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Optimal power flow with emission and non-smooth cost functions using backtracking search optimization algorithm

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ABSTRACT

Economic operation of electric energy generating systems is one of the prevailing problems in energy systems. In this paper, a new method called the Backtracking Search Optimization Algorithm (BSA) is proposed for solving the optimal power flow problem. This method is tested for 16 different cases on the IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus test systems. In addition to the traditional generating fuel cost, multi-fuels options, valve-point effect and other complexities have been considered. Furthermore, different objectives such as voltage profile improvement, voltage stability enhancement and emission reduction are considered. The obtained results are compared with those obtained using some well-known optimization algorithms. This comparison highlights the effectiveness of the BSA method for solving different OPF problems with complicated and non-smooth objective functions.

Introduction

There are three types of problems commonly referred to in power system literature: power flow, economic dispatch, and optimal power flow [1]. Economic dispatch (ED), applies several formulations to determine the least-cost generation dispatch to satisfy the total required demand, however these formulations simplify or even ignore power flow constraints [1]. The optimal power flow (OPF) has been initially proposed by French scholar Carpentier in 1962 [1]. Since then, it becomes one of the most important functions of operation, production, control and monitoring of power in modern energy systems [1,2].

A basic OPF problem seeks optimal distribution of the real power and/or the reactive power by adjusting the control variables, so that a specific objective in the operation of electric power system is optimized. During the optimization, the power flow balance, generator capability, transmission capability, voltage profile constraints must be satisfied.

Various traditional optimization techniques have been used to solve the OPF problem. These include linear programming (1979), Newton methods (1992), interior point methods (1998) and dynamic programming (2001). Pandya and Joshi in [3] and Frank et al. in [4] presented a comprehensive survey of various traditional optimization methods used to solve OPF problems. However, in practice, traditional methods suffer from some inadequacy. Some of their shortcomings among others are: firstly, they do not guarantee finding the global optimum, secondly, traditional methods involve complex calculations with long time, and they are not adapted for discrete variables [4].

Over the past few decades, many powerful metaheuristics have been developed. Some of them have been applied to the OPF problem with impressive success. Some of the recent applications of metaheuristics to OPF problem are: Artificial Bee Colony (ABC) [5,6], Black Hole (BH) [7], Teaching Learning Based Optimization (TLBO) [8], League Championship Algorithm (LCA) [9], Differential Search Algorithm (DSA) [10], Krill Herd Algorithm (KHA) [11], Gravitational Search Algorithm (GSA) [12,13], Imperialist Competitive Algorithm (ICA) [14] and Group Search Optimization (GSO) [15]. A review of many metaheuristics applied to solve the OPF problem is given in [16,17]. However, due to the variability of the objectives while solving OPF problems, no algorithm is the best in solving all OPF problems. Therefore, there is always a need for a new algorithm, which can efficiently solve the majority of the OPF problems.

The Backtracking Search Algorithm (BSA) which is developed by Civicioglu [18] is a new evolutionary algorithm (EA) developed to solve real-valued numerical optimization problems. As other EAs like genetic algorithm (GA) and differential evolution (DE), BSA is

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Nomenclature

a_i, b_i, c_i cost coefficient of the it ith generator
D dimensions (the number of parameter to be optimized)
d_i, e_i coefficients reflecting the valve-point effect
F Scale factor
$g(x, u)$ set of equality constraints
G_{ij}, B_{ij} conductance and susceptance of the admittance matrix entry ij, respectively
$h(x, u)$ set of inequality constraints
$J(x, u)$ objective function
L_j voltage stability local indicator of bus j
N population size (the number of individuals)
NB number of buses
NC number of VAR compensators
NG number of generators
NL number of load buses
nl number of transmission lines
NT the number of regulating transformers
$ObjFun$ objective function used in the problem
$oldP$ historical population
P population
$P_{G_1}, P_{G_1}^{\lim}$ active power generation of slack bus and its limit
$P_{G_i}^{\max}, P_{G_i}^{\min}$ upper and lower limits of active power generation of bus i, respectively
P_G, P_D active power generation and load demand, respectively
P_{loss}, Q_{loss} active and reactive power transmission losses, respectively
$Q_{C_i}^{\max}, Q_{C_i}^{\min}$ upper and lower limits of reactive power generation of the compensator capacitors j, respectively
$Q_{G_i}, Q_{G_i}^{\lim}$ reactive power generation of bus j and its limit
$Q_{G_i}^{\max}, Q_{G_i}^{\min}$ upper and lower limits of reactive power generation of unit i, respectively
Q_C shunt VAR compensation
Q_G, Q_D reactive power generation and load demand, respectively
$S_{l_i}, S_{l_i}^{\max}$ apparent power flow of ith line and its maximum value
$T_i^{\max}, T_i^{\min}$ upper and lower limits of tap settings of regulating transformer i, respectively
u vector of independent variables or control variables
up_j predefined upper limits of problem
$V_{G_i}^{\max}, V_{G_i}^{\min}$ upper and lower limits of voltage magnitude upper limits of bus i
$V_{L_i}, V_{L_i}^{\lim}$ voltage magnitude of load bus j and its limit
$V_{L_i}^{\max}, V_{L_i}^{\min}$ upper and lower limits of voltage magnitude load bus j, respectively
V_{Lj} voltage magnitude at load bus j
VD load bus voltage deviation
V_G voltage magnitude at PV buses
x vector of dependent variables or state variables
$x^{\max}, x^{\min}$ upper and lower limits of variable x
Y_{ij} admittance matrix between bus i and bus j
$\alpha_i, \beta_i, \gamma_i, \omega_i$ and μ_i coefficients of the ith generator emission characteristics
θ_i phase angle of bus i
θ_{ij} phase angle difference between buses i and j
$\lambda_{L_{\max}}$ weighting factor of the $L_{\max}$ term compared with the cost term
$\lambda_{Emission}$ weighting factor of the emission term compared with the cost term
λ_{VD} weighting factor of the VD term compared with the cost term.
$\lambda_P, \lambda_Q, \lambda_S, \lambda_V$ penalty factors of P, Q, S, V respectively.

based on three basic and well-known operators that are selection, mutation and crossover. Furthermore, unlike many other meta-heuristics, the BSA algorithm has only one control parameter and it is not very sensitive to the initial value of this parameter as reported in [18]. Since it was introduced, the BSA has attracted many researches and it has been applied to various optimization problems. The following are some successful examples. In [19] a comparative analysis of BSA with other evolutionary algorithms for global continuous optimization is given. In [20] the BSA has been used for antenna array design. In [21] the BSA was employed for the design of robust Power System Stabilizers (PSSs) in multimachine power systems. In [22] it has been used for the allocation of multi-type distributed generators along distribution networks.

Therefore, this paper seeks to apply to the OPF problem a new evolutionary algorithm that has not received yet much attention in the power systems community that is the BSA. Furthermore, in this paper, not only the basic OPF problem is investigated, but also some complex formulations with non-smooth cost functions and different objective functions are considered along with the environmental concern imposing the reduction of emission.

The remainder of the paper is organized as follows. First, the OPF formulation is presented in brief in section 2. Then, the main features of the BSA algorithm are presented in section 3. Next, the results after solving different cases of OPF problem using BSA are discussed in section 4. Finally, conclusions are drawn in the last section of this paper.

Problem formulation

The OPF is a power flow problem which gives the optimal settings of the control variables for a given settings of load by minimizing a predefined objective function such as the cost of active power generation or transmission losses. OPF considers the operating limits of the system and it can be formulated as a nonlinear constrained optimization problem as follows:

$$\textit{Minimize} \quad J(\mathbf{x}, \mathbf{u}) \tag{1}$$

$$\textit{Subject to} \quad g(\mathbf{x}, \mathbf{u}) = 0 \tag{2}$$

$$\textit{and} \quad h(\mathbf{x}, \mathbf{u}) \leqslant 0 \tag{3}$$

where $\mathbf{u}$ is the vector of independent variables or control variables, $\mathbf{x}$ is the vector of dependent variables or state variables, $J(x, u)$ is the objective function, $g(x, u)$ is the set of equality constraints and $h(x, u)$ is the set of inequality constraints.

The control variables $\mathbf{u}$ and the state variables $\mathbf{x}$ of the OPF problem are defined as follows.

Control variables

These are the set of variables which can be adjusted to satisfy the load flow equations [9]. The set of control variables in the OPF problem formulation are: