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Abatement of Real Power Loss by Using Improved Biogeography Algorithm

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Abstract: **In this paper, a new improved biogeography algorithm (IBA) is proposed to solve optimal reactive power dispatch problem. Biogeography technique based on opposition-based learning (OBL) is utilized to solve the optimal reactive power problem. Biogeography is a new global optimization algorithm based on the biogeography theory, which is the study of distribution of species. The idea behind OBL is the concurrent consideration of an estimate and its corresponding opposite estimate in order to accomplish a better approximation for the current candidate solution. The proposed IBA has been tested in standard IEEE 30bus test system and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss.**

Keywords: **Opposite numbers, Biogeography algorithm, Opposition-Based Learning, Optimal reactive power, Transmission loss.**

I. INTRODUCTION

Reactive power optimization places a significant role in optimal operation of power systems. Various numerical methods 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 have the complexity in managing inequality constraints. If linear programming is applied then the input- output function has to be uttered 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]. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is proposed to improve the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. 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 pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes a new improved B**io**geography algorithm (IBA) 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 updates the solution following immigration and emigration phenomena of the species from one place to the other which is referred as islands by Simon. The results demonstrated the good performance of BBO. BBO has good exploitation ability as solution is updated by exchanging the existing design variables among the solution. Tizhoosh introduced the perception of opposition-based learning (OBL) in [23]. This notion has been applied to quicken the reinforcement learning [24, 25] and the back propagation learning [26] in neural networks. The key idea behind OBL is the concurrent consideration of an estimate and

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its corresponding opposite estimate in order to accomplish a better approximation for the current candidate solution. The proposed IHS algorithm has been evaluated in standard IEEE 30 bus test system. The simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

II. PROBLEM FORMULATION

The OPF problem is considered as a general minimization problem with constraints, and can be written in the following form:

Minimize f(x, u) (1)

Subject to g(x,u)=0 (2)
and
$h(x, u) \leq 0$ (3)

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \quad (4)$$

The control variables are the generator bus voltages, the shunt capacitors/reactors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \quad (5)$$

or

$$u = \left(V_{g1}, \dots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \quad (6)$$

Where Ng, Nt and Nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

III. OBJECTIVE FUNCTION

A. 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:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (7)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

Where g_k: is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

B. Voltage profile improvement

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

$$F = PL + \omega_v \times VD \quad (9)$$

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \qquad (10)$$

C. Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \qquad (11)$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

D. Inequality Constraints

The inequality constraints h(x,u) reflect the limits on components 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, and reactive power of generators:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \qquad (12)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \qquad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \qquad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \qquad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \qquad (16)$$

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.

IV. 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,

$$\lambda_k = I\left(1 - \frac{k}{n}\right) \qquad (17)$$

$$\mu_k = E\left(\frac{k}{n}\right) \qquad (18)$$

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.

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A. 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 its randomly 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.

B. 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.

$$M(s) = m_{max}\left(1 - \frac{P_s}{P_{max}}\right) \qquad (19)$$

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

V. OPPOSITION-BASED LEARNING

Evolutionary optimizations methods start with some primary solutions and try to progress them toward some 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 headway 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 (20).

$$\breve{x} = lb + ub - x \qquad (20)$$

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 $\breve{x} = (\breve{x_1}, \breve{x_2}, ., \breve{x_n})$ is completely defined by its components as in (21).

$$\breve{x_i} = lb_i + ub_i - x_i \qquad (21)$$

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 to the definition of the opposite point. The opposite point $\breve{x} = (\breve{x_1}, \breve{x_2}, ., \breve{x_n})$ is opposite of $= (x_1, x_2, .., x_n)$.

Now, if $f(\breve{x}) \leq f(X)$ then point X can be replaced with

$\breve{x}$; Otherwise, we continue with X. Hence, the point and its opposite point are evaluated simultaneously in order to continue with the fitter one.

VI. IMPROVED BIOGEOGRAPHY ALGORITHM FOR SOLVING OPTIMAL REACTIVE POWER PROBLEM

The IBA 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 IBA technique for reactive power problem

Step 1: 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 2: Initialization of SIVs:

Initialize each SIV of a habitat arbitrarily

Step 3: Calculation of HSIs:

HSI for each habitat is calculated for given immigration and emigration rates.

Step 4: Calculation of opposition based learning (OBL) habitat set.

Step 5: 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 6: 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 7: Performing migration operation:

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

Step8: Performing opposite habitat jumping:

Opposition based -Learning (OBL) generation jumping is performed and Elite habitats are restored in the so formed habitat set.

Step 9: Stopping criterion: Go to step 5 for next iteration. If the predefined number of iterations is reached, stop the process.

VII. SIMULATION RESULTS

IBA algorithm has been tested on the IEEE 30-bus, 41 branch system. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. The considered security constraints are the voltage magnitudes of all buses, the reactive power limits of the shunt VAR compensators and the transformers tap settings limits. The variables limits are listed in Table 1.

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Table 1: Initial Variables Limits (PU)

Control variables	Min. value	Max. value	Type
Generator: Vg	0.92	1.10	Continuous
Load Bus: VL	0.94	1.01	Continuous
T	0.94	1.01	Discrete
Qc	-0.11	0.30	Discrete

The transformer taps and the reactive power source installation are discrete with the changes step of 0.01. The power limits generators buses are represented in Table 2. Generators buses are: PV buses 2,5,8,11,13 and slack bus is 1.the others are PQ-buses.

Table 2: Generators Power Limits in MW and MVAR

Bus n°	Pg	Pgmin	Pgmax	Qgmin
1	98.00	51	202	-21
2	81.00	22	81	-21
5	53.00	16	53	-16
8	21.00	11	34	-16
11	21.00	11	29	-11
13	21.00	13	41	-16

Table 3: Values of Control Variables after Optimization and Active Power Loss

Control Variables (p.u)	IBA
V1	1.0634
V2	1.0545
V5	1.0316
V8	1.0436
V11	1.0844
V13	1.0646
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.91
Q10	0.10
Q24	0.10
PLOSS	4.5314
VD	0.9071

Table 3 show that the proposed approach succeeds in keeping the dependent variables within their limits

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Table 4 summarizes the results of the optimal solution by different methods. It reveals the reduction of real power loss after optimization.

Table 4: Comparison Results of Different Methods

Methods	Ploss (MW)
SGA (27)	4.98
PSO (28)	4.9262
LP (29)	5.988
EP (29)	4.963
CGA (29)	4.980
AGA (29)	4.926
CLPSO (29)	4.7208
HSA (30)	4.7624
BB-BC (31)	4.690
IBA	4.5314

VIII. CONCLUSION

In this paper, the IBA has been successfully implemented to solve ORPD problem. The main advantages of the IBA 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 on the IEEE 30 bus system. The results are compared with the other heuristic methods and the proposed algorithm demonstrated its effectiveness and robustness in minimization of real power loss.

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