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Enhanced differential evolution algorithm for solving reactive power problem

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Abstract
Differential evolution (DE) is one of the efficient evolutionary computing techniques that seem to be effective to handle optimization problems in many practical applications. Conversely, the performance of DE is not always flawless to guarantee fast convergence to the global optimum. It can certainly get inaction resulting in low accuracy of acquired results. An enhanced differential evolution (EDE) algorithm by integrating excited arbitrary confined search (EACS) to augment the performance of a basic DE algorithm have been proposed in this paper. EACS is a local search method that is excited to swap the present solution by a superior candidate in the neighbourhood. Only a small subset of arbitrarily selected variables is used in each step of the local exploration for randomly deciding the subsequent provisional solution. The proposed EDE has been tested in standard IEEE 30 bus test system. The simulation results show clearly about the better performance of the proposed algorithm in reducing the real power loss with control variables within the limits.

Keywords
Enhanced differential evolution, Excited arbitrary confined search, Optimal reactive power, Transmission loss.

1.Introduction
To till date various methodologies have been applied to solve the optimal reactive power problem. The key aspect of solving reactive power problem is to reduce the real power loss. Previously, many types of mathematical methodologies like linear programming, gradient method has been utilized to solve the reactive power problem, but they lack in handling the constraints to reach a global optimization solution [1-8]. In the next level various types of evolutionary algorithms have been applied to solve the reactive power problem [9-12]. This paper proposes enhanced differential evolution (EDE) to solve reactive power dispatch problem with a good level of exploration, exploitation and better convergence speed. In this paper DE algorithm has been intermingled with excited arbitrary confined search (EACS) to augment the performance of a conventional DE algorithm. EACS is a local exploration method that is excited to move to a position that is identified as superior than the present one without considering other opportunities in the neighbourhood. The proposed EDE algorithm has been evaluated on standard IEEE 30 bus test system. The simulation results show that the proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

2.Objective function
2.1Active power loss
The objective of the reactive power dispatch problem is to minimize the active power loss and can be defined 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 is the objective function, P_L is a power loss, g_k is conductance of the branch, V_i and V_j are the voltages at buses i,j, Nbr are the total number of transmission lines in power systems.

2.2Voltage 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 is the voltage deviation, ω_v is a weighting factor of voltage deviation.
The voltage deviation can be calculated by the below formulla:

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

Where Npq is the number of load buses.

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2.3Equality 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 PG is the total power generation and P_D is the total power demand.

2.4Inequality 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 of the active power of slack bus (Pg), and reactive power of generators (Qg) are written as follows:

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

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

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

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

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

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

Upper and lower bounds on the compensators (Q_C) are given by:

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

Where N is the total number of buses, N_g is the total number of generators, N_T is the total number of transformers and N_C is the total number of shunt reactive compensators.

3.Differential evolution

In DE the population is created by common sampling within the stipulated minimum and maximum bounds [13-15]. After the start of creating population, DE move into the iteration process where the processes like mutation, crossover, and selection are followed. DE employs the mutation strategy to generate a mutant vector D and the strategies are listed as follows:

"DE/best/1":

$$D_i = Y_{best} + H(Y_{s1} - Y_{s2}) \quad (10)$$

"DE/current-to-best/1":

$$D_i = Y_i + H(Y_{best} - Y_i) + H(Y_{s1} - Y_{s2}) \quad (11)$$

"DE/best/2":

$$D_i = Y_{best} + H(Y_{s1} - Y_{s2}) + H(Y_{s3} - Y_{s4}) \quad (12)$$

"DE/rand/1":

$$D_i = Y_{s1} + H(Y_{s2} - Y_{s3}) \quad (13)$$

"DE/current-to-rand/1":

$$D_i = Y_i + H(Y_{s1} - Y_i) + H(Y_{s2} - Y_{s3}) \quad (14)$$

DE/rand/2":

$$D_i = Y_{r1} + H(Y_{s2} - Y_{s3}) + H(Y_{s4} - Y_{s5}) \quad (15)$$

Where the indices s1, s2, s3, s4, and s5 are homogenous different integers from 1 to N, Y_{best} denotes the best individual obtained so far D_i&Y_i are the ith vector of D and Y, rand indicates the term randomly and H is the constant respectively.

The crossover operator is performed to produce a trial vector G_i according to each pair of Y_i and D_i after the mutant vector D_i is generated. The most enhanced strategy is the binomial crossover described as follows:

$$g_{ij} = \begin{cases} d_{i,j} if rand(0,1) \le E_r \text{ or } l = l_{rand} \\ y_{i,j} otherwise \end{cases} \quad (16)$$

where E_r is called the crossover rate, l_{rand} is arbitrarily sampled from 1 to N, and $g_{i,j}$, $d_{i,j}$, and $y_{i,j}$ are the jth element of G_i, D_i, and Y_i, respectively.

Finally, DE utilizes a greedy mechanism to choose the best vector from each pair of Y_i and G_i. This can be defined as follows:

$$Y_i = \begin{cases} G_i if fitness(G_i) \le fitness(Y_i) \\ Y_i otherwise \end{cases} \quad (17)$$

4.Excited arbitrary confined search (EACS)

The key idea of EACS is to instantaneously move to an arbitrarily produced new-fangled position in the neighbourhood without considering other prospects as long as this new-fangled position obtains an enhanced fitness score than the existing position. This is different from some other conventional local search methods such as hill climbing in which the subsequent move is always the finest position in the surroundings. EACS is helpful to attain more arbitrariness and diversity of exploration for dodging local optima. Further, in exploiting the neighbourhood, only a minor subset of arbitrarily selected variables undergoes alterations to arbitrarily produce a provisional solution. If this provisional solution is superior, it solely swaps the present one. Otherwise a new-fangled provisional solution is produced with other arbitrarily selected variables. This technique is completed when a given number of provisional solutions have been produced without finding better ones. In Excited Arbitrary Confined Search (EACS), we modestly use a constant probability distribution when new-fangled provisional solutions are produced given a present solution. To be more definite, when dimension k is

designated for change, the provisional solution Y' will get the following values on this dimension irrespective of its preliminary value in the present solution:

$$Y'[k] = \text{arbitrary}\left(c_p, d_q\right) \quad (18)$$

Where $\text{arbitrary}\left(c_p, d_q\right)$ is a constant arbitrary number between c_p and d_q , and c_p, d_q are the minimum and maximum values correspondingly on dimension k. As equivalent chance is set to the whole range of a variable when altering a solution, EACS is more probable to produce new-fangled points with large variation, thus upsurge the chance to jump out from a local optimum.

EACS algorithm

Fix p = 1;
While $p \leq N$ do
Contenders = 1, 2. . . dimension;
Fix q = 1;
While $q < \varphi *$ dimension do
Arbitrarily pick k from contenders;
Allocate an arbitrary probable value to parameter k of the vector;
Eliminate k from contenders;
Fix $q = q + 1$;
End while
If this new-fangled solution is superior to the parent then
Swap the parent solution with the new one;
Fix p = 1;
Else
Fix $p = p + 1$
End if
End while

In the above, where φ symbolizes the portion of variables that are subject to local changes and N is the maximum number of times a provisional solution can be produced in order to find a superior position than the present one.

5.Enhanced differential evolution (EDE) algorithm

Here we propose a new-fangled EDE algorithm by combining basic DE with EACS. Excited arbitrary confined search is applied in each generation after completing the mutation, crossover and selection operators. The greatest individual in the population is used as the preliminary point when EACS is executed. If EACS ends with a superior solution, it is injected into the population and the present greatest member in the population is rejected.

EDE algorithm

Step 1: Initialize the population with arbitrarily produced individuals.
Step 2: Evaluate the fitness values of all individuals in the population.
Step 3: While the end condition is not fulfilled do Generate mutant vectors using a mutation approach. Generate provisional vectors by re-combine mutant vectors with parent's vector.
Step 4: Calculate provisional vectors with their fitness function.
Step 5: Pick winning vectors as individuals in the subsequent generation.
Step 6: Find the greatest individual in the population.
Step 7: Accomplish local exploration using EACS approach
Step 8: If the result from local exploration is better than new best then swap new best by local exploration in the population.
Step 9: End

6.Simulation results

Validity of EDE algorithm has been verified by testing in IEEE 30-bus, 41 branch systems and it has 6 generators-bus voltage magnitudes, 4 transformers-tap settings, and 2 bus shunt reactive compensators. Bus 1 is considered as slack bus and 2, 5, 8, 11 and 13 are considered as PV generator buses and others are PQ load buses. Control variable limits are given in *Table 1*. In *Table 2* the power limits of generators buses are listed.

Table 1 Primary variable limits (Pu)

Variables	Min.	Max.	Category
Generator Bus	0.90	1.10	Continuous
Load Bus	0.95	1.05	Continuous
Transformer-Tap	0.90	1.10	Discrete
ShuntReactive Compensator	-0.10	0.30	Discrete

Table 2 Generators power limits

Bus	Pg	Pgmin	Pgmax	Qgmin
1	96.00	49	200	-19
2	79.00	18	79	-19
5	49.00	14	49	-11
8	21.00	11	31	-14
11	21.00	11	28	-12
13	21.00	11	39	-14

Table 3 shows the proposed EDE approach successfully kept the control variables within limits. *Table 4* list out the overall comparison of the results of optimal solution obtained by various methods. Real loss has been reduced considerably by the projected algorithm.

Table 3 After optimization values of control variables

Control variables	EDE
V1	1.05
V2	1.04
V5	1.02
V8	1.03
V11	1.08
V13	1.05
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.91
Q10	0.10
Q24	0.10
Real power loss	4.29
Voltage deviation	0.90

Table 4 Comparison of results

References	Techniques	Real power loss (Mw)
[16]	Simple genetic algorithm (SGA)	4.98
[17]	Particle swarm optimization (PSO)	4.93
[18]	Linear programming (LP)	5.99
[18]	Expectation propagation (EP)	4.96
[18]	Conjugate gradient (CG)	4.98
[18]	Applied geometric algorithm (AGA)	4.92
[18]	Comprehensive learning (CL)-PSO	4.72
[19]	Harmony search algorithm (HAS)	4.76
[20]	Big bang-big crunch (BB-BC)	4.69
Proposed	EDE	4.29

7.Conclusion

In this paper, EDE algorithm has been effectively applied to solve optimal reactive power dispatch problem. The proposed EDE algorithm has been tested in the standard IEEE 30 bus system. Simulation results show that the robustness of proposed EDE have been effective in decreasing the real power loss. The control variables obtained after the optimization by EDE are well within the limits.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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