Electrical Power and Energy Systems 78 (2016) 29–40

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Quasi-oppositional differential evolution for optimal reactive power dispatch

M. Basu *

Department of Power Engineering, Jadavpur University, Kolkata 700098, India

ARTICLE INFO

Article history:
Received 7 April 2014
Received in revised form 20 November 2015
Accepted 25 November 2015
Available online 14 December 2015

Keywords:
Quasi-oppositional differential evolution
Differential evolution
Reactive power dispatch
Active power loss
Voltage profile
Voltage stability

ABSTRACT

This paper presents quasi-oppositional differential evolution to solve reactive power dispatch problem of a power system. Differential evolution (DE) is a population-based stochastic parallel search evolutionary algorithm. Quasi-oppositional differential evolution has been used here to improve the effectiveness and quality of the solution. The proposed quasi-oppositional differential evolution (QODE) employs quasi-oppositional based learning (QOBL) for population initialization and also for generation jumping. Reactive power dispatch is an optimization problem that reduces grid congestion with more than one objective. The proposed method is used to find the settings of control variables such as generator terminal voltages, transformer tap settings and reactive power output of shunt VAR compensators in order to achieve minimum active power loss, improved voltage profile and enhanced voltage stability. In this study, QODE has been tested on IEEE 30-bus, 57-bus and 118-bus test systems. Test results of the proposed QODE approach have been compared with those obtained by other evolutionary methods reported in the literature. It is found that the proposed QODE based approach is able to provide better solution.

Introduction

The reactive power dispatch (RPD) plays an important role for improving economy and security of power system operation. Although the reactive power generation has no production cost, however it affects the overall generation cost by the way of the active power loss. The RPD is a nonlinear, non-convex and non-differentiable optimization problem. It minimizes active power loss and improves voltage profile and voltage stability by adjusting control variables such as generator voltages, transformer tap settings, and reactive power output of shunt VAR compensators in a power system while satisfying several equality and inequality constraints.

Several classical mathematical methods [1–8] such as linear programming, quadratic programming, gradient projection method, interior point method, reduced gradient method and Newton method have been applied to solve RPD problem of power system. These methods are computationally fast but these methods optimize the objective function by linearizing it. The RPD is a non-linear multimodal optimization problem with a mixture of discrete and continuous variables. It has multiple local optima. Hence, it is so hard to find the global optimum of reactive power dispatch problem by using classical mathematical methods. For these reasons, researchers have developed computational intelligence-based techniques to solve the RPD problem.

In recent years, computational intelligence-based techniques, such as evolutionary programming [9], adaptive genetic algorithm [10], particle swarm optimization [11], hybrid stochastic search technique [12], hybrid particle swarm optimization [13], multiagent-based particle swarm optimization [14], bacterial foraging based optimization [15], differential evolution [16,21], quantum-inspired evolutionary algorithm [17], self adaptive real coded genetic algorithm [18], seeker optimization algorithm [19], comprehensive learning particle swarm optimization (CLPSO) [20], biogeography-based optimization [22], hybrid shuffled frog leaping algorithm and Nelder–Mead simplex search [23], gravitational search algorithm [24], quasi-oppositional teaching learning based optimization [25], and opposition-based gravitational search algorithm [26] have been applied to solve RPD problem. These techniques have shown effectiveness in overcoming the disadvantages of classical methods.

Since the mid 1990s, many techniques originated from Darwin's natural evolution theory have emerged. These techniques are usually termed by "evolutionary computation methods" including evolutionary algorithms (EAs), swarm intelligence and artificial immune system. Differential evolution (DE) [27–29], a relatively new member in the family of evolutionary algorithms, first

* Fax: +91 33 23357254.
E-mail address: mousumibasu@yahoo.com

http://dx.doi.org/10.1016/j.ijepes.2015.11.067
0142-0615/

proposed over 1995–1997 by Storn and Price at Berkeley is a novel approach to numerical optimization. It is a population-based stochastic parallel search evolutionary algorithm which is very simple yet powerful. The main advantages of DE are its capability of solving optimization problems which require minimization process with nonlinear, non-differentiable and multi-modal objective functions.

The basic concept of opposition-based learning (OBL) [31–33] was originally introduced by Tizhoosh. The main idea behind OBL is for finding a better candidate solution and the simultaneous consideration of an estimate and its corresponding opposite estimate (i.e., guess and opposite guess) which is closer to the global optimum. OBL was first utilized to improve learning and back propagation in neural networks by Ventresca and Tizhoosh [34], and since then, it has been applied to many EAs, such as differential evolution [35], particle swarm optimization [36] and ant colony optimization [37].

Quasi-oppositional based learning (QOBL) is implemented on differential evolution (DE). The proposed quasi-oppositional differential evolution (QODE) along with basic differential evolution (DE) is applied to solve the RPD problem. The RPD is a combinatorial optimization problem involving nonlinear functions having multiple local optima and nonlinear and discontinuous constraints. In order to evaluate the proposed method, the proposed QODE is tested on IEEE 30-bus, 57-bus and 118-bus test systems with different objective functions that reflect active power loss minimization, voltage profile improvement and voltage stability enhancement. Test results obtained from QODE have been compared with those obtained by other evolutionary methods reported in the literature. From numerical results, it is found that the proposed QODE based approach provides better solution.

Problem formulation

The objective of the RPD is to minimize the active power loss and to improve voltage profile and voltage stability while satisfying equality and inequality constraints. Three objective functions and constraints are formulated as follows.

Objective functions

Minimization of active power loss

Minimization of active power loss in the transmission lines can be formulated as follows

$$\text{Minimize } F_1 = \mathrm{P}_{loss} = \sum_{k=1}^{\mathrm{NT}L} g_k\left[V_i^2 + V_j^2 - 2V_iV_j\cos\left(\delta_i - \delta_j\right)\right] \tag{1}$$

where P_{loss} denotes active power loss of the power system, NTL is the number of transmission lines, g_k is the conductance of branch k connected between ith bus and jth bus, V_i and V_j are the voltage magnitudes of the ith and jth buses, δ_i and δ_j are the voltage phase angles of the ith and jth buses.

The vector of dependent variables x may be represented as

$$x^{\mathrm{T}} = [\mathrm{P}_{G1}, V_{L1}, \ldots, V_{L\mathrm{NPQ}}, Q_{G1}, \ldots, Q_{G\mathrm{NG}}] \tag{2}$$

where P_{G1} denotes the slack bus power, V_L is the PQ bus voltage, Q_G is the reactive power output of the generator, NG is the number of generator bus, NPQ is the number of PQ bus.

The vector of control variables u may be represented as

$$u^{\mathrm{T}} = [V_{G1}, \ldots, V_{G\mathrm{NG}}, \mathrm{Q}_{c1}, \ldots, \mathrm{Q}_{c\mathrm{NC}}, \mathrm{T}_1, \ldots, \mathrm{T}_{\mathrm{NT}}] \tag{3}$$

where NC and NT are the number of shunt VAR compensators and the number of tap changing transformers, V_G is the terminal voltage at the voltage controlled bus, Q_c is the output of shunt VAR compensator and T is the tap setting of the tap changing transformer.

Voltage profile improvement

The objective is to minimize the voltage deviation of all load (PQ) buses from 1 p.u. As a result the power system operates more securely and service quality is also improved. The objective function can be formulated as follows

$$\text{Minimize } F_2 = \sum_{i=1}^{\mathrm{NPQ}} |V_i - 1.0| \tag{4}$$

where NPQ is the number of load buses in the power system.

Voltage stability enhancement

Voltage stability problem is the ability of a power system to maintain acceptable voltages at all bus bars in the system under normal operating condition. A system experiences a state of voltage instability when the system is being subjected to a disturbance, increase in load demand or change in system configuration which causes a progressive and uncontrollable decrease in voltage. Weak system, system with long transmission lines and heavily loaded system are much prone to voltage instability problem.

Voltage instability is a major threat for secure and reliable operation of a large scale power system. The loss of voltage stability can manifest in the form of progressive drop of voltage magnitudes, triggering unintentional load shedding and even leading to cascading outages or system-wide blackouts. Recently, a number of major blackouts around the world [39] have taken place due to voltage instability.

Voltage stability can be classified into long-term and short-term concerns depending on the time frame of interest. Analysis techniques can generally fall into static method and dynamic method. The static method is necessary for analyzing long-term voltage stability problem where as dynamic method is necessary for analyzing short-term voltage stability problem. The former is based on steady state modeling of the network i.e. via algebraic equations and relies on power flow. The latter is based on the time domain simulation, which models the system via differential–algebraic equations to account for the dynamic nature of system components in particular loads. Here, long-term voltage stability problem has been considered.

Enhancement of voltage stability of a system is an important parameter of power system planning and operation. Voltage stability enhancement can be done by minimizing the voltage stability indicator i.e. L-index value at each bus of a power system. The L-index of a bus indicates the proximity of voltage collapse condition of that bus. L-index L_j of jth bus is defined as follows [40]

$$L_j = \left|1 - \sum_{i=1}^{\mathrm{NPV}} F_{ji}\frac{V_i}{V_j}\right| \quad \text{where } j = 1, 2, \ldots, \mathrm{NPQ} \tag{5}$$

$$F_{ji} = -[\Upsilon_1]^{-1}[\Upsilon_2] \tag{6}$$

where NPV is the number of PV bus and NPQ is the number of PQ bus. Υ_1 and Υ_2 are the sub-matrices of the system YBUS obtained after segregating the PQ and PV bus bar parameters as described in (5).

$$\begin{bmatrix} \mathrm{I}_{\mathrm{PQ}} \\ \mathrm{I}_{\mathrm{PV}} \end{bmatrix} = \begin{bmatrix} \Upsilon_1 \Upsilon_2 \\ \Upsilon_3 \Upsilon_4 \end{bmatrix} \begin{bmatrix} V_{\mathrm{PQ}} \\ V_{\mathrm{PV}} \end{bmatrix} \tag{7}$$

L-index is calculated for all the PQ buses. L_j represents no load case and voltage collapse case of bus j in the range of 0 and 1 respectively. Hence, a global system indicator L describing the stability of a complete system is given as follows:

$$L = \max(L_j), \quad \text{where } j = 1, 2, \ldots, \mathrm{NPQ} \tag{8}$$

Lower value of L represents a more stable system. In the RPD problem, inaccurate tuning of control variable settings may increase voltage stability margin of the system [21]. In order to improve voltage stability and to move the system far from the volt-