

Novel Genetic Algorithm Based Solutions for Optimal Power Flow under Contingency Conditions

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Abstract

Power system throughout the world is undergoing tremendous changes and developments due to rapid Restructuring, Deregulation and Open-access policies. Greater liberalization, larger market and increasing dependency on the electricity lead to the system operators to work on limited spinning reserve and to operate on vicinities to maximize the economy compromising on the reliability and security of the system for greater profits, which lead to establishment of a monitoring authority and accurate electronic system to prevent any untoward incidents like Blackouts.

In any power system, unexpected outages of lines or transformers occur due to faults or other disturbances. These events may cause significant overloading of transmission lines or transformers, which in turn may lead to a viability crisis of the power system. The main role of power system control is to maintain a secure system state, i.e., to prevent the power system, moving from secure state into emergency state over the widest range of operating conditions. Security Constrained Optimal Power Flow (SCOPF) is major tool used to improve the security of the system.

In this work, Genetic algorithm has been used to solve the OPF and SCOPF problems. As initial effort conventional GA (binary coded) based OPF and SCOPF is going to be attempted. The difficulties of binary coded GA in handling continuous search space lead to the evolution of real coded GA's. Solutions obtained using both the algorithms are compared.

Case studies are made on the IEEE30 bus test system to demonstrate the ability of real coded GA in solving the OPF and SCOPF problems.

keywords- Optimal Power Flow(OPF), Security Constrained Optimal Power Flow(SCOPF), Genetic Algorithm(GA).

I. INTRODUCTION

In power system operation, the economic dispatch problem is an important optimization problem. Modern control centres of electrical power systems are equipped with computational tools to help the operators in their daily work in order to achieve a high quality service with a minimum cost. the operation is done in a way to maintain the system in a secure mode, i.e., ensuring that the system will be operating continually even when components of the network fail. Most of the large power systems have equipments installed to allow the personnel of the operation to monitor and to operate the system in a reliable way.

The electric system monitoring is one of the functions designed to increase the security of the system. However, the inherent complexity of the electric system operation makes it necessary to have sophisticated functions of diagnosis, analysis and advising available at the Energy Management System(EMS), such as Network topology, State estimator, Emergency control, among others. The greater dependency on Electric Power has brought in the stage where the consumer depends not only on

the availability of the electricity, but also looks for Reliable, Secure, Quality and Uninterrupted supply. Optimal Power Flow(OPF) study plays an important role in the Energy Management System(EMS), where the whole operation of the system is supervised in each conceivable real time intervals.

It was first introduced by H. W. Dommel and W. F. Tinney in 1960. OPF problem aims at determining an optimal operating point for control variables which minimizes a given objective function subject to physical constraints and control limits. The most commonly considered objective function is total cost of generation.

The electric system is monitored by the Supervisory Control and Data Acquisition (SCADA) System, which periodically acquires analog measurements and status of switching devices from the network. The monitoring system also allows the operator to act in the system through remote controls, changing switches status and position of transformers tap, etc.

The OPF problem with the contingency constraints is often referred to as the security-constrained optimal power flow(SCOPF). The recent

blackouts lead to the importance of the system which is capable to withstand any contingencies, or to have system which can work on the specified limits when a contingency occurs, without effecting the overall operation of the system. SCOPF problem is the perfect incorporation of the contradictory doctrines of maximum economy, safer operation and augmented security.

SCOPF problem has been solved using classical optimization techniques like Gradient method [1] and Newton's method. However, these techniques have difficulty in attaining the global optimum value because of the large number of control variables involved and the discrete nature of the search space. Recent interest has been in solving the problem using evolutionary algorithms like Genetic Algorithm to overcome the problems encountered by the classical techniques

As a preliminary attempt in solving the SCOPF problem, OPF problem has been solved using Genetic Algorithm. A simple GA uses binary coded decision variable to explore the search space. However this approach has difficulties in handling problems with continuous search space. This lead to the evolution of a new version of GA in which the decision variables are real coded in nature. One such algorithm is Real Coded Genetic Algorithm. The effectiveness of the real coded GA is tested against the simple GA in terms of solution quality and computational efficiency using IEEE 30 bus test system.

A contingency is said to be more severe if it leads to more number of limit violations or large violations in small number of variables. A severity index is used to calculate the severity of each contingency. Based on this index, the contingencies are ranked in decreasing order of severity. This is called contingency ranking. Depending upon the computational facilities and the tolerances of the system equipment for contingency, a list of credible contingencies is prepared.

The base case OPF problem is then extended to solve for all the credible contingencies and each violation of these contingencies is penalized appropriately using GA. The solution obtained will be optimal in such a way that if any of the listed credible contingencies occur, the system is still in a feasible operating state. The effectiveness of GA in solving the SCOPF problem is evaluated using the IEEE 30 bus test system and the results are compared in solution quality against the results in [1] and [3]. The same problem is once again solved using real coded GA and compared in solution quality and computational efficiency against the result obtained using simple GA.

II. GENETIC ALGORITHMS

Genetic Algorithm(GA) was modelled and

developed by "John Holland at University Of Michigan in 1960s." It is based on the biological approach of human science. It is one kind of direct search algorithms based on the mechanics of **natural selection** and **natural genetics**. In brief, GA is the selection of initial points from the total search space. Each and every point in the search space corresponds to one set of values for the parameters of the problem. Each parameter is code with a string of bits. Individual bit is called **gene**. Total string of such genes written in a order is called **chromosome**. Each chromosome in GA represents a point in the search space. A number of such chromosomes are randomly generated in the first phase of the genetic algorithm. This is called **Initialization**. Together, the chromosome set is called **Population**. The population is evaluated through various operators of GA to generate a new population GA is capable of locating the near optimal solutions, but requires a large number of generations to converge. It is more flexible than other methods which is an advantage. Typically simple GA consists of three phases:

i) Generation, ii) Evaluation and iii) Genetic operation.

Simple Genetic Algorithm

As the name suggests, genetic algorithms (GAs) borrow their working principle from natural genetics. In this section, we will describe the principles of a GA's operation. To illustrate the working of GAs better, we will also show a hand-simulation of one iteration of GAs on a two-variable problem. A theoretical description of GA parameter interactions and other salient issues are then presented. Some fundamental ideas of genetics are borrowed and used artificially to construct search algorithms that are robust and require minimal problem information.

The working principle of GAs is very different from that of most classical optimization techniques.

$$\begin{aligned} \text{minimize } f(d, h) &= c\left(\frac{\pi d^2}{2} + \pi dh\right), \\ \text{subject to } g_1(d, h) &\equiv \frac{\pi d^2 h}{4} \geq 300, \\ \text{variable bounds } d_{min} &\leq d \leq d_{max} \\ &h_{min} \leq h \leq h_{max} \end{aligned} \quad \text{-eq (1)}$$

Coding the decision variables in a binary string is primarily used to achieve a pseudo chromosomal representation of a solution.

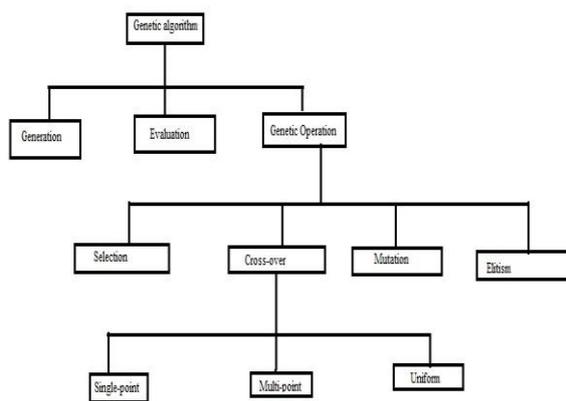


fig1: Hierarchy of Genetic algorithm

Real Coded Genetic Algorithm

When binary-coded GAs need to be used to handle problems having a continuous search space, a number of difficulties arise. One difficulty is the Hamming cliffs associated with certain strings (such as strings 01111 and 10000) from which a transition to a neighbouring solution (in real space) requires the alteration of many bits. Hamming cliffs present in a binary coding cause artificial hindrance to a gradual search in the continuous search space. The other difficulty is the inability to achieve any arbitrary precision in the optimal solution. In binary-coded GAs, the string length must be chosen a priori to enable GAs to achieve a certain precision in the solution.

The more the required precision, then the larger is the string length. For large strings, the population size requirement is also large, thereby increasing the computational complexity of the algorithm. Since a fixed coding scheme is used to code the decision variables, variable bounds must be such that they bracket the optimum variable values. Since in many problems this information is not usually known a priori, this may cause some difficulty in using binary-coded GAs in such problems.

The crossover operator used in the binary coding needs to be redesigned in order to increase the propagation of more meaningful schemata pertaining to a continuous search space. There exists a number of real-parameter GA implementations, where crossover and mutation operators are applied directly to real parameter values. Since real parameters are used directly (without any string coding), solving real-parameter optimization problems is a step easier when compared to the binary-coded GAs. Unlike in the binary-coded GAs, decision variables can be directly used to compute the fitness 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. However, the difficulty arises with the search operators. In the binary-coded GAs, decision variables are coded in finite-length strings and

exchanging portions of two parent strings is easier to implement and visualize. Simply flipping a bit to perform mutation is also convenient and resembles a natural mutation event. In real-parameter GAs, the main challenge is how to use a pair of real-parameter decision variable vectors to create a new pair of offspring vectors or how to perturb a decision variable vector to a mutated vector in a meaningful manner. As in such cases the term 'crossover' is not that meaningful, they can be best described as *blending* operators. However, most blending operators in real-parameter GAs are known as crossover operators.

Under a crossover operator:

1. the population mean should not change;
2. the population diversity should increase, in general.

Since real-parameter crossover operators directly manipulate two or more real numbers to create one or more real numbers as offspring, one may wonder whether there is a special need for using another mutation operator. The confusion arises because both operators seem to be doing the same task, i.e. perturb every solution in the parent population to create a new population. Most constraint handling methods which exist in the literature can be classified into five categories, as follows:

1. Methods based on preserving feasibility of solutions.
2. Methods based on penalty functions.
3. Methods biasing feasible over infeasible solutions.
4. Methods based on decoders.
5. Hybrid methods

Many crossover operators have been proposed for the real coded genetic algorithms. Some of them are Linear crossover, Naïve crossover, Blend crossover. Similarly many mutation operators like Random mutation, Non-uniform mutation, Normally distributed mutation have are also used. Blend crossover and Random mutation are used in the solution to both OPF and SCOPF using real coded genetic algorithm and they are discussed here.

III. Optimal Power Flow

The objective of load flows is to determine the complex nodal voltages from which all other quantities like line flows, currents and losses are derived. The power flow problem is one of the basic problems in which both load powers and generator powers are given or fixed. Today, this basic problem can be efficiently handled on the computer for practically any size system. Newton- Rhapsion (NR) technique has been used to calculate load flows in the present work.

For the planner and operator fixed generation corresponds to a snapshot only. Planning and operating requirements very often ask for an adjustment of the generated powers according to

certain criteria. One of the obvious ones is the minimum of the generating cost. The application of such a criterion immediately assumes variable input powers and bus voltages which have to be determined in such a way that a minimum of the cost of generating these powers is achieved.

The objective of optimal power flow is to find the correct combination of controllable system variables such as generator bus voltage and power output, transformer taps, shunt admittances etc., in such a way that for a given load demand, generating cost is minimal. The OPF might include other constraints such as interface limits and other decisions such as the optimal flow on DC lines and phase shifter angles.

Optimal Power Flow (OPF) has been widely used in power system operation and planning. The Optimal Power Flow module is an intelligent load flow that employs techniques to automatically adjust the Power System control settings while simultaneously solving the load flows and optimizing operating conditions with specific constraints. Optimal Power Flow (OPF) is a static nonlinear programming problem which optimizes a certain objective function while satisfying a set of physical and operational constraints imposed by equipment limitations and security requirements. In general, OPF problem is a large dimension nonlinear, non-convex and highly constrained optimization problem.

Beginning the creation of an OPF, it is useful to consider the goals that the OPF will need to accomplish. The primary goal of a generic OPF is to minimize the costs of meeting the load demand for a Power System while maintaining the security of the system. A secondary goal of an OPF is the determination of system marginal cost data.

Problem Formulation:

The standard OPF problem can be written in the following form

$$\begin{aligned} &\text{Minimize} \quad F(x) \quad (\text{Objective function}) \\ &\text{Subject to: } h_i(x) = 0, \quad i = 1, 2, \dots, m \\ &\quad \quad \quad (\text{Equality constraints}) \\ &\quad \quad \quad g_j(x) \leq 0 \quad j = 1, 2, \dots, n \\ &\quad \quad \quad (\text{Inequality constraints}) \end{aligned}$$

There are m- equality constraints and n- inequality constraints and the number of variables is equal to the dimension of the vector x.

The objective function for the OPF reflects the costs associated with generating power in the system. The quadratic cost model for generation of power will be utilized:

$$F(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad \$ \quad \text{-eq (2)}$$

Where P_{Gi} is the amount of generation in megawatts at generator i. The objective function for the entire Power System can then be written as the sum of the quadratic cost model at each generator.

The total fuel cost for an ng-generator system is calculated as

$$F(x) = \sum_{i=1}^{ng} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad \$ \quad \text{eq (3)}$$

This objective function will minimize the total system costs, and does not necessarily minimize the costs for a particular area within the Power System.

If the valve-point loading effect of thermal units is also taken into consideration, the fuel cost of a generator will be of the form

$$F(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i * \sin \left(e_i (P_{Gi}^{min} - P_{Gi}) \right) \right. \quad \text{eq(4)}$$

Where $i = 1, 2, \dots, ng$.

a_i, b_i, c_i, d_i are the cost coefficients of the unit i.

The sinusoidal term added to the fuel cost function which models the valve-point effect introduces ripples to heat-rate curve and therefore introducing more local minima to the search space. Genetic algorithm, being a heuristic search technique, will not have any difficulties in handling such systems.

Equality Constraint:

The physics of the Power System are enforced through the power flow equations which require that the net injection of real and reactive power at each bus sum to zero. The equality constraints of the OPF reflect the physics of the Power System as well as the desired voltage set points throughout the system. Equality constraints are the basic load flow equations given by:

$$P_p = \sum_{q=1}^n V_p V_q Y_{pq} \cos(\delta_{pq} - \theta_{pq}) \quad \text{-eq (5)}$$

$$Q_p = \sum_{q=1}^n V_p V_q Y_{pq} \sin(\delta_{pq} - \theta_{pq}) \quad \text{-eq (6)}$$

Inequality Constraint:

The inequality constraints of the OPF reflect the limits on physical devices in the Power System as well as the limits created to ensure system security. Physical devices that require enforcement of limits include generators, tap changing transformers, and phase shifting transformers.

Generators have maximum and minimum output powers and reactive powers which add inequality constraints.

$$P_{Gi}^{min} \leq P_G \leq P_{Gi}^{max}, \quad i \in N_g \quad \text{-eq (7)}$$

$$Q_{Gi}^{min} \leq Q_G \leq Q_{Gi}^{max}, \quad i \in N_g \quad \text{-eq (8)}$$

Load tap changing transformers have a maximum and a minimum tap ratio which can be achieved and shunt admittance limits of switchable capacitor/reactor devices have a maximum and a minimum limit, which can be achieved. Both of these create inequality constraints.

$$T_{pk}^{min} \leq T_{pk} \leq T_{pk}^{max}, \quad k \in N_{Tp} \quad \text{eq (9)}$$

$$Y_{hj}^{min} \leq Y_{hj} \leq Y_{hj}^{max}, \quad j \in N_{sh} \quad \text{-eq (10)}$$

For the maintenance of system security, Power Systems have transmission line as well as transformer

MVA ratings. These ratings may come from thermal ratings (current ratings) of conductors, or they may be set to a level due to system stability concerns. The determination of these MVA ratings will not be of concern in this thesis. It is assumed that they are given. Regardless, these MVA ratings will result in another inequality constraint.

$$|S_{lk}| \leq S_{lk}^{max}, \quad k \in N_l \quad \text{-eq (11)}$$

To maintain the quality of electrical service and system security, bus voltages usually have maximum and minimum magnitudes. These limits again require the addition of inequality constrain

$$V_j^{min} \leq V_j \leq V_j^{max}, \quad j \in N_g \quad \text{-eq(12)}$$

Applications of genetic algorithm to OPF:

Binary and real coded GAs are used to solve the OPF problem. The control variables modeled are generator active power outputs, voltage magnitudes, shunt devices, and transformer taps. To keep the GA chromosome size small, each control variable is encoded with different sizes. The continuous control variables include generator active power outputs, generator voltage magnitudes, and discrete control variables include transformer tap settings and switchable shunt devices. Whereas in simple GA each variable is represented by a string of bits, in real coded GA each variable is represented by single real value.

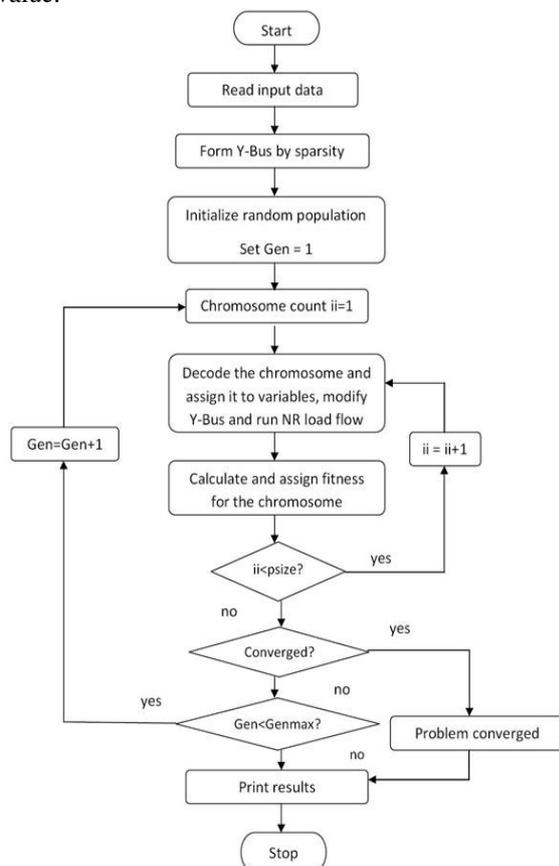


fig.2: Flow chart of OPF using GA

IV. Contingency Analysis And Ranking:

System assessment gives the security level of the system operating state. It involves two functions:

a. **System monitoring:** It provides the operator of the power system with pertinent up-to-date information on the current conditions of the power system. In its simplest form, this just detects the violations in the actual system operating state.

b. **Contingency analysis:** It is much more demanding and normally performed in three distinct states, i.e., contingency definition, selection and evaluation.

i. **Contingency definition:** It gives the list of contingencies to be processed whose probability of occurrence is high. This list, which is usually large, is in terms of network changes, i.e., branch and/or injection outages. These contingencies are ranked in rough order of severity employing contingency selection algorithms to shorten the list. limited accuracy results are required, therefore an approximate system model is utilized for speed.

ii. **Contingency Selection:** There are two main approaches:

Direct methods: These involve screening and direct ranking of contingency cases. they monitor the appropriate post-contingency quantities(flows, voltages).The severity measure is often a performance index.

Indirect methods: These gives the values of the contingency case severity indices for ranking, without calculating the monitored contingent quantities directly.

iii. **Contingency Evaluation:** It is performed after the process of selection. On the successive individual cases in decreasing order of severity. The evaluation process is continued up to the point where no post-contingency violations are encountered.

Hence, the purpose of contingency analysis is to identify the list of contingencies that, it occur, would create violations in system operating states. They are ranked in order of severity. Contingency analysis and ranking is the process in which various contingencies like line outage, generator outage, transformer outage etc., are simulated and ranked in descending order of severity. This is an offline study and is useful to check and improve the security of the system. Outage studies are usually approximate studies. The accuracy levels for convergence of load flows can be 0.001, 0.0005, 0.01 p.u. For rigorous calculations, 0.0001 is used.

In this work, contingency analysis and ranking is done offline using rigorous NR Q-adjusted load flow studies with an accuracy of 0.0001 p.u. During the formation of Y-Bus matrix, transformers are represented in the equivalent π representation. Also,

the transmission lines are represented in equivalent π representation. Hence, both transformers and transmission lines are treated in the same way.

The line outage simulation study can be summarized in the following steps:

1. Choose the line number 'k' for which line outage is to be simulated.
2. The sending and receiving ends of the line 'k' are stored in 'p' and 'q' respectively.
3. Take $R(k)=10^{20}$ p.u., $X(k)=10^{20}$ p.u. and $Y_{cp}(k)=0$, $Y_{cq}(k)=0$ Line outage is simulated.
4. Four locations of Y- Bus i.e., Y_{pp} , Y_{qq} , Y_{pq} , Y_{qp} are modified.
5. Load flow is run for the system with modified Y- Bus assuming the converged base case voltages as initial guess voltages. Voltages and phase angles for all buses are obtained.
6. Calculate the line flows and severity index.
7. Restore the Y- Bus and the resistance and reactance of the line to their original values.

Contingency selection involves the selection of lines or generators whose outage is more severe. To identify the severity of a transmission line, there is no specific approach by which a unique solution can be obtained. Different methods are suggested for identifying the severity. One such index used in [2] is discussed here

Severity Index:

For a line outage 'k', the severity index is defined as:

$$SI_k = \sum_{l=1}^L \left(\frac{S_l}{S_l^{\max}} \right)^{2m} \quad \text{- eq (13)}$$

where, SI = Severity Index (Overload index)

S_l =MVA flow in line l

S_l^{\max} =MVA rating of line l

L =set of overloaded lines

m =integer exponent

Based on the severity index assigned to each line outage, a list is prepared. This is done by first arranging the lines in the descending order of their severity and taking the first few lines with the highest severity. For a large power system, 5 to 10% of the lines can be chosen in the contingency list. It is assumed that since these are the more severe outages in the system, handling them in the SCOPF will be fairly enough to improve the security of the system. A value of $m=1$ has been used.

V. Security Constrained Optimal Power Flows

The security of the system can be improved either through preventive control or post contingency corrective action. Alsac and Stott [1] extended the penalty function method to security constrained optimal power flow problem in which all the contingency case constraints are augmented to the optimal power flow problem. In this method the

functional inequality constraints are handled as soft constraints using penalty function technique. The drawback of this approach is the difficulty involved in choosing proper penalty weights for different systems and different operating conditions which if not properly selected may lead to excessive oscillatory convergence. This combined with prohibitively large computing time makes this method unsuitable for online implementation.

Apart from using preventive approach for security enhancement, the post contingency state corrective action can also be used for security enhancement. The resulting stage has the same security level as the usual security – constrained optimal power flow case with lower operating cost. The power electronics-based FACTS devices can also be employed for corrective action due to its high speed of response.

The proposed algorithm solves the SCOPF problem subject to the power balance equality constraints, limits on control variables namely active power generation, controllable voltage magnitude pertaining to the base case and selected contingency cases. The effectiveness of the proposed approach is demonstrated through preventive and corrective control action for a few harmful contingencies in the IEEE -30 bus system.

PROBLEM FORMULATION

The objective of the SCOPF problem is the minimization of total fuel cost pertaining to base case and alleviation of line over load under contingency case. The adjustable system quantities such as controllable real power generations, controllable voltage magnitudes, controllable transformer taps are taken as control variables. The equality constraint set comprises of power flow equations corresponding to the base case as well as the postulated contingency cases. The inequality constraints include control constraints, reactive power generation and load bus voltage magnitude and transmission line flow constraints pertaining to the base case as well as the postulated contingency cases. The mathematical description of objective functions and its associated constraints are presented below. For each individual, the equality constraints (3.3) and (3.4) are satisfied both in base case as well as contingency cases by running NR algorithm and the constraints on the state variables are taken into consideration by adding penalty function to the objective function.

$$\text{Min } f = F_T + w * SI_l + S_p + \sum_{i=1}^{N_l} U_{pj} + \sum_{j=1}^{N_g} Q_{pj} + \sum_{j=1}^{N_l} L_{pj} \quad \text{- eq(14)}$$

where, F_T represents the total fuel cost,

SI_l represents the severity index for outage l,

S_p , U_{pj} , Q_{pj} and L_{pj} are the penalty terms for the reference bus generator active power limit violation, load bus voltage limit violation; reactive power

generation limit violation and the line flow limit violation respectively.

These quantities are defined by the following equations:

$$S_p = \begin{cases} K_S(P_S - P_S^{max}) & \text{if } P_S > P_S^{max} \\ K_S(P_S^{min} - P_S) & \text{if } P_S < P_S^{min} \\ 0 & \text{otherwise} \end{cases} \quad \text{-eq (15)}$$

$$U_{pj} = \begin{cases} K_U(U_j - U_j^{max})^2 & \text{if } U_j > U_j^{max} \\ K_U(U_j - U_j^{min})^2 & \text{if } U_j < U_j^{min} \\ 0 & \text{otherwise} \end{cases} \quad \text{- eq(16)}$$

$$Q_{pj} = \begin{cases} K_q(Q_j - Q_j^{max})^2 & \text{if } Q_j > Q_j^{max} \\ K_q(Q_j - Q_j^{min})^2 & \text{if } Q_j < Q_j^{min} \\ 0 & \text{otherwise} \end{cases} \quad \text{- eq(17)}$$

$$L_{pj} = \begin{cases} K_l(S_l - S_l^{max}) & \text{if } S_l > S_l^{max} \\ 0 & \text{otherwise} \end{cases} \quad \text{- eq(18)}$$

GA is usually designed to maximize the fitness function which is a measure of the quality of each candidate solution. Therefore a transformation is needed to convert the objective of the OPF problem to an appropriate fitness function to be maximized by GA. Therefore the GA fitness function is formed as $F=k/f$, where, 'k' is a large constant.

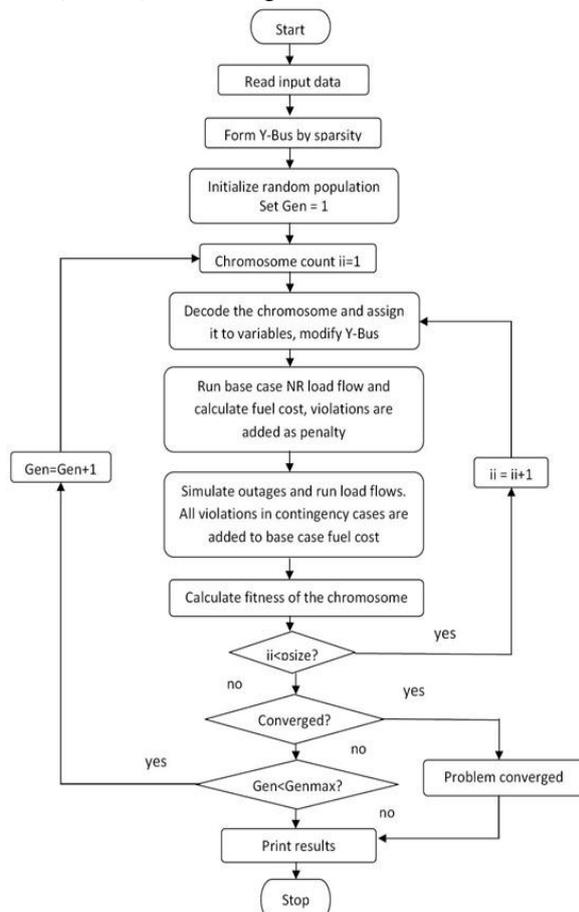


fig3. Flow chart of SCOPF using GA

I. 6. Results And Discussion

The SCOPF in its general form is a nonlinear, non convex, static, large scale optimization problem with both continuous and discrete variables in large number. As an initial attempt in solving SCOPF using binary and real coded genetic algorithms, OPF problem has first been solved. As the SGA has the difficulty in handling continuous search space, new versions of GAs are evolved. One such algorithm used here is real coded Genetic Algorithm. The effectiveness of real coded GA is compared in solution quality and computational efficiency against simple GA. The Optimal Power Flow (OPF) is a highly non-linear, large scale optimization problem due to large number of variables & constraints. It has both continuous and discrete variables as its decision variables. OPF with Fuel cost minimization as objective function is formulated as a single objective optimization case.

The algorithm is implemented using Mat lab® 2013b and is tested for its robustness on a standard IEEE 30 bus system. The network data is shown in Appendix A. The network consists of 6 Generator buses, 21 load buses & 41 lines, of which 4 lines are due to tap setting transformers. The total load on the network is 283.4 MW. The algorithms have been implemented on a personal computer with 2.44 GHz Intel Pentium 4 processor and 1.2 GB RAM.

Present thesis considers 24 control variables as explained below. 5 generator active power outputs, 6 generator-bus voltage magnitudes, 4 transformer tap-settings & 9 shunt susceptances.

OPF with simple Genetic Algorithm

The gene length for unit active power outputs is 12 bits, generator voltage magnitude is 8 bits, and both of them are treated as continuous control variables. As the transformer tap settings can take 17 discrete values each one is encoded using 5 bits & the step size is 0.0125 p.u. The bus shunt susceptance can take 6 discrete values each one is encoded using 3bits, & the step size is 0.01 p.u. (on system MVA basis). Thus, the total string length would be 155.

PARAMETERS: Population size =60, Uniform Crossover Probability =0.85, String length 155 bits, Mutation Probability=0.01 & elitism 0.15 & Maximum Number of iterations=100. Roulette wheel selection technique is used for parent selection.

OPF with Real coded Genetic Algorithm

The control variables considered are similar to the variables explained above. PARAMETERS: Population size =60, Maximum Number of iterations=100, Crossover Probability =0.85, Mutation Probability=0.01, string length = 24 variables & elitism 0.15. The results obtained for various control variables using simple and real coded

GA are given. If the problem did not converge in maximum number of generations, solution obtained at the last generation can be taken as the optimum value.

Table 1

Optimal settings of control variables for OPF using GA

Variables	Simple GA	Real Coded GA
Slack	178.014	177.17
PG2	48.48	48.80
PG5	21.39	21.25
PG8	21.25	21.11
PG11	12.33	11.81
PG13	12.00	12.09
VG1	1.0788	1.0799
VG2	1.0606	1.0610
VG5	1.0260	1.0280
VG8	1.0335	1.0377
VG11	1.0287	1.0594
VG13	1.0707	1.0494
TAP 6-9	0.9500	1.0625
TAP 6-10	0.9875	0.9625
TAP 4-12	1.0250	1.0125
TAP 28-27	0.975	0.985
SHUNT 10	0.03	0.03
SHUNT 12	0.04	0.04
SHUNT 15	0.01	0.01
SHUNT 17	0.01	0.01
SHUNT 20	0.02	0.02
SHUNT 21	0.05	0.05
SHUNT 23	0.03	0.03
SHUNT 24	0.00	0.02
SHUNT 29	0.03	0.03
OPTIMAL FUEL COST(\$/hr)	802.316	800.915
TIME(sec)	200.598	203.432

It is observed that the results obtained by real coded GA are more optimal than the one obtained using binary GA. Also, the result obtained using mathematical technique reported in [1] i.e., 802.4 \$/hr, is nearer to the one obtained using binary GA. This shows that GA works better than the mathematical techniques in finding the optimal solution for the OPF problem. Convergence characteristics for real and binary coded GA are plotted. Voltage profile of all the buses after

convergence is shown in bar graph. Red colour in the graph indicates generator bus.

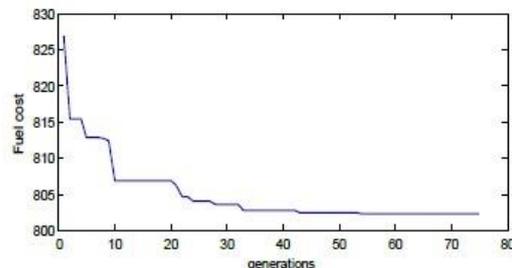


fig4. Convergence characteristics of binary GA for OPF

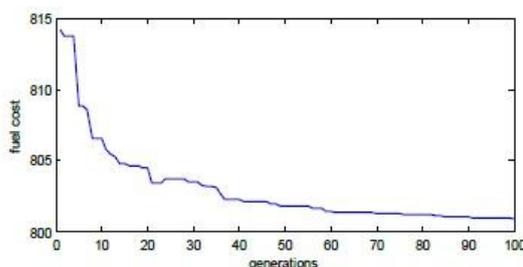


fig5. Convergence characteristics of real coded GA for OPF

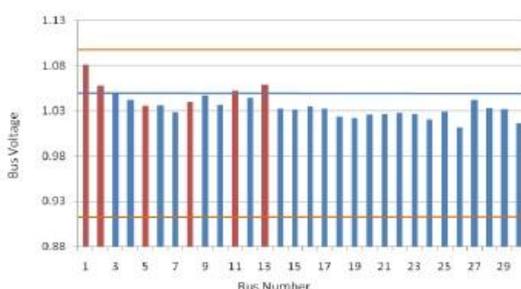


fig6. Voltage profile for OPF using binary coded GA

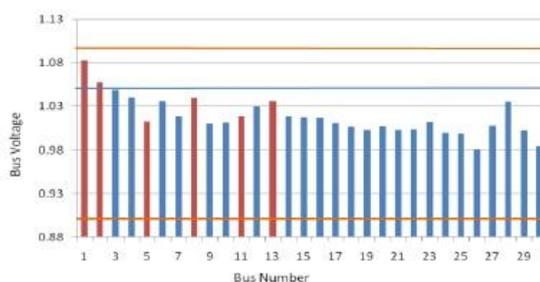


fig7. Voltage profile for OPF using real coded GA

Contingency Analysis And Ranking

Since contingency analysis and ranking is an offline study, rigorous analysis has been done using NR Q-adjusted load flows with a convergence criterion of 0.0001. The results of the analysis are summarized in the table hereunder.

Table II
 Summary of contingency analysis for
 IEEE 30-BUS system

Outage line No.	Overloaded lines	Line flow (MVA)	Line flow limit (MVA)	Severity index(SI)	Rank
1	1-3 3-4	150.9605 144.6517	130 130	2.2739	1
2	1-2	146.6654	130	1.1281	3
4	1-2	143.9518	130	1.1073	4
5	2-6 5-7	68.0396 76.7921	65 70	2.1437	2
25	15-18	16.3426	16	1.02141	5

From the above table it can be seen that the 25th line outage does not affect the operation of the system adversely as the line is overloaded only to a very small extent. Out of 41 lines, for a 30 bus system, 4 are transformers modelled as transmission lines. Transformer and generator outages are not considered in the present thesis because it is leading to an infeasible operating state and it is observed that nothing can be done to make the system secure under these outage conditions. Full SCOPF and contingency analysis, however, should take into account all the possible outages. This is not possible in this case as the system size is too small to consider the generator and transformer outages.

Security Constrained Optimal Power Flows

The data for the SCOPF program is the same as that for the OPF program, including the GA parameters for both real and binary coded SCOPF. The results obtained using binary and real coded GA are compared in the table hereunder.

Table III
 Optimal settings of control variables for
 SCOPF using GA

VARIABLES	BINARY GA	REAL CODED GA
SLACK	147.07	148.93
PG2	59.38	56.10
PG5	27.20	25.18
PG8	30.63	31.65
PG11	14.18	18.91
PG13	19.89	16.52
VG1	1.0545	1.0554
VG2	1.0643	1.0431
VG5	1.0187	1.0137
VG8	1.0351	1.0290

VG11	1.0847	1.0708
VG13	1.0615	1.0597
TAP 6-9	1.0250	1.0625
TAP 6-10	1.0000	0.9875
TAP 4-12	0.9875	1.0125
TAP 28-27	0.9625	0.9675
SHUNT 10	0.03	0.03
SHUNT 12	0.04	0.04
SHUNT 15	0.01	0.01
SHUNT 17	0.01	0.01
SHUNT 20	0.02	0.02
SHUNT 21	0.05	0.05
SHUNT 23	0.03	0.03
SHUNT 24	0.00	0.02
SHUNT 29	0.03	0.03
OPTIMAL FUEL COST (\$/hr)	812.950	810.291
TIME (sec)	1134.2509	974.1925

While solving SCOPF using simple GA, it is observed that the solution obtained is not consistently obtained over a large number of trails. The value of fuel cost obtained as the part of final solution varied from 812 to 818\$/hr. This when compared to the value obtained using mathematical technique in [1], i.e., 813.74 \$/hr does not fare better. The value of fuel cost obtained using real coded Genetic Algorithm varied from 810 to 813 \$/hr over a large number of trails and is better compared to the value reported in [1]. Here, it is to be observed that though some author reported a better value for SCOPF using genetic algorithm [2], it is because the penalty for voltage violations in the contingency cases has not been considered. Simple GA does not appear to be competent in handling a large number of penalty functions added to the basic objective function. Real coded GA, on the other hand worked better for both OPF and SCOPF. Given hereunder are the graphs of best fuel cost obtained for each generation in binary and real coded genetic algorithms. It is observed that there are no violations in base case or contingency cases in the solution obtained by using real or binary coded genetic algorithms. The generator bus voltages in the bar graph that follows are given in red and load bus voltages in blue. Similarly the bus limits are marked by straight lines in the bar graph.

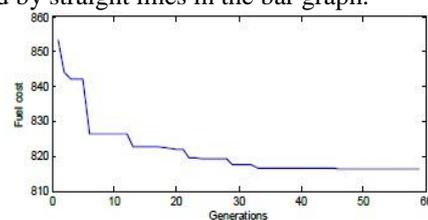


fig8. Convergence characteristics of binary coded GA for SCOPF

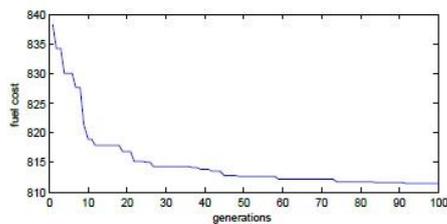


fig9. Convergence characteristics of real coded GA for SCOPF

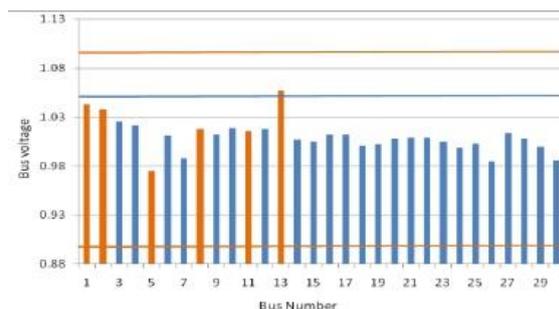


fig 10. Voltage profile for SCOPF using binary coded GA

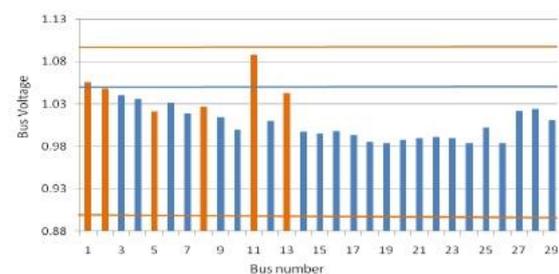


fig11. Voltage profile for SCOPF using real coded GA

VI. Conclusion

In this work, OPF problem is first attempted using binary and real coded Genetic Algorithms. Contingency analysis and ranking is done to find the most severe line outages. These severe contingencies are used in the solution of SCOPF problem using penalty factor method. All the violations in contingency cases are added to the base case fuel cost as penalty. The SCOPF problem is also attempted using binary and real coded Genetic Algorithms. It is also shown that the timing consumed in performing the case study is less compared with results in [13].

Case studies for all the algorithms are made on the standard IEEE 30 bus test system. Based on the investigations carried out at various stages of the thesis and presented in different chapters, the following conclusions can be drawn.

- Binary coded GA works on par with the classical mathematical techniques for solving the OPF problem. The average solution obtained using binary GA over a large number of trial runs is about 802.3 \$/hr, which is nearly same as the one

reported in [1], i.e., 802.4\$/hr, obtained using mathematical technique (Dommel- Tinney approach).

- Real coded GA works better in finding the global optimal solution for the OPF problem when compared with the binary coded GA. The average solution obtained using real coded GA is about 801.4\$/hr, which is a better value compared to the above mentioned values obtained using binary coded GA or the mathematical technique.
- The average time taken for convergence of real coded GA is less compared to that of the binary coded GA for the OPF problem. The average time taken for ten trial runs of the real coded GA is nearly 200 seconds. This is better compared to the average of about 500 seconds for the binary coded GA.
- Binary coded GA does not appear to be competent enough to handle the SCOPF problem. The solution obtained for SCOPF using binary GA showed a wide variation over a large number of trial runs. The value of fuel cost varied from 812 \$/hr to 818 \$/hr over ten trial runs. The average solution obtained does not fare better compared to the value 813.74\$/hr, obtained using mathematical technique reported in [1].
- Real coded GA works better than the mathematical approach for solving SCOPF problem. This is proved by the quality of the solution. The result varied from 810 \$/hr to 813 \$/hr over ten trial runs. This is a better average value compared to the above mentioned values obtained using binary coded GA or the mathematical technique.
- The average time taken for convergence is about 1100 seconds for solving the SCOPF using real coded GA. The time taken for convergence increases as the number of contingencies included in the contingency list of SCOPF increases.
- Overloading problem in line 15-18 in outage line 25 is overcome after 2-3 times of running the program.
- The quality of solution achieved & the speed with which it is attained are greatly influenced by the load flow technique used for solution of equality constraints & the optimization technique used for modifying the control variables.

VII. FUTURESCOPE

Solution of multi-objective optimization in the presence of FACTS devices may be attempted. Coordinated control of FACTS devices for optimizing various objective functions can also be further attempted using multi-objective evolutionary algorithms.

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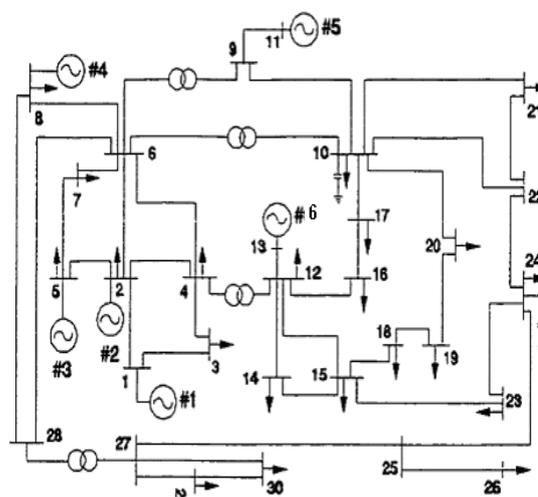
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APPENDIX



IEEE 30 BUS SYSTEM

Number of buses=30

Number of lines=41

Number of off nominal taps=4

Number of shunts=2

variable	Min	Max
Generator bus voltage	0.95	1.1
Load bus voltage	0.95	1.05
Transformer tap	0.9	1.1
Shunts	0.00	0.05

Variable limits