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Reduction of Real Power Loss by Improved Evolutionary Algorithm

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Abstract

This paper presents an Improved Evolutionary Algorithm (IEA), to solve optimal reactive power dispatch problem. In IEA 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 conceivable. The planned IEA has been tested in standard IEEE 30, 118 bus test systems and simulation results show clearly the improved performance of the planned algorithm in declining the real power loss.

Keywords: Evolutionary Algorithm, genetic operators, optimal reactive power, Transmission loss.

1. Introduction

Reactive power optimization places an important role in optimal operation of power systems. Various numerical methods like the gradient method [O.Alsac *et al* (1973); Lee K Y *et al* (1985)], Newton method [A.Monticelli *et al* (1987)] and linear programming [Deeb N *et al* (1990); E. Hobson (1980) ; K.Y Lee *et al* (1987); M.K. Mangoli (1993)] 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 [C.A. Canizares *et al* (1996)]. Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [S.R.Paranjothi *et al* (2002); D. Devaraj *et al* (2005); A. Berizzi *et al* (2012)]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [C.-F. Yang *et al* (2012)], Hybrid differential evolution algorithm is projected to increase the voltage stability index. In [P. Roy *et al* (2012)] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [B. Venkatesh *et al* (2000)], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [W. Yan *et al* (2004)], an improved evolutionary programming is used to elucidate the optimal reactive power dispatch problem. In [W. Yan *et al* (2006)], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [J. Yu *et al* (2008)], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [F. Capitanescu (2011)] proposes a two-step approach to calculate Reactive power reserves with respect to operating constraints and voltage stability. In [Z. Hu *et al* (2010)], a programming based approach is used to solve the optimal reactive power dispatch problem. In [A. Kargarian et al (2012)] present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes an Improved Evolutionary Algorithm (IEA) [K. C. Tan *et al* (2001); C. A. Coello *et al* (2002)] to solve optimal reactive power dispatch problem. In this paper, the objective space is disintegrated into a set of sub objective spaces by a set of route vectors. Each sub objective space has a solution. If a new-fangled solution will substitute the solution, the new-fangled solution must dictate the solution and its objective vector locates in the sub objective space. In such a way, the multiplicity of obtained solutions can be preserved. In addition, the thronging distance [K. Deb *et al* (2002); Cai Dai *et al* (2014)] is used to compute the fitness value of a solution for the selection operators. In this cause, if a solution is controlled by other solutions, the solution is more likely to be selected than other solutions, so it can produce more new-fangled solutions to rapidly find the optimal solution of the sub objective space, which makes the solution of each sub objective space converge to the optimal solutions as far as possible. Based on these attitudes, an improved evolutionary algorithm, IEA is designed. The proposed IEA algorithm has been evaluated in standard IEEE 30,118 bus test systems. The simulation results show that our proposed approach outclasses all the entitled reported algorithms in minimization of real power loss.

2. Problem Formulation

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

Minimize f(x, u) (1)

Subject to g(x,u)=0 (2)
and
$h(x,u) \leq 0$ (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:

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

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

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

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

3. Objective Function

3.1. 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:

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

or

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

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.

3.2. 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:

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

3.3. Equality Constraint

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

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

3.4. 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. Improved Evolutionary Algorithm

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.

4.1. Solutions organization

The objective space of an IEA 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 $(\gamma^1, \gamma^2, \ldots, \gamma^N)$ and the set of current obtained solutions being population (POP), these solutions will be categorized by the following formulation:

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

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

Where $Z = (Z_1, \ldots, Z_m)$ 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 $\Omega_1, \ldots, \Omega_N$, where $\Omega_k (k = 1, \ldots, N)$ is

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

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

4.2. update stratagem

The superior strategy is used to modernize solutions. 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 existing solution 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 existing solution is controlled by the novel solution.
The first update condition makes each sub objective space have a solution whose objective vector locates in this sub objective space, which can well uphold the multiplicity of obtained solutions. The second update condition makes non- dominated solution to be reserved, which can make solutions converge.

4.3. selection stratagem

Solutions are 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 [23] 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.

4.4. Algorithm of improved evolutionary algorithm for reactive power dispatch problem

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

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

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

5. Simulation Results

At first IEA algorithm has been tested on the IEEE 30-bus, 41 branch system. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. The considered security constraints are the voltage magnitudes of all buses, the reactive power limits of the shunt VAR compensators and the transformers tap settings limits. The variables limits are listed in Table 1.

Table 1: Initial Variables Limits (PU)

Control variables	Min. value	Max. value	Type
Generator: Vg	0.92	1.11	Continuous
Load Bus: VL	0.94	1.02	Continuous
T	0.94	1.02	Discrete
Qc	-0.11	0.31	Discrete

The transformer taps and the reactive power source installation are discrete with the changes step of 0.01. The power limits generators buses are represented in Table 2. Generators buses are: PV buses 2,5,8,11,13 and slack bus is 1.the others are PQ-buses.

Table 2: Generators Power Limits in MW and MVAR

Bus n°	Pg	Pgmin	Pgmax	Qgmin
1	98.00	51	202	-21
2	81.00	22	81	-21
5	53.00	16	53	-16
8	21.00	11	34	-16
11	21.00	11	29	-11
13	21.00	13	41	-16

Table 3: Values of Control Variables after Optimization and Active Power Loss

Control Variables (p.u)	IEA
V1	1.0647
V2	1.0538
V5	1.0298
V8	1.0467
V11	1.0832
V13	1.0645
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.91
Q10	0.10

Q24	0.10
PLOSS	4.5209
VD	0.9075

The proposed approach succeeds in keeping the dependent variables within their limits as shown in table 3.
Table 4 summarizes the results of the optimal solution and it reveals the reduction of real power loss after optimization.

Table 4: Comparison Results of Different Methods

Methods	Ploss (MW)
SGA [Q.H. Wu et al 1998]	4.98
PSO [B. Zhao et al 2005]	4.9262
LP [Mahadevan. K et al 2010]	5.988
EP [Mahadevan. K et al 2010]	4.963
CGA [Mahadevan. K et al 2010]	4.980
AGA [Mahadevan. K et al 2010]	4.926
CLPSO [Mahadevan. K et al 2010]	4.7208
HSA [A.H. Khazali et al 2011]	4.7624
BB-BC [S. Sakthivel et al 2014]	4.690
IEA	4.5209

Secondly IEA has been tested in standard IEEE 118-bus test system [www.ee.washington.edu/trsearch/pstca/.] .The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The line and bus data and their limits are given in [www.ee.washington.edu/trsearch/pstca]. The limits of voltage on generator buses are 0.95-1.1 per-unit., and on load buses are 0.95-1.05 per-unit. The limit of transformer rate is 0.9-1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 5, with the change step of 0.01.

Table 5.Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

In this case, the number of population is increased to 120 to explore the larger solution space. The total number of generation times is set to 200. The statistical comparison results of 50 trial runs have been list in Table 6 and the results clearly show the better performance of proposed algorithm.

Table 6.Comparison of simulation results in 118-bus system

Active power loss (p.u)	BBO [Jiangtao Cao et al 2014]	ILSBBO/ strategy1 [Jiangtao Cao et al 2014]	ILSBBO/ strategy1 [Jiangtao Cao et al 2014]	Proposed IEA
min	128.77	126.98	124.78	120.89
max	132.64	137.34	132.39	131.78
Average	130.21	130.37	129.22	128.86

6. Conclusion

In this paper, the IEA has been successfully implemented to solve Optimal Reactive Power Dispatch problem. The proposed algorithm has been tested on the standard IEEE 30,118 -bus systems. Simulation results indicate the toughness of projected IEA approach for providing better optimal solution in reducing the real power loss. The control variables obtained after the optimization by IEA is within the limits.

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