow is obtained through the adjustment of control variables u in a specific search direction to obtain the optimal objective function by satisfying the equality and inequality constraints given in equation (1). Convergence and time for convergence of the solution depends upon the technique and selections of the control and state variables. Conventionally, the voltages of buses with (minimum and maximum magnitude limits) are considered as the control variables, which are varied in a certain direction to obtain the state variables, which satisfies all constraints with optimal objective function. Here time required to obtain the solution depends on the size of the system.

Application of the genetic algorithm to optimal power flow with voltages as control vectors possesses 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, four algorithms 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 Classical Approach: LMMS

Solution to OPF problem using Langrange Multiplier method with a new set of control and state variables is given below:

The problem statement of OPF presented in the section II, equations (1-13) are solved using Langrange multiplier method with slack variables (LMMS) introduced in inequality constaraints , in which the control variables are considered to be-

$$u = [V, \delta] \tag{18}$$

The transformed unconstrained problem can be stated as

$$L = f(x,u) + \lambda^T g(x,u) + \alpha^T \left[h(x,u) + y^2\right] \tag{19}$$

Where, y is the set slack variable

The change in the control variable can be obtained by forming Jacobian and Hessian matrix as-

$$[\mathrm{H}]\left[\Delta\mathrm{V}\,\Delta\delta\,\Delta\lambda\,\Delta\alpha\,\Delta\mathrm{y}\right]^{\mathrm{T}} = -\left[\frac{\partial \mathrm{L}}{\partial \mathrm{V}}\frac{\partial \mathrm{L}}{\partial \delta}\frac{\partial \mathrm{L}}{\partial \lambda}\frac{\partial \mathrm{L}}{\partial \alpha}\frac{\partial \mathrm{L}}{\partial \mathrm{y}}\right]^{\mathrm{T}} \tag{20}$$

The Kuhn-Tucker condition for the optimal

$$\nabla f + \sum_{j=1}^{m} \alpha_j \nabla h_j - \sum_{k=1}^{mp} \lambda_k \nabla g_k = 0 \tag{21}$$

$$\alpha_j h_j = 0 \qquad \text{j=1,2,3….m} \tag{22}$$

$$h_j \leq 0 \qquad \text{j=1,2,3….m} \tag{23}$$

$$g_k = 0 \qquad \text{k=1,2,3….p} \tag{24}$$

$$\lambda_k \geq 0 \qquad \text{k=1,2,3….p} \tag{25}$$

Where, λ and α are Langrange multipliers for $g(x,u) = 0$ and $h(x,u) \leq 0$ set of constraints equations.

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
   $V_i = 1.0pu$ and $\delta_i = 0$ i=1,2……….N_b
4. Initialize the λ and α
5. Let $X = [V \quad \delta \quad \lambda \quad \alpha \quad y]^T$ (26)
6. Calculate the Jacobian and Hessian matrix elements and let
   $\Delta X = [\Delta V \quad \Delta\delta \quad \Delta\lambda \quad \Delta\alpha \quad \Delta y]^T$ (27)
7. Calculate the change in
   $\Delta V \quad \Delta\delta \quad \text{and} \quad \Delta\lambda \quad \Delta\alpha \quad \Delta y$
   using equation (20)
8. Check the converge of
   If $\|\Delta X\| \leq \varepsilon$ (28)
   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 is used to obtain the solution of OPF. But basically GA suffers from slow convergence rate for large number OPF variables; therefore selection of control variables is critical issue in GA application 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(Appendix-B). 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

$$u = \begin{bmatrix} V_G & P_G \end{bmatrix}^T \tag{29}$$

$$X = \begin{bmatrix} P_{TL} & Q_{TL} & V_L & \delta & Q_G \end{bmatrix}^T \tag{30}$$

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

$$F = f_c + \sum_{i=1}^{p} P_{eq}\left[g_i(x,u)\right]^2 + \sum_{j=1}^{m} \lambda_{ineq}\left[h_j(x,u)\right]^2 \tag{31}$$

OR

$$F = f_c + P_{eq}\sum_{i=1}^{p}\left[G_i(x,u)\right]^2 + P_{ineq}\sum_{j=1}^{m}\left[H_j(x,u)\right]^2 \quad \text{Where} \tag{32}$$

$$\left[G_i(x,u)\right]^2 = g_i^{\,2}(x,u) \tag{33}$$

$$\left[H_j(x,u)\right]^2 = \left(\max\left[0, h_j(x,u)\right]\right)^2 \tag{34}$$

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

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} H & 0 \\ 0 & L \end{bmatrix}\begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} \tag{35}$$

to get the load flow solution.

The obtained load flow solution is used to obtain fitness function given in (31 OR 32). 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 (31 or 32) 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-

$$\mathrm{u} = \left[V_{MG}\ P_G\ Q_G\ Q_C\right]^T$$
$$x = \left[P_{TL}\ Q_{TL}\ V_{G \notin MG}\ V_C\ V_L\ \delta\ \right]^T \tag{36}$$

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 %
Penalty term for equality constraints	10
Penalty term for in-equality constraints	100
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 (Appendix-A). 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 Fig. 1 for ordered pair (0.7,0.5). The Algorithm-C provides lesser cost amongst the entire Algorithm suggested. The fuel cost for cases of contingencies is shown in Fig. 2. During line loss (no. 36), fuel cost reduction of 0.58 \$/pu.h is achieved by Algorithm-C in comparison with Algorithm-A.

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

Parameter	CV=0.1, μ=0.1			CV=0.7, μ=0.5		
	Algo-A	Algo-B	Algo-C	Algo-A	Algo-B	Algo-C
Average	88.65	88.59	88.49	88.53	88.53	88.53
Minimum	88.55	88.47	88.46	88.47	88.48	88.45
Maximum	88.77	88.73	88.52	88.68	88.56	88.75
Kurtosis	2.044	1.578	1.44	3.195	1.267	3.08
Skewness	0.324	0.0514	-0.50	1.4602	0.259	1.38
Std. deviation	0.081	0.1063	0.0267	0.0879	0.0387	0.123

Algorithm-C 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 classical approach solution provides the minimum fuel cost value of \$ 88.47/pu.h. The Algorithm–C provides better estimate of average value \$ 88.49/pu.h for CV=0.1 and μ=0.1and \$ 88.53/pu.h for CV=0.7 and μ=0.5. Minimum and maximum values attained by different algorithms show that, Algorithm-C achieves the values less than the fuel cost achieved by LMM and Algorithm-A and Algorithm-B. While, Algorithm-A and Algorithm-B achieves minimum and maximum values more than the LMM algorithms. Skewness parameters shows that Algorithm-A and Algorithm-C are skewed than Algorithm-B.

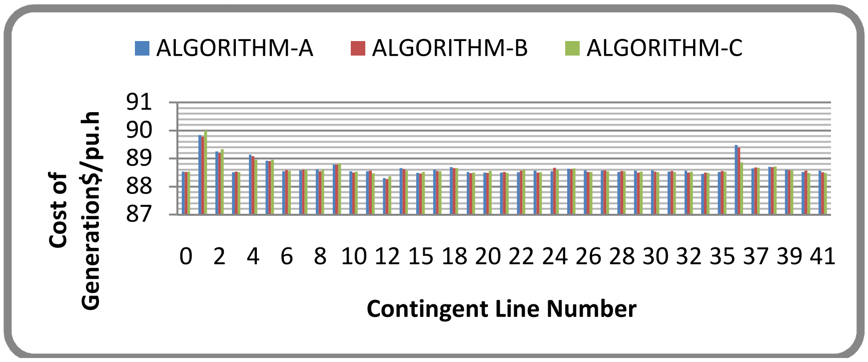

Fig. 1. Fuel cost comparison for different GA based Algorithms

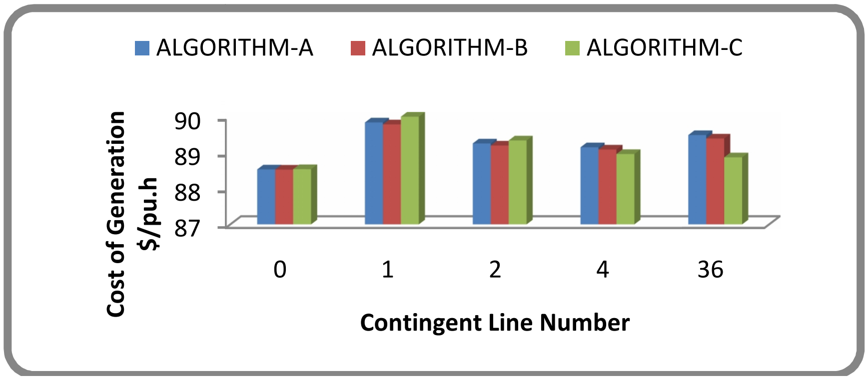

Fig. 2. Fuel cost comparison for different GA based Algorithms for selected contingent conditions (derived from Fig. 1)

Under contingent condition of transmission line 36, the performance of various GA based algorithms indicated in terms of statistical parameters is given in Table 4. Here also, Algorithm-C provides better estimate of fuel cost in comparisons with other algorithms. The standard deviation of objective function obtained for Algorithm-c in 10 runs is 0.12 and 0.04 under ordered pair (0.1, 0.1) and (0.7, 0.5) respectively. Under this situation kurtosis is approximately equal for all algorithms if ordered pair is (0.7, 0.5).

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=0.7, μ=0.5		
	Algo-A	Algo-B	Algo-C	Algo-A	Algo-B	Algo-C
Average	88.90	88.97	88.91	89.48	89.38	88.86
Minimum	88.81	88.84	88.76	89.13	89.10	88.80
Maximum	89.07	89.15	89.10	89.76	89.54	88.89
Kurtosis	2.95	1.58	2.28	2.53	2.58	1.85
Skewness	1.20	0.13	0.51	-0.44	-0.92	-0.57
Std. deviation	0.10	0.13	0.12	0.23	0.17	0.04

Fig. 3 provides the sample convergent plot of best value and mean value of fuel cost per generation Vs number of generation obtained for one of the sample run for Algorithm-A. The mean value is average value of population size in each generation. Similar plots are shown for Algorithm–B and Algorithm-C in Figs. 4 and 5 respectively.

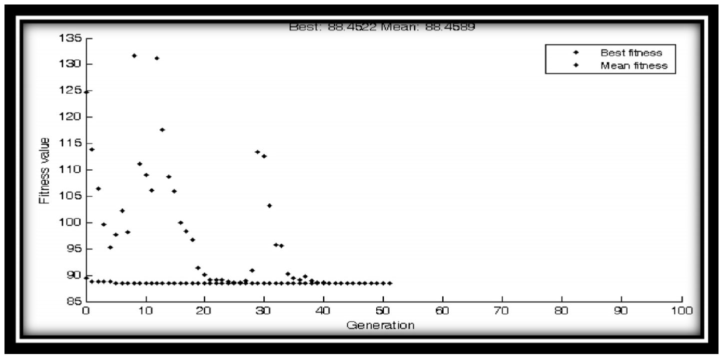

Fig. 3. Convergence plot for Algorithm-A

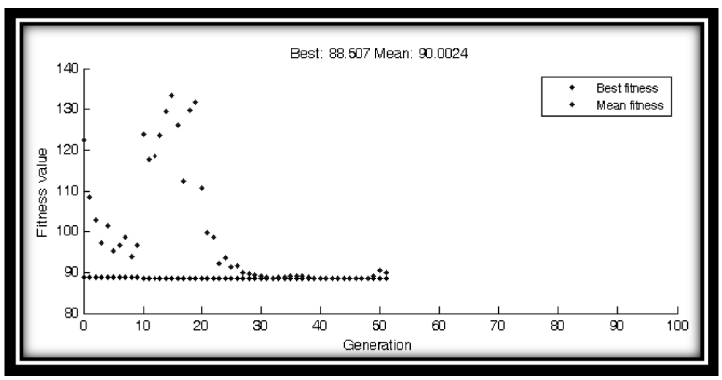

Fig. 4. Convergence plot for Algorithm-B

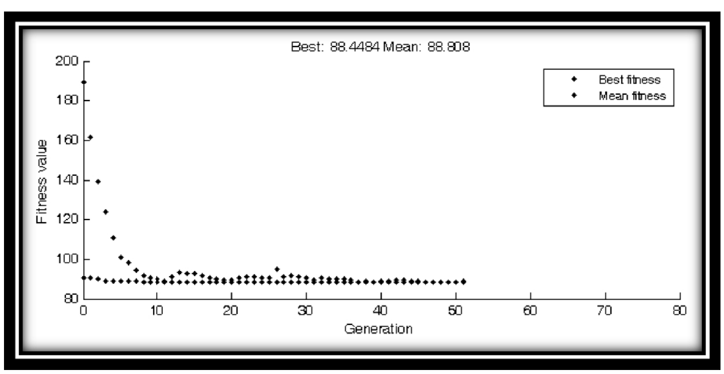

Fig. 5. Convergence plot for Algorithm-C

For the Algorithm-A, from the convergence plot it can be observed that the peak overshoot for mean fitness is found to be approximately $ 133, while the convergence time is found to be 52 generations. For the Algorithm-B, peak overshoot is found to be $ 135 and convergence time of 52 generations. The convergence plot for Algorithm-C indicates that peak overshoot of $ 190 occurs in initial parts of generations and decays exponentially and settles quickly towards the equilibrium position, which is indication of high damping exerted on system variables.

Table 5 provides comparative fuel cost values for the various GA and classical approach based Algorithms under specific transmission line contingencies (TLC). Under no contingency condition (TLC=0) Newton Based OPF (NBOPF) provides best estimation of fuel cost, while other provides slightly higher estimates. In TLC=2, the NBOPF provides the better estimate and proposed Algorithm LMMS fails to provide any answer to under this condition i.e. solution is do not converge (NC) to any specific equilibrium state. While in transmission line contingency no. 36, both classical approach Algorithms fails to converge. This shows the utility of GA based algorithm in solution of OPF. For this specific condition Algorithm-C provides minimum average fuel cost $/pu.h(88.86) amongst the all other algorithms. Hence, comparative study reveals the importance of choosing control variables for the solution of OPF in power system. Fig. 6 shows the variations of fuel cost in population of last generation for each algorithm Computation time indicates the time required by the method to obtain the optimum solution. Comparative average time required for various proposed algorithms are shown in Fig. 7. Referring to the Figs. 3-5, it can be seen that generation required for getting optimum solutions are approximately same, but as number of control variables for Algorithm-C are more than the other GA based algorithm, hence Algorithm-C requires more computation time as is can be seen from Fig. 7. The classical approaches like NBOPF and LMMS, requires lesser computation time than GA based algorithm, but these algorithms do not converge in line contingency number 2 and 36 (as also given in Table 5), these are appearing as peaks in Fig. 7 represented with data labels.

Table 5. Comparative fuel cost for all proposed algorithms

TLC	Algo-A	Algo-B	Algo-C	NBOPF	LMMS
0	88.53	88.53	88.53	86.46	87.74
2	89.25	89.19	89.33	86.47	NC
36	89.48	89.39	88.86	NC	NC

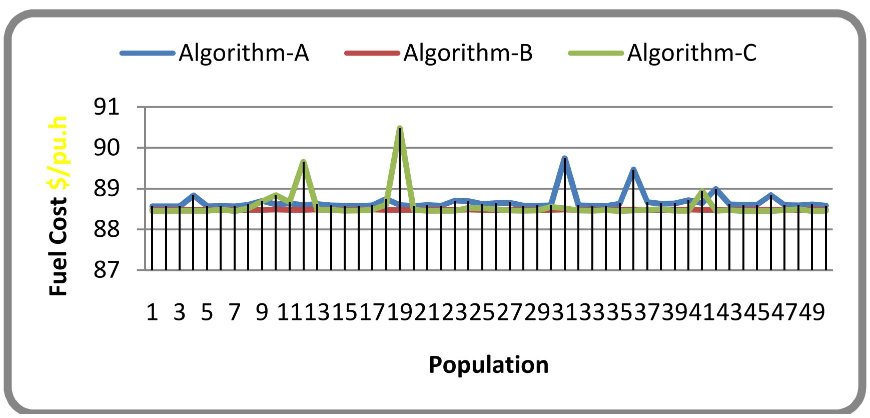

Fig. 6. Fuel cost during last population

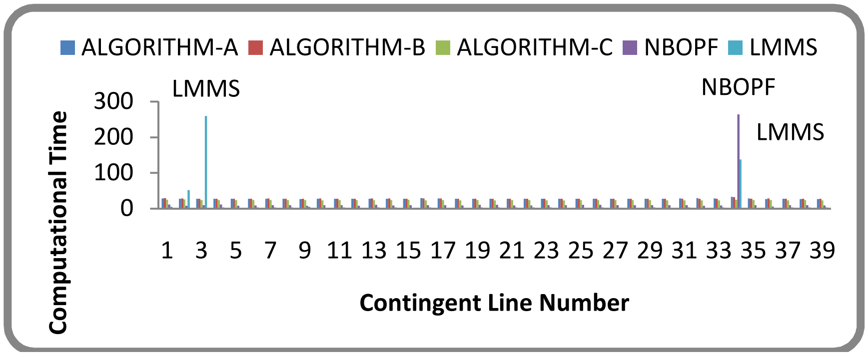

Fig. 7. Comparative chart for average solution time required by all Algorithms

After 10 run, average, minimum and maximum computational time obtained by various GA based algorithms under no contingency and contingency conditions for various ordered pairs are given in Table 6 and Table 7 respectively. Algorithm-C requires lesser average computational time as compared other methods. Average computational time for Algorithm A and B rises with increased cross-over and mutation probabilities. For Algorithm-C, the computational time decreases with increased probabilities.

Table 6. Computational time comparison based on statistical parameters under no contingency condition

Parameter	CV=0.1, μ=0.1			CV=0.7, μ=0.5		
	Algo-A	Algo-B	Algo-C	Algo-A	Algo-B	Algo-C
Average	29.09	29.39	25.33	29.85	29.70	24.49
Minimum	27.83	28.18	24.57	27.69	28.48	23.68
Maximum	30.15	30.24	25.83	32.60	32.40	25.17

Table 7. 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-A	Algo-B	Algo-C	Algo-A	Algo-B	Algo-C
Average	33.22	32.63	25.28	30.99	32.94	23.24
Minimum	27.64	29.64	23.16	27.85	26.95	21.76
Maximum	40.96	35.10	30.73	34.66	42.68	23.68

Under multi-equilibrium positions, it may possible that solution of optimization methods may produce the optimal solution which is not practical feasible to implement, hence forth here we will investigate the feasibility of optimal solution provided by the various GA based algorithm comparatively.

From the previous section, we observe that the Algorithm-C founds better estimate of objective functions under the contingency condition with less computational or solution time as compared to the other GA based algorithms. The analyses of system conditions are presented below are the results where minimum fuel cost is obtained in 10 runs.

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 Tables 8 and 9 respectively.

Table 8. Percentage share of each generator towards load under no contingency condition

Bus/Algorithm	% Share of Real Power Generation		
	Algo-A	Algo-B	Algo-C
1	38.42	38.39	36.73
2	5.7	10.69	15.91
5	14.75	11.47	32.82
8	17.29	10.44	3.25
11	14.86	17.18	13.30
13	10.59	13.58	0.71
% Total Gen.	101.61	101.75	102.71
% Load	100	100	100
% Loss	1.61	1.75	2.71
Fuel cost $/pu.h	88.47	88.48	88.45

Table 9. Percentage share of each generator towards load under contingent line number 36 conditions

Bus/Algorithm	% Share of Real Power Generation		
	Algo-A	Algo-B	Algo-C
1	38.44	38.34	38.48
2	17.14	16.53	9.99
5	11.54	8.30	11.24
8	14.46	15.64	15.62
11	12.70	10.30	17.61
13	8.13	13.48	9.24
% Total Gen.	102.40	102.60	102.17
% Load	100.00	100.00	100.00
% Loss	2.40	2.60	2.17
Fuel$/pu.h cost	89.13	89.10	88.80

From Tables 8 and 9, it can be seen that, under normal or no contingency condition Algorithm-C chooses the system condition which increase 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 8, Algorithm-C loads the costlier generator located at bus number 5 to its highest capacity, and still keeps the cost of generation minimum i.e. $88.45 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 2,8,11 and 13.

Comparative charts are provided for various algorithm in Figs. 8 and 9 under no contingency and contingent conditions for share of costlier and cheaper generating stations.

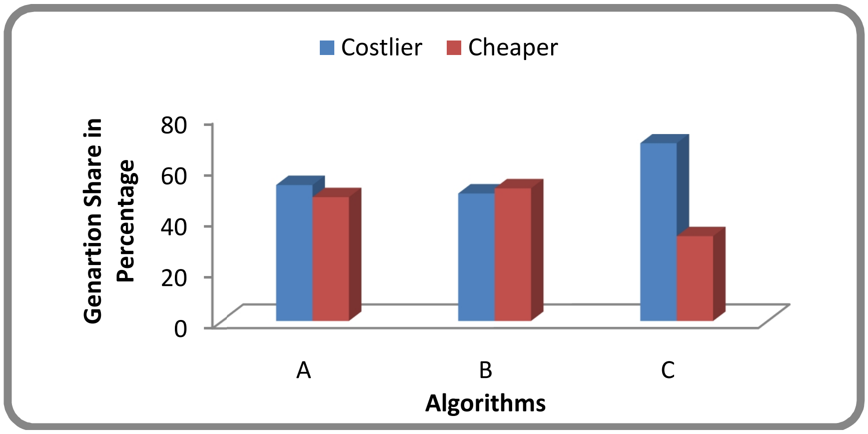

Fig. 8. Comparison chart for share of generation under no contingency condition

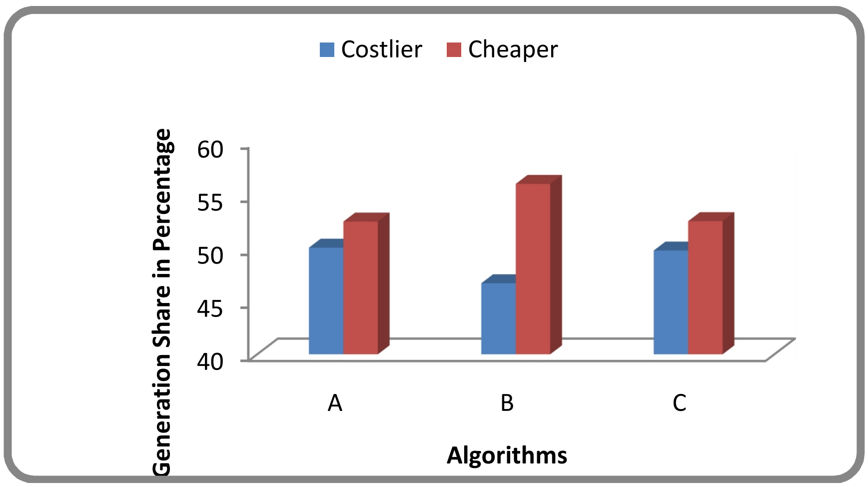

Fig. 9. Comparison chart for share of generation under contingency condition

5.3 Bus Voltage Profile

The voltage profile obtained during study are presented in Figs. 10 and 11 under normal and contingent conditions respectively. It can be observed that voltages achieved in Algorithm-C during normal operating condition are slightly lower than those obtained in the Algorithm-A and Algorithm-B. In contingent condition, Algorithm-C achieves the higher voltages than the Algorithm-A and Algorithm- B, 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 Fig. 12. Here, the +ve sign is considered for injection of the reactive power into bus and -ve sign is vice-versa of it.

In Algorithm-A and Algorithm-B voltage profile is almost same.

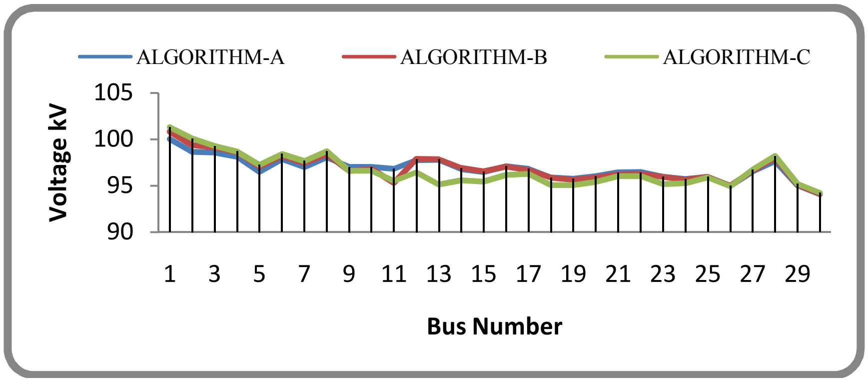

Fig. 10. Comparison chart for voltage profile of buses under no contingency condition

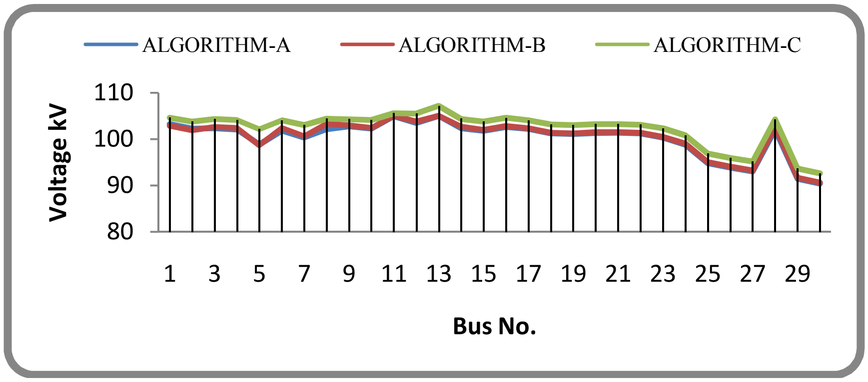

Fig. 11. Comparison chart for voltage profile of buses under contingency condition

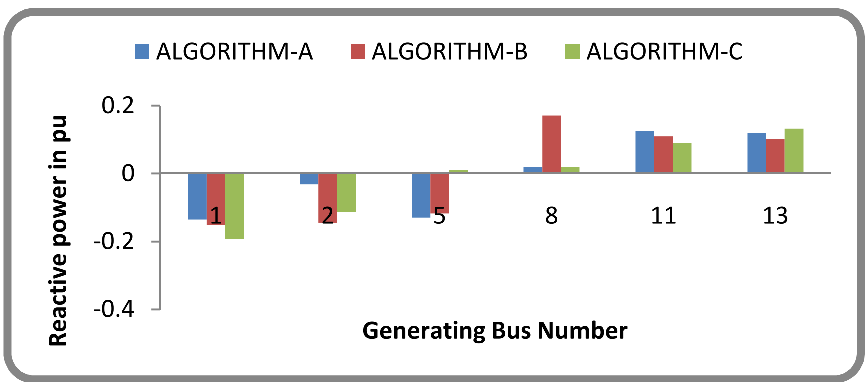

Fig. 12. Comparison chart for reactive power at generating buses

6. SIMULATION STUDIES ON 220KV TRANSMISSION NETWORK

The extensive study like IEEE-30 bus system is also been carried out on the Indian 220 kV Washi-Zone transmission line system consists of 52 buses and 86 transmission line.

6.1 SGA Based OPF using Fixed Penalty

The analysis of proposed algorithms on this system is presented in the form of-

- cost of generation,
- computation time,

6.1.1 Cost of generation

The performance of the SGA based proposed algorithms with fixed penalty under without contingency condition is given in Table 10.

Table 10. Fuel cost comparison based on statistical parameters under without contingency condition

Parameter	CV=0.1, μ=0.1			CV=0.7, μ=0.5		
	Algo-A	Algo-B	Algo-C	Algo-A	Algo-B	Algo-C
Average	**8.90**	9.46	8.96	9.67	9.39	8.95
Minimum	**8.90**	8.85	8.86	9.15	9.09	8.91
Maximum	**8.90**	9.53	9.59	10.19	9.42	8.96
Kurtosis	1.00	8.11	7.88	1.00	8.11	3.47
Skewness	-1.00	-2.66	2.59	-0.003	-2.66	-1.22
Std. deviation	0.00	0.215	0.22	0.54	0.105	0.016

Algorithm Algo - C 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 at higher CV(cross-over) and μ (mutation probability). The algorithm Algo - C provides better estimate of average value Rs. 8.96/KWh for CV=0.1 and μ=0.1and Rs. 8.95 /KWh for CV=0.7 and μ=0.5, from Table 10.

6.1.2 Computation time

After 10 runs, average, minimum and maximum computational time obtained by various GA based algorithms under no contingency conditions for various probability ordered pairs are given in Table 11.

Table 11. Computational time comparison based on statistical parameters under no contingency condition

Parameter	CV=0.1, μ=0.1			CV=0.7, μ=0.5		
	Algo-A	Algo-B	Algo-C	Algo-A	Algo-B	Algo-C
Average	81.63	94.22	69.44	77.98	97.17	59.93
Minimum	80.20	86.01	39.57	52.78	88.12	54.01
Maximum	83.25	144.5	87.21	94.39	110.84	64.35

6.2 SGA Based OPF using Fuzzy Penalty

For further improvement of the convergence criterion of SGA based proposed algorithms the fuzzy based penalty is being implemented on the 220 kV systems. Table 12, shows the comparison of the statistical parameters obtained after 10 runs of Algo - C for sample probability ordered pair (0.1, 0.1) and (0.7, 0.5). The performance of algorithm in terms of function value further improves with fuzzy based penalty at the cost of slight increase in computational time as observed from Table 13.

Table 12. Comparison of fuel cost for fixed and fuzzy penalty for Algo – C (without contingency)

Parameter	CV=0.1, μ=0.1		CV=0.7, μ=0.5	
	With Fixed Penalty	With Fuzzy Penalty	With Fixed Penalty	With Fuzzy Penalty
Average	8.96	8.19	8.95	8.27
Minimum	8.86	8.17	8.91	8.23
Maximum	9.59	8.23	8.96	8.34
Kurtosis	7.88	2.62	3.47	2.86
Skewness	2.59	0.919	-1.22	1.12
Std. deviation	0.22	0.019215	0.016	0.038

Table 13. Comparison of computational time for fixed and fuzzy penalty for Algo - C (without contingency)

Parameter	CV=0.1, μ=0.1		CV=0.7, μ=0.5	
	With Fixed Penalty	With Fuzzy Penalty	With Fixed Penalty	With Fuzzy Penalty
Average	69.44	74.49	59.93	60.75
Minimum	39.57	56.09	54.01	53.35
Maximum	87.21	99.17	64.35	66.875

7. CONCLUSION

In this paper, an extensive study was carried out to visualize the effect of control variables on the convergence of OPF using simple genetic algorithm. Overall best three suited set of control variables were suggested and their results are compared with classical approach like Langrange multiplier based OPF (LMMS) and Newton based OPF (NBOPF). This extensive study proves that set of control variables provided in Algorithm-C proved to be effective in obtaining global solution under normal and contingent conditions. In certain contingent conditions, it is found that the conventional approach fails to provide the desired solution but SGA based approach i.e. Algorithm-C has prove its suitability with global optimal solution and minimum computational time. Effect of solution obtained by these algorithms are also been analyzed for generation allocation and bus voltage profile. It is found that solution provided by Algorithm-C is realistic.

COMPETING INTERESTS

Authors declare that there are no competing interests.

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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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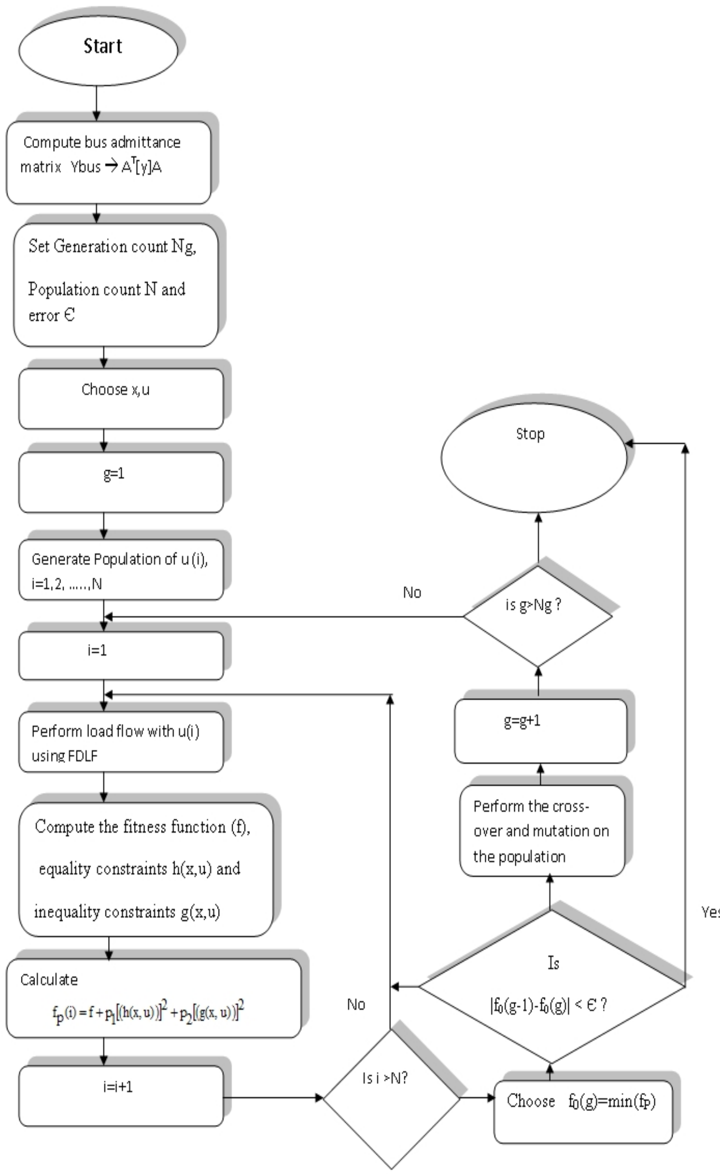
APPENDIX-B

Flow Chart for SGA Based Algorithm



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