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Augmented Biogeography Algorithm for Reduction of Active Power Loss

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Abstract

In this paper, an Augmented Biogeography (AB) algorithm proposed to solve optimal reactive power problem. Self-adaptive Differential Evolution Algorithm (SDE) is hybridized with Biogeography based optimization (BBO) algorithm to improve the exploration & exploitation capabilities. In the Proposed Augmented Biogeography (AB) algorithm Self-adaptive Differential Evolution Algorithm and Biogeography-Based Algorithm is executed in sequence manner in the iteration-level. Even though Self-adaptive Differential Evolution Algorithm acts separately it exchanges information to Biogeography-Based algorithm. Proposed Augmented Biogeography (AB) algorithm has been tested in standard IEEE 57 test system. Results show that Augmented Biogeography (AB) algorithm reduces the real power loss and voltage profiles are within the limits.

***Keywords:**, Augmented Biogeography, Self-Adaptive, Differential Evolution, Reactive power, Transmission loss.*

I. INTRODUCTION

To improve the economy and safety of power system optimal reactive power problem has been acknowledged huge attention. At the beginning, a huge number of classical methods such as gradient based [1-3], interior point [4], linear programming [5] and quadratic programming [6] have been productively applied to the problem. Poor convergence rate, long completing time, algorithmic intricacy, trapping in local optima are found in those classical methods. Researchers have fruitfully applied evolutionary and heuristic algorithms such as Genetic Algorithm (GA), Differential Evolution (DE) and Particle Swarm Optimization (PSO) [7-9] to overcome those disadvantages found in classical methods. In this paper, an Augmented Biogeography (AB) algorithm proposed to solve reactive power problem. Self-adaptive Differential Evolution Algorithm (SDE) is hybridized with Biogeography based optimization (BBO) algorithm to improve the exploration & exploitation capabilities. In the Proposed Augmented Biogeography (AB) algorithm Self-adaptive Differential Evolution Algorithm and Biogeography-Based Algorithm is executed in sequence manner in the iteration-level. Even though Self-adaptive Differential Evolution Algorithm acts separately it exchanges information to Biogeography-Based algorithm [10-12]. Proposed Augmented Biogeography (AB) algorithm has been tested in standard IEEE 57 bus test system. Results show that Augmented Biogeography (AB) algorithm reduces the real power loss and voltage profiles are within the limits.

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II. PROBLEM FORMULATION

Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

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

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.

Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \tag{2}$$

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

Voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \tag{3}$$

Where Npq- number of load buses

Equality Constraint

The equality constraint of the problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \tag{4}$$

Where P_G- total power generation,P_D - total power demand.

Inequality Constraints

The inequality constraints 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 (Pg), and reactive power of generators (Q_g) are written in mathematically as follows:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \tag{5}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \tag{6}$$

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

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \tag{7}$$

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

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \tag{8}$$

Upper and lower bounds on the compensators reactive powers (Q_c):

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \tag{9}$$

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.

III. SELF-ADAPTIVE DIFFERENTIAL EVOLUTION

Differential evolution (DE) is a simple evolutionary algorithm that creates new candidate solutions by combining the parent solution and several other candidate solutions. A candidate solution replaces the parent solution if it has better fitness. This is a greedy selection scheme that often outperforms traditional evolutionary algorithms. Self-adaptive Differential Evolution Algorithm (SDE) is one of the best DE variants. It uses a self-adaptive mechanism on control parameters F and CR. Each candidate solution in the population is extended with control parameters F and CR that are adjusted during evolution. Better values of these control parameters lead to better candidate solutions, which in turn are more likely to survive the selection process to produce the next solution and propagate the good parameter values. SDE is highly independent of the optimization problem's characteristics and complexity, and it involves self-adaptation and learning by experience. SDE demonstrates consistently good performance on a variety of problems, including both unimodal and multimodal problems.

IV. BIOGEOGRAPHY-BASED OPTIMIZATION (BBO)

Biogeography based optimization (BBO) algorithm is a new population-based optimization algorithm inspired by the natural biogeography distribution of different species. In BBO each individual is considered as a “habitat” with a habitat suitability index (HIS). A good solution is analogous to an island with a high HSI, and a poor solution indicates an island with a low HSI. High HSI solutions tend to share their features with low HSI solutions. Low HSI solutions accept a lot of new features from high HSI solutions. In BBO, each individual has its own immigration rate λ and emigration rate μ. A good solution has higher μ and lower λ and vice versa. The immigrant ion rate and the emigration rate are functions of the number of species in the habitat. They can be calculated as follows,

$$\lambda_k = I\left(1 - \frac{k}{n}\right) \tag{10}$$

$$\mu_k = E\left(\frac{k}{n}\right) \tag{11}$$

Where I is the maximum possible immigration rate; E is the maximum possible emigration rate; k is the number of species of the k-th individual; and n is the maximum number of species. In BBO, there are two main operators, the migration and the mutation.

Migration

Consider a population of candidate which is represented by design variable. Each design variable for particular population member is considered as SIV for that population member. Each population member is considered as individual habitat/Island. The objective function value indicates the HSI for the particular population member. S value represented by the solution depends on its HSI. S1 and S2 represent two solutions with different HSI. The emigration and immigration rates of each solution are used to probabilistically share information between habitats. If a given solution is selected to be modified, then its immigration rate λ is used to probabilistically modify each suitability index variable

(SIV) in that solution. If a given SIV in a given solution Si is selected to be modified, then its emigration rates μ of the other solutions is used to probabilistically decide which of the solutions should migrate randomly for selected SIV to solution Si. The above phenomenon is known as migration in BBO. Because of this migration phenomenon BBO is well suited for the discrete optimization problems as it deals with the interchanging of design variables between the population members.

Mutation

In nature a habitat's HSI can change suddenly due to apparently random events (unusually large flotsam arriving from a neighboring habitat, disease, natural catastrophes, etc.). This phenomenon is termed as SIV mutation, and probabilities of species count are used to determine mutation rates. This probability mutates low HSI as well as high HSI solutions. Mutation of high HSI solutions gives them the chance to further improve. Mutation rate is obtained using following equation.

$$M(s) = m_{max}\left(1-\frac{P_s}{P_{max}}\right) \tag{12}$$

Where, m_{max} is a user-defined parameter called mutation coefficient.

Steps of iteration-level hybridization combining SDE with BBO

Step 1.Generate the initial population P

Step 2.Maximum number of function evaluations reached? If Yes output result. If No go to step 3.

Step 3.Create offspring O from P using SaDE.

Step 4.Improve offspring O using BBO.

Step 5.Replace parent P with O.

Step 6.Output.

Where P is the parent population and O is the offspring population.

We implement iteration-level hybridization for optimal reactive power problem by combining recently developed SDE with BBO. The goal of this hybridization approach is to balance the exploration and exploitation ability.

Augmented Biogeography (AB) algorithm for solving reactive power problem

1: Arbitrarily initialize the parent population P

2: Calculate the fitness of all candidate solutions in P

3: Whereas the halting criterion is not satisfied do

4: Perform a recently developed SDE to create offspring population O

5: Calculate the fitness of each solution in offspring population O

6: Compute the immigration rate λ and emigration rate μ of each solution

7: Accomplish one generation of BBO to improve the solutions in offspring population O

8: Swap the parent population P with the offspring population O

9: End while

One generation of an iteration-level hybridization of SDE and BBO, where N is the population size. y and z comprise the entire population of candidate solutions, yk is the kth candidate solution, and yk(a) is the ath decision variable of yk. CR and F are the probability of crossover and the scaling factor of SDE respectively, and δ is a BBO control parameter between 0 and 1.

a) z←y
b) For each candidate solution $z_k(k = 1 \text{ to } N)$ do
c) For each candidate solution decision variable index a do
d) Pick three random solutions yr1, yr2 and yr3 mutually distinct from each other and from zk.
e) Pick a random index n between 1 and N
f) Use CR (probabilistic) or n (deterministic) to decide on recombination
g) If recombination then
h) $z_k(a) \leftarrow y_{r1}(a) + F\big(y_{r2}(a) - y_{r3}(a)\big)$
i) End if
j) Update the control parameters F and CR using the SDE adaptive mechanism
k) End for
l) Evaluate the fitness of each candidate solution zk in the population
m) For each zk define emigration rate μk proportional to the fitness of zk, where μk ∈ A[0,1]
n) For each candidate solution zk define immigration rate $\lambda_k = 1 - \mu_k$
o) For each candidate solution decision variable index "a" do
p) Use λk to probabilistically decide whether to immigrate to zk
q) If immigrating then
r) Use {μ} to probabilistically select the migrating solution yj
s) $z_k(a) \leftarrow \delta z_k(a) + (1 - \delta) y_j(a)$
t) End if
u) End for
v) End for
w) y←z

V. SIMULATION RESULTS

Augmented Biogeography (AB) algorithm has been tested in standard IEEE-57 bus power system. The reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. The system variable limits are given in Table 1.

The preliminary conditions for the IEEE-57 bus power system are given as follows:

P_{load} = 12.102 p.u. Q_{load} = 3.038 p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G$ = 12.386 p.u. $\sum Q_G$ = 3.3102 p.u.
P_{loss} = 0.25764 p.u. Q_{loss} = -1.2048 p.u.

Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after optimization which are within the acceptable limits. In Table 3, shows the comparison of optimum results obtained from proposed methods with other optimization techniques. These results indicate the robustness of proposed approaches for providing better optimal solution in case of IEEE-57 bus system.

TABLE 1, VARIABLE LIMITS

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50

Voltage And Tap Setting Limits					
vgmin	Vgmax	vpqmin	Vpqmax	tkmin	tkmax
0.9	1.0	0.91	1.05	0.9	1.0

Shunt Capacitor Limits			
Bus no	18	25	53
Qcmin	0	0	0
Qcmax	10	5.2	6.1

TABLE 2, CONTROL VARIABLES OBTAINED AFTER OPTIMIZATION

Control Variables	AB
V1	1.100
V2	1.024
V3	1.028
V6	1.031
V8	1.053
V9	1.001
V12	1.090
Qc18	0.0648
Qc25	0.200
Qc53	0.0451
T4-18	1.001
T21-20	1.040
T24-25	0.852
T24-26	0.839
T7-29	1.046
T34-32	0.839
T11-41	1.010
T15-45	1.029
T14-46	0.910
T10-51	1.010
T13-49	1.049

T11-43	0.910
T40-56	0.900
T39-57	0.941
T9-55	0.939

TABLE 3, COMPARISON RESULTS

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [13]	0.25902	0.30854	0.27858
2	CGA [13]	0.25244	0.27507	0.26293
3	AGA [13]	0.24564	0.26671	0.25127
4	PSO-w [13]	0.24270	0.26152	0.24725
5	PSO-cf [13]	0.24280	0.26032	0.24698
6	CLPSO [13]	0.24515	0.24780	0.24673
7	SPSO-07 [13]	0.24430	0.25457	0.24752
8	L-DE [13]	0.27812	0.41909	0.33177
9	L-SACP-DE [13]	0.27915	0.36978	0.31032
10	L-SaDE [13]	0.24267	0.24391	0.24311
11	SOA [13]	0.24265	0.24280	0.24270
12	LM [14]	0.2484	0.2922	0.2641
13	MBEP1 [14]	0.2474	0.2848	0.2643
14	MBEP2 [14]	0.2482	0.283	0.2592
15	BES100 [14]	0.2438	0.263	0.2541
16	BES200 [14]	0.3417	0.2486	0.2443
17	Proposed AB	0.22088	0.23026	0.22216

CONCLUSION

In this paper, an Augmented Biogeography (AB) algorithm proposed to solve reactive power problem. In the Proposed Augmented Biogeography (AB) algorithm Self-adaptive Differential Evolution Algorithm and Biogeography-Based Algorithm is executed in sequence manner in the iteration-level. Even though Self-adaptive Differential Evolution Algorithm acts separately it exchanges information to Biogeography-Based algorithm. Proposed Augmented Biogeography (AB) algorithm has been tested in standard IEEE 57 test system. Results show that Augmented Biogeography (AB) algorithm reduces the real power loss and voltage profiles are within the limits.

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