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Advanced Biogeography Algorithm for Solving Optimal Reactive Power Problem

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Abstract
In this paper, an Advanced Biogeography (AB) algorithm is projected to solve optimal reactive power dispatch problem.Biogeography procedure based on opposition-based learning (OBL) is utilized to improve the searching ability. Biogeography based on the theory of fundamental biogeography, which is the study of distribution of species. The plan behind opposition-based learning is the simultaneous consideration of estimation and its parallel opposite estimate in order to achieve a enhanced estimate for the existing candidate solution. The proposed Advanced Biogeography (AB) algorithm has been tested in standard IEEE 30 bus test system and simulation results show clearly the better performance of the projected algorithm in reducing the real power loss and voltage stability index also enhanced.

Key words
Biogeography algorithm, Opposition-Based Learning, optimal reactive power dispatch, opposite numbers, Transmission loss.

1. Introduction
Optimal Reactive Power Dispatch Problem (ORPD) is subject to number of uncertainties and at least in the best case to uncertainty parameters given in the demand and about the availability equivalent amount of shunt reactive power compensators. Optimal reactive power dispatch plays a major role for the operation of power systems, and it should be carried out in a proper manner, such that system reliability is not got affected. The main objective of the optimal reactive power dispatch is to maintain the level of voltage and reactive power flow within the specified limits under various operating conditions and network configurations. By utilizing a number of control tools such as switching of shunt reactive power sources, changing generator voltages or by adjusting transformer tap-settings the reactive power dispatch can be done. By doing optimal adjustment of these controls in different levels, the redistribution of the reactive power would minimize transmission losses. This procedure forms an optimal reactive power dispatch problem and it has a major influence on secure and economic operation of power systems. Various mathematical techniques like the gradient method [1,2] Newton method [3]and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods has the difficulty in handling inequality constraints. If linear programming is applied then the input- output function has to be expressed as a set of linear functions which mostly lead to loss of accuracy. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Enhancing the voltage stability, voltage magnitudes within the limits alone will not be a reliable indicator to indicate that, how far an operating point is from the collapse point. The reactive power support and voltage problems are internally related to each other. This paper formulates by combining both the real power loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Global optimization has received extensive research attention, and a great number of methods have been applied to solve this problem. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem[9,10].Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [11], by using Genetic algorithm optimal reactive power flow has been solved, and the main aspect considered is network security maximization. In [12] is proposed to improve the voltage stability index by using Hybrid differential evolution algorithm. In [13] Biogeography Based algorithm proposed to solve the reactive power dispatch problem. In [14] a fuzzy based method is used to solve the optimal reactive power scheduling method and it minimizes real power loss and maximizes Voltage Stability Margin. In [15] an improved evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16] the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17] a standard algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits .In [18] proposed a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19] a programming based proposed approach used to solve the optimal reactive power dispatch problem. In [20] is presented a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads.This paper proposes an Advanced B**io**geography algorithm (AB) to solve reactive power dispatch problem. Biogeography-Based Optimization (BBO), proposed by Simon (2008) [21, 22], is a new global optimization algorithm based on the biogeography theory, which is the study of distribution of species. In the original BBO algorithm, each solution of the population is a vector of integers. BBO modernize the solution following immigration and emigration phenomenon of the species from one place to the other which is referred as islands by Simon. The key idea behind opposition-based learning (OBL) [23-26] is the simultaneous consideration of an approximation and its analogous opposite estimate in order to achieve a superior estimate for the existing candidate solution. The projected Advanced B**io**geography algorithm (AB) has been evaluated in standard IEEE 30 bus test system. The simulation results show that our projected approach outperforms all the entitled reported algorithms in minimization of real power loss & voltage stability index also enhanced.

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2. Voltage Stability Evaluation

2.1.Modal analysis for voltage stability evaluation

Modal analysis is one among best methods for voltage stability enhancement in power systems. The steady state system power flow equations are given by.

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} = \begin{bmatrix}J_{p\theta} & J_{pv}\\ J_{q\theta} & J_{QV}\end{bmatrix}\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \quad (1)$$

Where

ΔP = Incremental change in bus real power.

ΔQ = Incremental change in bus reactive Power injection

$\Delta\theta$ = incremental change in bus voltage angle.

ΔV = Incremental change in bus voltage Magnitude

$J_{p\theta}$, JPV , $J_{Q\theta}$, JQV jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q.

To reduce (1), let $\Delta P = 0$, then.

$$\Delta Q = \left[J_{QV} - J_{Q\theta}J_{P\theta^{-1}}J_{PV}\right]\Delta V = J_R\Delta V \quad (2)$$

$$\Delta V = J^{-1} - \Delta Q \quad (3)$$

Where

$$J_R = \left(J_{QV} - J_{Q\theta}J_{P\theta^{-1}}JPV\right) \quad (4)$$

J_R is called the reduced Jacobian matrix of the system.

2.2. Modes of Voltage instability:

Voltage Stability characteristics of the system have been identified by computing the Eigen values and Eigen vectors.

Let

$$J_R = \xi\wedge\eta \quad (5)$$

Where,

ξ = right eigenvector matrix of JR

η = left eigenvector matrix of JR

$\wedge$ = diagonal eigenvalue matrix of JR and

$$J_{R^{-1}} = \xi\wedge^{-1}\eta \quad (6)$$

From (5) and (8), we have

$$\Delta V = \xi\wedge^{-1}\eta\Delta Q \quad (7)$$

or

$$\Delta V = \sum_I \frac{\xi_i\eta_i}{\lambda_i}\Delta Q \quad (8)$$

Where ξi is the ith column right eigenvector and η the ith row left eigenvector of JR.

λi is the ith Eigen value of JR.

The ith modal reactive power variation is,

$$\Delta Q_{mi} = K_i\xi_i \quad (9)$$

where,

$$K_i = \sum_j \xi_{ij^2} - 1 \quad (10)$$

Where

ξji is the jth element of ξi

The corresponding ith modal voltage variation is

$$\Delta V_{mi} = [1/\lambda_i]\Delta Q_{mi} \quad (11)$$

If | λi | =0 then the ith modal voltage will collapse .

In (10), let ΔQ = ek where ek has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} \quad (12)$$

η_{1k} k th element of η_1

V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \quad (13)$$

3. Problem Formulation

The objectives of the reactive power dispatch problem is to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

3.1. Minimization of Real Power Loss

Minimization of the real power loss (Ploss) in transmission lines is mathematically stated as follows.

$$P_{loss} = \sum_{\substack{k=1\\ k=(i,j)}}^{n} g_{k(V_i^2+V_j^2-2V_i V_j \cos\theta_{ij})} \quad (14)$$

Where n is the number of transmission lines, gk is the conductance of branch k, Vi and Vj are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

3.2. Minimization of Voltage Deviation

Minimization of the voltage deviation magnitudes (VD) at load buses is mathematically stated as follows.

$$\text{Minimize VD} = \sum_{k=1}^{nl} |V_k - 1.0| \quad (15)$$

Where nl is the number of load busses and Vk is the voltage magnitude at bus k.

3.3. System Constraints

Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} V_j \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots, nb$$
(16)

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nb} V_j \begin{bmatrix} G_{ij} & \sin\theta_{ij} \\ +B_{ij} & \cos\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots, nb \qquad (17)$$

where, nb is the number of buses, PG and QG are the real and reactive power of the generator, PD and QD are the real and reactive load of the generator, and Gij and Bij are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage (V_{Gi}) inequality constraint:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng \qquad (18)$$

Load bus voltage (V_{Li}) inequality constraint:

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl \qquad (19)$$

Switchable reactive power compensations (QCi) inequality constraint:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc \qquad (20)$$

Reactive power generation (Q_{Gi}) inequality constraint:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng \qquad (21)$$

Transformers tap setting (T_i) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \qquad (22)$$

Transmission line flow (S_{Li}) inequality constraint:

$$S_{Li}^{min} \leq S_{Li}^{max}, i \in nl \qquad (23)$$

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

4. Biogeography-based optimization (BBO)

BBO 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,

$$\lambda_k = I\left(1 - \frac{k}{n}\right) \qquad (24)$$

$$\mu_k = E\left(\frac{k}{n}\right) \qquad (25)$$

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. S_1 and S_2 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 S_i 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 by arbitrarily selected SIV to solution S_i. 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 arbitrary events. This happening 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.

$$M(s) = m_{max}\left(1 - \frac{P_s}{P_{max}}\right) \qquad (26)$$

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

5. Opposition-based learning (OBL)

Evolutionary optimizations methods start with some primary solutions and try to progress them toward some

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optimal solution. The progression of searching terminates when some predefined criteria are satisfied. In the absence of a priori information about the solution, we, usually, start with arbitrary guesses. The computation time, among others, is related to the distance of these primary guesses from the optimal solution. We may progress our chance of starting with a closer solution by simultaneously checking the opposite solution. By doing this, the fitter one can be chosen as an initial solution. In fact, according to the theory of possibility, 50% of the time a guess is auxiliary from the solution than its opposite guess. Therefore, starting with the closer of the two guesses has the potential to accelerate convergence. The same method may be applied not only to initial solutions but also continuously to each solution in the current population.

Definition of opposite number

Let $x \in [lb, ub]$ be a real number. The opposite number is defined as in (27).

$$\breve{x} = lb + ub - x \qquad (27)$$

Similarly, this definition can be extended to higher dimensions.

Definition of opposite point

Let $X = (x_1, x_2, .., x_n)$ be a point in n-dimensional space, where $(x_1, x_2, .., x_n) \in R$ and $x_i \in [ub_i, lb_i] \forall_i \in \{1,2, .., n\}$. The opposite point $\breve{x} = (\overline{x_1}, \overline{x_2}, ., \overline{x_n})$ is completely defined by its components as in (28).

$$\breve{x}_i = lb_i + ub_i - x_i \qquad (28)$$

Now, by employing the opposite point definition, the opposition-based optimization is defined in the following subsection.

Opposition-based optimization

Let $X = (x_1, x_2, .., x_n)$ be a point in n-dimensional space, Assume $f = (\cdot)$ is a fitness function which is used to measure the candidate's fitness. According tothe definition of the opposite point. The opposite point$\breve{x} = (\overline{x_1}, \overline{x_2}, ., \overline{x_n})$ is opposite of $= (x_1, x_2, .., x_n)$.

Now, if $f(\breve{x}) \le f(X)$then point X can be replaced with $\breve{x}$;Otherwise, we continue with X. Hence, the point and itsopposite point are evaluated simultaneously in order to continue with the fitter one.

6. Advanced biogeography (AB) algorithm for solving optimal reactive power dispatch problem

The Advanced Biogeography (AB) algorithm combines the features of both biogeography algorithm and opposition based learning. By combining it improves the performance of the proposed algorithm to reach optimal solution.

Following are the major computational steps based on AB technique for reactive power problem

Step a: Initialization of parameters:
Choose the number of SIVs, number of habitats.Also BBO parameters are initialized i.e. habitat modification probability P_{modify}= 1, mutation probability = 0.01, maximum mutation rate $m_{\max}$, maximum immigration rate I = 1, maximum emigration rate E = 1, step size for numerical integration dt = 1, elitism parameter = 2, jumping rate (J_r) = 0.3

Step b: Initialization of SIVs:
Initialize each SIV of a habitat arbitrarily

Step c: Calculation of HSIs:
HSI for each habitat is calculated for given immigration and emigration rates.

Step d: Calculation of opposition based learning (OBL) habitat set.

Step e: Forming new habitat set:
A new habitat set is formed by sorting out best HSIs from the old habitat set and the (OBL) habitat set.

Step f: Identification of elite habitats:
Identification of elite habitats is done based on the HSI values. In this process those habitats for which the fuel cost is minimum, are selected from the newly formed habitat set.

Step g: Performing migration operation:
For each of the non-elite habitats, migration operation is performed. HSI for each habitat is recomputed.

Step h: Performing opposite habitat jumping:
Opposition based -Learning (OBL) generation jumping is performed and Elite habitats are restoredin the so formed habitat set.

Step i: Stopping criterion: Go to step e for next iteration. If the predefined number of iterations is reached, stop the process.

7. Simulation Results

The efficiency of the proposed Advanced Biogeography (AB) algorithm for solving the multi-objective reactive power dispatch problem is demonstrated by testing it on standard IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus. The simulation results have been presented in Tables 1, 2, 3 &4. And in the Table 5 shows the proposed algorithm powerfully reduces the real power losses when compared to other given algorithms. The optimal values of the control variables along with the minimum loss obtained are given in Table 1. Corresponding to this control variable setting, it was found that there are no limit violations in any of the state variables.

Table 1 : Results of AB – ORPD optimal control variables

Control variables	Variable setting
V1	1.046
V2	1.044
V5	1.042
V8	1.033
V11	1.001
V13	1.031
T11	1.00
T12	1.00
T15	1.01
T36	1.01
Qc10	2
Qc12	2
Qc15	3
Qc17	0
Qc20	2
Qc23	3
Qc24	3
Qc29	2
Real power loss	4.2892
SVSM	0.2478

Optimal Reactive Power Dispatch (ORPD) problem together with voltage stability constraint problem was handled in this case as a multi-objective optimization problem where both power loss and maximum voltage stability margin of the system were optimized simultaneously. Table 2 indicates the optimal values of these control variables. Also it is found that there are no limit violations of the state variables. It indicates the voltage stability index has increased from 0.2478 to 0.2486, an advance in the system voltage stability. To determine the voltage security of the system, contingency analysis was conducted using the control variable setting obtained in case 1 and case 2. The Eigen values equivalents to the four critical contingencies are given in Table 3. From this result it is observed that the Eigen value has been improved considerably for all contingencies in the second case.

Table 2 : Results of AB -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	Variable Setting
V1	1.048
V2	1.049
V5	1.046
V8	1.038
V11	1.003
V13	1.034
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	3
Qc15	2
Qc17	3
Qc20	0
Qc23	2
Qc24	2
Qc29	3
Real power loss	4.9894
SVSM	0.2486

Table 3. Voltage Stability under Contingency State

Sl.No	Contingency	ORPD Setting	VSCRPD Setting
1	28-27	0.1409	0.1424
2	4-12	0.1649	0.1652
3	1-3	0.1769	0.1779
4	2-4	0.2029	0.2041

Table 4 : Limit Violation Checking Of State Variables

State variables	limits		ORPD	VSCRPD
	Lower	upper		
Q1	-20	152	1.3422	-1.3269
Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400

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V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452
V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

Table 5 : Comparison of Real Power Loss

Method	Minimum loss (MW)
Evolutionary programming [27]	5.0159
Genetic algorithm [28]	4.665
Real coded GA with Lindex as SVSM [29]	4.568
Real coded genetic algorithm [30]	4.5015
Proposed AB method	4.2892

8. Conclusion

In this paper, the Advanced Biogeography (AB) algorithm has been successfully implemented to solve Optimal Reactive Power Dispatch Problem (ORPD) problem. The main advantages of the AB to the ORPD problem are optimization of different type of objective function, real coded of both continuous and discrete control variables, and easily handling nonlinear constraints.The optimal setting of control variables are obtained in both continuous and discrete value. The proposed algorithm has been tested in standard IEEE 30 bus system. The results are compared with the other heuristic methods and the projected AB algorithm demonstrated its effectiveness in minimization of real power loss voltage stability profile also enhanced.

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