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Enriched Differential Evolution Algorithm for Active Power Loss Reduction

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Abstract
In this paper an Enriched Differential Evolution (EDE) algorithm is proposed to solve optimal reactive power problem. Differential Evolution (DE) algorithm is a prominent population based stochastic algorithm used to solve optimization problems. But, DE like other nature inspired algorithms sporadically trapped in local optima and also endures the problem of stagnation. To resolve this problem and enhancing the convergence speed of DE algorithm, Artificial Bee Colony algorithm's fitness based position update strategy is incorporated with it. In the proposed Enriched Differential Evolution (EDE) algorithm, first of all the solutions & positions are modernized using the DE algorithm than the ABC investigate strategy is applied to perk up the convergence speed of the exploration progression. The proposed Enriched Differential Evolution (EDE) algorithm has been tested on standard IEEE 30, 118 bus test systems and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss and voltage profiles are within the limits.

Key words
Evolutionary Algorithm, optimal reactive power, Transmission loss, Artificial Bee Colony, Differential Evolution.

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 maintain voltage stability of the system. It involves a nonlinear 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 many global optimization techniques have been proposed to solve the reactive power flow problem [8-10]. This paper proposes an Enriched Differential Evolution (EDE) algorithm is proposed to solve optimal reactive power problem.DE algorithm [11] as a novel version of GA is a population-based stochastic direct search method for global optimization. DE has four advantages: ability to handle non-differentiable, nonlinear and multi-modal cost functions; ability to parallel cope with computation intensive cost functions; ease of use; and good convergence properties. Conversely, it has been shown that DE may occasionally stop continuing towards the global optimum even though the population has not converged to a local optimum [12]. Consequently, to maintain the proper balance between exploration and exploitation behaviour of DE, a novel position update process is introduced based on the fitness of the solution. The position update takes place in two phases in the projected strategy. In the first phase, the basic DE is used to generate the new solutions and in the second phase each solution is updated based on its fitness. The proposed update process is stimulated from onlooker bee phase of Artificial Bee Colony algorithm (ABC) [13]. In this process, superior candidate gets more chance to update its position. Further, the solution updates only in single dimension in each chance, hence produces the new solution in the neighbourhood of the old one and in this way exploits the exploration space. The proposed Enriched Differential Evolution (EDE) algorithm has been tested in standard IEEE 30, 118 bus test systems and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss and voltage profiles are within the limits.

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:

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

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.

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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:

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

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

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

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

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

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:

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

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:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \qquad (12)$$

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

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \qquad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \qquad (15)$$

Upper and lower bounds on the compensators reactive powers:

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

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. Differential Evolution

The Differential Evolution (DE) algorithm was originally introduced by Price and Storn about fifteen years ago [11]. At present, there are a number of variants of DE. The particular variant used throughout this investigation is the DE/rand/1/bin scheme, *rand* means randomly chosen population vector, *1* is the number of difference vectors used, *bin* means crossover due to independent binomial experiments. This scheme will be discussed here briefly.

$$P_{x,g} = \left(x_{i,g}\right), i = 0,1,..,N_P - 1; g = 0,1,..,G_{max}$$
(17)

$$x_{i,g} = \left(x_{j,i,g}\right), j = 0,1,..,D - 1.$$
(18)

Where $N_p$denotes the number of population vectors, gdefines the generation counter, and D stands for the dimensionality, i.e. the number of parameters. In case apreliminary solution is available, the initial population might be generated by adding normallydistributed random deviations to the nominal solution $x_{nom;0}$.

DE generates new parameter vectors by adding the weighted difference between two population vectors to a third vector. Let this operation be called mutation.

$$v_{i,g+1} = x_{r1,g} + F.\left(x_{r2,g} - x_{r3,g}\right)$$
(19)

Where random indexes r1, r2, *r*3 ϵ1, 2, ...,N_p, cross rate F ∈[0, 2].

In order to increase the diversity of the perturbed parameter vectors, crossover is operated.

$$u_{ji,g+1} = \begin{cases} v_{ji,g+1} if(rand(j) \leq CR) or j = rand(i) \\ x_{ji,g} if(rand(j) > CR) or j \neq rand(i) \end{cases}$$
(20)

where rand(j) is the jth evaluation of a uniform random number generator with outcome ∈[0, 1], rand(i) is a randomly chosen index ∈1, 2, ...,Dwhich endures that $u_{i;g+1}$ gets at least oneparameter from $v_{i;g+1}$. CR is the crossover constant ∈[0, 1].If the trial vector yields a lower cost function value than the target vector, the trial vectorreplaces the target vector in the following generation. This last operation is called selection.Each population vector has to serve once as the target vector so that $N_p$competitions takePlace in one generation.

5. Enriched Differential Evolution Algorithm

Exploration of the entire search space and exploitation of the near optimal solution region may be balanced by upholding the diversity in early and later iterations of any arbitrary number based search algorithm. DE explores the search space based on the value of CR and F. In DE, exploration and exploitation of the search space depend on the value of CR and F i.e. for high value of CR and F exploration will be high and for low value, exploitation. In this paper, we are suggesting a new probability phase, which balances the exploration and exploitation of the search space. The position update process is inspired from the Artificial Bee Colony (ABC) algorithm's onlooker bee phase [13]. In employed bee phase of ABC, all the employed bees search the food source and calculate their fitness using equation (21):

$$fitness_i = \begin{cases} 1/(1+f_i) \ if \ f_i \geq 0 \\ 1 + abs(f_i) \ if \ f_i < 0 \end{cases}$$
(21)

And then in the onlooker bee phase, Onlooker bees analyse the available information and select a solution with a probability, $prob_i$, related to its fitness. The probability $prob_i$ may be calculated by using equation (22) ,

$$prob_i(G) = \frac{0.9 * fitness_i(G)}{maxfit(G)} + 0.1$$
(22)

where G is the iteration counter, $fitness_i(G)$ is the fitness value of i^{th} solution and *maxfit*(G) is the maximum fitness of the solutions in G^{th} iteration. Position update of ABC is done by equation (23) as follows,

$$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) + \Psi_{ij}(x_{bestj} - x_{ij})$$
(23)

where k ϵ {1, 2, ...,NP}, j ϵ {1, 2, ...,D} are randomly chosen indices, *k* must be different from i, Φ_{ij} is a random number between [-1, 1] and x_{kj} is a random individual in the current population and Ψ_{ij} is a uniform random number in [0,C], where C is a non-negative constant.

Execution of Enriched algorithm for optimal reactive power problem

In the basic ABC, at any given time, only one dimension is updated in employed or onlooker bee phase. In onlooker bee phase this update takes place based on a probability which is a function of fitness. The proposed strategy Enriched Differential Evolution (EDE) algorithm is inspired from ABC's onlooker bee phase as discussed above. In the process improved Algorithm is applied after basic DE operators. The insertion of improved Algorithm is more capable of exploitation in the better search regions.

Improved algorithm: Fitness based search strategy inspired from Artificial Bee Colony (ABC) algorithm
For each individual, $x_i$do
if$prob_i$> rand(0, 1) then
$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) + \Psi_{ij}(x_{bestj} - x_{ij})$
Calculate fitness of v_i
Apply greedy selection betweenv_i andx_i ,
End if
End for

6. Simulation Results

Validity of proposed Enriched Differential Evolution (EDE) 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 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	0.95	1.1	Continuous
Load Bus	0.95	1.05	Continuous
Transformer-Tap	0.9	1.1	Discrete
Shunt Reactive Compensator	-0.11	0.31	Discrete

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

Table 2 Generators Power Limits

Bus	Pg	Pgmin	Pgmax	Qgmin	Qmax
1	96.00	49	200	0	10
2	79.00	18	79	-40	50
5	49.00	14	49	-40	40
8	21.00	11	31	-10	40
11	21.00	11	28	-6	24
13	21.00	11	39	-6	24

Table 3 shows the proposed EDE approach successfully kept the control variables within limits.Table 4 narrates about the performance of the proposed EDE algorithm. Table 5 list out the overall comparison of the results of optimal solution obtained by various methods.

Table 3 After optimization values of control variables

Control Variables	EDE
V1	1.0402
V2	1.0416
V5	1.0224
V8	1.0308
V11	1.0698
V13	1.0497
T4,12	0.00
T6,9	0.00
T6,10	0.90
T28,27	0.90
Q10	0.10
Q24	0.10
Real power loss	4.2658
Voltage deviation	0.9086

Table 4 Performance of EDE algorithm

Iterations	35
Time taken (secs)	10.04
Real power loss	4.2658

Table 5 Comparison 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
MCS(Tejaswini sharma et al.,2016) [19]	4.87231
Proposed EDE	4.2658

Proposed Enriched Differential Evolution (EDE) algorithm has been tested in standard IEEE 118-bus test system [20].The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. 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 6, with the change in step of 0.01.

Table 6. 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

The statistical comparison results of 50 trial runs have been list in Table 7 and the results clearly show the better performance of Enriched Differential Evolution (EDE) algorithm .

Table 7. Comparison results

Active power loss (MW)	BBO [21]	ILSBBO/ strategy1 [21]	ILSBBO/ strategy1 [21]	Proposed EDE
Min	128.77	126.98	124.78	113.04
Max	132.64	137.34	132.39	120.86
Average	130.21	130.37	129.22	115.92

7. Conclusion

In this paper, Enriched Differential Evolution (EDE) algorithm has been successfully solved optimal reactive power problem. In the proposed Enriched Differential Evolution (EDE) algorithm, first of all the solutions & positions are modernized using the DE algorithm than the ABC investigate strategy is applied to perk up the convergence speed of the exploration progression. The proposed Enriched Differential Evolution (EDE) algorithm has been tested in standard IEEE 30, 118 bus test systems and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss and voltage profiles are within the limits.

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