# Optimal Power Flow for Hybrid HVDC-AC Transmission System: A Genetic Algorithm Approach

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## Abstract

*One of the most important requirements in power system operation, control and planning in energy management system (EMS) of modern power system control centers is optimal power flow (OPF). It is characterized as a difficult optimization problem and involves the optimization of an objective function, For example, minimization of total generation cost, and minimization of total loss in transmission networks, subject to a set of equality and inequality constraints such as generation and load balance, bus voltage limits, power flow equations, and active and reactive power limits.*
*In recent years, the incorporation of High Voltage Direct Current (HVDC) link in an existing AC transmission networks brought significant techno-commercial changes in the transmission of the electric power in developing countries. This paper aims at (1) presenting Genetic Algorithm approach to solve OPF, (2) problem formulation with incorporation of HVDC link in a AC transmission system, (3) demonstrating the proposed methodology for standard power systems and (4) to assess the performance of GAOPF with the traditional OPF method. The paper concludes that the proposed scheme is effective for the real network situation in developing countries.*

***Index Terms –*** *Electricity Transmission, Optimal Power Flow, Genetic Algorithms, HVDC transmission*

## I. INTRODUCTION

In electrical power systems, Optimal Power Flow (OPF) is a nonlinear programming problem, used to determine generation outputs, bus voltages and transformer tap with an objective to minimize total generation cost [1]. Presently, application of OPF is of much importance for power system operation and analysis. In a deregulated environment of electricity industry, OPF recently been used to assess the spatial variation of electricity prices and transmission congestion study etc [2].

In most of its general formulation, the OPF is a nonlinear, non-convex, large-scale, static optimization problem with both continuous and discrete control variables [3]. It is due to the presence of nonlinear power flow equality constraints. The presence of discrete control variables, such as switchable shunt devices, transformer tap positions, and phase shifters etc., complicates the solution [2]. However, they are not assured to converge to the global optimum of the general nonconvex OPF problem, although there exists some empirical evidence on the uniqueness of the OPF solution within the domain of interest [4].

Effective OPF is limited by the high dimensionality of power systems and the incomplete domain dependent knowledge of power system engineers. Numerical optimization procedures addressed the former one based on successive linearization using the first and the second derivatives of objective functions and their constraints as the search directions or by linear programming solutions to imprecise models [5-9]. The advantages of such methods are in their mathematical underpinnings, but disadvantages exist also in the sensitivity to problem formulation, algorithm selection and usually converge to a local minimum. The lateral one precludes also the reliable use of expert systems where rule completeness is not possible.

Since OPF was introduced in 1968 [10], several methods have been employed to solve this problem, e.g. *Gradient base*, *Linear programming* method [11] and *Quadratic programming* [12]. However, all these methods suffer from problems. First, they may not be able to provide optimal solution and usually get stuck at a local optimal. Some methods, instead of solving the original problem, solve the problem's Karush–Kuhn–Tucker (KKT) optimality conditions. For equality-constrained optimization problems, the KKT conditions are a set of nonlinear equations, which can be solved using a Newton-type algorithm. In Newton OPF [13], the inequality constraints have been added as quadratic penalty terms in the problem objective, multiplied by appropriate penalty multipliers. Interior Point (IP) method [14-16], converts the inequality constraints to equalities by the introduction of nonnegative slack variables. A logarithmic barrier function of the slack variables are added to the objective function, multiplied by a barrier parameter, which is gradually reduced to zero during the solution process. The unlimited point algorithm [17] uses a transformation of the slack and dual variables of the inequality constraints, converts the OPF problem KKT conditions to a set of nonlinear equations, thus avoiding the heuristic rules for barrier parameter reduction required by IP method. Recent attempts to overcome the limitations of these mathematical programming approaches include the application of simulated annealing-type methods [18-19], and genetic algorithms (GAs) etc., [20-21].

GAs are essentially search algorithm based on mechanics of nature and natural genetics [22]. They combine solution evaluation with randomized, structured exchanges of information between solutions to obtain optimality. GAs are a robust method because restrictions on solution space are not made during the process. The power of GAs stem from its ability to exploit historical information structures from previous solution guesses in an attempt to increase performance of future solutions [23]. GAs have recently found extensive applications in solving global optimization searching problem when the closed form optimization technique cannot be applied. GAs are parallel and global search techniques that emulate natural genetic operators. The GA is more likely to converge toward the global solution because it, simultaneously, evaluates many points in the parameter space. It does not need to assume that the search space is differentiable or continuous [24]. In [25], the Genetic Algorithm Optimal Power Flow (GAOPF) problem is solved based on the use of a genetic algorithm load flow, and to accelerate the concepts, it is proposed to use the gradient information by the steepest decent method. The method is not sensitive to the starting points and capable to determining the global optimum solution to the OPF for a range of constraints and objective functions. In Genetic Algorithm approach, the control variables modeled are generator active power outputs and voltages, shunt devices, and transformer taps. Branch flow, reactive generation, and voltage magnitude constraints have treated as quadratic penalty terms in the GA Fitness Function (FF). In [21], GA is used to solve the optimal power dispatch problem for a multi-node auction market. The GA maximizes the total participants' welfare, subject to network flow and transport limitation constraints. The nodal real and reactive power injection that clears the market have selected as the problem control variables.

The GAOPF approach overcomes the limitations of the conventional approaches in the modeling of non-convex cost functions, discrete control variables, and prohibited unit-operating zones. However, they do not scale easily to larger problems, since the solution deteriorates with the increase of the chromosome length, i.e., the number of control variables.

In the coming years, power consumption in developing and transition countries is expected to more than double, whereas in developed countries, it will increase only for about 35-40%. In addition, many developing and transition countries are facing the problems of infrastructure investment especially in transmission and distribution segment due to fewer investments made in the past. To reduce the gap between transmission capacity and power demand, the trend is to adopt HVDC transmission system in the existing AC networks to gain techno-economical advantages of the investment. In such scenario, it is obvious to address this trend to design optimal power flow scheme for a real network system. In this paper full ac-dc based GAOPF is developed. This methodology also discussed the redesign of fitness function by refining penalty scheme for system constraints to get faster convergence. This avoids the necessity to perform early load flows as reported in several literatures [1-3, 9, 22].

After this introduction, section II presents the ac-dc based optimal power flow formulation. The Genetic Algorithm methodology is explained in section III. The performance of AC-DC based GAOPF is assessed and demonstrated with the IEEE 6-Bus, IEEE14-Bus, IEEE 30-Bus test systems in section IV. Finally, the conclusions are presented in section V.

## II. AC-DC OPTIMAL POWER FLOW FORMULATION

### Problem Formulation:

Optimal power flow (OPF), which is characterize as a difficult optimization problem, involves the optimization of an objective function that can take various forms. For example, minimization of total generation cost, and minimization of total loss in transmission networks, subject to a set of physical and operating constraints such as generation and load balance, bus voltage limits, power flow equations, and active and reactive power limits. The objective function considered in this paper is to minimize the total generation cost. OPF formulation consists of three main components: objective function, equality constraints, and inequality constraints. The methodology is as follows,

### AC System Equations

Let P = ($p_1$,…..,$p_n$) and Q = ($q_1$,…..,$q_n$) for a n buses system, where $p_i$ and $q_i$ be active and reactive power demands of bus-i, respectively. The variables in power system operation to be X = ($x_1$,….,$x_m$), such as real and imaginary parts of each bus voltage. So the operational problem of a power system for given load (P, Q) can be formulated as OPF problem [26]

$$\text{Minimize} \quad f\,(X, P, Q) \quad \text{for } X \tag{1}$$

$$\text{Subject to} \quad S\,(X, P, Q) = 0 \tag{2}$$

$$T\,(X, P, Q) \le 0 \tag{3}$$

$f$ (X, P, Q) is a scalar, short term operating cost, such as fuel cost. The generator cost function $f_i(P_{Gi})$ in \$/MWh is considered to have cost characteristics represented by,

$$f = \sum_{i=1}^{NG} a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{4}$$

Where, $P_{Gi}$ is the real power output; $a_i$ , $b_i$ and $c_i$ represents the cost coefficient of the i[th] generator, $NG$ represents the generation buses, The various constraints to be satisfied during optimization are as follows,

(1) Vector of equality constraint such as power flow balance (i.e. Kirchoff's laws) is represented as,

S (X, P, Q) = 0 or $P_G = P_D + P_{DC} + P_L$ and $Q_G = Q_D + Q_{DC} + Q_L$ (5)

Where $D$ represents the demand, $G$ is the generation, $DC$ represents dc terminal and $L$ is the transmission loss.

(2) The vector, inequality constraints including limits of all variables i.e. all variables limits and function limits, such as upper and lower bounds of transmission lines, generation outputs, stability and security limits may be represented as,

T (X, P, Q) $\leq 0$ (6)

(i) $P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max}$ $(i \in G_B)$ and

$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}$ $(i \in G_B)$ (7)

Where, $P_{Gi}^{\min}, P_{Gi}^{\max}$ $Q_{Gi}^{\min}, Q_{Gi}^{\max}$ are the minimum and maximum real and reactive power outputs.

(ii) Voltage limits (Min/Max) may be denoted by the following constraints,

$\left|V_i^{\min}\right| \leq \left|V_i\right| \leq \left|V_i^{\max}\right|$ (i= 1,……,$N_B$) (8)

Where, $N_B$ represents number of buses.

(iii) Power flow limits refer to the transmission is expressed by the following constraints,

$P_f^{\min} \leq P_f \leq P_f^{\max}$ (f= 1,…, $Noele$ ) (9)

Where, $Noele$ represents number of transmission lines connected to grid.

Then the operating conditions of an AC-DC system is described by the vector,

$X = [\delta, V, x_c, x_d]^t$ (10)

Where, $\delta$ and $V$ are the vectors of the phases and magnitude of the phasor bus voltages; $x_c$ is the vector of control variables and $x_d$ is the vector of dc variables.

**DC System Equations**

The following relationship is for the dc variables. Using the per unit system [27], the average value of the dc voltage of a converter connected to bus 'i' is

$V_{di} = a_i V_i \cos\alpha_i - r_{ci} I_{di}$ (11)

Where, $\alpha_i$ is the gating delay angle for rectifier operation or the extinction advance angle for inverter operation; $r_{ci}$ is the commutation resistance, and $a_i$ is the converter transformer tap setting.

By assuming a lossless converter, the equation of the dc voltage is given by,

$$V_{di} = a_i V_i \cos\varphi_i \tag{12}$$

Where, $\varphi_i = \delta_i - \xi_i$, and $\varphi$ is the angle by which the fundamental line current lags the line-to-neutral source voltage.

The real power flowing in or out of the dc network at terminal 'i' can be expressed as,

$$P_{di} = V_i I_i \cos\varphi_i \tag{13}$$

The reactive power flow into the dc terminal is

$$Q_{di} = V_i I_i \sin\varphi_i \quad \text{or} \quad Q_{di} = V_i a I_i \sin\varphi_i \tag{14}$$

The equation (13) and (14) is submitted in the equation (5) to form part of the equality constraints. Based on these relationships, the operating condition of the dc system can be described by the vector,

$$X_d = [V_d, I_d, a, \cos\alpha, \varphi]^t \tag{15}$$

The dc currents and voltages are related by the dc network equations. As in the ac case, a reference bus is specified for each separate dc system; usually the bus of the voltage controlling dc terminal operating under constant voltage (or constant angle) control is chosen as the reference bus for that dc network equation.
Equations (1) – (3) are an OPF problem for the demand (P, Q). There are many efficient approaches which can be used to get an optimal solution such as linear programming, Newton method, quadratic programming, nonlinear programming, interior point method, artificial intelligence (i.e. artificial neural network, fuzzy logic, genetic algorithm, evolutionary programming, ant colony optimization and particle swarn optimization etc.) methods [26, 28].

## II. GENETIC ALGORITHM BASED OPTIMAL POWER FLOW

### 2.1 Genetic Algorithms

GAs operate on a population of candidate solutions encoded to finite bit string called chromosome. To attain optimality, each chromosome exchanges the information using operators borrowed from natural genetics to produce the better solution. GAs differ from other optimization and search procedures in four ways [24]: firstly, it works with a coding of the parameter set, not the parameters themselves. Therefore, GAs can easily handle integer or discrete variables. Secondly, it searches within a population of points, not a single point. Therefore, GAs can provide a globally optimal solution. Thirdly, GAs use only objective function information, not derivatives or other auxiliary knowledge. Therefore, it can deal with the non-smooth, non-continuous and non-differentiable functions that actually exist in a practical optimization problem. Finally, GAs use probabilistic transition rules, not deterministic rules, Although GAs seem to be a good method to solve optimization problems, sometimes the solution obtained from GAs is only a near global optimum solution.

**2.2 GA applied to Optimal Power Flow:** A simple Genetic Algorithm is an iterative procedure, which maintains a constant size population of candidate solutions. During each iteration step, (generation) three genetic operators (reproduction, crossover, and mutation) are performing to generate new populations (offspring), and the chromosomes of the new populations have evaluated via the value of the fitness, which is related to cost function. Based on these genetic operators and the evaluations, the better new populations of candidate solutions are formed. If the search goal has not achieved, again, GA creates offspring strings through above three operators and this process is continued until the search goal is achieved. This paper now describes the details in employing the simple GA to solve the optimal power flow problem.

**2.2.1 Coding and Decoding of Chromosome:** GAs perform with a population of binary string instead the parameters themselves. This study used binary coding. Here the active generation power set of n-bus system ($PG_1$, $PG_2$, $PG_3$, ….$PG_n$ ) would be coded as binary string (0 and 1) with length $L_1$, $L_2$, ……,$L_n$. Each parameter PGi has upper bound $b_i(p_{G_i}^{\max})$ and lower bound $a_i(p_{G_i}^{\min})$. The choice of $L_1$, $L_2$, ……,$L_n$ for the parameters is concerned with the resolution specified by the designer in the search space. In this method, the bit length $B_i$ and the corresponding resolution $R_i$ is associated by,

$$R_i = \frac{b_i - a_i}{2^{Li} - 1} \tag{16}$$

This transforms the $PG_i$ set into a binary string called *chromosome* with length $\Sigma L_i$ and then the search space has to be explored. The first step of any GA is to generate the initial population. A binary string of 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.

**2.2.2 Genetic Operator: Crossover:** It 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 the convergence speed of the GA and is usually applied with high probability (0.5 – 0.9). The chromosomes of the two parents selected have combined to form new chromosomes that inherit segments of information stored in parent chromosomes. The strings to be crossed have been selected according to their scores using the roulette wheel [24]. Thus, the strings with larger scores have more chances to be mixed with other strings because all the copies in the roulette have the same probability to select. Many crossover schemes, such as single point, multipoint, or uniform crossover have been proposed in the literature. A single point crossover [1] has been used in our study.

**2.2.3 Genetic Operator: Mutation:** 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. In this study, the mutation operator has been applied with a relatively small probability (0.0001-0.001) to every bit of the chromosome. A sample mutation process has shown as below.

$$\underbrace{0110}_{P_{G1}}\underbrace{0101}_{P_{G2}}\underbrace{0110}_{P_{G3}}\underbrace{0100}_{P_{G4}}\underbrace{1100}_{P_{G5}}\underbrace{0011}_{P_{G6}}\underbrace{1110}_{P_{G7}} \quad \xrightarrow[\text{mutation}]{\text{After}} \quad \underbrace{0110}_{P_{G1}}\underbrace{0101}_{P_{G2}}\underbrace{0110}_{P_{G3}}\underbrace{0100}_{P_{G4}}\underbrace{1110}_{P_{G5}}\underbrace{0011}_{P_{G6}}\underbrace{1110}_{P_{G7}}$$

**2.2.4 Genetic Operator: Reproduction:** Reproduction is based on the principle of survival of the fittest. It is an operator that obtains a fixed number of copies of solutions according to their fitness value. If the score increases, then the number of copies increases too. A score value is associated with a given solution according to its distance from the optimal solution (closer distances to the optimal solution mean higher scores).

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**2.2.5 Fitness of Candidate Solutions and Cost Function:** The cost function has defined as:

$$f = \sum_{i=1}^{NG} a_i P_{Gi}^2 + b_i P_{Gi} + c_i \,; \quad P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}$$

(18)

To minimize F(x) is equivalent to getting a maximum fitness value in the searching process. A chromosome that has lower cost function be assigning a larger fitness value. The objective of OPF is changed to the maximization of fitness to be used in the simulated roulette wheel. The fitness function is used [3] as follows:

$$FitnessFunction\,(FF) = \frac{C}{\sum_{i=1}^{NG} F_i\,(P_{Gi}) + \sum_{i=1}^{Nc} w_j * Penalty_j}$$

(19)

$$Penalty_j = h_j\,(x,t)\,|.\,H\,(h_j\,(x,t))$$

(20)

Where $C$ is the constant; $F_i\,(P_{Gi})$ is cost characteristics of the generator $i$; $w_j$ is weighting factor of equality and inequality constraints $j$; $Penalty_j$ is the penalty function for equality and inequality constraints $j$; $h_j\,(x,t)$ is the violation of the equality and inequality constraints if positive; $H$ (.) is the Heaviside (step) function; $N_c$ is the number of equality and inequality constraints.

The fitness function is implemented in Matlab in such a way that it should firstly satisfy all inequality constraints by heavily penalizing if they have been violated. Then the equality constraints is satisfied by less heavily penalizing for any violation. Here this penalty weight is not the price of power. Instead, the weight is a coefficient set large enough to prevent the algorithm from converging to an illegal solution. Then the GA tries to generate better offspring to improve the fitness. Using these components, a standard GA procedure for solving the OPF problem is shown in Figure 1.

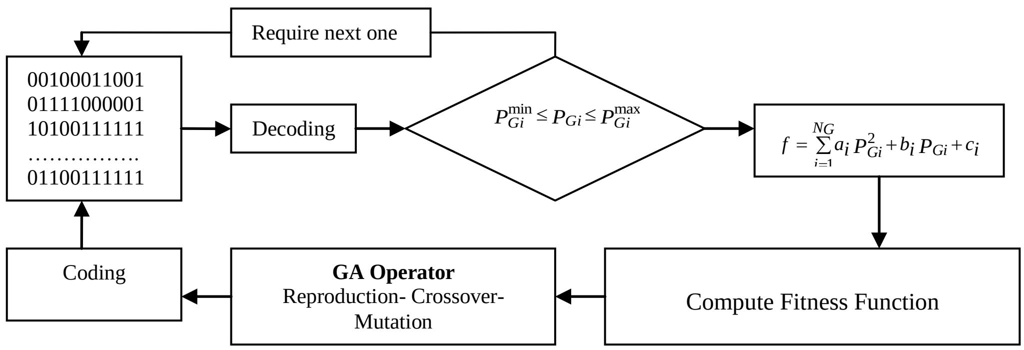


Fig.1: Flowchart of a Simple Genetic Algorithm for OPF

## III. EXAMPLE, SIMULATION AND RESULTS

### 3.1 IEEE-6 Bus System

The performance of the proposed methodology has been assessed through the results obtained for IEEE-6 Bus system (Figure 2-(Appendix-I)) with 7 circuits and 2 generators. The generator and circuit data are given in Appendix-A. A dc link is connected between bus 1 and bus 5. The ratings of the converter at buses 1 and 5 were 1.0 p.u. The voltage values for all buses are bounded between 0.95 and 1.05. The fuel cost function for generators is expressed as $(f_i = a_i P_{Gi}^2 + b_i P_{Gi} + c_i)$ in ($/MWh) and demand at various buses are as shown in table A2. All the values have indicated in Per Unit (PU). The results obtained for best and worst GAOPF solution and that for traditional OPF have shown in Table 1.

The best GAOPF solution gives the improved bus voltage profile and lower total cost of generation as compared to traditional i.e Newton's OPF method.

Table 1: IEEE- 6 Bus System: GAOPF results and Comparison with Traditional OPF Method

| Bus No. | GAOPF | | | | | | Traditional Method | | |
|---|---|---|---|---|---|---|---|---|---|
| | Best Solution | | | Bad Solution | | | | | |
| | Voltage (PU) | P (PU) | Cost ($/MWh) | Voltage (PU) | P (PU) | Cost ($/MWh) | Voltage (PU) | P (PU) | Cost ($/MWh) |
| 1 | 0.97 | 0.14 | 24.67 | 0.99 | 0.69 | 128.00 | 1.00 | 0.16 | 25.73 |
| 2 | 1.01 | 0.03 | 6.64 | 0.98 | 0.32 | 57.70 | 0.95 | 0.04 | 6.58 |
| 3 | 1.00 | | | 1.02 | | | 0.96 | | |
| 4 | 1.00 | | | 0.99 | | | 1.05 | | |
| 5 | 0.99 | | | 1.00 | | | 1.02 | | |
| 6 | 0.99 | | | 1.00 | | | 1.04 | | |
| **Total** | | **0.17** | **31.31** | | **1.1** | **185.70** | | **0.20** | **33.83** |

### 4.2 IEEE-14 Bus System

The performance of the proposed methodology has been assessed through the results obtained with the well-known IEEE-14 Bus (Figure 3-(Appendix-I)) with 18 circuits and 4 generators. The generator and circuit data have been given in Appendix-B. A dc link is connected between bus 1 and bus 14. The ratings of the converter at buses 1 and 14 were 1.0 p.u. The voltage values for all buses have bounded between 0.95 and 1.05. The fuel cost function for generators is expressed as $(f_i = a_i P_{Gi}^2 + b_i P_{Gi} + c_i)$ in ($/MWh) and demand at buses are shown in Table B2. All the values have indicated by PU. The results are obtained with given methodology is shown in Table 2.

The voltage at several buses obtained by GAOPF best solution has shown improvement as compared to the Newton method. In addition, total cost of generation obtained by GAOPF best solution is low.

Table 2: IEEE- 14 Bus System: GAOPF results and Comparison with Traditional OPF Method

| Bus No. | GAOPF | | | | | | Traditional Method | | |
|---|---|---|---|---|---|---|---|---|---|
| | Best Solution | | | Bad Solution | | | | | |
| | Voltage (PU) | P (PU) | Cost ($/MWh) | Voltage (PU) | P (PU) | Cost ($/MWh) | Voltage (PU) | P (PU) | Cost ($/MWh) |
| 1 | 0.99 | | | 1.02 | | | 0.99 | | |
| 2 | 1.00 | 0.75 | 65.40 | 1.03 | 0.92 | 120.01 | 0.98 | 0.86 | 90.94 |
| 3 | 1.00 | 0.70 | 50.30 | 0.98 | 0.92 | 180.20 | 0.97 | 0.72 | 90.46 |
| 4 | 0.99 | | | 0.98 | | | 0.96 | | |
| 5 | 1.00 | | | 1.00 | | | 0.96 | | |
| 6 | 0.97 | 0.50 | 106.2 | 1.00 | 0.87 | 85.51 | 1.02 | 0.66 | 89.87 |
| 7 | 1.00 | | | 0.99 | | | 0.97 | | |
| 8 | 0.98 | 0.70 | 112.8 | 1.03 | 0.75 | 120.91 | 1.02 | 0.64 | 88.40 |
| 9 | 0.97 | | | 0.97 | | | 0.95 | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 0.97 | | | 0.98 | | | 0.96 | | |
| 11 | 1.00 | | | 1.04 | | | 0.99 | | |
| 12 | 0.99 | | | 0.95 | | | 1.00 | | |
| 13 | 1.01 | | | 0.97 | | | 0.99 | | |
| 14 | 0.99 | | | 1.01 | | | 0.95 | | |
| **Total** | | **2.65** | **334.70** | | **3.46** | **506.63** | | **2.88** | **359.67** |

### 4.3 Modified IEEE-30 Bus System

This system consists of 6 generators and 43 transmission lines as shown in figure 4 (Appendix-I). A dc link connected between bus 1 and bus 28. The ratings of the converter at buses 1 and 28 were 1.0 p.u. The upper and lower bounds (real power) for all generators have shown in table C1. In addition, the upper and lower bounds (reactive power) for all generators are $-0.4 \le Q_{Gi} \le 0.4$ . The voltage values for all buses have bounded between 0.95 and 1.05. The fuel cost function for generators is expressed as $(f_i = a_i P_{Gi}^2 + b_i P_{Gi} + c_i)$ in ($/MWh) and demand at various buses are shown in table C1. All the values are indicated in PU. For this system there are 2 × 24 equality constraints of S corresponding with their respective real and reactive power balances of the buses without a generator, and about 72 inequality constraints of T corresponding to 30 pairs of voltage, 2 × 6 pairs of generation output and one pair of line flow upper and lower bounds respectively. Table 3 indicates the results for GAOPF best and worst solutions and for Newton method.

Again, results indicates that the voltage profile at few buses have improved for best GAOPF solution as compared to Newton's OPF method. In addition, total cost of generation by best GAOPF is marginally low as compared to Newton's OPF method.

Table 3: IEEE- 30 Bus System: GAOPF results and Comparison with Traditional OPF Method

| Bus No. | GAOPF | | | | | | Traditional Method | | |
|---|---|---|---|---|---|---|---|---|---|
| | Best Solution | | | Bad Solution | | | | | |
| | Voltage (PU) | P (PU) | Cost ($/MWh) | Voltage (PU) | P (PU) | Cost ($/MWh) | Voltage (PU) | P (PU) | Cost ($/MWh) |
| 1 | 0.99 | 0.30 | 8.17 | 0.99 | 1.67 | 30.40 | 1.00 | 0.37 | 10.55 |
| 2 | 0.97 | 0.21 | 7.23 | 1.00 | 1.06 | 21.33 | 0.99 | 0.10 | 6.53 |
| 3 | 0.97 | | | 0.98 | | | 0.99 | | |
| 4 | 0.99 | | | 0.96 | | | 0.98 | | |
| 5 | 1.03 | 0.25 | 8.03 | 1.02 | 1.40 | 26.41 | 0.99 | 0.10 | 6.52 |
| 6 | 0.98 | | | 1.00 | | | 0.97 | | |
| 7 | 0.99 | | | 0.95 | | | 0.98 | | |
| 8 | 0.95 | 0.20 | 8.05 | 0.99 | 0.57 | 16.02 | 1.03 | 0.10 | 6.93 |
| 9 | 0.99 | | | 1.01 | | | 0.99 | | |
| 10 | 1.03 | | | 1.02 | | | 1.02 | | |
| 11 | 0.99 | 0.14 | 8.17 | 1.00 | 0.54 | 13.07 | 1.01 | 0.46 | 11.87 |
| 12 | 1.02 | | | 0.95 | | | 1.00 | | |
| 13 | 0.98 | 0.07 | 5.01 | 1.01 | 0.56 | 15.64 | 1.01 | 0.10 | 6.90 |
| 14 | 0.99 | | | 0.96 | | | 0.99 | | |
| 15 | 1.02 | | | 1.00 | | | 0.99 | | |
| 16 | 0.97 | | | 0.97 | | | 1.00 | | |
| 17 | 0.98 | | | 0.96 | | | 1.00 | | |
| 18 | 0.99 | | | 1.01 | | | 0.99 | | |
| 19 | 1.00 | | | 0.98 | | | 0.99 | | |
| 20 | 0.97 | | | 1.01 | | | 1.03 | | |
| 21 | 0.98 | | | 0.97 | | | 0.99 | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 22 | 0.99 | | | 0.99 | | | 0.98 | | |
| 23 | 0.99 | | | 1.01 | | | 0.99 | | |
| 24 | 1.03 | | | 1.01 | | | 1.02 | | |
| 25 | 0.96 | | | 0.97 | | | 1.03 | | |
| 26 | 0.98 | | | 1.01 | | | 1.02 | | |
| 27 | 0.97 | | | 0.97 | | | 1.05 | | |
| 28 | 0.98 | | | 0.95 | | | 0.99 | | |
| 29 | 1.02 | | | 0.98 | | | 1.05 | | |
| 30 | 0.97 | | | 0.98. | | | 1.05 | | |
| **Total** | | **1.17** | **44.66** | | **5.8** | **122.88** | | **1.23** | **49.30** |

## IV. PERFORMANCE EVALUATION

The performance evaluation of AC-DC based GAOPF and traditional OPF method has tested with reference to parameters given in Table 4 and in Table 5. The Newton's method takes less iteration to perform the OPF for the test system and real network mentioned in Table 5. The program execution time depends on the equality and inequality constraints handled by the methodology. The advantage of Newton's method is that the OPF results have obtained in one run only. The performance parameters for GA based AC-DC OPF for various test system and real networks is shown in Table 5. However, program execution time varies from smaller system to larger system and it depends on the number of iterations assigned initially to obtain the best OPF results.

Table 4: Newton's Parameters/performance for Best Optimal Power Flow

| SN | Parameters | IEEE-6 Bus System | IEEE-14 Bus System | IEEE-30 Bus System |
|---|---|---|---|---|
| 1 | No. of iterations | 11 | 53 | 64 |
| 2 | Execution Time (sec.) | 12 sec. | 25 sec. | 45 sec. |
| 3 | No. of Runs | 1 | 1 | 1 |

Table 5: GA Parameters/performance for Best Optimal Power Flow

| SN | Parameters | Values | | |
|---|---|---|---|---|
| | | IEEE-6 Bus System | IEEE-14 Bus System | IEEE-30 Bus System |
| 1 | Initial Population | 160 | 210 | 520 |
| 2 | No. of iterations | 100 | 150 | 200 |
| 3 | Probability of crossover | 0.5 | 0.5 | 0.5-0.9 |
| 4 | Probability of mutation | 0.001 | 0.001 | 0.0001-0.001 |

## V. CONCLUSION

Optimal power flow has been received considerable attentions from reseachers for the past few decades as it is one of the most important tools in energy management system (EMS). This study proposes an AC-DC based GA optimal power flow solution, which may be applied to different size power systems. Application of Genetic approach to Optimal Power Flow has been explored and tested. A simulation results show that 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. It is clear that in large-scale system the number of constraints is very large consequently, the GA accomplished in a large CPU time. Finally, the result obtained by this scheme is quite comparable with the traditional OPF methodology.

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**Appendix-I**

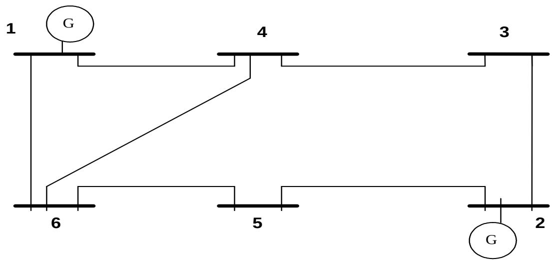


Fig.2: One line diagram of IEEE-6Bus System

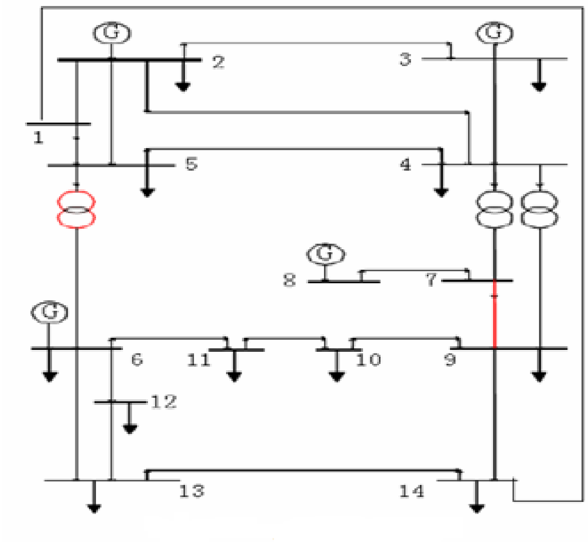


Fig. 3: One Line diagram of IEEE-14 Bus System

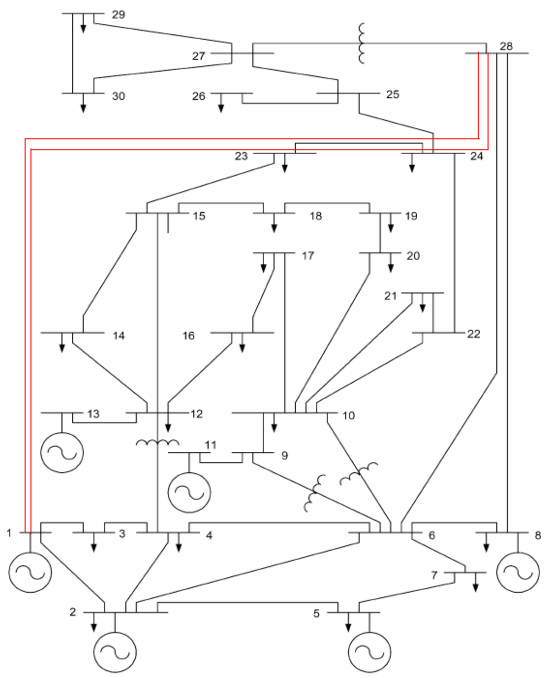


Fig. 4: One line diagram of modified IEEE-30 Bus system