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A REDUCTION OF REAL POWER LOSS BY ENRICHED GENETIC ALGORITHM

Dr.K.Lenin [*1]

[*1] Professor, Department of EEE, Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh -520007, India

Abstract

In this paper Enriched Genetic Algorithm (EGA) is proposed to solve the optimal reactive power problem. In order to overcome the drawbacks of standard genetic algorithm (GA) and particle swarm optimization (PSO) algorithm, some improved mechanisms based on non-linear ranking selection, competition and selection among several crossover offspring and adaptive change of mutation scaling are adopted in the genetic algorithm, and dynamical parameters are adopted in PSO. The new population is produced through three approaches to improve the global optimization performance. Proposed algorithm has been tested in standard IEEE 57 bus test system and simulation results reveal the better performance of the proposed algorithm in reducing the real power loss.

Keywords: Genetic Algorithm; Particle Swarm; Optimal Reactive Power; Transmission Loss.

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1. Introduction

Reactive power optimization places an important role in optimal operation of power systems. Various numerical methods like the gradient method [1,2], Newton method [3] and linear programming [4-7] have been implemented to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the intricacy in managing inequality constraints. The problem of voltage stability and collapse play a key role in power system planning and operation [8] Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is projected to increase the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to elucidate the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is

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solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18-20] proposes a two-step approach to calculate Reactive power reserves with respect to operating constraints and voltage stability. In this paper Enriched Genetic Algorithm is proposed to solve the optimal reactive power problem. Genetic algorithm (GA) is very efficient at exploring the entire search space, but it is relatively poor in finding the precise local optimal solution in the region where the algorithm converges. A new method of optimization, Particle Swarm optimization (PSO), is able to accomplish the same goal as GA optimization in a new and faster way [21-25]. Since PSO and GA both work with a population of solutions, combining the searching abilities of both methods seems to be a good approach. Some attempts have been made in this direction, but with a weak integration of the two strategies. In order to improve the speed of convergence of evolutionary algorithms, in this paper, GA and PSO are strong combined for solving optimal reactive power problem. Firstly, some improved mechanisms such as non-linear ranking selection, competition and selection among several crossover offspring and adaptive change of mutation scaling are adopted in the genetic algorithm. Then, the genetic algorithm is combined with PSO that is improved by dynamical parameters. During each iteration, the population is divided into three parts, which are evolved with the elitist strategy, PSO strategy and genetic algorithm strategy respectively. Therefore, this kind of technique can make balance between acceleration convergence and averting precocity as well as stagnation. Proposed algorithm has been tested in standard IEEE 57 bus test system and simulation results reveal the better performance of the proposed algorithm in reducing the real power loss.

2. Problem Formulation

Main objective of the reactive power problem is to minimize the real power loss.

2.1. Active Power Loss

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.

2.2. 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:

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

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Where Npq- number of load buses

2.3. 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.

2.4. 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:

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

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

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

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

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

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

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

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

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.

3. Hybridization of Standard Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) Algorithm

The proposed Enriched Genetic Algorithm (EGA) combines standard genetic algorithm (GA) and particle swarm optimization (PSO) algorithm to form a hybrid algorithm. Due to combination of different optimization mechanisms, not only the offspring can keep diversity, but also PSO can keep the balance of global search and local search, so the entire search ability of the algorithm can be improved.

Genetic Algorithm (GA)

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Floating-point GA uses floating-point number representation for the real variables and thus is free from binary encoding and decoding. It takes less memory space and works faster than binary GA. Some practical schemes to improve GA performance are introduced in this paper. According to the optimal results, we can conclude that these measures are effective and helpful in improving convergence property and accuracy.

Nonlinear Ranking Selection

Ranking methods only require the evaluation function to map the solutions to a partially ordered set. All individuals in a population are ranked from best to worst based on their fitness values. It assigns the probability of an individual based on its rank (r) and it is expressed as follows:

$$\begin{cases} p(r) = q'(1-q)^{r-1} \\ q' = \frac{q}{1-(1-q)^p} \end{cases} \quad (10)$$

Such that

$$\sum_{r=1}^{P} p(r) = 1 \quad (11)$$

Where
q = the probability of selecting the best individual = [0, 1],
r = the rank of the individual =
$\begin{cases} 1, \text{for the best individual} \\ P, \text{for the worst individual} \end{cases}$
P = the population size
It can be seen that this selection probability doesn't use the absolute value information of fitness value so that it avoid the fitness value scale transformation and control the prematurity to some extent.

Competition and Selection

In natural biological evolution, two parents after crossover can produce several offspring, and the competition also exists among the offspring which are produced by the same parents. Motivate by this phenomenon, we adopt competition and selection among several crossover offspring. Different from the conventional algorithm in which two parents only produce two offspring, the two parents, chromosomes as $a_s = [x_1^s, x_2^s, \dots, x_n^s]$and $a_t = [x_1^t, x_2^t, .., x_n^t]$ in this algorithm will produce four chromosomes according to the following mechanisms :

$$b_1 = [b_1^1, b_2^1, .., b_n^1] = \frac{a_s + a_t}{2} \quad (12)$$

$$b_2 = [b_1^2, b_2^2, .., b_n^2] = a_{max}(1-\omega) + max(a_s, a_t)\omega \quad (13)$$

$$b_3 = [b_1^3, b_2^3, .., b_n^3] = a_{min}(1-\omega) + min(a_s, a_t)\omega \quad (14)$$

$$b_4 = [b_1^4, b_2^4, .., b_n^4] = \frac{(a_{max} + a_{min})(1-\omega) + (a_1 + a_2)\omega}{2} \quad (15)$$

$$a_{max} = [x_1^{max}, x_2^{max}, .., x_n^{max}] \quad (16)$$

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$$a_{min} = \left[x_1^{min}, x_2^{min}, .., x_n^{min}\right] \quad (17)$$

Where $\omega\epsilon$ [0, 1] denotes the weight to be determined by users, $max(a_s, a_t)$ denotes the vector with each element obtained by taking the maximum among the corresponding element of a_s and a_t.Among b_1 to b_4, the two with the largest fitness value are used as the offspring of the crossover operation. As seen from Eqs. (12) to (16), the potential offspring spreads over the domain. At the same time, (12) and (16) results in searching around the centre region of the domain, (13) and (14) can move b_2 and b_3 to be near a_{max} and a_{min} respectively. Thus, the offspring generated by this operator, is better than that obtained by arithmetic crossover or heuristic crossover.

Mutation

This is the unary operator responsible for the fine tuning capabilities of the system, so that it can escape from the trap of local optimum. It is defined as follows: For a parent *p*, if variable p_k was selected at random for this mutation, the result is:

$$\bar{P} = (P_1, .., \overline{P_k}, .., P_n) \quad (18)$$

$$\overline{P_k} = \epsilon\left\{max\left(P_k - \mu\frac{P_k^{max} - P_k^{min}}{2}, P_k^{min}\right), min\left(P_k + \mu\frac{P_k^{max} - P_k^{min}}{2}, P_k^{max}\right)\right\} \quad (19)$$

And P_k^{max}, P_k^{min} are upper and lower bounds of P_k respectively,μ decreased with the increase of iterations.

$$\mu(\tau) = 1 - r^{[1-(\tau/T)]^b} \quad (20)$$

Where *r* is uniform random number in [0, 1], T is the maximum number of iterations, $\boldsymbol{\tau}$ is the current iteration number, and *b* is the shape parameter. From (20), at the initial stage of evolution, for small value of *r*, μ ($\boldsymbol{\tau}$) ≈1, the mutation domain is large in this case. However, in the later evolution, when $\boldsymbol{\tau}$ approaches *T*, μ ($\boldsymbol{\tau}$) ≈ 0, the mutation domain become small and search in the local domain.

Particle Swarm Algorithm (PSO)

The PSO conducts searches using a population of particles which correspond to individuals in GAs. The population of particles is randomly generated initially. Each particle represents a potential solution and has a position represented by a position vector $\overrightarrow{x_i}$. A swarm of particles moves through the problem space, with the moving velocity of each particle represented by a position vector$\overrightarrow{v_i}$ At each time step, a function f_i representing a quality measure is calculated by using $\overrightarrow{x_i}$ as input. Each particle keeps track of its own best position, which is associated with the best fitness it has achieved so far in a vector $\overrightarrow{p_i}$. Furthermore, the best position among all the particles obtained so far in the population is kept track of as $\overrightarrow{p_g}$. At each time step $\boldsymbol{\tau}$, by using the individual best position, $\overrightarrow{p_i}(\boldsymbol{\tau})$ and global best position, $\overrightarrow{p_g}(\boldsymbol{\tau})$a new velocity for particle i *is* updated by

$$\overrightarrow{v_i}(\boldsymbol{\tau}+\mathbf{1}) = \boldsymbol{\omega}\overrightarrow{\boldsymbol{v_i}}(\boldsymbol{\tau}) + \boldsymbol{c_1}\emptyset_1(\overrightarrow{\boldsymbol{p_i}}(\boldsymbol{\tau})\text{-}\overrightarrow{\boldsymbol{x_i}}(\boldsymbol{\tau})) + \boldsymbol{c_2}\emptyset_2(\overrightarrow{\boldsymbol{p_g}}(\boldsymbol{\tau}) - \overrightarrow{\boldsymbol{x_i}}(\boldsymbol{\tau})) \quad (21)$$

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Where $\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ are acceleration constants and $\boldsymbol{\emptyset_1 \& \emptyset_2}$ are uniformly distributed random numbers in [0, 1]. The term $\overrightarrow{v_i}$ is limited to its bounds. If the velocity violates this limit, it is set to its proper limit.

ω is the inertia weight factor and in general, it is set according to the following equation:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{T} . \boldsymbol{\tau} \quad (22)$$

Where ω_{max} and ω_{min} is maximum and minimum value of the weighting factor respectively. *T* is the maximum number of iterations and τ is the current iteration number. Based on the updated velocities, each particle changes its position according to the following:

$$\overrightarrow{x_i}(\tau + 1) = \overrightarrow{x_i}(\tau) + h(\tau)\overrightarrow{v_i}(\tau + 1) \quad (23)$$

Where

$$h(\tau) = h_{max} - \frac{(h_{max} - h_0).\tau}{T} \quad (24)$$

Where h_{max} and h_0 are positive constants.

According to (21) and (23), the populations of particles tend to cluster together with each particle moving in a random direction. The computation of PSO is easy and adds only a slight computation load when it is incorporated into GA. Furthermore, the flexibility of PSO to control the balance between local and global exploration of the problem space helps to overcome premature convergence of elite strategy in GAs, and also enhances searching ability. The global best individual is shared by the two algorithms, & also it can avoid the premature convergence in PSO.

Integration of GA & PSO for the entire run, which consists chiefly of genetic algorithm, combined with PSO , the sequential steps of the algorithm are given below;

Step 1: Randomly initialize the population of *P* individuals within the variable constraint range.
Step 2: Calculate the fitness of the population from the fitness function, and order ascendingly.
Step 3: The top *N* individuals are selected as the elites and reproduce them directly to the next generation.
Step 4: The S individuals followed are evolved with PSO and their best positions are updated.
Step 5: The bottom individuals are evolved with GA and produce P-S-N offspring.
Step 6: Combine the three parts as the new generation and calculate the fitness of the population. Choose the best position among all the individuals obtained so far kept as the global best.
Step 7: Repeat steps 3–6 until a stopping criterion, such as a sufficiently good solution being discovered or a maximum number of generations being completed, is satisfied. The best scoring individual in the population is taken as the final answer.

4. Simulation Results

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Proposed Enriched Genetic Algorithm (EGA) has been tested in standard IEEE-57 bus power system. The reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. The system variable limits are given in Table 1.
The preliminary conditions for the IEEE-57 bus power system are given as follows:
P_{load}= 12.010 p.u. Q_{load} = 3.011 p.u.
The total initial generations and power losses are obtained as follows:
$\sum P_G$ = 12.5501 p.u. $\sum Q_G$ = 3.3228 p.u.
P_{loss}= 0.25758 p.u. Q_{loss} = -1.2047 p.u.
Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after EGA based optimization which are within the acceptable limits. In Table 3, shows the comparison of optimum results obtained from proposed EGA with other optimization techniques. These results indicate the robustness of proposed EGA approach for providing better optimal solution in case of IEEE-57 bus system.

Table 1: Variable limits

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50

Voltage And Tap Setting Limits					
vgmin	**Vgmax**	**vpqmin**	**Vpqmax**	**tkmin**	**tkmax**
0.9	1.0	0.91	1.05	0.9	1.0

Shunt Capacitor Limits			
Bus no	18	25	53
Qcmin	0	0	0
Qcmax	10	5.2	6.1

Table 2: Control variables obtained after optimization

Control Variables	**EGA**
V1	1.10
V2	1.039
V3	1.028
V6	1.029
V8	1.027
V9	1.024
V12	1.019
Qc18	0.0656
Qc25	0.200
Qc53	0.0472
T4-18	1.011
T21-20	1.054
T24-25	0.879
T24-26	0.864
T7-29	1.060
T34-32	0.872

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T11-41	1.021
T15-45	1.036
T14-46	0.914
T10-51	1.028
T13-49	1.062
T11-43	0.912
T40-56	0.901
T39-57	0.951
T9-55	0.951

Table 3: Comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [26]	0.25902	0.30854	0.27858
2	CGA [26]	0.25244	0.27507	0.26293
3	AGA [26]	0.24564	0.26671	0.25127
4	PSO-w [26]	0.24270	0.26152	0.24725
5	PSO-cf [26]	0.24280	0.26032	0.24698
6	CLPSO [26]	0.24515	0.24780	0.24673
7	SPSO-07 [26]	0.24430	0.25457	0.24752
8	L-DE [26]	0.27812	0.41909	0.33177
9	L-SACP-DE [26]	0.27915	0.36978	0.31032
10	L-SaDE [26]	0.24267	0.24391	0.24311
11	SOA [26]	0.24265	0.24280	0.24270
12	LM [27]	0.2484	0.2922	0.2641
13	MBEP1 [27]	0.2474	0.2848	0.2643
14	MBEP2 [27]	0.2482	0.283	0.2592
15	BES100 [27]	0.2438	0.263	0.2541
16	BES200 [27]	0.3417	0.2486	0.2443
17	Proposed EGA	0.22106	0.23178	0.22142

5. Conclusion

In this paper, Enriched Genetic Algorithm (EGA) successfully solved optimal reactive power problem. In order to improve the speed of convergence of evolutionary algorithms, in this paper, GA and PSO are strong combined for solving optimal reactive power problem. Firstly, some improved mechanisms such as non-linear ranking selection, competition and selection among several crossover offspring and adaptive change of mutation scaling are adopted in the genetic algorithm. Then, the genetic algorithm is combined with PSO that is improved by dynamical parameters. Proposed algorithm has been tested in standard IEEE 57 bus test system and simulation results reveal the better performance of the proposed algorithm in reducing the real power loss.

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*Corresponding author.
E-mail address: gklenin@ gmail.com