Enhanced Genetic Algorithm Based Model for Power System Optimal Load Flow

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Abstract-* An Enhanced genetic algorithm (EGA) which is used to the solution of the optimal load flow (OPF) with both continuous and discrete control variables. The tenuous control variables modeled are unit active power outputs and generator–bus voltage magnitudes while the discrete ones are transformer – tap settings and switchable shunt devices. A number of functional operating constraints, such as branch flow limits, load bus voltage magnitude limits, and generator reactive capabilities, are included as penalties in the GA fitness function (FF). Advanced and problem specific Operators are introduced in order to enhance the algorithm's efficiency and accuracy. A load flow analysis solves for the flows and voltages at all points in the system. On a typical system, those values are measured at only a handful of points (typically substations). A load flow lets you determine conditions throughout the entire system. Load flow analysis is fast, versatile, and powerful. Traditional load flow algorithms are not always suitable for the configuration, size or loading conditions found on distribution systems. Numerical results for the given test systems are compared with the results of other approaches.

Keywords-* Enhanced genetic algorithm (EGA), optimal power flow (OPF), Bus admittance matrix, Generator bus voltage modeling, load flow analysis, network layers, fitness function (FF), and penalty factor.

I. INTRODUCTION

The OPF optimizes a power system operating objective functions (such as the operating cost of thermal resources) while satisfying a set of system operating constraints, including constraints dictated by the electric network. OPF has been widely used in power system operation and planning. After the electricity sector restructuring, OPF has been used to assess the spatial variation of electricity prices and as a congestion management and pricing tool.

In its most general formulation, the OPF is a nonlinear, non-convex, large-scale, static optimization problem with both continuous and discrete control variables. Even in the absence of non convex unit operating cost functions, unit prohibited operating zones, and discrete control variables, the OPF problem is non convex due to the existence of the nonlinear (AC) power flow equality constraints. The presence of discrete control variables, such as switchable shunt devices, transformer tap positions, and phase shifters, further complicates the problem solution.

The literature on OPF is vast, and presents the major contributions in this area. Mathematical programming approaches, such as nonlinear programming (NPL), quadratic programming (QP), and linear programming (LP), have been used for the solution of the OPF problem. 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, the inequality constraints are added as quadratic penalty terms to the problem objective, multiplied by appropriate penalty multipliers. Interior point (IP) methods, convert the inequality constraints to equalities by the introduction of nonnegative slack variables. A logarithmic barrier function of the slack variables is then added to the objective function, multiplied by a barrier parameter, which is gradually reduced to zero during the solution process. The unlimited point algorithm uses a transformation of the slack and dual variables of the inequality constraints which converts the OPF problem KKT conditions to a set of nonlinear equations, thus avoiding the heuristic rules for barrier parameter reduction required by IP methods.

OPF programs based on mathematical programming approaches are used daily to solve very large OPF problems. However, they are not guaranteed 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. To avoid the prohibitive computational requirements of mixed-integer programming, discrete control variables are initially treated as continuous, and post-processing discretization logic is subsequently applied. Whereas the effects of discretization on load tap changing transformers are small and usually negligible, the rounding of switch able shunt devices may lead to voltage infeasibility, especially when the discrete VAR steps are large, and requires special logic. The handling of non-convex OPF objective functions, as well as the unit prohibited operating zones, also present problems to mathematical programming OPF approaches.

Recent attempts to overcome the limitations of the mathematical programming approaches include the application of simulated annealing-type methods, and genetic algorithms (GAS).

In a simple genetic algorithm (SGA) is used for OPF solution. The control variables modeled are generator active power outputs and voltages; shunt devices, and transformer taps. Branch flow, reactive generation, and voltage magnitude constraints are treated as quadratic penalty terms I the GA fitness function (FF). To deep the GA chromosome area is used for the encoding of each control variable. A sequential GA solution scheme is employed to achieve acceptable control variable resolution. Test results on the IEEE 30-bus system, comprising 25 control variables, are presented.

In a GA is used to solve the optimal power dispatch problem for a multimode 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. A GA with two advanced operators, namely, elitism and hill climbing, is used. A 10-bit chromosome area is devoted to each control variable. Test results on a 17-node, 34-control variable system are presented.

The GA-OPF approaches overcome the limitations of the conventional approaches in the modeling on nonconvex 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, the number of control variables. Thus, the test results in the existing GA-OPF literature are limited to very small problems.

This paper presents an enhanced genetic algorithm (EGA) for the solution of the OPF. The control variables and constraints included in the OPF and the penalty method treatment of the functional operating constraints is similar to the ones in with the following improvements: switchable shunt devices and transformer taps are modeled as discrete control variables. Variable binary string length is used for different types of control variables, so as to achieve the desired resolution for each type of control variable, without unnecessarily increasing the size of the GA chromosome. In addition to the basic genetic operators of the SGA used in and the advanced ones used in, problem-specific operators, inspired by the nature of the OPF problem, have been incorporated in our EGA. With the incorporation of the problem-specific operators, the GA can solve larger OPF problems. Test results on systems with up to 242 buses and 500 control variables demonstrate the improvement achieved with the aid of problem-specific operators.

II. Optimal Power Flow Problem Formulation

The OPF problem can be formulated as a mathematical optimization problem as follows:

Min $f(x,u)$
S.t g(x,u) = o
h (x,u) £ 0
u ä U

where

X= »θ^T $U^T{}_L]^T$

U= $[P^T{}_G\, U^T{}_G\, t^T\, b^T{}_{SH}]^T$

The equality constraints area the nonlinear power flow equations. The inequality constraints are the functional operating constraints, such as

- Branch flow limits (MVA, MW or A);
- Load bus voltage magnitude limits,
- Generator reactive capabilities;
- Slack bus active power output limits,
- Constraints define the feasibility region of the problem control variables such as
- Unit active power output limits;
- Generation bus voltage magnitude limits;
- Transformer-tap setting limits (discrete values);
- Bus shunt admittance limits (Continuous or discrete control).

A. Genetic Algorithms

Genetic algorithms are general-purpose optimization algorithm based on the mechanics of natural selection and genetics. They operate on string structures (chromosomes), typically a concentrated list of binary digits representing a coding of the control parameters of a given problem. Chromosomes themselves are composed of genes. The real value of a parameters, encoded in a gene, is called an allele.

GAs are an attractive to other optimization methods because of Their robustness. There are three major difference between Gas and conventional optimization algorithms. First, Gas operate on the encoded string of the problem parameters rather than actual parameters of the problem, Each string can be thought of as a chromosome that completely describes one candidate solution to the problem. Second, Gas use a population of points rather than a string point in their search. [1]

This allows the GA to explore several areas of the search space simultaneously, reducing the probability of finding local optima. Third, Gas do not require any prior knowledge,

Space limitations, or special properties of the function to be optimized, such as smoothness, convexity, unimodality, or existence of derivatives. They only require the evaluation of the so-called fitness function (FF) to assign a quality value to every solution produced.

Assuming an initial random population produced and evaluated, genetic evaluation takes place by means of three basic genetic operators:

1) Parent selection;
2) Crossover;
3) Mutation.

Parent selection is a simple procedure where by two chromosomes are selected from the parent population based on their fitness value. Solutions with high fitness values have probability of contributing new offspring to the next generation. The selection rule used in our approach is a simple roulette-wheel selection.

Crossover is an extremely important operator for the GA. It 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 (0.6 – 0.9). The chromosomes of the two parents selected are combined to from new chromosomes that inherit segments of information stored in parent chromosomes. Until now, many crossover schemes, such as single point, multipoint, or uniform crossover has been used in our implementation.

While crossover is the main genetic operator exploiting the information included in the current generation, it does not produce new information.

Mutation is the operator responsible for the injected of new information. With a small probability, random bit of the off spring chromosomes flip from 0 to 1 and vice versa and give new characteristics that do not exist in the parent population. In our approach, the mutation operator is applied with a relatively small probability (0.0001 – 0.001) to every bit of the chromosomes.

The FF evaluation and genetic evaluation take part in an iterative procedure, which ends when a maximum number of generations is reached.

B. *Genetic Algorithm Solution To Optimal Power Flow [2]*

The control variables namely 1) PG; 2) UG; 3) t; 4) bsh. The Encoding is performed using different gene-lengths for each set of control variables, depending on the desired accuracy. The decoding of a chromosome to the problem physical variables is performed as follows:

The continuous controls variable in the interval [PG_i^{min}, PG_i^{max}]

$$PGi = PG_i^{min} + (PG_i^{max} - PG_i^{min}) \times \frac{\text{Decoded value of (PGi)}}{2^{li} - 1}$$

Where

li = sub-string length

1) *Fitness Function*

GAs are usually designed so as to maximize the FF, which is a measure of the quality of each candidate solution. The objective of the OPF problem is to minimize the total operating cost.

$$FF = \frac{1}{\sum_{i=1}^{NG} Fi\,(PGi) + \sum_{i=1}^{Nc} (\text{control variable})}$$

where

Fi (PGi) = Generator fuel cost
λ = Penalty factor
Pg , Ug , t , bsh = Control variables

The canonical form of genetic algorithm is presented as follows:

STEP 1. Define the problem based on genetic representation
STEP 2. Initialize all strings and genetic operators.
STEP 3. Evaluate fitness for each string.
STEP 4. Select pairs of strings of highest fitness value or using selection operator.
STEP 5. Create offsprings using crossover and mutation.
STEP 6. Check whether population size exceed the specified value or not. If yes go to step7 otherwise go to step 8.
STEP 7. Replace the weakest offspring by strong offsprings.

STEP 8. Mix offsprings with population.
STEP 9. Calculate fitness for offsprings and check whether optimized solution is reached. If yes exit or otherwise go to step 4.

III. ENHANCED GENETIC ALGORITHM (EGA) [4]

One of the most important issues in the genetic evaluation is the effective rearrangement of the gene type information. In the SGA (simple genetic algorithm) crossover is the main genetic operator responsible for the exploitation of information while mutation brings new nonexistent bit structure. It is widely recognized that the SGA scheme is capable of locating the neibourood of the optimal or near –optimal solutions, but, in general, require a large number of generation to converge. This problem becomes more intense for large-scale optimization problems with difficult search spaces and lengthy chromosomes. Where the possibility for the SGA to get trapped in local optima

Increases and the convergence speed of the SGA decrease. At this point, a suitable combination of the basic, advanced, in order to enhance the performance of the GA. Advanced and problem-specific genetic operators usually combine local search techniques and expertise derived from the nature of the problem.

A set of advanced and problem-specific genetic operators has been added to the SGA in order to increase its convergence speed and improve the quality of solutions. Our interest was focused on constructing simple yet powerful enhanced genetic operators that effectively explore the problem search space. The advanced features included in our GA implementation are as follows.

i) Fitness Scalling: In order to avoid early domination of extraordinary strings and to converge a healthy completion among equals, a scaling of the fitness of the population is necessary. In our approach, the fitness is scaled by a linear transformation.

ii) Elitism: Elitism ensures that the best solution found thus far is never lost when moving from one generation to another. The best solution of each generation replaces a randomly selected chromosome in the new generation.

iii) Hill Climbing: In order to increase the GA search speed at smooth areas of the search space a hill-climbing operator is introduced, which perturbs a randomly selected control variable. The modified chromosome is accepted if there is an increase in FF valve; otherwise, the old chromosome remains unchanged. This operator is applied only to the best chromosome (elite)of every generation.

In addition to the above advanced features, which are called "advanced" despite their wide use in most recent GA implementations to distinguish between the SGA and our EGA, operators specific to the OPF problem have been added.

All problem-specific operators introduce random modification to all chromosomes of a new generation. If the modified chromosome proves to have better fitness, it replaces the original one in the new population. Otherwise the original chromosome is retained in the new population. All problem-specific operators are applied with a probability of 0.2. The following problem-specific operators have been used.

1) *Gene Swap Operators (GSO):*

1st control					…					Nth control				
1	0	0	1	0	.	.	.	.	.	0	0	1	0	1

This operator randomly selects two genes in a chromosome and swaps their values, as shown. These operators swaps the active power output of two units, the voltage magnitude of two generation buses, etc. Swapping among different types of control variables in not allowed.

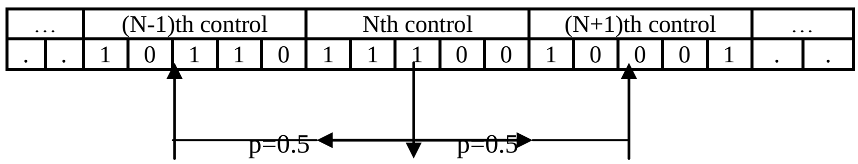
2) *Gene Cross-Swap Operator (GCSO):*

1st control					. . .					Nth control				
1	0	1	1	0	.	.	.	.	.	1	1	1	0	0

1	0	1	1	0	.	.	.	.	.	1	0	0	0	1

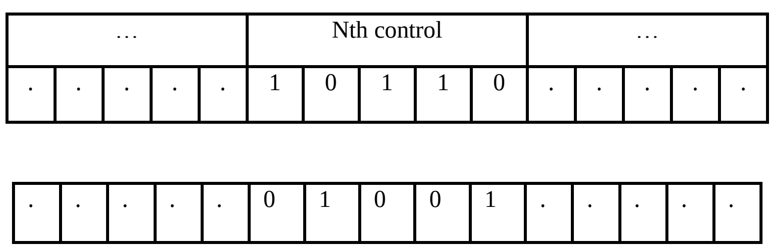
The GCSO is a variant of the GSO. It randomly selects two different chromosomes from the population and two genes, one from every selected chromosome, and swaps their values, as shown. While crossover exchanges information between high-fit chromosomes, the GCSO searches for alternative alleles, exploiting information stored even in low-fit strings
.

3) Gene Copy Operator (GCO):



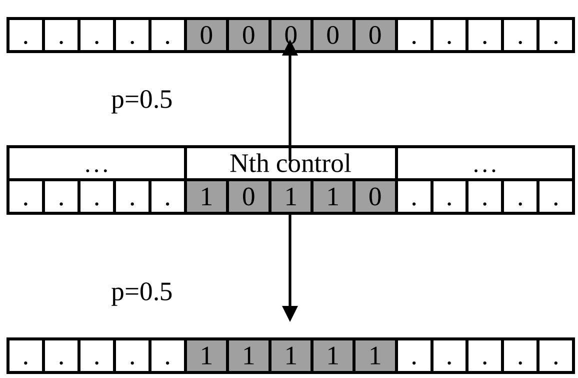
This operator randomly selects one gene in a chromosome and wit equal probability copies its value to the predecessor or the successor gene of the same control type as shown. This operator has been introduced in order to force consecutive controls to operate at the same output level.

4) Gene Inverse Operator (GIO):



This operator acts like a sophisticated mutation operator. It randomly selects one gene in a chromosome and inverses its bit-values from one to zero and vice versa. The GIO searches for bit-structures of improved performance, exploits new areas of the search space far away from the current solution, and retains the diversity of the population.

5) Gene Max-Min Operator (GMMO):



The GMMO tries to identify binding control variable upper/lower limit constraints. It selects a random gene in a chromosome and, wit the same probability (0.5), fills its area with 1's or 0's as shown.

IV. FLOWCHART

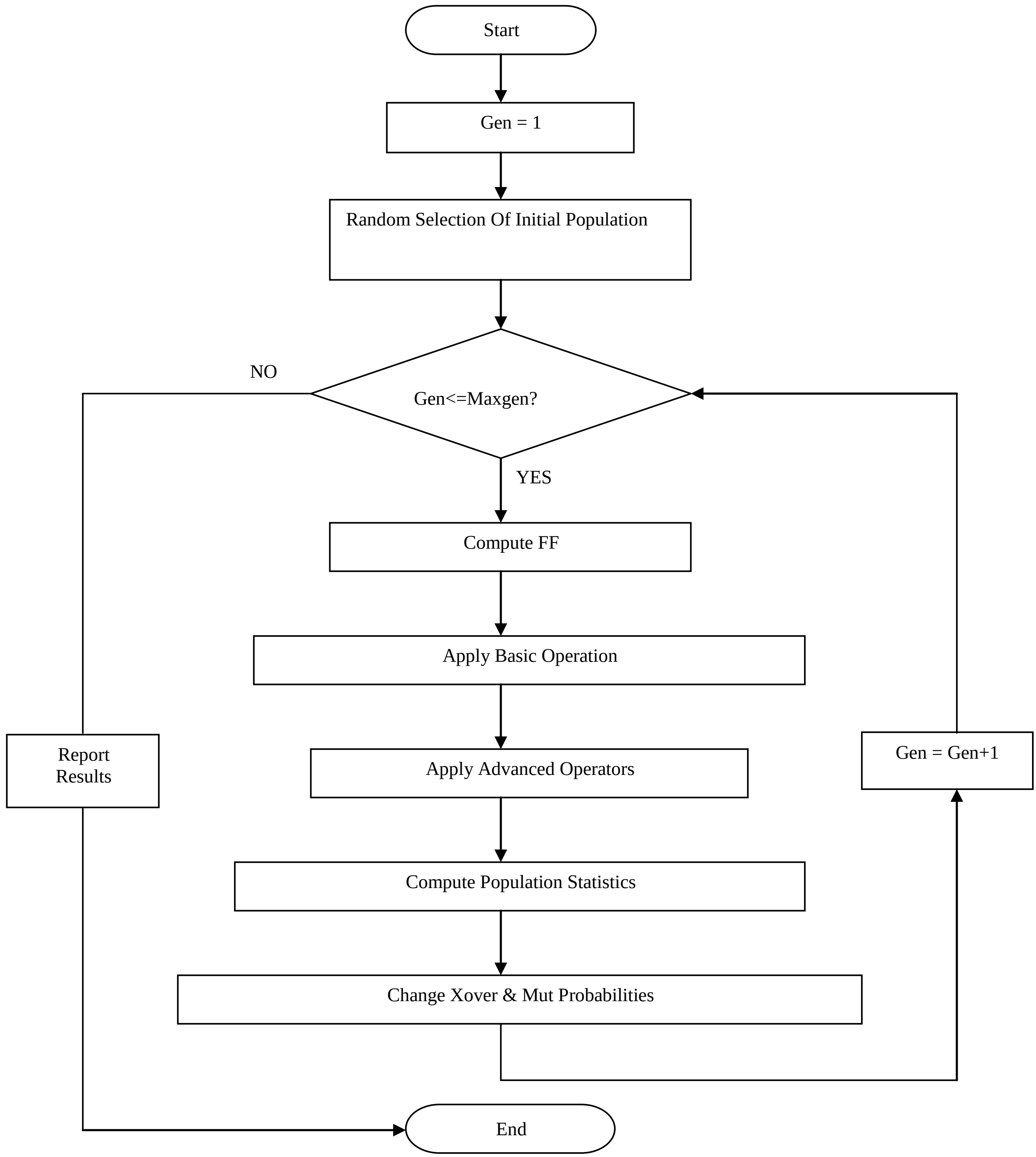


Fig 1: Enhanced Genetic Algorithm (EGA)

The canonical form of enhanced genetic algorithm is presented in figure 1 with step by step by procedure.

V. RESULTS

In this section the proposed EGA solution of the OPF is evaluated using the IEEE 30 – Bus system. The system consists of 30 Bus, 41 branch and 24 control variables. The 5 unit active power outputs, 6 generator bus voltage magnitudes, 4 transformers – tap settings, and 9 bus shunt admittances.

TABLE – I

Generator bus voltage magnitude and unit real power output cost								
Unit No	Bus N0	Worst solution			Best Solution			
		V_G [pu]	P_G [MW]	Cost [Rs/h]	V_G [pu]	P_G [MW]	Cost [Rs/h]	Marg. Cost Rs/MWh
1	1	1.050	175.94	23397	1.050	176.204	2344.2	166.1
2	2	1.039	49.33	6446	1.038	48.75	6344.5	172.8
3	5	1.011	21.50	2520.50	1.012	21.44	2509.5	184.05
4	8	1.020	22.48	3863.50	1.020	21.95	3767.5	180.80
5	11	1.074	11.55	1900	1.082	12.42	2065	181.05
6	13	1.066	12.00	1980	1.067	12.02	1983.5	180.05
		Total	292.80	40107	Total	292.79	19014.2	

BUS SHUNT ADMITTANCES									
SHUNT NO	1	2	3	4	5	6	7	8	9
BUS NO	10	12	15	17	20	21	23	24	29
WORST CASE b_{SH} [pu]	0.02	0.04	0.05	0.05	0.04	0.05	0.05	0.05	0.04
BEST CASE B_{SH} [PU]	0.05	0.05	0.03	0.05	0.05	0.05	0.04	0.05	0.03

TRANSFORMER – TAP SETTINGS				
Transformer No	1	2	3	4
From / To Bus No	6-9	6-10	4-12	28-27
Worst case Tap position	1.0250	0.9375	1.0000	0.9750
Best case Tap position	1.0125	0.9500	1.0000	0.9625

VI. CONCLUSION

A GA solution to the OPF problem has been presented and applied to small and medium size systems. The main advantage of the GA solution to the OPF problem is its modeling flexibility; nonconvex unit cost functions, prohibited unit operating zones, discrete and control variables and complex non linear constrains can be easily model. Another advantage is that can be easily coded to work on parallel computers.

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