Electric Power Systems Research 79 (2009) 374–381

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Optimal reactive power dispatch using self-adaptive real coded genetic algorithm

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ARTICLE INFO

Article history:
Received 7 December 2007
Received in revised form 5 June 2008
Accepted 27 July 2008
Available online 18 September 2008

Keywords:
Real coded genetic algorithm
Simulated binary crossover
Evolutionary programming
Optimal reactive power dispatch

ABSTRACT

In this paper, self-adaptive real coded genetic algorithm (SARGA) is used as one of the techniques to solve optimal reactive power dispatch (ORPD) problem. The self-adaptation in real coded genetic algorithm (RGA) is introduced by applying the simulated binary crossover (SBX) operator. The binary tournament selection and polynomial mutation are also introduced in real coded genetic algorithm. The problem formulation involves continuous (generator voltages), discrete (transformer tap ratios) and binary (var sources) decision variables. The stochastic based SARGA approach can handle all types of decision variables and produce near optimal solutions. The IEEE 14- and 30-bus systems were used as test systems to demonstrate the applicability and efficiency of the proposed method. The performance of the proposed method is compared with evolutionary programming (EP) and previous approaches reported in the literature. The results show that SARGA solves the ORPD problem efficiently.

1. Introduction

Generally, the optimal reactive power dispatch (ORPD) problem is a large-scale highly constrained non-linear non-convex optimization problem. One of the major operating tasks of a power system is to maintain the load bus voltages within the limits for high quality consumer services. The electric power loads are not constant and varies from time to time. Any change in the power demand causes lower or higher voltages [1]. The objective of the ORPD problem is to minimize the transmission line losses and improve the voltage profiles. This objective can be achieved by employing the various reactive compensation devices such as automatic voltage regulators (continuous), tap changing transformers (discrete) [2] and shunt capacitors/reactors (binary).

In the past, a wide variety of conventional optimization techniques such as Newton method, linear programming, dynamic programming, quadratic programming and interior point methods [3–7] had been developed to solve ORPD problem. Generally these techniques suffer due to algorithmic complexity, insecure convergence, sensitive to initial search point, etc. [8].

The evolutionary programming (EP) [9], hybrid EP [10], genetic search (GS) [11], genetic algorithm (GA) [12], fuzzy [13], particle swarm optimization (PSO) [14], multi agent PSO [15] and differential evolution (DE) [16] are some of the heuristic techniques that have been used, recently, to solve the ORPD problem.

Iba [12] proposed genetic algorithm (GA) with interbreeding between the sub-systems to solve power system planning problem. The interbreeding is a kind of crossover using partial evaluation of each subsystem. The gene recombination and manipulation using AI based stochastic "if-then" rules are used to improve the power system profiles.

Yan et al. [17] proposed hybrid GA-interior point method for solving optimal reactive power flow (ORPF) problem. The original problem is divided into two parts. In first part, the ORPF is solved by using interior point method by relaxing the discrete variables. The second part comprises two sub problems: Continuous and Discrete optimization. The GA is used to solve the discrete optimization where as the interior point method is used to solve continuous optimization. The dynamic adjustment strategy is used to increase the efficiency of the method.

Bakirtzis et al. [18] proposed enhanced genetic algorithm for solving the optimal power flow problem. In addition to the basic genetic operators, advanced and problem specific operators such as Gene Swap operator, Gene cross swap operator, Gene copy operator, Gene inverse operator and Gene Min–Max operator are introduced to enhance the performance of the GA.

This paper proposes SARGA to solve the ORPD problem. Genetic algorithm (GA) is a search and optimization technique that is

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doi:10.1016/j.epsr.2008.07.008

motivated by Darwinian principles of natural evolution. For real valued optimization problems, floating point representations outperform binary representations because they are more consistent, more precise and lead to faster convergence [19]. Hence, in this paper, real coded GA with self-adaptation is used to solve ORPD problem. Self-adaptation is a phenomenon which makes evolutionary search algorithms flexible and closer to natural evolution. The self-adaptive behavior is introduced in RGA (SARGA) by employing simulated binary crossover (SBX) operator. In the optimization problem the function landscapes and optimal solutions change with time. The search procedure needs to be flexible enough to adapt to a new function landscape as quick as possible. The diversity in the search method is maintained by implementing self-adaptation through a SBX operator [20].

This paper is organized as follows: the problem formulation is given in Section 2. Self-adaptive real coded genetic algorithm (SARGA) is briefed in Section 3. The evolutionary programming (EP) is briefed in Section 4. The test systems, numerical results are presented in Section 5. The discussion is given in Section 6 and the conclusion is drawn in Section 7.

2. Problem formulation

The purpose of the ORPD is to minimize the real power losses of the power system. The general ORPD problem under normal operating condition can be formulated as follows:

$$\min\ P_{\mathrm{L}} = \sum_{k=1}^{\mathrm{nl}} \mathrm{Loss}_k, \tag{1}$$

where P_{L} is the network real power loss and nl is the number of lines.

The power loss is a non-linear function of bus voltages. The bus voltages are represented by implicit functions of control variables. The minimization problem is subject to operating constraints. The operating constraints are limits on control variables and power flow.

The constraints are described as follows:

- Equality constraints:

$$\begin{aligned} 0 &= P_i - V_i \sum_{j\varepsilon N_i} V_j (G_{ij}\ \cos\theta_{ij} + B_{ij}\sin\theta_{ij}), \quad i\varepsilon N_{B-1}, \\ 0 &= Q_i - V_i \sum_{j\varepsilon N_i} V_j (G_{ij}\ \sin\theta_{ij} - B_{ij}\cos\theta_{ij}), \quad i\varepsilon N_{\mathrm{PQ}}, \end{aligned} \tag{2}$$

  where V_i is the voltage magnitude at ith bus, G_{ij} and B_{ij} are the mutual conductance and susceptance between bus i and j, respectively θ_{ij} is the voltage angle difference between bus i and j, N_{B-1} is the total number of buses excluding slack bus, N_{PQ} is the set of PQ buses and N_i is the number of buses.
- Inequality constraints:

  In the control variables, the generator bus voltages (AVR operating values) are taken as continuous variable; the transformer tap settings are taken as discrete variable and shunt susceptance values are taken as binary variable. The load bus voltages and reactive power generation Q_g are taken as state variables.
- Continuous control variable:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max}; \quad i\varepsilon N_G. \tag{3}$$

- Discrete control variable:

$$T_k^{\min} \le T_k \le T_k^{\max}; \quad k\varepsilon N_T. \tag{4}$$

- Binary control variable:

$$B_{\mathrm{sh}_i}^{\min} \le B_{\mathrm{sh}_i} \le B_{\mathrm{sh}_i}^{\max}; \quad i\varepsilon N_{\mathrm{sh}}. \tag{5}$$

- State variables:

$$V_{\mathrm{PQ}_i}^{\min} \le V_{\mathrm{PQ}_i} \le V_{\mathrm{PQ}_i}^{\max}; \quad i\varepsilon N_{\mathrm{PQ}}, \tag{6}$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}; \quad i\varepsilon N_G. \tag{7}$$

  State variables are restricted by adding them as a quadratic penalty terms to the objective function. Therefore, Eq. (1) is changed to the following form:

$$\min\ F = P_L + \sum_{i\varepsilon N_{V\lim}} \lambda_{V_i}(V_i - V_i^{\lim})^2 + \sum_{i\varepsilon N_{Q\lim}} \lambda_{Q_{G_i}}(Q_{G_i} - Q_{G_i}^{\lim})^2, \tag{8}$$

  where λ_{V_i} and $\lambda_{Q_{G_i}}$ is the penalty terms.$V_i^{\lim}$ and $Q_{G_i}^{\lim}$ in Eq. (8) are defined as follows:

$$\begin{aligned} V_i^{\lim} &= \begin{cases} V_i^{\min} & \text{if } V_i < V_i^{\min}, \\ V_i^{\max} & \text{if } V_i > V_i^{\max}, \end{cases} \\ Q_i^{\lim} &= \begin{cases} Q_{G_i}^{\min} & \text{if } Q_{G_i} < Q_{G_i}^{\min}, \\ Q_{G_i}^{\max} & \text{if } Q_{G_i} > Q_{G_i}^{\max}. \end{cases} \end{aligned} \tag{9}$$

  The objective function of the target power system is calculated using load flow calculation with the above-mentioned equality and inequality constraints.

3. Self-adaptive real coded genetic algorithm

3.1. Overview

GA is a search algorithm based on the mechanics of natural genetics and natural selection. GA is computationally simple and provides robust search in complex problem space [21]. Since, the real coded genetic algorithm is most suitable for real valued optimization problems [19], this paper deals with the performance improvement of real coded GA with self-adaptation.

The self-adaptive (SA) feature of evolutionary algorithms (EA) is commonly regarded as a specialty of evolution strategies (ES) and evolutionary programming (EP). Recently, this SA feature is incorporated in the RGA using special crossover operator like simulated binary crossover (SBX) [20] and blend crossover (BLX) [22] that creates offspring statistically located in proportion to the difference of the parents in the search space [23]. This paper employs the SBX operator which uses the bimodal probability distribution.

3.2. SARGA

(1) *Initialization*: A set of initial populations are created randomly within the minimum and maximum limits of the control variables and it is chosen as a parent population. For discrete control variables, the generated populations are rounded off to the nearest integer value.

(2) *Function evaluation*: The function evaluation (using Eq. (8)) is used to determine the fitness of the each population. In this paper the static penalty factor approach is used. A small value of penalty factor produces near optimal solutions. A large value of penalty factor, though produces more feasible solutions, the solutions are far away from the optimum values and lead to premature convergence. The inclusion of penalty term distorts the objective function. The Evolutionary Algorithms such as genetic algorithm (GA) can handle this distortion efficiently due to their