A GENETIC ALGORITHM APPROACH FOR SOLVING AC-DC OPTIMAL POWER FLOW PROBLEM

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ABSTRACT

In the past decades, electricity markets have significantly restructured in both developed and developing countries. In it, Optimal Power Flow (OPF) is emerging as the main function of power generation, operation and control. OPF is an optimization problem, in which the utility strives to minimize its generation costs while satisfying all its equality and inequality constraints, while the system is operating within its security limits. In recent years, the incorporation of subsets of transmission High Voltage Direct Current (HVDC) in 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 IEEE test system and a complex and real power system of India 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.

Keywords – *Optimal Power Flow, Genetic Algorithms, HVDC transmission.*

1. 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

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(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 is 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 injections that clear the market are 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 efficiency of the methodology applied to the optimal power flow problem demonstrated by the IEEE- 14, IEEE -30-bus test systems and to a complex and real network power system (i.e. 400 kV, MSETCL, India) in section IV. Finally, the conclusions are presented in section V.

2. AC-DC OPTIMAL POWER FLOW FORMULATION

Problem Formulation:

As has been discussed, 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]

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

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

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

Where S (X) = (s_1(X, P, Q),…….,s_{n1} (X, P, Q))^T and T (X) = (t_1(X, P, Q),……., t_{n2}(X, P, Q))^T have n_1 and n_2 equations respectively, and are column vectors. Here A^T represents the transpose of vector A.

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 ith 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 to be represented as:

$$S(X, P, Q) = 0 \quad \text{or}$$

$$P_G = P_D + P_{DC} + P_L \text{ and}$$

$$Q_G = Q_D + Q_{DC} + Q_L \tag{5}$$

Where suffix 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,

$$T(X, P, Q) \le 0 \text{ or} \tag{6}$$

(i) The maximum and minimum real and reactive power outputs of the generating sources are given by,

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \text{ and } Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad (i \in G_B) \tag{7}$$

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

(ii) Voltage limits (Min/Max) signals the system bus voltages to remain within a narrow range. These limits may be denoted by the following constraints,

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

Where, N_B represents number of buses.

(iii) Power flow limits refer to the transmission line's thermal or stability limits capable of transmitting maximum power represented in terms of maximum MVA flow through the lines and it is expressed by the following constraints,

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

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

Thus, the operating condition of a combined ac-dc electric power system is described by the vector,

$$X = [\delta, V, x_c, x_d]^t \tag{10}$$

Where, δ 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

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

Where, α_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,

$$V_{di} = a_i V_i \cos\varphi_i \quad (12)$$

Where, $\varphi_i = \delta_i - \xi_i$, and φ 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,

$$P_{di} = V_i I_i \cos\varphi_i \quad \text{or} \quad P_{di} = V_{di} I_{di} \quad (13)$$

The reactive power flow into the dc terminal is

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

The equations (13) - (14) can be substituted into 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,

$$X_d = [V_d, I_d, a, \cos\alpha, \varphi]^t \quad (15)$$

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.

Here (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].

3. GENETIC ALGORITHM IN OPF PROBLEM

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.

3.2 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 solution are formed. If the search goal has not been achieved, again GA creates offspring strings through above three operators and the 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.

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3.2.1 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 $b_i(p_{Gi}^{max})$ and lower bound $a_i(p_{Gi}^{min})$. 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,

$$R_i = \frac{b_i - a_i}{2^{Li} - 1} \quad (16)$$

This transforms the PG_i set into a binary string called *chromosome* with length ΣL_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.

3.2.2 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.

3.2.3 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.

$$\underbrace{0110}_{P_{G1}}\underbrace{0101}_{P_{G2}}\underbrace{0110}_{P_{G3}}\underbrace{0100}_{P_{G4}}\underbrace{1100}_{P_{G5}}\underbrace{0011}_{P_{G6}}\underbrace{1110}_{P_{G7}}$$

$$\xrightarrow{\text{After mutation}}$$

$$\underbrace{0110}_{P_{G1}}\underbrace{0101}_{P_{G2}}\underbrace{0110}_{P_{G3}}\underbrace{0100}_{P_{G4}}\underbrace{1110}_{P_{G5}}\underbrace{0011}_{P_{G6}}\underbrace{1110}_{P_{G7}}$$

3.2.4 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).

3.2.5 Fitness of Candidate Solutions and Cost Function

The cost function has defined as:

$$f = \sum_{i=1}^{NG} a_i P_{Gi}^2 + b_i P_{Gi} + c_i ; \qquad P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \quad (17)$$

To minimize F(x) 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. The fitness function is used [3] as follows:

$$FitnessFunction(FF) = \frac{C}{\sum_{i=1}^{NG} F_i(P_{Gi}) + \sum_{i=1}^{Nc} w_j * Penalty_j} \quad (18)$$

$$Penalty_j = h_j(x,t)|.H(h_j(x,t)) \quad (19)$$

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 has been programmed in Matlab 7.1 in such a way that it should firstly satisfy all inequality constraints by heavily penalizing if they have been violated. Then the equality constraints are 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 the above components, a standard GA procedure for solving the OPF problem is shown in figure 1.

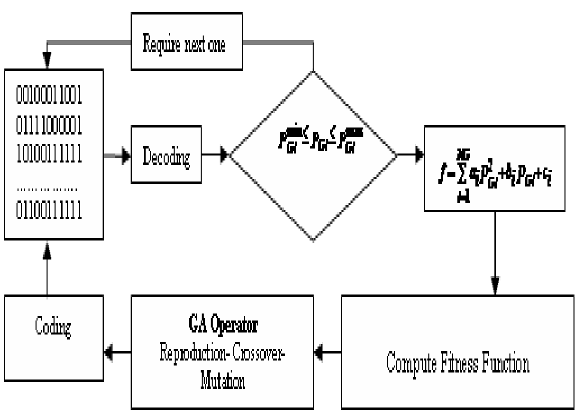

Figure 1: *Flowchart of a Simple Genetic Algorithm for OPF*

4. EXAMPLE, SIMULATION AND RESULTS

4.1 IEEE-14 Bus System

The performance of the proposed methodology has been assessed through the results obtained with the well-known IEEE-14 Bus as shown in figure 2 (See Appendix) with 18 circuits and 4 generators. The generator and circuit data have been given in Table A1 (See Appendix). 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 been 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 A2 (See Appendix). All the values have been indicated by p.u. The results obtained with given methodology are shown in Table 1.

Table 1: GAOPF results and Comparison with Traditional OPF Method

No.	Voltage (PU)			Generator Cost ($/MWh)		
	GAOPF		Newton OPF	GAOPF		Newton OPF
	Best	Worst		Best	Worst	
1	0.98	1.02	0.99			
2	0.99	1.00	0.98	68.47	120.01	90.94
3	1.01	0.97	0.97	60.34	180.20	90.46
4	0.96	0.96	0.96			
5	0.97	0.99	0.96			
6	0.99	0.99	1.02	102.6	85.51	89.87
7	1.02	0.98	0.97			
8	0.99	1.01	1.02	118.6	120.91	88.40
9	0.98	0.98	0.95			
10	0.97	0.95	0.96			
11	1.01	1.01	0.99			
12	0.98	0.95	1.00			
13	1.03	0.99	0.99			
14	0.97	1.02	0.95			

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.

4.2 Modified IEEE-30 Bus System

This system consists of 6 generators and 43 transmission lines as shown in figure 2 (See Appendix). 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 B1. 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 have been indicated in p.u. 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

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and lower bounds respectively. Table 2 indicates the results for GAOPF and for Newton method.

Table 2: OPF Result: GA and Newton Method

Bus No.	**Voltage (PU)**			**Generator Cost ($/MWh)**		
	GAOPF		Newton OPF	GAOPF		Newton OPF
	Best	Worst		Best	Worst	
1	1.00	0.99	1.00	9.77	1.67	10.55
2	0.99	1.00	0.99	7.97	1.06	6.53
3	0.96	0.98	0.99			
4	0.98	0.96	0.98			
5	1.01	1.02	0.99	8.13	1.40	6.52
6	0.99	1.00	0.97			
7	0.98	0.95	0.98			
8	0.96	0.99	1.03	8.15	0.57	6.93
9	0.96	1.01	0.99			
10	1.01	1.02	1.02			
11	0.99	1.00	1.01	8.40	0.54	11.87
12	1.01	0.95	1.00			
13	0.99	1.01	1.01	6.12	0.56	6.90
14	0.97	0.96	0.99			
15	1.00	1.00	0.99			
16	0.98	0.97	1.00			
17	0.99	0.96	1.00			
18	0.99	1.01	0.99			
19	1.01	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	1.01	1.01	1.02			
25	0.98	0.97	1.03			
26	0.99	1.01	1.02			
27	0.98	0.97	1.05			
28	0.99	0.95	0.99			
29	1.01	0.98	1.05			
30	0.99	0.98.	1.05			

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.

4.3 Real 400 kV network of Maharashtra State Electricity Transmission Company Limited (MSETCL), India

India's electricity sector has grown from 1,362 MW in 1947 to 143,061 MW till 30th March 2008. This sector has been characterized by shortage of supply vis-à-vis demand. To improve the techno-financial performances of this sector, *Ministry of Power* Government of India enacted Electricity Act 2003 and subsequent policy initiatives to outline the counters of a suitable enabling framework for the overall development of wholesale electricity market.

On the electricity transmission front, the Indian grid has been divided into five sub regional grids. Each has number of constituent sub grids formed by state and private utility networks. All these sub grids and networks have been connected to form a 400 kV national grid.

Maharashtra State utility has the largest installed capacity of 15,580 MW in India. In 2005, it was unbundled into Generation, Transmission and Distribution Company. At present transmission sector is feeling the strain due to low investment made in the past. The transmission infrastructure consists of ±500 kV HVDC, 400 kV, 220 kV, 132 kV, 110 kV, 100 kV, 66 kV lines, 486 EHV sub-stations, and 35626 ckt-km lines with total transformation capacity of 22,168 MVA.

This study considers a real network of 400 kV *Maharashtra State Electricity Transmission Company Limited* shown in figure 4 (See Appendix). It consists of 19 intra-state and 7 inter-state buses (BHILY, KHANDWA, SDSRV, BDRVT, TARAPUR, BOISR and SATPR) through which power is purchased to fulfill demand. The real demand and generator data have shown in Table C1 and C2 (See Appendix). The voltage values for all buses have been bounded between 0.96 and 1.04. The active power flow constraints of intra-state transmission line lie between -0.5 and 0.5, and that for inter-state lines is -1.0 and 1.0. The data for ±500 kV HVDC link that has connected between CHDPUR to PADGE have been given in Table C3. All the values are indicated in p.u. CHDPUR has been taken as a reference bus. There are 2 × 16 equality constraints corresponding with their respective real and reactive power balances of the buses without a generator, and 48 inequality constraints of 27 pairs of voltage, 2 × 11 pairs of generation output and one pair of line flow upper and lower bounds respectively. The result obtained with given methodology has been shown in Table 3.

Table 3: 400 kV, MSETCL, India: GAOPF results and comparison with traditional OPF method

Bus Name	Voltage (PU)			Generator Cost ($/MWh)		
	GAOPF		Newton OPF	GAOPF		Newton OPF
	Best	Worst		Best	Worst	
CHDPUR	1.01	0.97	1.02	55.52	43.3	58.27
KORDY	0.99	1.01	1.05	31.02	25.1	32.38
BHSWL2	0.97	1.01	1.03			
ARGBD4	1.02	0.98	1.02			
BBLSR2	1.00	0.96	1.03			
DHULE	0.97	0.99	1.05			
PADGE	1.00	1.00	1.01			
KALWA	1.00	0.97	1.00			
KARGAR	1.00	0.97	1.00			
LONKAND	1.02	0.98	1.01			
NGOTNE	1.00	1.00	0.99			
DABHOL	0.96	1.02	0.99	25.72	141.2	21.91
KOYNA-N	0.96	0.97	0.99			
KOYNA-4	0.98	0.97	0.99	35.51	28.4	34.33
KLHPR3	0.99	1.00	1.03			
JEJURY	0.97	1.02	0.99			
KARAD2	0.97	1.01	1.01			
SOLPR3	0.99	0.98	1.03			
PARLY2	1.03	0.96	1.05			
BHILY	0.97	1.01	1.05	2.86	26.1	2.87
KHNDWA	1.00	0.97	1.03	12.04	34.3	12.11
SDSRV	0.96	0.96	1.03	11.02	87.2	10.67
BOISR	0.96	1.02	1.04	10.82	162.3	10.75
MAPUSA	0.98	0.95	1.05			
BDRVT	1.00	0.97	1.02	28.98	46.1	27.71
TARAPR	1.00	0.98	1.03	13.06	34.5	12.87
SATPR	1.01	0.99	1.05	10.82	81.0	14.34

The voltage profile at few buses by the best GAOPF solution has improved as compared to traditional OPF method. In addition, generation cost is marginally low as compared to Newton's OPF method.

5. PERFORMANCE EVALUATION

The performance evaluation of AC-DC based GAOPF and traditional OPF method has been tested with reference to parameters given in Table 4 and in Table 5. Newton's method takes less iterations to perform the OPF for the test system and real network of MSETCL. 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 are obtained in one run only. The performance parameters for GA based AC-DC OPF for various test system and real networks are shown in Table 8. 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-14 Bus System	IEEE-30 Bus System	400 kV MSETCL System
1	No. of iterations	43	58	28
2	Execution Time (sec.)	20 sec.	40 sec.	25 sec.
3	No. of Runs	1	1	1

Table 5: GA Parameters/performance for Best OPF

SN	Parameters	Values		
		IEEE-14 Bus System	IEEE-30 Bus System	400 kV MSETCL
1	Initial Population	210	520	1040
2	No. of iterations	120	150	150
3	Probability of crossover	0.5	0.5-0.9	0.5-0.9
4	Probability of mutation	0.001	0.0001-0.001	0.0001-0.001
5	Execution Time (Second) (approx.)	120	825	987 sec.
6	No. of Runs (for best solution)	15	19	27

6. CONCLUSION

This study proposes an AC-DC based GA optimal power flow solution which may be applied to different size power systems. This method also employs its techno-commercial advantage over the traditional method of optimal power flow. The GAOPF method avoids early load flow as reported in other published literatures. This scheme is more effective for the real network situation in developing countries. Finally, the result obtained by this scheme is quite comparable with the traditional OPF methodology.

REFERENCES

[1] M. Younes, M. Rahli and Abdelhakem-Koridak, "*Optimal Power Flow Based on Hybrid Genetic Algorithm*", Journal of Information Science and Engineering 23, pp. 1801-1816, 2007.

[2] Anastasios G. Bakirtzis, Pandel N. Biskas, Christoforos E. Zoumas, , and Vasilios Petridis, *"Optimal Power Flow by Enhanced Genetic*

Algorithm", IEEE Transactions on Power Systems, Vol. 17, No. 2, pp. 229-236, May 2002.

[3] I. G. Damousis, A.G. Bakirtzis, and P.S. Dokopouloset, *"Network Constrained Economic Dispatch Using Real-Coded Genetic Algorithm",* IEEE Transactions on Power Systems, Vol. 18, No. 1, February 2003.

[4] D. Papalexopoulos, C. F. Imparato, and F. F. Wu, "*Large-scale optimal power flow: Effects of initialization decoupling and discretization*," IEEE Transactions on Power Systems., Vol. 4, pp. 748–759, May 1989.

[5] H. W. Dommel, W. F. Tinney, "*Optimal Power Flow Solutions"*, IEEE Transactions on power apparatus and systems, Vol. PAS-87, No. 10, pp. 1866-1876, October 1968.

[6] K. Y. Lee, Y.M. Park, and J.L. Ortiz, "*A United Approach to Optimal Real and Reactive Power Dispatch"*, IEEE Transactions on Power Systems, Vol. PAS-104, p. 1147-1153, May 1985.

[7] M. Sasson, "*Non linear Programming Solutions for load flow, minimum loss, and economic dispatching problems"*, IEEE Transactions on Power Apparatus and Systems, Vol. PAS-88, No. 4, April 1969.

[8] T. Bouktir, M. Belkacemi, K. Zehar, "*Optimal power flow using modified gradient method"*, Proceeding ICEL'2000, U.S.T.Oran, Algeria, Vol. 2, p. 436-442, 13-15 November 2000.

[9] Tarek Bouktir, Linda Slimani, M. Belkacemi, "*A Genetic Algorithm for Solving the Optimal Power Flow Problem*", Leonardo Journal of Sciences, Issue 4, pp. 44-58, January-June 2004.

[10] H. W. Dommel, "*Optimal power dispatch*," IEEE Transactions on Power Apparatus and Systems, Vol. PAS93, pp. 820-830, 1974.

[11] O. Alsac, J. Bright, M. Prais, and B. Stott, "*Further developments in LP-based optimal power flow*," IEEE Transactions on Power Systems, Vol. 5, pp. 697-711, 1990.

[12] J. Nanda, D. P. Kothari, and S. C. Srivatava, "*New optimal power-dispatch algorithm using Fletcher's quadratic programming method*," in *Proceedings of the IEE*, Vol. 136, pp. 153-161, 1989.

[13] D. I. Sun, B. Ashley, B. Brewer, A. Hughes, and W. F. Tinney, "*Optimal power flow by Newton approach*," IEEE Transactions on Power Apparatus and Systems., Vol. PAS-103, pp. 2864–2880, 1984.

[14] H. Wei, H. Sasaki, J. Kubokawa, and R. Yokoyama, "*An interior point nonlinear programming for optimal power flow problems with a novel data structure*," IEEE Transactions on Power Systems, Vol. 13, pp. 870–877, August 1998.

[15] G. L. Torres and V. H. Quintana, "*An interior-point method for nonlinear optimal power flow using voltage rectangular coordinates*," IEEE Transactions on Power Systems, Vol. 13, pp. 1211–1218, November 1998.

[16] J. A. Momoh, M. E. El-Hawary, and R. Adapa, "*A review of selected optimal power flow literature to 1993*," IEEE Transactions on Power Systems, pt. I and II, Vol. 14, pp. 96–111, February 1999.

[17] G. Tognola and R. Bacher, "*Unlimited point algorithm for OPF problems*," IEEE Transactions on Power Systems, Vol. 14, pp. 1046–1054, August 1999.

[18] L. Chen, H. Suzuki, and K. Katou, "*Mean field theory for optimal power flow*," IEEE Transactions on Power Systems, Vol. 12, pp. 1481–1486, Nov. 1997.

[19] L. Chen, S. Matoba, H. Inabe, and T. Okabe, "*Surrogate constraint method for optimal power flow*," IEEE Transactions on Power Systems, Vol. 13, pp. 1084–1089, August 1998.

[20] L. L. Lai, J. T. Ma, R. Yokoyama, and M. Zhao, "*Improved genetic algorithms for optimal power flow under both normal and contingent operation states*," Electric Power Energy System, Vol. 19, no. 5, pp. 287–292, 1997.

[21] T. Numnonda and U. D. Annakkage, "*Optimal power dispatch in multinode electricity market using genetic algorithm*," Elecric Power System Research., vol. 49, pp. 211–220, 1999.

[22] M. M. El-Saadawi, "*A Genetic-Based Approach For Solving Optimal Power Flow Problem*", Mansoura Engineering Journal, (MEJ), Vol. 29, No. 2, June 2004.

[23] D. Walters, G. Sheble, *"Genetic Algorithm Solution for Economic Dispatch with Valve Point Loading"*, IEEE Transactions on Power Systems, Vol.8, No.3, August 1993.

[24] D. E. Goldberg, "*Genetic Algorithms in Search, Optimization and Machine Learning"*, Addison Wesley Publishing Company, 1989.

[25] J. Yuryevich, K. P. Wong, "*Evolutionary Programming Based Optimal Power Flow Algorithm"*, IEEE Transaction on Power Systems, Vol. 14, No. 4, November 1999.

[26] Luonan Chen, Hideki Suzuki, Tsunehisa Wachi, and Yukihiro Shimura, "*Components of Nodal Prices for Electric Power Systems*", IEEE Transactions on Power Systems, Vol. 17, No. 1, pp 41-49, 2002.

[27] C. N. Lu, S. S. Chen, C. M. Ong, *"The Incorporation of HVDC Equations in Optimal Power Flow Methods using Sequential Quadratic Programming Techniques*", IEEE Transactions on Power Systems, Vol. 3, No.3, pp 1005-1011, August 1988.

[28] Pandya K.S., Joshi S. K., "*A survey of Optimal Power Flow Methods*", Journal of Theoretical and Applied Information Technology, pp 450-458, 2008.

APPENDIX

A) IEEE-14 Bus System

Bus	Demand (PU)		Real Generation (PU)		Reactive Generation (PU)		Generation Cost ($?MWh)		
	P	Q	Max	Min	Max	Min	a_i	b_i	c_i
1	0.1	0.02	2.1	0.1	0.5	-0.1	0.1	15.0	5
2	0.16	0.1	1.5	0.1	0.5	-0.1	0.1	15.3	5
3	0.02	0.0							
4	0.08	0.0							
5	0.09	-0.06	1.5	0.1	0.5	-0.1	0.1	15.2	5
6	0.00	0.0							
7	0.30	0.0							
8	0.30	0.30	1.5	0.1	0.5	-0.1	0.1	19.3	5
9	0.00	0.0							
10	0.06	0.0							
11	0.0	-0.18	1.5	0.1	0.6	-0.1	0.1	15.0	5
12	0.01	0.0							
13	0.0	-0.16	1.5	0.1	0.5	-0.1	0.1	19.0	5
14	0.06	0.0							
15	0.08	0.0							
16	0.04	0.0							
17	0.09	0.0							
18	0.03	0.0							
19	0.10	0.0							
20	0.02	0.0							
21	0.02	0.01							
22	0.08	0.10							
23	0.03	0.0							
24	0.09	0.0							
25	0.0	0.0							
26	0.04	0.0							
27	0.08	-0.14							
28	0.0	0.0							
29	0.02	0.0							
30	0.01	0.0							

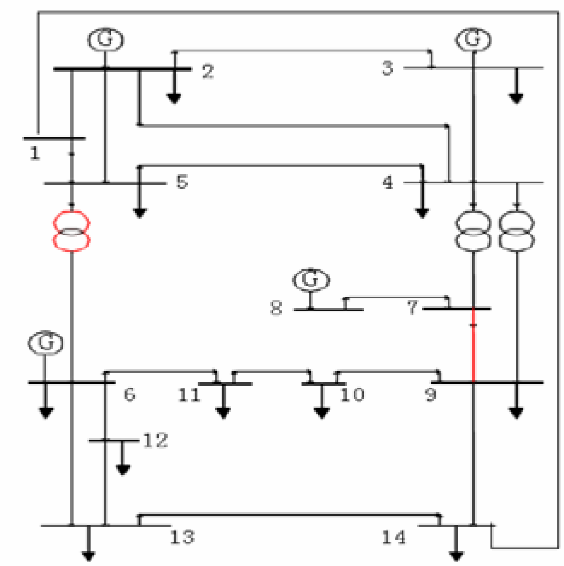

Figure 2: *Line diagram of IEEE-14 Bus System*

Table A1: Bus data of Modified IEEE-14 Bus system

Bus	Demand		Real Gen. (PU)		Reactive Gen. (PU)		Generation cost ($/MWh)		
	P	Q	Max	Min	Max	Min	a_i	b_i	c_i
1	0.0	0.0							
2	0.22	0.13	1.5	.01	1	-1	190	12	0.0076
3	0.94	0.19	1.5	.01	1	-1	200	10	0.0095
4	0.48	0.0							
5	0.08	0.16							
6	0.10	0.07	2.0	.01	1	-1	190	12	0.0075
7	0.0	0.0							
8	0.0	0.0	1.5	.01	1	-1	200	10.8	0.0091
9	0.25	0.17							
10	0.08	0.06							
11	0.04	0.02							
12	0.06	0.02							
13	0.14	0.06							
14	0.15	0.05							

B) IEEE-30 Bus System

Table B1: Bus data of Modified IEEE-30 Bus system

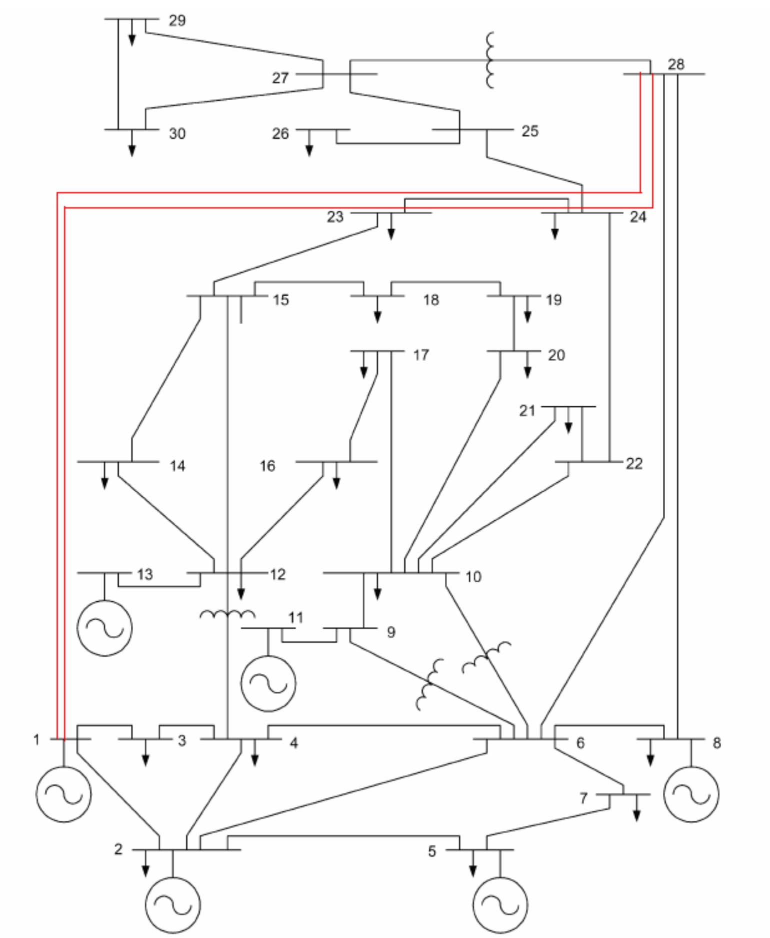

Figure 3: *Line diagram of modified IEEE-30 Bus system*

C) 400 kV MSETCL, India

Table C1: 400 kV MSETCL: Demand Data (PU)

Bus Name	Demand (p.u.)		Bus Name	*Demand (p.u.)*	
	P	Q		P	*Q*
CHDPUR	0.302	0.101	NGOTNE	0.239	*0.180*
KORDY	0.393	0.097	DABHOL	0.000	*0.000*
BHSWL2	0.434	0.099	KOYNA-N	0.275	*0.001*
ARGBD4	0.390	0.081	KOYNA-4	0.000	*0.000*
BBLSR2	0.407	0.170	KLHPR3	0.337	*0.008*
DHULE	0.287	0.152	JEJURY	0.257	*0.102*
PADGE	0.325	0.153	KARAD2	0.383	*0.123*
KALWA	0.259	0.155	SOLPR3	0.270	*0.011*
KARGAR	0.229	0.146	PARLY2	0.313	*0.011*
LONKAND	*0.369*	*0.225*			

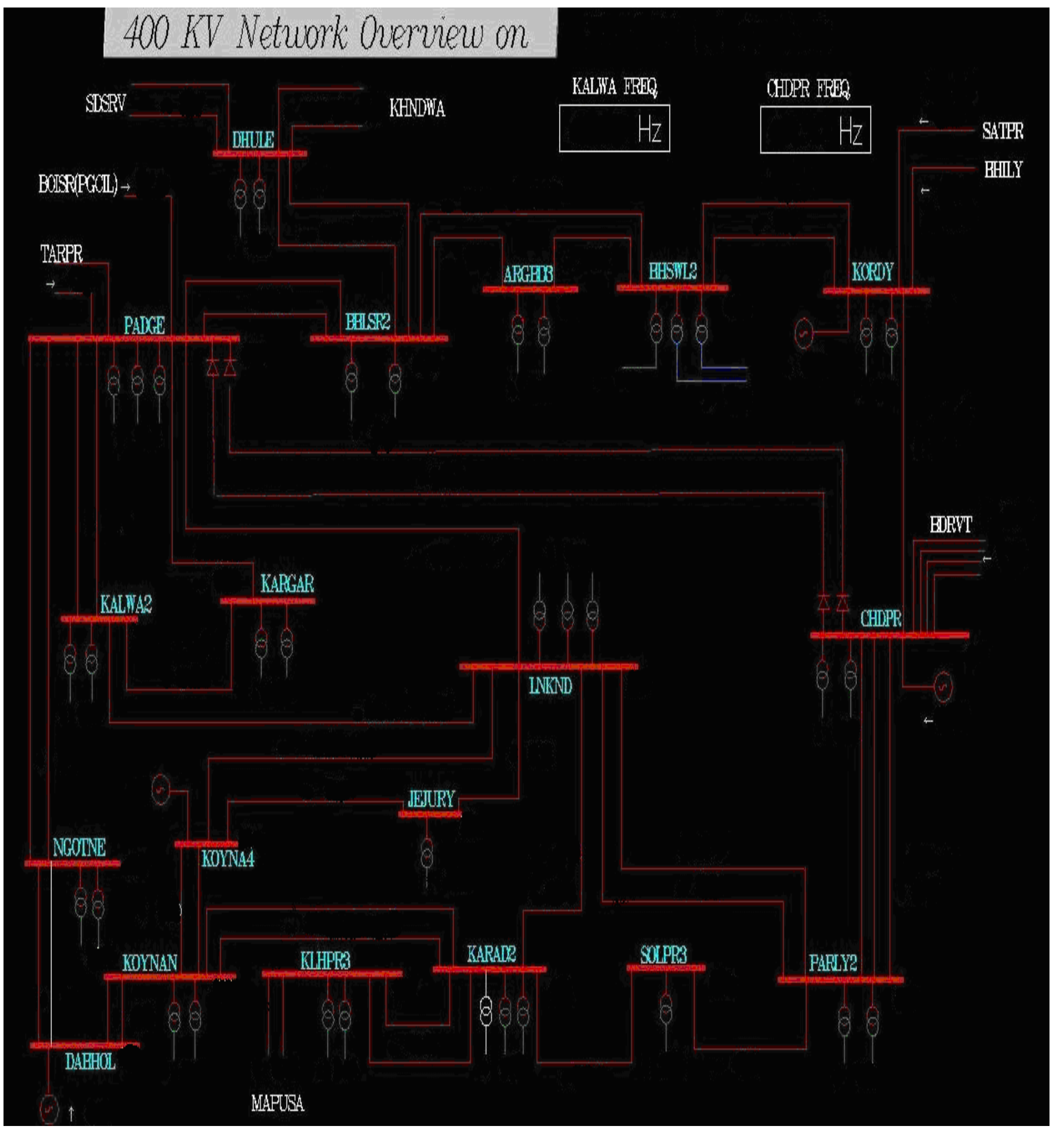

Figure 4: *A 400 kV MSETCL, India*

Table C2: 400 kV MSETCL: Generator Data (PU) and Demand Data

Bus Name	Generation Capacity		Generation Real Power		*Generation cost ($/MWh)*		
	Max	Min	Max	Min	a_i	b_i	c_i
CHDPUR	2.30	0.2	1.72	0.2	0.20	20.41	*10.21*
KORDY	1.04	0.2	0.54	0.2	0.20	21.43	*10.21*
BHSWL2							
ARGBD4							
BBLSR2							
DHULE							
PADGE							
KALWA							
KARGAR							
LONKAND							
NGOTNE							
DABHOL	1.20	0.2	1.44	0.2	1.02	71.44	*10.21*
KOYNA-N							
KOYNA-4	1.50	0.1	0.19	0.1	0.20	20.41	*10.21*
KLHPR3							
JEJURY							
KARAD2							
SOLPR3							
PARLY2							
BHILY			0.6	0.05	0.20	36.94	*10.21*
KHANDWA			0.7	0.05	1.02	36.94	*10.21*
SDSRV			0.5	0.01	1.02	77.56	*10.21*
BOISR			0.2	0.05	1.02	55.72	*10.21*
BDRVT			1.8	0.10	0.20	21.43	*10.21*
TARAPUR			0.4	0.05	1.02	58.58	*10.21*
SATPR			*0.2*	*0.01*	*1.02*	*55.72*	*10.21*

Table C3: Data: ±500kV CHDPUR-PADGE HVDC Link

Particulars	**Data**	**Particulars**	**Data**
Nominal Continuous Power Flow Rating	1500 MW	Thyristor Valves: Max. voltage	7 kV
Converter Xmer: voltage of each pole of DC line	500 kV	Thyristor Valves: Rated current	1700 A dc
Converter Xmer: Rated power unit	298.6 MVA	Length of the line	753 Km
Operation: Chdpur Converter/Rectifier	12.5 to 15 degree	Number of poles	2
Operation: Padge- Inverter	17 to 22 degree	Resistance: Chdpur-Padge	7.5 Ω