Enhanced Evolutionary Algorithm for Solving Optimal Reactive Power Problem

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Abstract

This paper presents an Enhanced Evolutionary Algorithm (EEA) for solving optimal reactive power problem. In Enhanced Evolutionary Algorithm (EEA) objective space is disintegrated into a set of sub objective spaces by a set of route vectors. In the evolutionary procedure, each sub objective space has a solution. In such a way, the diversity of achieved solutions can be upheld. In addition, if a solution is conquered by other solutions, the solution can produce more newfangled solutions than those solutions, which makes the solution of each sub objective space converge to the optimal solutions as far as feasible. Projected Enhanced Evolutionary Algorithm (EEA) has been tested in standard IEEE 57 bus test system and simulation results show clearly the improved performance of the Enhanced Evolutionary Algorithm (EEA) in decreasing the real power loss.

Keywords

Evolutionary Algorithm, Genetic Operators, Optimal Reactive Power, Transmission Loss.

1. 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 non linear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1-2], Newton method [3] and linear programming [4-7].The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input-output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently Global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8, 9]. This paper presents an Enhanced Evolutionary Algorithm (EEA) for solving optimal reactive power problem. In Enhanced Evolutionary Algorithm (EEA) objective space is disintegrated into a set of sub objective spaces [10-13] by a set of route vectors. In the evolutionary procedure, each sub objective space has a solution. In such a way, the diversity of achieved solutions can be upheld. In addition, if a solution is conquered by other solutions, the solution can produce more newfangled solutions than those solutions, which makes the solution of each sub objective space converge to the optimal solutions as far as feasible. Projected Enhanced Evolutionary Algorithm (EEA) has been tested in standard IEEE 57 bus test system and simulation results show clearly the improved performance of the Enhanced Evolutionary Algorithm (EEA) in decreasing the real power loss.

2. Problem Formulation

The reactive power problem is considered as a common minimization problem with constraints, and can be written in the following form:

$$\text{Minimize } f(x, u) \quad (1)$$

$$\text{Subject to } g(x,u)=0 \quad (2)$$

and

$$h(x, u) \le 0 \quad (3)$$

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \quad (4)$$

The control variables are the generator bus voltages, the shunt capacitors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \quad (5)$$

or

$$u = \left(V_{g1}, \dots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \quad (6)$$

Where Ng, Nt and Nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

3. Objective Function

Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be mathematically described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (7)$$

Or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

Where g_k: is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (9)$$

Where ω_v: is a weighting factor of voltage deviation.
VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (10)$$

Equality Constraint

The equality constraint g(x,u) of the reactive power problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \quad (11)$$

Inequality Constraints

The inequality constraints h(x,u) imitate the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (12)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \quad (16)$$

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

4. Enhanced Evolutionary Algorithm (EEA)

This novel algorithm contains of three parts: (i) solutions organization, (ii) update stratagem, and (iii) selection stratagem which will be presented one by one in this segment.

Solutions organization

The objective space of Enhanced Evolutionary Algorithm (EEA) is disintegrated into a set of sub objective spaces by a set of route vectors, and then obtained solutions are categorized by these route vectors to make each sub objective space have a solution. For a given set of route vectors$(\gamma^1, \gamma^2, .., \gamma^N)$and the set of current obtained solutions being population (POP), thesesolutions will be categorized by the following formulation:

$$P^i = \left\{x \middle| x \in POP, \Delta(F(X), \gamma^i) = \max_{1 \leq j \leq N} \{\Delta(F(x), \gamma^j)\}\right\}, \quad (17)$$

Where $\Delta(F(x), \gamma^i) = \frac{\gamma^i * (F(x)-Z)^T}{\|\gamma^i\| * \|F(x)-Z\|}, i = 1, .., m,$

Where $Z = (Z_1, .., Z_m)$ is a reference point and $Z_i = min\left\{\{f_i(x) | x \in \Omega\}, \Delta(F(x), \gamma^k)\right\}$ is the cosine of the angle between γ^i and $F(x) - Z$. These solutions are alienated into N classes by the formulation (17) and the objective space Ω divided into N sub objective spaces $\Omega_1, .., \Omega_N$, where $\Omega_k (k = 1, .., N)$ is

$$\Omega_k = \left\{F(x) | x \in \Omega, \Delta(F(X), \gamma^k) = \max_{1 \leq j \leq N} \{\Delta(F(x), \gamma^j)\}\right\} \quad (18)$$

If $P^i (1 \leq i \leq N)$ is empty, a solution is arbitrarily selected from Population and put to P^i.

Update stratagem

The superior strategy is used to modernizesolutions. When it meets one of the following conditions, a novel solution will substitute the existing solution of a sub objective space:
(i) If the objective vector of the existing solution does not locate in this sub objective space, the objective vector of the new-fangled solution locates in this space or the existingsolution is controlled by the novel solution.
(ii) If the objective vector of the existing solution locates in this sub objective space, the objective vector of the novel solution also locates in this space and the existingsolution is controlled by the novel solution.
The first update condition makes each sub objective space have a solution whose objective vector locates in thissub objective space, which can well uphold the multiplicityof obtained solutions. The second update condition makes non- dominated solution to be reserved, which can make solutions converge.

Selection stratagem

Solutionsare more to be expected to be selected to produce new solutions, and then their sub objective spaces can rapidly find their optimal solutions. In order to achieve the goalmouth, the crowding distance is used to compute the fitness value of a solution for the selection operators. Because these solutions are controlled by other solutions and the objective vectors of those solutions do not locate in this sub objective spaces of these solutions, so in the term of the objective vector, these solutions have scarcer solutions in their frame than other solutions. Thus, by using the crowding distance to compute the fitness value of a solution, the fitness values of these solutions are healthier than those solutions and these solutions are more likely to be selected to produce new-fangled solutions.

Enhanced Evolutionary Algorithm (EEA) for solving optimal reactive power problem

Step 1.Initialize .given N route vectors $(\gamma^1, \gamma^2, .., \gamma^N)$, arbitrarily produce an preliminary population POP(k) , and its size is N ; let k =0 , set $Z_i = min\{f_i(x)|x \in POP(k)\}, 1 \leq i \leq m$.

Step 2 .Fitness. Solutions of POP (k) are firstly alienated into N classes by the equation (17) and the fitness value of each solution in POP (k) is computed by the crowding distance. Then, some improved solutions are choosing from the population POP (k) and place into the population POP. In this research, binary tournament selection is utilized.

Step 3. New-fangled solutions. Apply genetic operators to the parent population to produce offspring. The set of all these offspring is represented as O.

Step 4. Modernize. Z is first modernized. For each $\mathrm{j} = 1, .., \mathrm{m}, \mathrm{if} \mathrm{Z_j} > min\{\mathrm{f_j}(\mathrm{x})|\mathrm{x} \in \mathrm{O}\}$, then set $\mathrm{Z_j} = \min\{\mathrm{f_j}(\mathrm{x})|\mathrm{x} \in \mathrm{O}\}$.The solutions of $\mathrm{POP(k)} \cup \mathrm{O}$ are first categorized by the equation (17); then N best solutions are picked by the update strategy and put into $\mathrm{POP(k + 1)}$. let $\mathrm{k} = \mathrm{k} + 1$.

Step 5 .End. If stop condition is satisfied, stop; or else, go to Step 2.

5. Simulation Results

Enhanced Evolutionary Algorithm (EEA) 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} = 12.002 p.u. Q_{load} = 3.014 p.u.
The total initial generations and power losses are obtained as follows:
$\sum P_G$ = 12.118 p.u. $\sum Q_G$ = 3.3092 p.u.
P_{loss} = 0.25432 p.u. Q_{loss} = -1.2014 p.u.
Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after optimization which are within the acceptable limits. In Table 3, shows the comparison of optimum results obtained from proposed methods with other optimization techniques. These results indicate the robustness of proposed approaches 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	**EEA**
V1	1.1
V2	1.028
V3	1.024
V6	1.019
V8	1.018
V9	1.000
V12	1.012
Qc18	0.0628
Qc25	0.100
Qc53	0.0210
T4-18	1.001
T21-20	1.002
T24-25	0.802
T24-26	0.806
T7-29	1.008
T34-32	0.802
T11-41	1.010
T15-45	1.031
T14-46	0.911
T10-51	1.010
T13-49	1.010
T11-43	0.910
T40-56	0.900
T39-57	0.950
T9-55	0.950

Table 3. Comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [14]	0.25902	0.30854	0.27858
2	CGA [14]	0.25244	0.27507	0.26293
3	AGA [14]	0.24564	0.26671	0.25127
4	PSO-w [14]	0.24270	0.26152	0.24725
5	PSO-cf [14]	0.24280	0.26032	0.24698
6	CLPSO [14]	0.24515	0.24780	0.24673
7	SPSO-07 [14]	0.24430	0.25457	0.24752
8	L-DE [14]	0.27812	0.41909	0.33177
9	L-SACP-DE [14]	0.27915	0.36978	0.31032
10	L-SaDE [14]	0.24267	0.24391	0.24311
11	SOA [14]	0.24265	0.24280	0.24270
12	LM [15]	0.2484	0.2922	0.2641
13	MBEP1 [15]	0.2474	0.2848	0.2643
14	MBEP2 [15]	0.2482	0.283	0.2592
15	BES100 [15]	0.2438	0.263	0.2541
16	BES200 [15]	0.3417	0.2486	0.2443
17	Proposed EEA	0.22082	0.23092	0.22274

6. Conclusion

In this paper, Enhanced Evolutionary Algorithm (EEA) has been successfully solved optimal reactive power problem. In the evolutionary procedure, each sub objective space has a solution. In such a way, the diversity of achieved solutions can be upheld. In addition, if a solution is conquered by other solutions, the solution can produce more newfangled solutions than those solutions, which makes the solution of each sub objective space converge to the optimal solutions as far as feasible. Projected Enhanced Evolutionary Algorithm (EEA) has been tested in standard IEEE 57 bus test system and simulation results show clearly the improved performance of the Enhanced Evolutionary Algorithm (EEA) in decreasing the real power loss.

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