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An Enriched Adaptive Genetic Algorithm for Solving Reactive Power Problem

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ABSTRACT: This paper presents Enriched Adaptive Genetic Algorithm (EAGA) for solving reactive powerproblem .The projected algorithm is based on the newly developed adaptive strategy and introduces a normalized fitness between the current individual and other individuals in the population to the control probability of mutation. In the projected adaptive genetic algorithm the probability of cross over and mutation p_c and p_m are varied depending on the fitness values of the solutions and the normalized fitness distance between the solutions in the evaluation process to prevent premature convergence and refine the convergence performance of genetic algorithms. These ideas are entrenched into projected algorithm for solving Reactive power problem.

KEYWORDS: Enriched adaptive genetic algorithm, probability of crossover, probability of mutation, reactive power problem.

I. INTRODUCTION

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a nonlinear optimization problem. Generally, the optimal VAR dispatch problem has many objectives such as: reducing the fuel costs: ameliorating the supply quality and reliability by improving the voltage profile over the system; and enhancing the system security by uploading the system equipment. The reactive power optimization problem is a nonlinear combinatorial optimization problem.Previously many types of mathematical methodologies like linear programming, gradient method (Alsac et al., 1973; Lee et al., 1985; Monticelli et al., 1987; Deeb et al., 1990; Hobson, 1980; Lee et al., 1993; Mangoli et al., 1993; Canizares et al., 1996) [1-8] has been utilized to solve the reactive power problem, but they lack in handling the constraints to reach a global optimization solution. In the next level various types of evolutionary algorithms (Berizzi et al., 2012; Roy et al., 2012; Hu et al., 2010; Eleftherios et al., 2010) [9-12] has been applied to solve the reactive power problem. The proposed algorithm is based on the recently developed adaptive strategy (Srinivas, M and Patnaick, L.M,1994) [13]and introduces a normalized fitness between the current individual and other individuals in the population to the control probability of mutation. In the adaptive genetic algorithm the probability of cross over and mutation p_c and p_m are varied depending on the fitness values of the solutions and the normalized fitness distance between the solutions in the evaluation process to prevent premature convergence and refine the convergence performance of genetic algorithms. The performance of proposed algorithm is evaluated on standard IEEE 30 bus power system.

II. PROBLEM FORMUMATION

The objective of the reactive power dispatch problem is to minimize the active power loss and can be written in equations as follows:

$$F = P_L = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \quad (1)$$

Where F- objective function, P_L – power loss, g_k- conductance of branch,V_i and $V_j$are voltages at buses i,j, Nbr- total number of transmission lines in power systems.

A Voltage profile improvement

To minimize the voltage deviation in PQ buses, the objective function (F) can be written as:

$$F = P_L + \omega_v \times VD \quad (2)$$

Where VD - voltage deviation,ω_v- is a weighting factor of voltage deviation.

And the Voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (3)$$

Where Npq- number of load buses

B Equality Constraint

The equality constraint of the problem is indicated by the power balance equation as follows:

$$P_G = P_D + P_L \quad (4)$$

Where P_G- total power generation, P_D - total power demand.

C Inequality Constraints

The inequality constraint implies the limits on components in the power system in addition to the limits created to make sure system security. Upper and lower bounds on the active power of slack bus (P_g), and reactive power of generators (Q_g) are written as follows:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \quad (5)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \quad (6)$$

Upper and lower bounds on the bus voltage magnitudes (V_i) is given by:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \quad (7)$$

Upper and lower bounds on the transformers tap ratios (T_i) is given by:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \quad (8)$$

Upper and lower bounds on the compensators (Q_c) is given by:

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \quad (9)$$

Where N is the total number of buses, N_g is the total number of generators, N_T is the total number of Transformers,N_c is the total number of shunt reactive compensators.

III. SIMPLE GENETIC ALGORITHM

GAs is search algorithms based on the mechanics of natural genetics and natural selection. The GA is a population search method. A population of strings is kept in each Generation. The simulation of the natural processes of reproduction, gene crossover and mutation produces the next generation.

A Reproduction

Reproduction is simply an operation whereby an old chromosome is copied into a “mating pool” according to its fitness value. More highly fitted chromosomes receive a greater number of copies in the next generation. Copying chromosomes according to their fitness values means that chromosomes with a higher value have a higher probability of contributing one or more offspring in the next generation.

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BCrossover

Crossover is the primary genetic operator, which promotes the exploration of new regions in the search space. It is a structured, yet randomized mechanism of exchanging informing between strings. This operation is similar to that of two scientists exchanging information. Crossover begins by selecting at random two members previously placed in the mating pool during reproduction. A crossover point is then selected at random and information from one parent, up to the crossover point is exchanged with the other member, thus creating two new members for the next generation.

CMutation

Although reproduction and crossover effectively search and recombine existing chromosomes, they do not create any new genetic material in the population. Mutation is capable of overcoming this shortcoming. It is an occasional (with small probability) random alternation of a chromosome position.

DSelection Method

Here, Roulette wheel selection method is followed. This is fitness proportional selection mechanism. The better fit strings get selected often to pass on their information to their off springs.

IV. ENRICHEDADAPTIVE GENETIC ALGORITHM (EAGA)

EAGA is developed based on the canonical genetic algorithm (CGA). The CGA consists of an n-tuple of binary strings b_i of length l, where the bits of each string are considered to be the genes of an individual chromosome and where the n-tuple of individual chromosomes is said to be a population. In a multiple variable optimization problem, the individual variable coding is usually concatenated into a complete string. To decode a string, bit strings with specified string length are extracted successfully from the concatenated string and the sub strings are then decoded and mapped into the value in the corresponding search space. There are three main GA operators: reproduction, crossover, and mutation. The reproduction operator allows highly productive chromosomes (strings) to live and produce off springs in the next generation. The crossover operator, used with a specified probability, exchanges genetic information by splitting two chromosomes at a random site and joining the first part of one chromosome with second part of another chromosome. Mutation introduces occasional changes of a random string position with a specified mutation probability.

A Reproduction, Crossover and Mutation

The significance of P_c and P_m in controlling GA performance has long been acknowledged in GA research. The crossover probability P_c controls the rate at which solutions are subjected to crossover. The higher value of P_c, the quicker are the new solutions introduced into the population. As P_c increases, however, solutions can be disrupted faster than selection can exploit them. Mutation is only a secondary operator to restore genetic material. Nevertheless, the choice of P_m is critical to GA performance. Large values of P_m transform in the GA into a purely random search algorithm, while some mutation is required to prevent the premature convergence of the GA to sub optimal solutions. Identifying optimal settings for P_c and P_m is an important problem for improving the convergence performances of GAs and has been studied by many researchers.

B Adaptive Strategy

The key idea of the EAGA is to adapt the probabilities of crossover and mutation based on the fitness statistics of population at each generation. In (Srinivas, M and Patnaick, L.M., 1994), it has been observed that the difference between the maximum fitness value and average fitness value of the population. f_{max} - f, like to be less for a population scattered in the solution space. Therefore, the values of P_c and P_m should be varied depending on the value of f_{max} - f. On the other hand, if P_c and P_m have the same values for all the solutions of the population, which means solutions with high fitness values as well as the solutions with low fitness values are subjected to the same level of mutation and crossover, this will certainly deteriorate the performance of GAs. The adaptive strategy for updating P_c and P_m developed in (Srinivas, M and Patnaick, L.M., 1994) takes the following forms.

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$$P_c = \begin{cases} k_1 (f_{max} - f_c)/(f_{max} - f), f_c > f \\ k_3, f_c \leq f \end{cases} \quad (10)$$

$$P_m = \begin{cases} k_2 (f_{max} - f_i)/(f_{max} - f), f_i > f \\ k_4, f_i \leq f \end{cases} \quad (11)$$

Where k_1, k_2, k_3 and k_4 have to be less than 1.0 to constrain P_c and P_m to the range 0.0 - 1.0 f_c is the larger of fitness values of the individuals selected for crossover and f_i is the fitness of the i^{th} chromosome to which the mutation with probability P_m is applied.

V. EAGA IMPLEMENTATION TO REACTIVE POWER PROBLEM

When applying EAGAs to solve a particular optimization problem, two main issues are taken into consideration namely:(i) Representation of the decision variables(ii) Treatment of constraints

A. Representation of the decision variables

While solving optimization problems using EAGA, each individual in the population represents a candidate solution. In the reactive power dispatch problem, the elements of the solution consists of the control variables namely; Generator bus voltage (Vgi), reactive power generated by the capacitor (QCi), and transformer tap settings (tk). These variables are represented in their natural form that is generator bus voltage magnitude and reactive power generation of capacitor are represented as floating point numbers whereas, the transformer tap setting , being a discrete quantity with tapping ranges of ± 10% and a tapping step of 0.025 p.u is represented from the alphabet (0, 1, ….8). The use of floating point numbers and integers to represent the solution alleviates the difficulties associated with the binary-coded GA for real variables.

B. Treatment of constraints

The function of each individual in the population is evaluated according to its ‘fitness’ which is defined as the non-negative figure of merit to be maximized. It is associated mainly with the objective function. In the RPD problem here the objective is to minimize the active power loss and maximize Eigen values of the jacobian matrix of the singular value decomposition while satisfying the equality and inequality constraints.

C. EAGA for Reactive power Problem

a. Start.
b. Read line data, bus data.
c. Generate random variables for V,G, T, Q_C for NP.
d. Decode the n^h population and carryout load flow and get the solution.
e. The fitness function is calculated
f. By Roulette wheel selection from the mating pool.
g. Carry out crossover, Mutation and form new children.
h. Repeat steps (e) and (f) until the child population of size is generated.

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EAGA Flow chart in Fig .1 has been given below for solving reactive power Dispatch problem

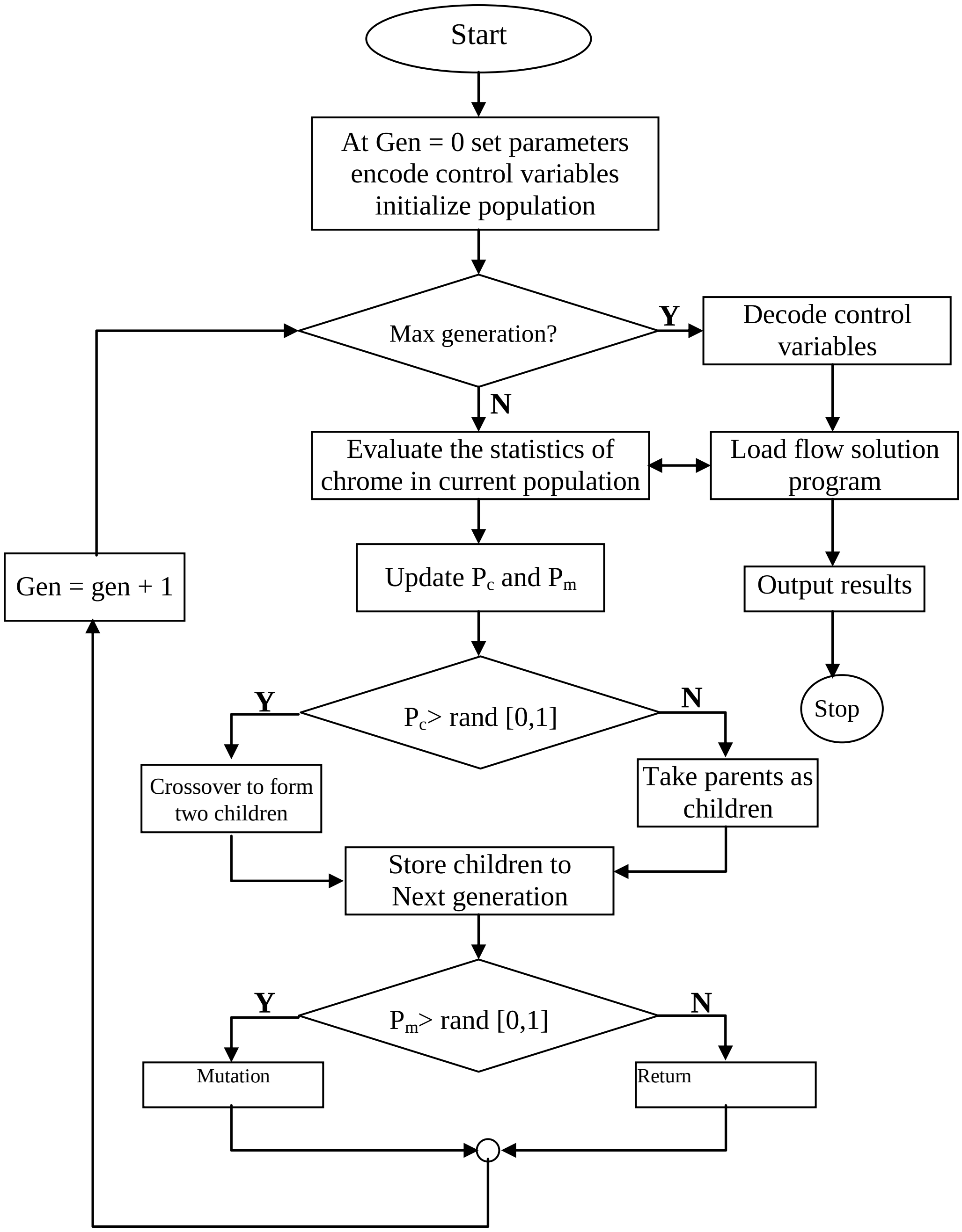

Fig 1. Flow Chart of EAGA Algorithm for Reactive Power Optimization Problem

VI. SIMULATION RESULTS

Validity of proposed EAGA algorithm has been verified by testing in IEEE 30-bus, 41 branch system and it has 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is taken as

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slack bus and 2, 5, 8, 11 and 13 are considered as PV generator buses and others are PQ load buses. Control variables limits are given in Table 1.

Table 1 Primary Variable Limits (Pu)

Variables	Min.	Max.	category
Generator Bus	0.90	1.10	Continuous
Load Bus	0.90	1.05	Continuous
Transformer-Tap	0.92	1.01	Discrete
Shunt Reactive Compensator	-0.10	0.30	Discrete

In Table 2 the power limits of generators buses are listed.

Table 2Generators Power Limits

Bus	Pg	Pgmin	Pgmax	Qgmin
1	96.00	49	200	-19
2	79.00	18	79	-19
5	49.00	14	49	-11
8	21.00	11	31	-14
11	21.00	11	28	-12
13	21.00	11	39	-14

Table 3 shows the proposed EAGA approach successfully kept the control variables within limits.Table 4 narrates about the performance of the proposed EAGA algorithm.Fig 1 shows about the voltage deviations during the iterations and Table 5 list out the overall comparison of the results of optimal solution obtained by various methods.

Table 3After optimization values of control variables

Control Variables	EAGA
V1	1.0519
V2	1.0479
V5	1.0299
V8	1.0398
V11	1.0786
V13	1.0562
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.91
Q10	0.10
Q24	0.10
Real power loss	4.2939
Voltage deviation	0.9073

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Table 4 Performance of EAGA algorithm

Iterations	32
Time taken (secs)	8.92
Real power loss	4.2939

Table 5Comparison of results

Techniques	Real power loss (MW)
SGA(Wu et al., 1998) [14]	4.98
PSO(Zhao et al., 2005) [15]	4.9262
LP(Mahadevan et al., 2010) [16]	5.988
EP(Mahadevan et al., 2010) [16]	4.963
CGA(Mahadevan et al., 2010) [16]	4.980
AGA(Mahadevan et al., 2010) [16]	4.926
CLPSO(Mahadevan et al., 2010) [16]	4.7208
HSA (Khazali et al., 2011) [17]	4.7624
BB-BC (Sakthivel et al., 2013) [18]	4.690
Proposed EAGA	4.2939

VII. CONCLUSION

In this paper, a new approach called Enriched Adaptive Genetic Algorithm (EAGA) has been demonstrated and applied to solve optimal reactive power dispatch problem. In the adaptive GA, low values of Pc and Pm , are assigned to high fitness solutions, while low fitness solutions have very high values of Pc and Pm . The best solution of every population is ‘protected’. The proposed approach is applied to optimal reactive power dispatch problem and tested on the IEEE 30 bus system. The simulation results indicate the effectiveness and robustness of the proposed EAGA approach in solving optimal reactive power dispatch problem.

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