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Opposition based red wolf algorithm for solving optimal reactive power problem

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ABSTRACT

This paper presents an opposition based red wolf optimization (ORWO) algorithm for solving optimal reactive power problem. Each red wolf has a flag vector in the algorithm, and length is equivalent to the whole sum of numbers which features in the dataset of the wolf optimization (WO). In this proposed algorithm, red wolf optimization algorithm has been intermingled with opposition-based learning (OBL). By this amalgamate procedure the convergence speed of the proposed algorithm will be increased. To discover an improved candidate solution, the concurrent consideration of a probable and its corresponding opposite are estimated which is closer to the global optimum than an arbitrary candidate solution. Proposed algorithm has been tested in standard IEEE 14-bus and 300-bus test systems. The simulation results show that the proposed algorithm reduced the real power loss considerably.

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1. INTRODUCTION

In this work the key objective is actual power loss reduction. Optimal reactive power problem has been solved by a variety of methods [1]-[6]. However many technical hitches are found while solving problem due to an assortment of constraints. Evolutionary techniques [7]-[16] are applied to solve the reactive power problem, but the key problem is some algorithms stuck in local optimal solution, and failed to balance the exploration and exploitation during the search of global solution. This paper proposes an opposition based red wolf optimization (ORWO) algorithm for solving optimal reactive power problem. Each red wolf has a flag vector in the algorithm and length is equivalent to the whole sum of numbers which features in the dataset of the wolf optimization (WO) [17]-[19]. In this proposed algorithm red wolf optimization algorithm has been intermingled with opposition based learning (OBL) [20]. By this convergence speed will be increased. To discover an improved candidate solution, the concurrent consideration of a probable and its corresponding opposite are estimated which is closer to the global optimum than an arbitrary candidate solution. Proposed algorithm has been tested in standard IEEE 14-bus and 300-bus test systems. The simulation results show that the proposed algorithm reduced the real power loss considerably.

2. PROBLEM FORMULATION

Objective of the problem is to reduce the true power loss:

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

Voltage deviation given as (2).

$$\mathbf{F = P_L + \omega_v \times Voltage\ Deviation} \quad (2)$$

Voltage deviation given by (3).

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

Equality constraint given by (4).

$$\mathbf{P_G = P_D + P_L} \quad (4)$$

Inequality constraints are given by (5)-(9).

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

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

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

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

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

3. OPPOSITION BASED RED WOLF OPTIMIZATION

Red wolf optimization mimics the communal management and hunt deeds of red wolves in nature. There are three fittest candidate solutions assumed as α, β and γ to lead the population toward promising regions of the exploration space in each iteration of red wolf optimization. φ is named for the rest of red wolves and it will assist α, β and γ to encircle, hunt, and attack prey, that is to find enhanced solutions. In order to scientifically replicate the encompassing behavior of red wolves, The (10) is proposed.

$$\vec{G} = \left|\vec{F}.\overrightarrow{Y_P}(t) - \vec{Y}(t)\right|, \vec{Y}(t+1) = \overrightarrow{Y_P}(t) - \vec{H}.\vec{G} \quad (10)$$

Where t indicates the current iteration, $\vec{H} = 2\vec{b}.\vec{r_1} - \vec{b}$, $\vec{F} = 2.\vec{r_2}$, $\widehat{Y_P}$ the position vector of the prey, $\vec{Y}$ is the position vector of a red wolf, $\vec{b}$ is linearly decreased from 2.0 to 0, and $\vec{r_1}$ and $\vec{r_2}$ are arbitrary vectors in [0, 1].

In order to mathematically simulate the hunting behavior of red wolves, The (11), (12), and (13) are proposed.

$$\begin{aligned} \overrightarrow{G_\alpha} &= \left|\overrightarrow{F_1}, \overrightarrow{Y_\alpha} - \vec{Y}\right| \\ \overrightarrow{G_\beta} &= \left|\overrightarrow{F_2}, \overrightarrow{Y_\beta} - \vec{Y}\right| \\ \overrightarrow{G_\gamma} &= \left|\overrightarrow{F_3}, \overrightarrow{Y_\gamma} - \vec{Y}\right| \end{aligned} \quad (11)$$

$$\begin{aligned} \overrightarrow{Y_1} &= \overrightarrow{Y_\alpha} - \overrightarrow{H_1}.\overrightarrow{G_\alpha} \\ \overrightarrow{Y_2} &= \overrightarrow{Y_\beta} - \overrightarrow{H_2}.\overrightarrow{G_\beta} \\ \overrightarrow{Y_3} &= \overrightarrow{Y_\gamma} - \overrightarrow{H_3}.\overrightarrow{G_\gamma} \end{aligned} \quad (12)$$

$$\vec{Y}(t+1) = \frac{\overrightarrow{Y_1} + \overrightarrow{Y_2} + \overrightarrow{Y_3}}{3} \quad (13)$$

The position of a red wolf was updated by (13) and (14) is used to discrete the position.

$$flag_{i,j} = \begin{cases} 1 & Y_{i,j} > 0.50 \\ 0 & otherwise \end{cases} \quad (14)$$

Where i, indicates the jth position of the ith red wolf, $flag_{i,j}$ is features of the wolf.

OBL is one of the influential optimization tools to boost the convergence speed of different optimization techniques. The thriving implementation of the OBL engages evaluation of opposite population and existing population in the similar generation to discover the superior candidate solution of a given reactive power problem. The conception of opposite number requirements is to be defined to explain OBL. Let N ($N \in [x, y]$) be a real number and the N^o (opposite number) can be defined as (15).

$$N^o = x + y - N \tag{15}$$

In the exploration space it has been extended as (16).

$$N_i^o = x_i + y_i - N_i \tag{16}$$

Where $(N_1, N_2, .. N_d)$ is a point in the dimensional search space, $N_i \in [x_i, y_i]$, $i \rightarrow \{1,2,3, .. d\}$.

In all oppositional based optimization, the conception of OBL is used in the initialization procedure and as well as in each iteration using the generation jumping rate, Jr.

Step 1: The positions of red wolves (search agents) are initialized arbitrarily in the exploration space. Population size (number of wolves) and number of iterations are fixed.
Step 2: Compute fitness value of each search agent which represents the distance of wolf from the prey.
Step 3: Initialize opposite points and use them to generate opposite population and compute the fitness of each individual populations.
Step 4: Perform sorting among existing population (pop) and opposite population (opop), based on their fitness values.
Step 5: Select nP number of fittest solutions from the combination of the existing and the equivalent opposite population.
Step 6: Based on the fitness values, solutions are identified which represent the alpha, beta and delta category wolves, respectively.
Step 7: Modify the positions of the red wolves
Step 8: Update the fitness value using the modified position of the Red wolves.
Step 9: Using jumping rate, the opposite population are generated from the current population.
Step 10: Select nP number of fittest solutions from the combination of the current and the opposite population.
Step 11: Repeat step 6 to step 10 until the maximum number of iterations is reached.
Step 12: Output the best solution.

The pseudocode is shown in Algorithm 1.

Algorithm 1. Pseudocode optimization

Commence
Initialize the parameters
Initialize b, $\vec{H}$ and $\vec{F}$; beginning positions of Red wolves has been stimulated.
Generate opposite population; for j=; population size for i=1; number of control variables
$N_i^o = x_i + y_i - N_i$
Classify the existing population and the opposite population from best to worst
Depending upon the population size nP, choose nP number of fittest solutions from the existing and the opposite population
Modernize the control variables
By utilizing the jumping rate, opposite population are generated from the existing population:
End if
End for
Work out the maximum fitness of Red wolves as follows,
Primary maximum fitness of the Red wolf is designated as "α"
Second maximum fitness of the Red wolf is designated as "β"
Third maximum fitness of the Red wolf is designated as "γ"
While k < maximum iteration
For i=1; population size
For j=1; number of variables
If $jumping\ rate > random$
$opop(i, j) = \min(j) + \max(j) - pop(i, j)$
Else
$opop(i, j) = pop(i, j)$
End if
End for
Intermittently modify the values of b, $\vec{H}$ and $\vec{F}$;
Fitness of Red wolves has been calculated

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The assessment of red wolves "α","β" and "γ" has to be revised
       k=k+1;
End while
Revise the value of" α "as the optimal characteristic division;
End
```

4. SIMULATION RESULTS

At first in standard IEEE 14-bus system the validity of the proposed ORWO algorithm has been tested and comparison results are presented in Table 1. Figure 1 provides the details of comparison of real power loss. Then IEEE 300-bus system [22] is used as test system to validate the performance of the ORWO algorithm. Table 2 shows the comparison of real power loss obtained after optimization. Compared to EEA method, the proposed ORWO reduces 5.58% real power loss. Real power loss has been considerably reduced when compared to the other standard reported algorithms.

Table 1. Comparison results

Control variables	ABCO [21]	IABCO [21]	Proposed ORWO
V1	1.06	1.05	1.02
V2	1.03	1.05	1.01
V3	0.98	1.03	1.00
V6	1.05	1.05	1.00
V8	1.00	1.04	0.90
Q9	0.139	0.132	0.100
T56	0.979	0.960	0.900
T47	0.950	0.950	0.900
T49	1.014	1.007	1.000
Ploss (MW)	5.92892	5.50031	4.54826

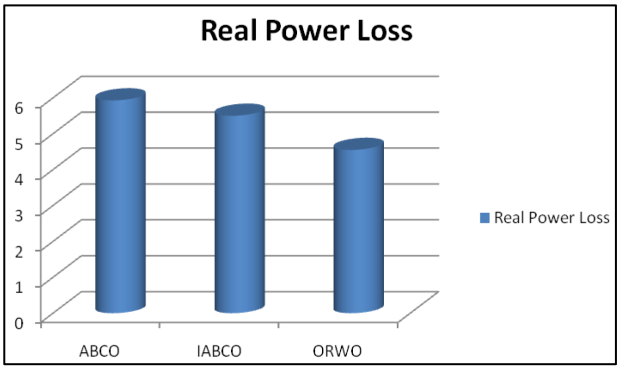

Figure 1. Comparison of real power loss

Table 2. Comparison of real power loss

Parameter	EEA Method [23]	EGA Method [23]	CSA Method [24]	Proposed ORWO
PLOSS (MW)	650.6027	646.2998	635.8942	614.2846

5. CONCLUSION

ORWO algorithm has successfully solved the reactive power optimization problem. In this proposed ORWO algorithm has been intermingled with OBL. By this amalgamate procedure the convergence speed of the proposed algorithm has been increased. Proposed algorithm has been tested in standard IEEE 14-bus and 300-bus test systems. Simulation results show that the proposed ORWO algorithm reduced the real power loss considerably. Compared to EEA method, the proposed ORWO has reduced 5.58% real power loss.

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