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Reduction of Power Loss by Enhanced Algorithms

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ABSTRACT

In this paper improved evolutionary algorithm (IEA) and enriched firefly algorithm (EFA) has been used to solve optimal reactive power problem. In the improved evolutionary algorithm by using the set of route vectors the search has been enhanced and in the enriched firefly algorithm differential evolution algorithm has been mingled to improve the solution. Both the proposed IEA&EFA has been tested in practical 191 (Indian) utility system and 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: Improved evolutionary algorithm, Enriched firefly algorithm, Differential evolution, Optimal reactive power, Transmission loss.

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1. INTRODUCTION

To till date various methodologies had 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 (Alsac and Scott, 1973; Hobson, 1980; Lee *et al.*, 1985; Monticelli *et al.*, 1987; Deeb and Shahidehpur, 1990; Lee *et al.*, 1993; Mangoli and Lee, 1993; Canizares *et al.*, 1996) has been utilized to solve the reactive power problem, but they lack in handling the constraints to reach a global optimization solution. In the next level various types of evolutionary algorithms (Eleftherios *et al.*, 2010; Hu *et al.*, 2010; Berizzi *et al.*, 2012; Roy *et al.*, 2012) has been applied to solve the reactive power problem. But each and every algorithm has some merits and demerits. This paper proposes improved evolutionary algorithm (IEA) and enriched firefly algorithm (EFA) to solve optimal reactive power problem. In the improved evolutionary algorithm by using the set of route vectors the search has been enhanced and in the enriched firefly algorithm differential evolution algorithm has been mingled to improve the solution. Both the proposed IEA&EFA has been tested in practical 191 (Indian) utility system. The simulation results show that the proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

2. OBJECTIVE FUNCTION

2.1. Active 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:

$$\mathrm{F} = P_L = \sum_{\mathrm{k \in Nbr}} \mathrm{g_k} \left(\mathrm{V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}}\right) \qquad (1)$$

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:

$$\mathrm{F} = P_L + \omega_\mathrm{v} \times \mathrm{VD} \qquad (2)$$

Where VD - voltage deviation, ω_v- is a weighting factor of voltage deviation.

And the Voltage deviation given by:

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

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:

$$\mathrm{P_G = P_D + P_L} \qquad (4)$$

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:

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

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

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

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

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

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

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

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

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. IMPROVED EVOLUTIONARY ALGORITHM (IEA)

The objective space of an IEA is degenerated into a set of sub objective spaces by a set of route vectors, and then obtained solutions are regarded as 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 existing obtained solutions being population (POP), these solutions will be regarded as by the following formulation:

$$P^i = \left\{x \,\middle|\, x \in POP, \Delta(F(X),\gamma^i) = \max_{1\le j\le N}\{\Delta(F(x),\gamma^j)\}\right\}, \qquad (10)$$

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

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 $(x) - Z$. These solutions are alienated into N classes by the formulation (6.1) and the objective space Ω divided into N sub objective spaces $\Omega_1,..,\Omega_N$, where $\Omega_k(k = 1,..,N)$ is

$$\Omega_k = \left\{F(x)|x \in \Omega, \Delta(F(X),\gamma^k) = \max_{1\le j\le N}\{\Delta(F(x),\gamma^j)\}\right\} \qquad (11)$$

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

Solutions are more to be anticipated to be designated to create new-fangled solutions, and then their sub objective spaces can quickly find their optimal solutions. In order to attain the goalmouth, the crowding distance is used to calculate the fitness value of a solution for the selection operators. Since 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 rarer solutions in their frame than other solutions. Thus, by using the crowding distance to calculate the fitness value of a solution, the fitness values of these solutions are better than those solutions and these solutions are more likely to be designated to create new-fangled solutions.

Algorithm of improved evolutionary algorithm for reactive power dispatch 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 $Z_i = min\{f_i(x)|x \in POP(k)\}, 1 \le i \le m$.

Step 2 .Fitness. Solutions of POP (k) are firstly alienated into N classes by the equation (10) 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 $\mathrm{j} = 1,..,\mathrm{m}$, if$\mathrm{Z_j} > min\left\{\mathrm{f_j(x)}|\mathrm{x} \in \mathrm{O}\right\}$, then set $\mathrm{Z_j} = \min\left\{\mathrm{f_j(x)}|\mathrm{x} \in \mathrm{O}\right\}$.The solutions of $\mathrm{POP(k)} \cup \mathrm{O}$ are first categorized by the equation (10); then N best solutions are picked by the update strategy and put into $\mathrm{POP(k+1)}$. let $\mathrm{k = k + 1}$.

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

4. ENRICHED FIREFLY ALGORITHM (EFA)

In this method (Storn and Price, 1997) each solution in a population represents a solution which is located arbitrarily within a specified penetrating space. The *i*th solution, X_i, is represented as follows:

$$X_{i(t)} = \{X_{i1(t)}, X_{i2(t)}, .., X_{id(t)}\} \quad (12)$$

Where, $X_{i(t)}$ is the vector with k = 1, 2, 3, ..., d, and *t* is the time step. Initially, the fitness value of each solution was evaluated. The fitness value of each *i*th solution in this sub-population was then compared with its *j*th neighbouring solution. If the fitness value of the neighbouring solution was better, the distance between every solution would then be calculated using the standard Euclidean distance measure. The distance was used to compute the attractiveness, β:

Where

$$\beta = \beta_0 e^{-\gamma r_i j^2} \quad (13)$$

Where β_0, γ and r_{ij} are the predefined attractiveness, light absorption coefficient, and distance between *i*th solution and its *j*th neighbouring solution. Later, this new attractiveness value was used to update the position of the solution, as follows:

$$x_{id} = x_{id} + \beta\left(x_{jd} - x_{id}\right) + \alpha\left(\delta - \frac{1}{2}\right) \quad (14)$$

Where α and δ are uniformly distributed random values between 0 to 1. Thus, the updated attractiveness values assisted the population to move towards the solution that produced the current best fitness value .

On the other hand, the second sub-population contained solutions that produced less significant fitness values. The solutions in this population were subjected to undergo the evolutionary operations of DE method. Firstly, the trivial solutions were produced by the mutation operation performed on the original counterparts. The ith trivial solution, V_i , was generated based on the following equation:

$$V_{i(t)} = \{v_{i1(t)}, v_{i2(t)}, .., v_{id(t)}\} \quad (15)$$

$$v_{i(t)} = x_{best(t)} + F.\left(x_{r1(t)} - x_{r2(t)}\right) \quad (16)$$

Where $x_{best(t)}$ is the vector of current best solution, F is the mutation factor, $x_{r1(t)}$ and $x_{r2(t)}$ are arbitrarily chosen vectors from the adjacent solutions. Following, the offspring solution was produced by the crossover operation that involved the parent and the trivial solution. The vectors of the ith offspring solution, Y_i, were created as follows

$$Y_{i(t)} = \{y_{i1(t)}, y_{i2(t)}, .., y_{id(t)}\} \quad (17)$$

$$y_{i(t)} = \begin{cases} v_{i(t)}\ if\ R < CR \\ x_{i(t)}\ otherwise \end{cases} \quad (18)$$

Where R is a regularly distributed random value between 0 to 1 and C R is the predefined crossover constant . As the population of the offspring solution was produced, a selection operation was required to keep the population size constant. The operation was performed as follows:

$$X_{i(t+1)} = \begin{cases} Y_{i(t)}\ if\ f\left(Y_{i(t)}\right) \le f\left(X_{i(t)}\right) \\ X_{i(t)}\ if\ f\left(Y_{i(t)}\right) > f\left(X_{i(t)}\right) \end{cases} \quad (19)$$

Enriched Firefly Algorithm (EFA) for optimal dispatch problem.

Input**:** Arbitrarily initialize position of *d* dimension problem: X_i

Output**:** Position of the approximate global optima: X_G

Begin

Initialize population; Evaluate fitness value;

X_G ←Select current best solution;

For t ← 1 to *max*

Sort population based on the fitness value;

$X_{good} \leftarrow first_{half(X)}; X_{worst} \leftarrow second\_half(X);$

For *i* ← 0 to number of X_{good} solutions

For *j* ← 0 to number of X_{good} solutions

If $(f(X_i) > f(X_j))$ then

Compute distance and attractiveness;

Update position;

End If

End For

End For

For *i* ← 0 to number of X_{worst} solutions

Create trivial solution, $V_{i(t)}$;

Perform crossover, $Y_{i(t)}$;

Perform selection, $X_{i(t)}$;

End For

$X \leftarrow combine(X_{good}, X_{worst});$

X_G ←Select current best solution;

t← $t + 1$; 1;

End For

End Begin

5. SIMULATION STUDY

Both algorithms have been tested in practical 191 test system and the following results has been obtained

In Practical 191 test bus system – Number of Generators = 20, Number of lines = 200, Number of buses = 191 Number of transmission lines = 55. Table 1&2 shows the optimal control values of practical 191 test system obtained by IEA and EFA methods. And table 3 shows the results about the value of the real power loss by obtained by both proposed improved evolutionary algorithm and enriched firefly algorithm. Although both the projected algorithms successfully applied to the problem IEA has the edge over EFA in reducing the real power loss.

Table-1. Optimal Control values of Practical 191 utility (Indian) system by IEA method

VG1	1.17	VG 11	0.90
VG 2	0.81	VG 12	1.01
VG 3	1.06	VG 13	1.04
VG 4	1.01	VG 14	0.98
VG 5	1.10	VG 15	1.01
VG 6	1.16	VG 16	1.08
VG 7	1.12	VG 17	0.90

VG 8	1.01	VG 18	1.01
VG 9	1.10	VG 19	1.13
VG 10	1.04	VG 20	1.11

T1	1.01	T21	0.90	T41	0.90
T2	1.06	T22	0.96	T42	0.92
T3	1.07	T23	0.98	T43	0.95
T4	1.10	T24	0.91	T44	0.93
T5	1.02	T25	0.92	T45	0.96
T6	1.06	T26	1.00	T46	0.91
T7	1.01	T27	0.93	T47	0.97
T8	1.04	T28	0.92	T48	1.03
T9	1.02	T29	1.06	T49	0.92
T10	1.01	T30	0.92	T50	0.91
T11	0.92	T31	0.96	T51	0.94
T12	1.05	T32	0.95	T52	0.92
T13	1.04	T33	1.04	T53	1.02
T14	1.03	T34	0.92	T54	0.91
T15	1.01	T35	0.90	T55	0.90
T19	1.08	T39	0.98		
T20	1.08	T40	0.90		

Table 2. Optimal Control values of Practical 191 utility (Indian) system by EFA method

VG1	1.11	VG 11	0.90
VG 2	0.79	VG 12	1.01
VG 3	1.01	VG 13	1.04
VG 4	1.04	VG 14	0.92
VG 5	1.09	VG 15	1.01
VG 6	1.15	VG 16	1.04
VG 7	1.12	VG 17	0.90
VG 8	1.01	VG 18	1.02
VG 9	1.10	VG 19	1.11
VG 10	1.02	VG 20	1.10

T1	**1.03**	**T21**	**0.90**	**T41**	**0.90**
T2	1.07	T22	0.94	T42	0.92
T3	1.08	T23	0.93	T43	0.91
T4	1.08	T24	0.91	T44	0.92
T5	1.01	T25	0.93	T45	0.94
T6	1.03	T26	1.00	T46	0.91
T7	1.07	T27	0.92	T47	0.96
T8	1.06	T28	0.92	T48	1.03
T9	1.05	T29	1.01	T49	0.91
T10	1.02	T30	0.92	T50	0.92
T11	0.90	T31	0.94	T51	0.93
T12	1.05	T32	0.93	T52	0.91
T13	1.08	T33	1.06	T53	1.01
T14	1.02	T34	0.92	T54	0.92
T15	1.01	T35	0.90	T55	0.90
T19	1.08	T39	0.98		
T20	1.08	T40	0.90		

Table-3. Optimum real power loss values obtained for practical 191 utility (Indian) system by IEA &EFA.

Real power Loss (MW)	**EFA**	**IEA**
min	149.001	148.241
max	152.786	151.995
average	149.276	148.615

6. CONCLUSION

In this paper, both the improved evolutionary algorithm and enriched firefly algorithm has been successfully implemented to solve Optimal Reactive Power Dispatch problem. The proposed algorithms have been tested in practical 191 (Indian) utility system. Simulation results show the robustness of proposed algorithms for providing better optimal solution in decreasing the real power loss. The control variables obtained after the optimization by both algorithms are well within the limits.

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