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Optimal power flow for a deregulated power system using adaptive real coded biogeography-based optimization

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ABSTRACT

The optimization is an important role in the wide geographical distribution of electrical power market, finding the optimum solution for the operation and design of power systems has become a necessity with the increasing cost of raw materials, depleting energy resources and the ever growing demand for electrical energy. Using adaptive real coded biogeography-based optimization (ARCBBO), we present the optimization of various objective functions of an optimal power flow (OPF) problem in a power system. We aimed to determine the optimal settings of control variables for an OPF problem. The proposed approach was tested on a standard IEEE 30-bus system and an IEEE 57-bus system with different objective functions. Simulation results reveal that the proposed ARCBBO approach is effective, robust and more accurate than current methods of power flow optimization in literature.

Introduction

In the competitive electrical power market, electrical energy must be offered at a least cost with high quality, which is a very difficult task for the market operator in deregulated power system. Optimal power flow (OPF) is the tool for solving these complicated problems. The main objective of optimal power flow is to obtain the optimal operating schedule for each generator which minimizes the cost of production and satisfies the system equality and inequality constraints [1].

The literature discusses numerous OPF problems [2–4], including those involving reactive power control, voltage control, loss minimization, contingency dispatching, and load shedding, using traditional optimization techniques such as gradient methods, linear programming, nonlinear programming, quadratic programming, newton method, P–Q decomposition, and interior point method. An OPF problem is generally a nonlinear and a multiobjective optimization problem, with more than one local optimum solution. Thus, local optimization techniques are lesser suitable for such complex problems, because they may not be able to provide a global optimum solution.

Recently, many of the evolutionary algorithms have been successfully applied in solving OPF problems. These evolutionary algorithms include evolutionary programming (EP) [5–7], improved evolutionary programming (IEP) [8], genetic algorithm (GA) [9], improved genetic algorithm (IGA) [10], enhanced genetic algorithm (EGA) [11,12], tabu search (TS) [13], simulated annealing (SA) [14], particle swarm optimization (PSO) [15,16], differential evolution (DE) [17,18], modified differential evolution (MDE) [19], gravitational search algorithm (GSA) [20], modified shuffle frog leaping algorithm (MSFLA) [21], harmony search algorithm (HS) [22], biogeography-based optimization (BBO) [23], and artifial bee colony algorithm (ABC) [24].

Using any of the above algorithms, OPF problems with different objective functions, such as fuel cost minimization, emission minimization, system loss minimization, piecewise quadratic cost function, fuel cost with valve point effects, enhancement of voltage stability, voltage profile improvement, fuel cost and emission minimization, and system loss minimization, can be optimized. The solutions to OPF problems have been reported for IEEE 9-bus, IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems in literature.

The power of adaptive real coded biogeography-based optimization (ARCBBO) to solve the OPF problem is discussed in this paper. Bhattacharya and Chattopadhyay employed biogeography-based optimization (BBO) to solve OPF problems [23]. However, the BBO method was reported to lack exploration ability and poorly supports population diversity. In the ARCBBO approach, therefore, an adaptive Gaussian mutation is integrated into the OPF problem, thereby avoiding premature convergence, improving population diversity, and enhancing the exploration ability.

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Problem formulation

Generally, an OPF problem is a large-scale, highly constrained nonlinear optimization problem. It may be defined as

$$\min f(x,u) \quad (1)$$

subject to

$$g(x,u) = 0 \quad (2)$$

$$h(x,u) \leqslant 0 \quad (3)$$

where f is the objective function to be minimized, x and u are the vectors of dependent and independent control variables, respectively, g is the equality constraint, and h is the operating inequality constraint.

The vector of dependent variables can be represented as:

$$x^T = [P_{G1}, V_{L1} \ldots V_{LNpq}, Q_{G1} \ldots Q_{GNg}, S_{L1} \ldots S_{LNl}] \quad (4)$$

where P_{G1} denotes the slack bus power; V_L denotes the load bus voltage; Q_G denotes the reactive power output of the generator; S_L denotes the transmission line flow; Npq is the number of load buses; Ng is the number of voltage-controlled buses and Nl is the number of transmission lines.

The vector of independent control variables can be represented as:

$$u^T = [P_{G2} \ldots P_{GNg}, V_{G1} \ldots V_{GNpq}, T_1 \ldots T_{Nt}, Q_{C1} \ldots Q_{CNc}] \quad (5)$$

where P_G is the active power output of generators; V_G is the voltage at the voltage-controlled bus; T is the tap setting of the tap-changing transformer; and Q_C is the output of shunt VAR compensators; Nt and Nc are the number of tap-changing transformers and shunt VAR compensators, respectively.

Equality constraints (g)

$$P_{Gi} - P_{Di} - \sum_{j=1}^{Nb} V_i V_j [G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)] = 0 \quad i = 1,2,\ldots,Nb \quad (6)$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{Nb} V_i V_j [G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)] = 0 \quad i = 1,2,\ldots,Nb \quad (7)$$

where P_{Gi} and Q_{Gi} are the injected active and reactive power at ith bus, respectively; P_{Di} and Q_{Di} are the demanded active and reactive power at ith bus, respectively; V_i and V_j are the magnitude of voltage at ith and jth bus, respectively; G_{ij} and B_{ij} are the real and imaginary part of the admittance of line connected between ith and jth bus; δ_i and δ_j are the phase angle of voltage at ith and jth bus, respectively; Nb is the number of buses.

Inequality constraints (h)

(i) *Generator constraints:* The generator active and reactive power outputs and voltage are restricted by their upper and lower limits.

$$P_{Gi}^{\min} \leqslant P_{Gi} \leqslant P_{Gi}^{\max} \quad i = 1,2,\ldots,Ng \quad (8)$$

$$Q_{Gi}^{\min} \leqslant Q_{Gi} \leqslant Q_{Gi}^{\max} \quad i = 1,2,\ldots,Ng \quad (9)$$

$$V_{Gi}^{\min} \leqslant V_{Gi} \leqslant V_{Gi}^{\max} \quad i = 1,2,\ldots,Ng \quad (10)$$

(ii) *Transformer constraints:* Tap-changing transformers have minimum and maximum setting limits:

$$T_i^{\min} \leqslant T_i \leqslant T_{Gi}^{\max} \quad i = 1,2,\ldots,Nt \quad (11)$$

(iii) *Switchable VAR sources:* These have minimum and maximum limits:

$$Q_{Ci}^{\min} \leqslant Q_{Ci} \leqslant Q_{Ci}^{\max} \quad i = 1,2,\ldots,Nc \quad (12)$$

(iv) *Security constraints:* These include the limits on load bus voltage and transmission line flow.

$$V_{Li}^{\min} \leqslant V_{Li} \leqslant V_{Li}^{\max} \quad i = 1,2,\ldots,Npq \quad (13)$$

$$MVA_k \leqslant MVA_k^{\max} \quad (14)$$

where MVA_k is the power flow at kth line; $MVA_k^{\max}$ is the power flow capacity of kth transmission line.

Finally, the objective function with all constraints combined for the OPF problem is given by

$$\min F = f + \lambda_{Pg}(P_{G1} - P_{G1}^{\lim})^2 + \sum_{i\in Ng} \lambda_{Qg}(Q_{Gi} - Q_{Gi}^{\lim})^2 + \sum_{i\in Npq} \lambda_V (V_{Li} - V_{Li}^{\lim})^2 + \sum_{i\in Nl} \lambda_{Pf}(MVA_i - MVA_i^{\max})^2$$

where $\lambda_{Pg},\ \lambda_{Qg},\ \lambda_V$ and λ_{Pf} are the penalty factors.

$$\begin{aligned}
&\textit{If}\quad P_{G1} > P_{G1}^{\max}\quad \textit{then}\quad P_{G1}^{\lim} = P_{G1}^{\max}\quad \textit{elseif}\\
&\qquad\qquad P_{G1} < P_{G1}^{\min}\quad \textit{then}\quad P_{G1}^{\lim} = P_{G1}^{\min}\\
&\textit{If}\quad Q_{Gi} > Q_{Gi}^{\max}\quad \textit{then}\quad Q_{Gi}^{\lim} = Q_{Gi}^{\max}\quad \textit{elseif}\\
&\qquad\qquad Q_{Gi} < Q_{Gi}^{\min}\quad \textit{then}\quad Q_{Gi}^{\lim} = Q_{Gi}^{\min}\\
&\textit{If}\quad V_{Li} > V_{Li}^{\max}\quad \textit{then}\quad V_{Li}^{\lim} = V_{Li}^{\max}\quad \textit{elseif}\\
&\qquad\qquad V_{Li} < V_{Li}^{\min}\quad \textit{then}\quad V_{Li}^{\lim} = V_{Li}^{\min}
\end{aligned}$$

Biogeography-based optimization

Dan [25] proposed a comprehensive algorithm (BBO) for solving optimization problems based on the study of geographical distribution of species. A BBO algorithm has two main operators: migration operator and mutation operator.

Migration operator

Migration is a process of probabilistically modifying each individual in the habitat randomly. A geographical area with high habitat suitability index (HSI) tends to have a large number of species, high emigration rate, and low immigration rate. Suitability index variables (SIVs) define the characteristics of a habitat. A habitat with a high HSI tends to be more static in its species distribution. Such an habitat signifies a good solution in terms of an optimization problem. Immigration rate, λ_k, and emigration rate, μ_k, are functions of the number of species in a habitat. For a habitat with no species, its immigration rate can be the highest. λ_k is given by:

$$\lambda_K = I\left(1 - \frac{k}{n}\right) \quad (15)$$

where I is the maximum possible immigration rate, k is the number of species of kth individual, and n is the maximum number of species. μ_k is given by:

$$\mu_K = E\left(\frac{k}{n}\right) \quad (16)$$

where E is the maximum possible emigration rate.

Mutation operator

Mutation tends to increase the diversity of a species in a habitat. Due to natural events, the HSI of a habitat can change dramatically, causing the species count to shift away from its equilibrium value. Species count may be a probability value (P_i). If this probability value is very low, an individual solution is thought to have been