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Reactive Power Planning using Real GA Comparison with Evolutionary Programming

S.K.Nandha Kumar[1], and Dr.P.Renuga[2]

[1] PSNA College of Engineering & Technology / Department of EEE, Dindigul, Tamilnadu, India

Email: nandhaaaa@ gmail.com

[2] Thiagarajar College of Engineering / Department of EEE, Madurai, Tamilnadu, India

Email: preee@ tce.edu

***Abstract*— This paper proposes an application of real coded genetic algorithm (RGA) to reactive power planning (RPP). Several techniques have been developed to make RGA practicable to solve a real power system problem and other practical problems. The proposed approach has been used in the IEEE 30-bus system. Simulation results, compared with those obtained by using the evolutionary programming(EP), are presented to show that the present method is better for power system planning. In the case of optimization of non-continuous and non-smooth function, RGA gives much better results than EP. The comprehensive simulation results show a great potential for applications of RGA in power system economical and secure operation, planning and reliability assessment.**

***Index Terms*—Power systems, real coded genetic algorithm, reactive power planning, artificial intelligence, evolutionary programming.**

I. Introduction

The reactive power planning (RPP) is one of the most complex problems of power systems as it requires the simultaneous minimization of two objective functions. The first objective deals with the minimization of operation cost by reducing real power loss and improving the voltage profile. The second objective minimizes the allocation cost of additional reactive power sources. RPP is a nonlinear optimization problem for a large scale system with a lot of uncertainties. During the last decade there has been a growing concern in the RPP problems for the security and economy of power systems [1-15]. Conventional calculus-based optimization algorithms have been used in RPP for years [l-6]. Conventional optimization methods are based on successive linearization and use the first and second differentiations of objective function and its constraint equations as the search directions. The conventional optimization methods are good enough for the optimization problems of deterministic quadratic objective function which has only one minimum. However, because the formulae of RPP problem are hyper quadric functions, such linear and quadratic treatments induce lots of local minima. The conventional optimization methods can only lead to a local minimum and sometimes result in divergence in solving RPP problems. Over the last decade, Evolutionary Algorithms (EAs), such as, EP and RGA have been extensively used as search and optimization tools in RPP to solve local minimum problems and uncertainties [8-15].

This paper proposes an application of real coded genetic algorithm (RGA) to solve the RPP, 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 selection operator works with the fitness value, any selection operator used with binary coded GAs can also be used in real parameter GAs.

The proposed method is compared with EP, another Evolutionary Algorithm method. Both RGA and EP uses population of potential solutions, not single point, which can move over hills and across valleys to discover a globally optimal point. Because the computation for each individual in the population is independent of others, RGA and EP has inherent parallel computation ability. Both RGA and EP uses payoff (fitness or objective functions) information directly for the search direction, not derivatives or other auxiliary knowledge, therefore can deal with non-smooth, non- continuous and non-differentiable functions that are the real-life optimization problems. RPP is one of such problems. This property also relieves RGA and EP of approximate assumptions for a lot of practical optimization problems, which are quite often required in traditional optimization methods. Both RGA and EP uses probabilistic transition rules to select generations, not deterministic rules, so they can search a complicated and uncertain area to find the global optimum which makes RGA and EP, a more flexible and robust than the conventional methods.

The difference between RGA and EP is that, the RGA is based on the mechanics of natural selections-selection, crossover and mutation, whereas EP is based on mutation, competition and evolution.

The proposed approach has been used in the RPP problems for the IEEE 30-bus system [18] which consists of six generator buses, 21 load buses and 41 branches of which four branches, (6,9), (6,10), (4,12) and (28,27) are under load tap-setting transformer branches. The reactive power source installation buses are buses 10 and 24. There are totally 12 control variables. The results using

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RGA are compared with another evolutionary algorithm based method, EP.

II. PROBLEM FORMULATION

List of Symbols

N_l = set of numbers of load level durations
N_E = set of branch numbers
N_c = set of numbers of possible VAR source installment buses
N_i = set of numbers of buses adjacent to bus *i,* including bus *i*
N_{PQ} = set of PQ - bus numbers
N_g = set of generator bus numbers
N_T = set of numbers of tap - setting transformer branches
N_B = set of numbers of total buses
h = per - unit energy cost
d_l = duration of load level *1*
g_k = conductance of branch *k*
V_i = voltage magnitude at bus *i*
θ_{ij} = voltage angle difference between bus *i* and bus j
e_i = fixed VAR source installment cost at bus *i*
C_{ci} = per - unit VAR source purchase cost at bus *i*
Q_{ci} = VAR source installed at bus *i*
Q_i = reactive power injected into network at bus *i*
G_{ij}, B_{ij} = mutual conductance and susceptance between bus *i* and bus *j*
G_{ii}, B_{ii} = self conductance and susceptance of bus *i*
Q_{gi} = reactive power generation at bus *i*
T_k = tap -setting of transformer branch *k*
N_{Vlim} = set of numbers of buses of voltage overlimits
N_{Qglim} = set of numbers of buses of reactive power generation overlimits

The objective function in RPP problem comprises two terms [14]. The first term represents the total cost of energy loss as follows:

$$W_c = h \sum_{l \in N_l} d_l P_{loss,l} \qquad (1)$$

where $P_{loss,l}$ is the network real power loss during the period of load level *1*. The $P_{loss,l}$ can be expressed in the following equation in the duration d_l :

$$P_{loss} = \sum_{\substack{k \in N_E \\ k \in (i,j)}} g_k \left(V_i^2 + V_j^2 - 2V_i V_j Cos\theta_{ij}\right) \qquad (2)$$

The second term represents the cost of VAR source installments which has two components, namely, fixed installment cost and purchase cost:

$$I_c = \sum_{i \in N_c} \left(e_i + C_{ci} Q_{ci}\right) \qquad (3)$$

The objective function, therefore, can be expressed as follows:

$$\begin{aligned}
&\min f_C = I_C + W_C \\
&s.t. \\
&0 = Q_i - V_i \sum_{j \in N_i} V_j \left(G_{ij} Sin\,\theta_{ij} - B_{ij} Cos\,\theta_{ij}\right) && i \in N_{PQ} \\
&Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max} && i \in N_c \\
&Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} && i \in N_g \\
&V_i^{\min} \le V_i \le V_i^{\max} && i \in N_B \\
&T_k^{\min} \le T_k \le T_k^{\max} && k \in N_T
\end{aligned} \qquad (4)$$

where reactive power flow equations are used as equality constraints; VAR source installment restrictions, reactive power generation restrictions, transformer tap-setting restrictions and bus voltage restrictions are used as inequality constraints. $Q^{min}{}_{ci}$ can be less than zero and if Q_{ci} is selected as a negative value, say in the light load period, variable reactance should be installed at bus i. The transformer tap setting *T,* generator bus voltages V_g and VAR source installments Q_c are control variables so they are self restricted. The load bus voltages V_{load} and reactive power generations Q_g are state variables, which are restricted by adding them as the quadratic penalty terms to the objective function to form a penalty function. Equation (4) is therefore changed to the following generalized objective function:

$$\min F_C = f_C + \sum_{i \in N_{V\lim}} \lambda_{Vi}\left(V_i - V_i^{\lim}\right)^2 + \sum_{i \in N_{Qg\lim}} \lambda_{Qgi}\left(Q_{gi} - Q_{gi}^{\lim}\right)^2$$

s.t.

$$0 = Q_i - V_i \sum_{j \in N_i} V_j \left(G_{ij} Sin\,\theta_{ij} - B_{ij} Cos\,\theta_{ij}\right)$$
$$i \in N_{PQ}$$

where λ_{vi} and λ_{Qgi} are the penalty factors which can be increased in the optimization procedure; $V^{lim}{}_i$ and $Q^{lim}{}_{gi}$ are defined in the following equations:

$$V_i^{lim} = \begin{cases} V_i^{min} & if\ V_i < V_i^{min} \\ V_i^{max} & if\ V_i > V_i^{max} \end{cases}$$

$$Q_{gi}^{lim} = \begin{cases} Q_{gi}^{min} & if\ Q_{gi} < Q_{gi}^{min} \\ Q_{gi}^{max} & if\ Q_{gi} > Q_{gi}^{max} \end{cases}$$

It can be seen that the generalized objective function F_C is a nonlinear and non-continuous function. Furthermore, it contains a lot of uncertainties because of uncertain loads and other factors.

III. REAL CODED GENETIC ALGORITHM (RGA)

In RGA, the 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. However, the difficulty arises with the search operators. 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. To create the offspring using RGA, this paper proposes tournament selection, Blend Crossover (BLX-α) and the Normally Distributed Mutation [19].

Tournament Selection

In the tournament selection, tournaments are played between two solutions and the better solution is chosen and placed in the mating pool. Two other solutions are picked again and another slot in the mating pool is filled with the better solution. If carried out systematically, each solution can be made to participate in exactly two tournaments.

Blend Crossover (BLX-α)

In Blend Crossover operator (BLX-α), for two parent solutions $x^{(1,t)}_{i,}$ and $x^{(2,t)}_{i}$, the BLX-α randomly picks a solution in the range $[x^{(1,t)}_{i,} - \alpha\ (x^{(2,t)}_{i} - x^{(1,t)}_{i,})\ ,\ x^{(2,t)}_{i} + \alpha\ (x^{(2,t)}_{i} - x^{(1,t)}_{i,})]$. Thus, if u_i is a random number between 0 and 1, the following is an offspring.
$x^{(1,t+1)}_{i} = (1-\gamma_i)\ x^{(1,t)}_{i,} + \gamma_i\ x^{(2,t)}_{i}$, where $\gamma_i = (1+2\alpha)u_i - \alpha$.

Normally Distributed Mutation

It represents a zero-mean Gaussian probability distribution. Thus the offspring is represented by,

$$y^{(1,t+1)}_{i} = x^{(1,t+1)}_{i} + N(0,\sigma_i)$$

Essential steps of the Real GA:

The essential steps of the real GA are summarized as follows:

1. Initialize a starting population
2. Evaluate and assign fitness value to individuals
3. Is termination criteria met? Yes, turn to Step 8, otherwise, continue
4. Perform reproduction using tournament selection
5. Perform Blend Crossover
6. Perform Normally Distributed Mutation
7. Perform genetic post-processing to reconstruct GA population; go to 2
8. Output the optimal individual of the current population, end.

IV. COMPARISON METHOD

The comparison method used here is the evolutionary programming (EP) method. The general process of EP is described in [13]. The procedure of EP for RPP is briefed as follows:

1. Initialization: The initial control variable population is selected randomly. The fitness score is obtained by running P-Q decoupled power flow.
2. Statistics: The maximum fitness, minimum fitness, sum of fitness and average fitness of this generation are calculated.
3. Mutation: Each parent population is mutated and the corresponding fitness is obtained by running power flow. A combined population is formed with the old generation and the mutated old generation.
4. Competition: Each individual in the combined population has to compete with some other individuals to get its chance to be transcribed to the next generation.
5. Determination: The convergence of maximum fitness to minimum fitness is checked. If the convergence condition is not met, the mutation and competition processes will run again. If it converges, the program will check over limits of state variables. If there is no over limit, the program stops. If one or more state variables exceed their limits, the penalty factors of these variables will be increased, and then another loop of the process will start.

V. NUMERICAL RESULTS

In this section, IEEE 30-bus system [18] has been used to show the effectiveness of the algorithm. The network consists of 6 generator-buses, 21 load-buses and 41 branches, of which four branches, (6, 9), (6, 10), (4, 12) and (28, 27), are under load-tap setting transformer

TABLE I
PARAMETERS AND LIMITS

S_B (MVA)	*h ($/kWh)*	*e_i($)*	*C_{ci} ($/kVAR)*		
100	*0.06*	*1000*	*30*		
Reactive Power Generation Limits					
Bus	*2*	*5*	*8*	*13*	
Q^{max}_{g}	*0.5*	*0.4*	*0.4*	*0.155*	
Q^{min}_{g}	*-0.4*	*-0.4*	*-0.1*	*-0.078*	
Voltage and Tap-setting Limits					
V^{max}_{g}	*V^{min}_{g}*	*V^{max}_{load}*	*V^{min}_{load}*	*T^{max}_{k}*	*T^{min}_{k}*
1.1	*0.9*	*1.05*	*0.95*	*1.05*	*0.95*
Var source Installments and Voltage limits					
Q^{max}_{c}	*Q^{min}_{c}*	*V^{max}_{c}*	*V^{min}_{c}*		
0.36	*-0.12*	*1.05*	*0.95*		

branches. The parameters and variable limits are listed in Table I. The possible VAR source installment buses are Buses 10 and 24. All power and voltage quantities are per-unit values and the base power is used to compute the energy cost.

5.1 Initial Condition

All transformer taps are set to *1.0.* The initial generator voltages are set to *1.0.* The loads are given as,

TABLE II
INITIAL GENERATIONS AND POWER LOSSES

P_g	Q_g	P_{loss}	Q_{loss}
3.0099	1.2514	0.1759	0.2224

P_{load} = 2.834 and Q_{load} = 1.262

The initial generations and power losses are obtained as in Table II.

TABLE III
GENERATOR BUS VOLTAGES

Bus	1	2	5	8	11	13
RGA	1.1	1.1	1.0538	1.0655	1.0756	1.0992
EP	1.1	1.0964	1.0734	1.0625	1.0730	1.0999

TABLE IV
TRANSFORMER TAP-SETTINGS

Branch	(6,9)	(6,10)	(4,12)	(28,27)
RGA	0.9969	0.9721	1.0003	0.9631
EP	1.0055	0.9955	1.0139	0.9666

TABLE V
VAR SOURCE INSTALLMENTS

Bus	10	24
RGA	27.7332	12.0972
EP	30.7346	12.4436

TABLE VI
GENERATIONS AND POWER LOSSES

	P_g	Q_g	P_{loss}	Q_{loss}
RGA	2.99461	0.98111	0.160595	0.11826
EP	2.99461	0.94943	0.160611	0.11913

5.2 Optimal Results and comparison

The optimal generator bus voltages, transformer tap-settings, VAR source installments, generations and power losses are obtained as in Tables III-VI.

The real power savings, annual cost savings and the total costs are given as follows

RGA:

$$P_{loss}\% = \frac{P_{loss}^{init} - P_{loss}^{opt}}{P_{loss}^{init}} \times 100 = \frac{0.1759 - 0.160595}{0.1759} \times 100 = 8.7\%$$

$$W_c^{save} = hd_l \left(P_{loss,l}^{init} - P_{loss,l}^{opt}\right)$$
$$= 0.06 \times 8760 \times (0.1759 - 0.160595) \times 10^5$$
$$= \$8,04,430$$

Fc = I_C + W_c = 1196912 + 804430 = $20,01,342

EP:

$$P_{loss}\% = \frac{P_{loss}^{init} - P_{loss}^{opt}}{P_{loss}^{init}} \times 100 = \frac{0.1759 - 0.160611}{0.1759} \times 100 = 8.69\%$$

$$W_c^{save} = hd_l \left(P_{loss,l}^{init} - P_{loss,l}^{opt}\right)$$
$$= 0.06 \times 8760 \times (0.1759 - 0.160611) \times 10^5$$
$$= \$8,03,589$$

Fc = I_C + W_c = 1297346 + 803589 = $21,00,935

TABLE VII
COMPARISON BETWEEN RGA and EP

	W_C^{save}($)	F_C($)
RGA	8,04,430	20,01,342
EP	8,03,589	21,00,935

Table VII gives the comparison. From the comparison, we can see that, RGA gives better results than EP.

VI. CONCLUSIONS

An RGA approach has been developed for solving the RPP problem in large-scale power systems. The application studies on the IEEE 30-bus system show that RGA gives better results and always leads to the global optimum points of the multi-objective RPP problem, compared to EP. By the RGA approach, more savings on the energy and installment costs are achieved and the violations of the voltage and reactive power limits are eliminated.

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