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An Improved Biogeography-based Optimization Algorithm for Optimal Reactive Power Flow

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Abstract

Optimal reactive power flow (OPRF) reduces power system losses and provides better system voltage control by adjusting the reactive power control variables. It has significant influence on economic and secure operation of power systems. In this article, an improved biogeography-based optimization algorithm based on local search strategy (ILSBBO) is presented for solving optimal reactive power flow. The proposed method integrates local search strategy and selection operation of differential evolution (DE) with migration operator in original BBO to improve the efficiency of migration and overcome the premature convergence in BBO algorithm. It has been applied to standard IEEE 30-bus and IEEE 118-bus test systems, and the comparison results show that the proposed approach is feasible and efficient.

Keywords: *Power system, biogeography-based optimization algorithm, local search strategy, reactive power flow problem*

1. Introduction

Optimal reactive power flow (ORPF) aims to minimize the real power loss, improve the quality of voltage, while satisfying a set of operational and physical constraints. It determines controllable variables such as the terminal voltages at the voltage controlled buses, the tap ratio of the tap changing transformers and the output of shunt VAR compensators, etc. to obtain an optimal state of power system [1]. ORPF is a complex combinatorial optimization problem, which involve nonlinear functions, and has multiple local minima and nonlinear and discontinuous constraints [2]. Since optimal power flow (OPF) was first proposed by J.CarPentier in 1962, there are many optimization techniques have been applied in this field. Traditional methods like Nonlinear programming (NLP), Linear programming (LP),Newton-based method, interior point methods (IPM) and Quadratic programming (QP). Evolutionary algorithms (EAs) like Genetic algorithm (GA) [3]and Evolutionary programming (EP). Others like Simulated annealing approach (SA) [4]. Bio-inspired computing algorithms like Particle swarm optimization (PSO) [5, 6], Ant Colony Search algorithm(ACS) [7], Artificial Neural Network(ANN)[8] and Differential evolution(DE)[9, 10].

Biogeography-Based Optimization (BBO) algorithm is a new kind of population-based global optimization method, which was first proposed by D.Simon in 2008 [11]. As in other population-based algorithms, in BBO, individuals are represented by islands (or habitats), and genes are represented by geography features in these islands, through simulating species distribution characteristics, information can be shared by probability-based migration among

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individuals. Therefore, poor individuals can be improved after getting new feature information from good ones. It has been improved that compared with other EAs, BBO has a better performance. And it also have been applied successfully for solving ELD problems [12-16], OPF problem [17-19], and ORPF problem [2].

In order to exploit the exploration and the exploitation capabilities of BBO, and quickly obtain an optimal solution when applied to OPRF, enlightened by DEBBO (a hybrid technique combining DE with BBO) [20-22], this article presents an improved BBO method which is referred to as improved biogeography-based optimization algorithm based on local search strategy (ILSBBO). By integrating a local search strategy from DE with migration operator of BBO, and adding a selection operator to BBO, the ILSBBO can quickly find high quality solutions. The performance of the proposed method has been tested on IEEE 30-bus and IEEE 118-bus systems. Simulation results show that the proposed approach converges to better solution faster than other compared methods in both cases.

The organization of this article is as follows. Section 2 is the introduction of ORPF. Section 3 is a description of both BBO and ILSBBO. Section 4 is the application of ILSBBO on ORPF. Section 5 is the simulation results and analysis. Section 6 is the concluding remarks.

2. ORPF Problem Formulation

The optimal reactive power flow problem is a large nonlinear programming problem with multivariable and numerous equality and inequality constraints. Mathematically OPRF problem can be represented as:

$$\begin{aligned} &Min\ J(x,u) \\ &Subject\ to\ g(x,u) = 0 \\ &h(x,u) \le 0 \end{aligned} \tag{1}$$

J is the objective function to be minimized. To minimize the system active power loss, the objective function can be described as [23]:

$$J = f_Q = \sum_{i=1}^{NB} V_i \sum_{j \in l} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \tag{2}$$

Where, G_{ij} and B_{ij} are the mutual conductance and susceptance between bus i and bus , G_{ii} and B_{ii} are the self-conductance and susceptance of bus i respectively, V_i is the voltages of bus i and Vj is the voltage connected with bus I, θ_{ij} is the voltage angle difference between bus i and j,NB is the total number of buses.

u is the set of control variables. In this work, u is represented as Eq.(3). It includes: the terminal voltages at the voltage controlled bus V_G, the tap ratio of the tap changing transformers T_k, and the output of shunt VAR compensators Qc, which can be adjusted and controlled by operators.

$$u = \left[\mathrm{V_{G1}}, \mathrm{V_{G2}}, \ldots \mathrm{V_{GNG}}, \mathrm{T_{k1}}, \mathrm{T_{k2}}, \ldots \mathrm{T_{kNT}}, \mathrm{Q_{C1}}, \mathrm{Q_{C2}}, \ldots \mathrm{Q_{CNQC}} \right] \tag{3}$$

Where, NG is the number of generators, NT is the number of tap changing transformers and NQC is the number of shunt VAR compensators.

x is the set of dependent variables. It includes the active power of slack bus P_{G1}, the voltages of PQ bus V, the reactive power output of generators Q_G.

$$x = \left[\mathrm{P_{G1}, V_1, V_2, \ldots V_{NPQ}, Q_{G1}, Q_{G2}, \ldots Q_{GNG}} \right] \tag{4}$$

Where, *NPQ* is the number of *PQ* bus.

$g(x, u) = 0$ is equality constrains. The power flow equations are the most fundamental equality constraints that the power system must satisfied.

For each *PQ* bus and *PV* bus:

$$P_i^{spe} - V_i \sum V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0, \quad (i, j \in NB-1) \tag{5}$$

For each *PQ* bus:

$$Q_i^{spe} - V_i \sum V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) = 0, \quad (i, j \in NPQ) \tag{6}$$

NB-1 means slack bus is not considered in flow calculation [24]. P_i^{spe} and Q_i^{spe} are the specified active power and reactive power of bus i respectively, they can be described as:

$$P_i^{spe} = P_{Gi} - P_{Li} \tag{7}$$

$$Q_i^{spe} = Q_{Gi} - Q_{Li} \tag{8}$$

The installation of shunt capacitors in electricity contributes to releasing system capacity and improving voltage level[4].Considering the input of shunt VAR compensators, the specified reactive power in certain buses should include the output of shunt VAR compensators, thus in those buses, the specified reactive power can be described as:

$$Q_i^{spe} = Q_{Gi} - Q_{Li} + Q_{Ci}, \qquad (i \in NQc) \tag{9}$$

Where, P_{Gi} and Q_{Gi} the active and reactive power output of the generator in bus *i*, P_{Li} and Q_{Li} are the active and reactive power demand at bus *I*, G_{ij} and B_{ij} are the transfer conductance and transfer susceptance between bus *i* and *j* (p.u.), Q_{ci} is reactive power generated by *i*th capacitor bank.

h(x,u) ⩽0 is a set of inequality constrains, which include:

1) Generator constraints

$$P_{Gi}^{\min} < P_{Gi} < P_{Gi}^{\max} \qquad i \in S_G \tag{10}$$

$$Q_{Gi}^{\min} < Q_{Gi} < Q_{Gi}^{\max} \qquad i \in S_G \tag{11}$$

Where $P_{Gi}^{\max}$ and $P_{Gi}^{\min}$ are upper and lower limits of P_{Gi}, $Q_{Gi}^{\max}$ and $Q_{Gi}^{\min}$ are upper and lower limits of Q_{Gi}, S_G is the set of generator buses.

2) Voltage constraints

For all network buses, the voltages must be restricted within their permissible lower and upper limits.

$$V_i^{\min} < V_i < V_i^{\max} \qquad i \in S_B \tag{12}$$

$V_i^{\max}$ and $V_i^{\min}$ are the upper and lower limits of voltage in bus *i*; S_B is the set of buses.

3) Transformer constraints

$$K_{Ti}^{\min} < K_{Ti} < K_{Ti}^{\max} \qquad i \in S_T \tag{13}$$

Where K_{Ti} is the *i*th adjustable transformer, $K_{Ti}^{\max}$ and $K_{Ti}^{\min}$ are the upper and lower limits. S_T is the set of voltage regulating transformer.

4) Shunt VAR compensator constraints

Capacitor can only provide reactive power to the system, while the shunt reactor can only absorb reactive power, the reactive power the provided or absorbed is proportional to their terminal voltage as follows:

$$Q_{Ci} = B_{Ci} V_i^2 \tag{14}$$

$$Q_{Ci}^{\min} < Q_{Ci} < Q_{Ci}^{\max} \qquad i \in S_C \tag{15}$$

Where, B_{Ci} is the susceptance ,and $B_{Ci}^{\max}$ 、 $B_{Ci}^{\min}$ are the upper and lower limit of B_{Ci}. S_C is the set of buses which have the installation of shunt VAR compensators. Usually, the quadratic term are considered as 1, thus the compensations can be described as:

$$Q_{Ci} = B_{Ci} \tag{16}$$

In most of non-linear optimization problems, the constraints are considered as terms in the objective function to make the final optimal result more precise. In ORPF, the inequality constraints of the dependent variable are incorporated with the objective function as quadratic penalty terms. Therefore, the objective function is modified to:

$$J_{\mathrm{mod}} = f_Q + \lambda_P \Delta P_{G1}{}^2 + \lambda_V \sum_{i=1}^{NPQ} \Delta V_{Li}{}^2 + \lambda_Q \sum_{i=1}^{NPV+slack} \Delta Q_{Gi}{}^2 \tag{17}$$

Where λ_p， λ_V， λ_Q are the penalty factors, $P_{G1}^{\lim}$,$V_{Li}^{\lim}$ and $Q_{Gi}^{\lim}$ are defined as:

$$\Delta V_{Li} = \begin{cases} V_{Li} - V_{Li}^{\max}; V_{Li} > V_{Li}^{\max} \\ V_{Li}^{\min} - V_{Li}; V_{Li} < V_{Li}^{\min} \\ 0; V_{Li}^{\min} < V_{Li} < V_{Li}^{\max} \end{cases} \tag{18}$$

$$\Delta Q_{Gi} = \begin{cases} Q_{Gi} - Q_{Gi}^{\max}; Q_{Gi} > Q_{Gi}^{\max} \\ Q_{Gi}^{\min} - Q_{Gi}; Q_{Gi} < Q_{Gi}^{\min} \\ 0; Q_{Gi}^{\min} < Q_{Gi} < Q_{Gi}^{\max} \end{cases} \tag{19}$$

$$\Delta P_{G1} = \begin{cases} P_{G1} - P_{G1}^{\max}; P_{G1} > P_{G1}^{\max} \\ P_{G1}^{\min} - P_{G1}; P_{G1} < P_{G1}^{\min} \\ 0; P_{G1}^{\min} < P_{G1} < P_{G1}^{\max} \end{cases} \tag{20}$$

3. Overview of BBO and ILSBBO

Biogeography is a new kind of evolutional algorithm based on biogeography theory. In the context of biogeography, habitats are isolated from others, and the distribution of species among different habitats depend on their suitability index variables (*SIVs*), which include factors such as water resource, diversity of vegetation, diversity of topographic features, and *etc*. *SIVs* are considered as the independent variables of the habitat and be used to calculate habitat suitability index *(HSI*). Habitat with a high *HSI* tends to have a large number of species. Also, there are more species to emigrate to other habitats when the habitat is too crowed. On the country, in a habitat with lower *HSI*, a smaller number of species can live and few species can move out of it.

3.1 BBO Algorithm

Supposing all individuals in a population have the same total capability of species, and the largest number of species is S_{max}. Based on different *SIVs*, each habitat has its own emigration rate and immigration rate. Through migration operation, individuals can share information with others. For instance, habitats with low *HSI* may get better feature (*SIV*) information, and thus be improved. In this process, the features selected from high *HSI* habitats do not disappear. Figure 1 illustrates a model of species abundance in a single habitat [25]. *I* is the maximum immigration rate, which occurs then there are no species in the habitat. *E* is the maximum emigration rate, which occurs when the habitat is completely saturated with species.

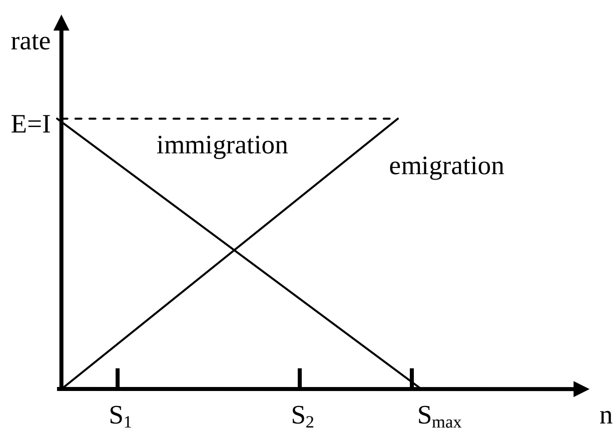

Figure 1. Species model of a single habitat

Similar as other population-base algorithm, suppose an optimal problem has a population of candidate solutions and the set of solutions can be quantified by fitness function like *HSI*. Thus, good solutions are analogous to habitats with high *HSI*, and poor solutions are equivalent to habitats with low *HSI* [26]. Through sharing features information between good and poor solutions, a poor solution can obtain lots of good features and may become to a better ones, and a good solution can also be improved by features which from other better solutions than itself. $Ps(t)$ denotes the probability that a habitat contains exactly s species at time t, then at $t+\triangle t$, Ps changes to:

$$P_s(t+\Delta t) = P_s(t)(1-\lambda_s\Delta t-\mu_s\Delta t)+P_{s-1}\lambda_{s-1}\Delta t+P_{s+1}\mu_{s+1}\Delta t \quad (21)$$

Where, λ and μ are immigration rate and emigration rate respectively when there are s species in the habitat. If Δt is small enough so that the probability of more than one immigration or emigration can be ignored, then taking the limit of Eq.(21) as $\Delta t \to 0$, there are three different situations listed in Eq.(22).

$$\tilde{P}_s = \begin{cases} -(\lambda_s + \mu_s)P_s + P_{s+1}\mu_{s+1}; S = 0 \\ -(\lambda_s + \mu_s)P_s + P_{s+1}\mu_{s+1} + P_{s-1}\lambda_{s-1}; 1 \le S \le S_{\max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1}; S = S_{\max} \end{cases} \tag{22}$$

When the number of species is given as $s=k$, then

$$\mu_k = \frac{E*k}{S_{\max}}, \quad \lambda_k = I(1 - \frac{k}{S_{\max}}) \tag{23}$$

When $E = I$, $\lambda_k + \mu_k = E$.

BBO concept is mainly based on migration and mutation. The migration operator can be described as:

For i=1to NP
 Select a habitat X_i with habitat modification probability P_{mod};
 If X_i is selected
  For j=1to D
   Select *SIV*s $X_i(i, j)$ use immigration rate λ_i;
   Select a habitat X_k with μ_i, from which to obtain a feature $X_k(i, j)$;
   Replace $X_i(i, j)$ with $X_k(i, j)$;
  EndFor
 EndIf
EndFor

Where *Pmod* is a habitat modification probability, with which each solution can be modified based on other solutions.

In BBO, species count probabilities P_s indicates the likelihood that it exists as a solution for a given problem. It is used to determine mutation rates, and can be calculated by Eq. (22). By the mutation of *SIV*, the diversity of the population can be increased. The mutation rate $m(x_i)$ is inversely proportional to the solution probability, and can be calculated by Eq. (24).

$$m(x_i) = m_{\max}(\frac{1 - P(s_i)}{P_{\max}}) \tag{24}$$

Where, m_{max} is a user-defined parameter, and $P_{\max} = max\ P_i$, i=1,2,⋯NP, NP is the total number of population. The mutation operator can be described as:

For i=1 to NP
 Use $\lambda(si)$ and $\mu(si)$ to compute the probability $P(si)$;
 Select $X(i, j)$ with $P(si)$;
 If $X(i, j)$ is selected

Replace $X(i, j)$ with a randomly generated SIV;
EndIf
EndFor

Where NP is the total number of individuals, j=1,2,…D, D is the dimension of the individuals, rand (0, 1) is a uniformly distributed real random number in (0, 1).

3.2 DELSS

Differential evolution (DE) algorithm is a global search approach with randomness, parallelism and directness. It has a good exploiting ability and can effectively search in decision variables space [25]. DE has three main operators: mutation, crossover and selection. Mutation procedure generates new offspring called mutated individual based on the differences between parent individuals and a "scaling factor". Crossover represents a typical case of a "genes" exchange. The parent individual is mixed with the mutated individual to create a trial individual. Selection procedure is used among the set of trial individuals and the parent individuals to choose the best ones to form the new population. It has been proved that DE can yield better and faster solution, satisfying all the constraints. But when complexity and scale of the system increase, with the increasing of iteration, the difference between individuals reduce, and the diversity of the population decrease, the speed of the method may slow down and can not converge to an idea solution. To overcome this drawback, [27] proposed Differential Evolutionary Algorithm with a New Local Search Strategy (DELSS). The main improvement is as following:

Supposing the current evolution population is P_{op}, the best solution is X^{G}_{best}。 Select an individual X_i randomly, $X_i \in P_{op}, X_i=(X_1, X_2, \ldots, X_D)$, calculate the new individual $X^{G\prime}_{best}$ with Eq. (25).

$$X^{G\,\prime}_{best} = X^{G}_{best}(j) + R(-1,1) * (X^{G}_{best}(j) - X_i(j)), \qquad j=1,2,\ldots,D \tag{25}$$

Where, R(-1,1) is an uniformly distributed real random number. Replacement of the worse individual with the new generated individual helps to jump out of the local optimum. Motivated by DELSS, an improved biogeography-based optimization algorithm based on local search strategy (ILSBBO) is proposed in this article.

3.3 ILSBBO

In the original BBO, the emigration rate and immigration rate are used to determine where to emigrate and from where to get immigration. The habitat which has high *HSI* has a high probability of emigrating rate to emigrate to other habitats. On the other hand, habitats with low *HSI* have high probability to get immigration. However, for those low *HSI* habitats, the features obtained are not always better than their own. If the poorer features were immigrated to a habitat, the *HSI* of the habitat would decrease. That means before the optimal solution could be found ultimately, there are plant of time was wasted on migration operator. Also, this migration operator may lead to premature convergence. In ILSBBO, the features selected with migration rate are modified to enhance the efficiency of the migration operation and avoid those problems.

There are two different modification strategies.

Strategy 1: Supposing a feature selected with emigration rate is X(select, j) , modified with Eq.(26), then replace $X(k, j)$. Where $X(k, j)$ is the jth feature in kth individual which is selected to be modified; r_1 is a uniformly distributed real random number between (0,1); X_{r1} is an randomly selected individual. The new generated feature can be considered as an offspring of X(selected, j) and a random X_{r1}, it has nothing to do with original X_k, differs from $X_{selected}$, but has the information of $X_{selected}$.

$$X(k,j) = X(selected,j) + R(-1,1) * (X(selected,j) - X(r1,j)),\quad j=1,2,\ldots,D \tag{26}$$

Strategy 2: Each habitat has its own geography characteristics, which determines the states of *SIV*s. Thus, the features information obtained from other habitat will present to be some new states which are different from their original states. Based on this, in the new migration process, using Eq.(27) to modify the selected feature, instead of changing $X(k, j)$ directly with $X(selected, j)$. The new feature generated by the migration operator has both feature information from both $X(k, j)$ and $X(selected, j)$.

$$X(k,j) = X(selected,j) + R(-1,1) * (X(selected,j) - X(k,j)),\quad j=1,2,\ldots,D \tag{27}$$

The modified migration operator with strategy 1 is described in the following:

For i=1 to NP
  Select a habitat X_i with habitat modification probability P_{mod} ;
  For j=1 to D
    Select a feature in X_i with the probability of λ_i ;
    If rand < λ_i
      Select a habitat X_{r1} randomly;
      Select another habitat X_k with the probability of μ_i ,from which to obtain features;
      If rand < μ_i
        Modify the selected feature from $X_{selected}$ by using Eq. (26) to obtain a trial individual;
      Else $U(i, j)=X(i, j)$;
      EndIf
    EndIf
  EndFor
EndFor

With the modification, the migration operator can not only maintain the ability to utilize information but also increase the diversity of the population and help the algorithm escape from the local optimum.

In this article, a selection operation is also added to make the migration more efficient. In the selection operation, original population is considered as father population, and changes during the iteration. The modified individuals form a new population, which is called trial population. After migration and mutation operators, individuals in the trial population are compared with their parent individuals one by one to check if they have been improved. If an individual was better than its father individual, it would replace the father one to the next generation, else it would be abandoned.

It has been improved in [28] over 13 benchmark functions that ILSBBO have better performance than both original BBO and DE/BBO.

4. ILSBBO Implementation in ORPF Problem

To verify the effectiveness and efficiency of the proposed ILSBBO based reactive power optimization approach, two power systems are used as the test systems. Main steps of the application can be described as follows, and the detail in the next section.

Step 1: Some parameters of BBO should be defined firstly such as the size of population, the migration rates and the maximum mutation rate, step size for numerical integration *dt*, maximum number of iteration and the number of elite habitats.

Step 2: Read the original data of the test system such as the number of control variables and their limits, and etc. The number of control variables is used to define the dimension of the individual. The limits of control variables are used to make sure the *SIVs* is within the search space. A set of candidate solutions randomly created in the D-dimensional space, and each habitat in biogeography represents a candidate solution. *SIV*s in each habitat are represented as Eq. (28).

$$u=\left[\mathrm{V}_{\mathrm{G1}},\mathrm{V}_{\mathrm{G2}},\ldots\mathrm{V}_{\mathrm{GNG}},\mathrm{T}_{\mathrm{k1}},\mathrm{T}_{\mathrm{k2}},\ldots\mathrm{T}_{\mathrm{kNT}},\mathrm{Q}_{\mathrm{C1}},\mathrm{Q}_{\mathrm{C2}},\ldots\mathrm{Q}_{\mathrm{CNQC}}\right] \tag{28}$$

Where, NG is the number of generators, NT is the number of tap changing transformers and NQC is the number of shunt VAR compensators. VG are continues variables, T_k and Q_c are discrete variables.

Step 3: Run the Newton-Raphson (NR) load flow program using these *SIV*s and determine the dependent variables of Eq.(4) to check whether they satisfy the inequality constraints of Eq.(11),and Eq.(12). If the values of dependent variables for any habitat set do not satisfy these constraints, then calculate the amount of violation of each dependent variable from their respective operating limits.

Step 4: Compute the *HSI* (fitness) for each habitat set. Fitness function is directly called from the objective function. Dependent variables of Eq.(4) are restricted by adding their violations as the quadratic penalty terms to the objective function.

Step 5: Based on *HSI* to calculate species count of each habitat to given emigration rate and immigration.

Step 6: Based on the *HSI* value, elite habitats are identified. Here elite habitats are those whose *HSI* values are best in the population.

Step 7: Migration operation is performed probabilistically among those non-elite habitats to create new habitats. Here the modified migration operation (strategy 1 or strategy 2)is used.

Step 8: Mutation operation is performed probabilistically on the worst half of the habitats. After the migration and mutation operation, the modified population is called trial population, and do not enter the next iteration directly.

Step 9: Check the feasibility of each habitat in trial population. If any of the newly generated *SIV*s does not satisfy the operational constraints of ORPF problem, using the following method to map them to the set of feasible solutions.

Suppose X_i is the *i*th *SIV*, which is changed after migration and mutation. X_{imax} and X_{imin} are the upper and lower operating limit of X_i respectively. The operating limit constraints are satisfied in the following manner:

If $X_i > X_{imax}$

$X_i = X_{imax}$;

Else if $X_i < X_{imin}$

$X_i = X_{imin}$

Else

$X_i = X_i$

EndIf

Step 10: If the newly generated *SIV*s are feasible, then use the selection operation to determine whether the new individual can replace its parent to enter the next iteration.

Step 11: Go to step 3 for the next iteration. The loop is terminated after a predefined number of iterations I_{germax}.

5. Simulation Results

In this section, ILSBBO is applied for minimization of active power loss in two different test systems, IEEE 30-bus test system and IEEE 118-bus system. The program has been implemented in Matlab R2010a and the numerical tests are carried on a Core Ⅱ 2.93GHz computer with 2.93 GB RAM. These parameters have been settled for all cases: habitat modification probability is 1,immigration probability bounds per *gene*= [0,1],step size for numerical integration is 1, maximum immigration *I* and emigration rate *E* for each island is 1,the number of elite habitat *p* is set to 2 and mutation probability is 0.005.

5.1 Description of IEEE 30-bus Test System and Simulation Results

The original data of 30-bus power system is the same as [29].The system consists of 41 branches, 22 load-buses. The generator-buses are 1, 2, 5, 8, 11, and13 respectively, in which bus 1 is selected as slack bus and the others are PV-bus. 4 branches (6-9, 6-10, 4-12, 27-28) are under load tap setting transformer branches. The transformer rate limit is 0.9-1.1, with the changes step of 0.025. The reactive power source installation sources are selected at buses 10, 12, 15, 17, 20, 21, 23, 24, and 29. The limit of shunt VAR compensating devices is 0.0-5.0 per-unit with the changes step of 0.01. The voltages on all load bus and generator buses have been constrained with the limits of 0.95 -1.1 per-unit. The total power demand of the system is 2.834 per-unit on 100 MVA base.The active and reactive power of generators buses have been listed in Table 1.

Table 1. Limitation of generators power output

	P1	P2	P5	P8	P11	P13	Q1	Q2	Q5	Q8	Q11	Q13
Lower	50	20	15	10	10	12	-20	-20	-15	-15	-10	-15
Upper	200	80	50	35	30	40	200	100	80	60	50	60

In this case, the habitat size is set to 50, the total number of generation times is 300. For the fairness in comparison, the random number R in both strategy 1 and 2 are get in the same pre-prepared matrix. Each method was executed 100 times when applied to the test system. Table 2 lists the best and the worst active power loss results together with average execution time.

It can be seen that ILSBBO with both modified strategies are faster than BBO, especially the improved method with strategy 1. However, compared with ILSBBO s1(ILSBBO with modified strategy 1), ILSBBO s2(ILSBBO with modified strategy 2) can converge to an optimal solution with fewer iteration times. Also, BBO and ILSBBO s2 show better consistency by keeping the difference between the best and worst solutions. The convergence characteristics and the profiles of voltage are shown in Figure 2. It clearly shows that the proposed method can not only discover higher quality solution with fewer iteration times but also improve the voltage profile.

The optimum setting of the control variables and power loss obtained from the above settings are presented in Table 3. It also shows the initial settings of control variables from [30]. Initially, the real power loss was 0.05812. The loss value obtained by BBO algorithm is 0.045511 and by ILSBBO algorithm are 0.045683 and 0.045217 respectively. Thus loss reductions of 21.3988% and 22.2006% from initial values are achieved by ILSBBO.

Table 2. Comparison of simulation results in 30-bus system

Methods	Active Power Loss (p.u)			Time(sec.)
	Max.	Min.	Average	
BBO	0.0494	0.0458	0.0483	87.9097
ILSBBO(strategy1)	0.0506	0. 0457	0.0476	48.4140
ILSBBO(strategy2)	0.0486	0.0451	0.0456	78.6605

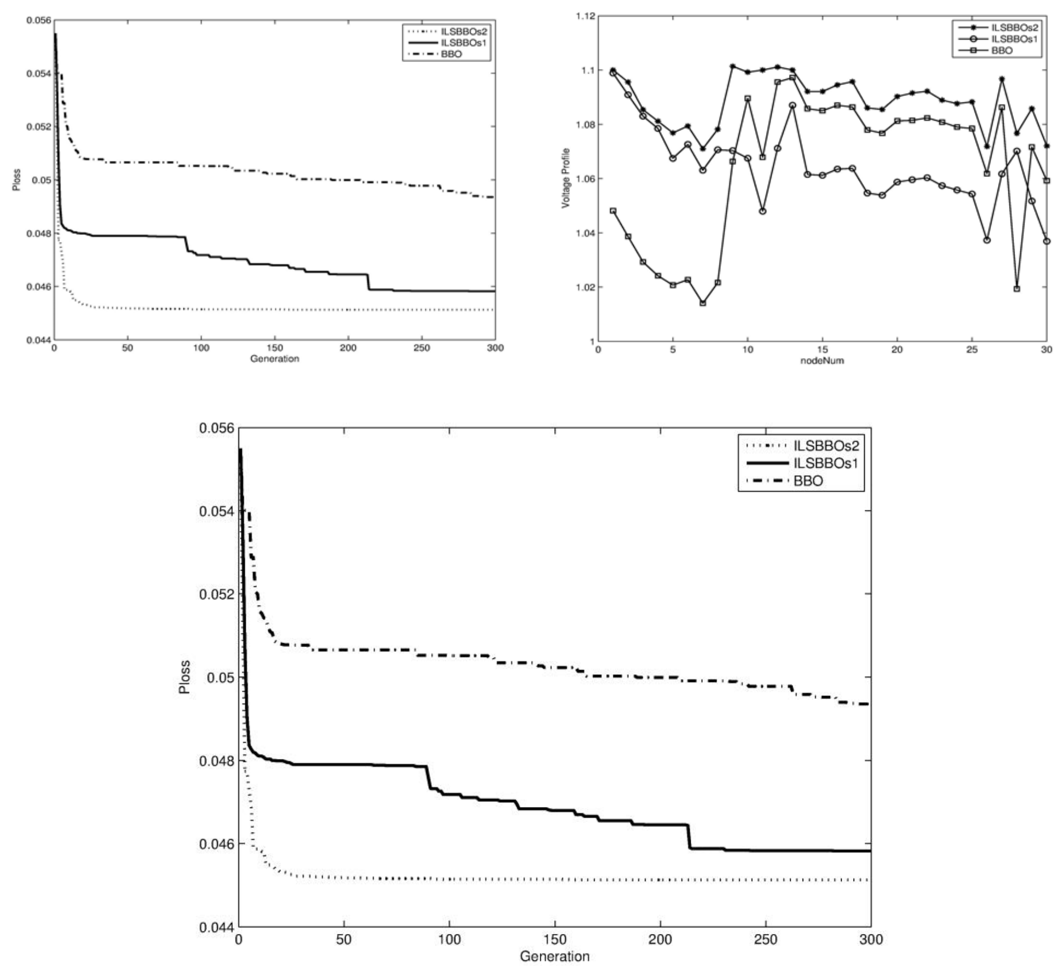

Figure 2. Simulation results on IEEE 30-buses(1)

5.2. IEEE 118-bus Test System and Simulation Results

To test the potential of BBO and ILSBBO algorithms in solving larger systems, a standard IEEE 118-bus test system is considered. The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The line and bus data and their limits are given in [30]. 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 4, with the change step of 0.01.

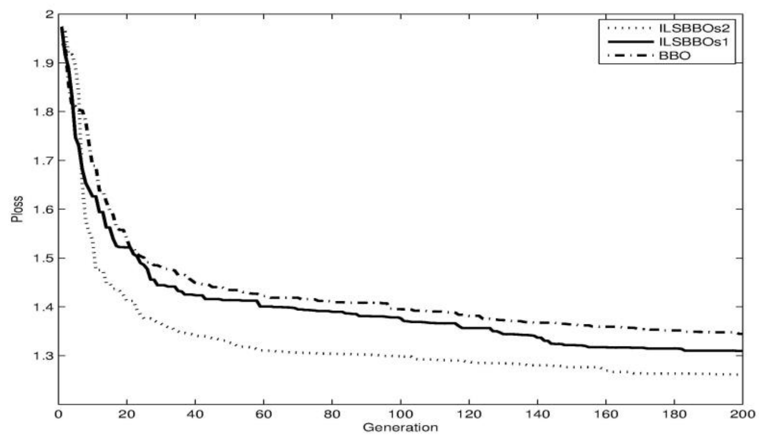

Figure 3. Simulation results on IEEE 118-buses

Table 3. The simulation results of control parameters on IEEE 30-buses(p.u.)

Control variable setting(p.u.)	Active Power Loss (p.u.)			
	Base Case	BBO	ILSBBO/strategy1	ILSBBO/strategy2
V1	1.050	1.1000	1.1000	1.1000
V2	1.040	1.0859	1.0936	1.0950
V5	1.010	1.0764	1.0695	1.0762
V8	1.010	1.0541	1.0742	1.0780
V11	1.050	1.0579	1.0261	1.0947
V13	1.050	1.0962	1.0981	1.1000
T11	1.078	1.0000	1.1000	0.9922
T12	1.069	0.9500	0.9250	1.0736
T15	1.032	0.9750	1.0250	0.9796
T36	1.068	0.9500	1.0006	0.9750
Qc10	0.000	0.04901	0.0357	0.0500
Qc12	0.000	0.04746	0.0417	0.0500
Qc15	0.000	0.03708	0.0465	0.0500
Qc17	0.000	0.04758	0.0354	0.0500
Qc20	0.000	0.04374	0.0458	0.0454
Qc21	0.000	0.04728	0.0391	0.0500
Qc23	0.000	0.02634	0.0298	0.0246
Qc24	0.000	0.04365	0.0448	0.0410
Qc29	0.000	0.03263	0.0379	0.0300
Active Power Loss (p.u)	0.05812	0.046177	0.045683	0.045217
Save (%)		20.54886%	21.3988%	22.2006%

Table 4. 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

Table 5. Comparison of simulation results in 118-bus system

Methods	Active Power Loss (p.u)			Time(sec.)
	Max.	Min.	Average	
BBO	132.64	128. 77	130.21	599.6098
ILSBBO(strategy1)	137.34	126.98	130.37	526.3511
ILSBBO(strategy2)	132.39	124.78	129.22	608.1684
PSO	134.5	131.99	132.37	1215
CLPSO	132.74	130.96	131.15	1472

In this case, the number of population is increased to 120 to explore the larger solution space. The total number of generation times is set to 200. The statistical comparison results of 50 trial runs have been list in Table 5. Here the results of PSO and CLPSO from [5] are also listed. Under the initial operating condition, system loss is 141.84MW (Megawatt), after operating with the set of approaches, it can be reduced to a better level. The loss reductions are 8.19% obtained by BBO, 8.08% by ILSBBO s1, and 8.90% by ILSBBO s2. Both BBO and ILSBBO can generate better solution with the bigger possibility than PSO and CLPSO. ILSBBO s1 costs least iteration time among these methods. However, its consistency between the best solution and the worst solution is not as good as initial BBO and ILSBBO s2. Figure 3 shows the variation of the power loss, it is clear that ILSBBO s2 has good convergence property.

6. Conclusion

In this paper, the ILSBBO is proposed to solve ORPF problem for minimization of active power loss. The performance of the proposed method has been evaluated on the IEEE 30-bus and IEEE 118-bus power systems, and the comparison results show that ILSBBO is able to find the optimal solution with better performance than original BBO. The modified migration strategy takes island proximity and the variation between islands into account, and makes the migration operator more efficient. The future research is about the effect of random factor R on this method, and the proximity among islands can extent to larger scale to take a good use of information using ability of BBO.

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