



Contents lists available at ScienceDirect

Applied Soft Computing

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

Optimal power flow using an Improved Colliding Bodies Optimization algorithm

H.R.E.H. Boucekara^{a,b,*}, A.E. Chaib^a, M.A. Abido^c, R.A. El-Sehiemy^d

^a Constantine Electrical Engineering Laboratory, LEC, Department of Electrical Engineering, University of Freres Mentouri Constantine, 25000 Constantine, Algeria

^b Laboratory of Electrical Engineering of Constantine, LGEC, Department of Electrical Engineering, University of Freres Mentouri Constantine, 25000 Constantine, Algeria

^c Electrical Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

^d Electrical Engineering Department, Faculty of Engineering, Kafrelsheikh University, Egypt

ARTICLE INFO

Article history:

Received 24 October 2015

Received in revised form 9 January 2016

Accepted 22 January 2016

Available online xxx

Keywords:

Colliding Bodies Optimization

Optimal power flow

Security-constrained optimal power flow

Power system optimization

Metaheuristics

ABSTRACT

This paper proposes Improved Colliding Bodies Optimization (ICBO) algorithm to solve efficiently the optimal power flow (OPF) problem. Several objectives, constraints and formulations at normal and preventive operating conditions are used to model the OPF problem. Applications are carried out on three IEEE standard test systems through 16 case studies to assess the efficiency and the robustness of the developed ICBO algorithm. A proposed performance evaluation procedure is proposed to measure the strength and robustness of the proposed ICBO against numerous optimization algorithms. Moreover, a new comparison approach is developed to compare the ICBO with the standard CBO and other well-known algorithms. The obtained results demonstrate the potential of the developed algorithm to solve efficiently different OPF problems compared to the reported optimization algorithms in the literature.

© 2016 Published by Elsevier B.V.

1. Introduction

The optimal power flow (OPF) problem is among the tools used in operation and planning of energy systems [1]. Since its introduction by Carpentier in 1962, the OPF usefulness is progressively being recognized, and nowadays it becomes the most important tool used by the system operator in power systems exploitation and planning [2]. Several models have been developed and adopted to formulate different kinds of OPF problems, objectives, sets of design variables and constraint types [3].

The OPF can be defined as an optimization problem which aims to adjust two sets of control variables (continuous and discrete) in order to optimize a predefined objective function while satisfying operational equality and inequality constraints. Further, the purpose of traditional OPF is mainly concerned with the minimization of total generating cost. However, more realistic operating conditions should be investigated when solving OPF problems. Complexities and constraints like multi-fuels, valve-point effect,

security constraints and prohibited zones have to be included. Therefore, the OPF problem is generally a highly constrained, mixed-integer, nonlinear and nonconvex optimization problem [2,4,5,6].

Initially, several traditional (deterministic) optimization techniques were employed successfully to solve the OPF problem [7]. Surveys of various traditional methods used to solve the OPF problem are given in [8–10].

Nevertheless, traditional methods rely on some simplification assumptions such as convexity, smoothness, continuity and differentiability. However, actual OPF problems may have nonlinear characteristics such as valve point effects, prohibited operating zones and piecewise quadratic cost function [11]. Therefore, traditional methods for example quasi-Newton method or conjugate gradient method generally fail in solving such OPF problems due to their rugged search landscape.

The evolution of computational resources over the last few decades had motivated the development of what is called metaheuristics. These methods can overcome many drawbacks of the traditional methods [12]. Some of these methods have been used to solve the OPF problem such as: Genetic Algorithm (GA) [13,14], Tabu Search (TS) [15], Particle Swarm Optimization (PSO) [16], Simulated Annealing (SA) [17], Differential Evolution (DE) [18], Imperialist Competitive Algorithm (ICA) [19,20], Biogeography

* Corresponding author at: Constantine Electrical Engineering Laboratory, LEC, Department of Electrical Engineering, University of Freres Mentouri Constantine, 25000 Constantine, Algeria. Tel.: +213 666605628; fax: +213 31908113.

E-mail address: boucekara.housssem@gmail.com (H.R.E.H. Boucekara).

Based Optimization (BBO) [21,22], Gravitational Search Algorithm (GSA) [23,24], Harmony Search (HS) [25], Artificial Bee Colony (ABC) [26,27], Black Hole (BH) [28], Teaching Learning based Optimization (TLBO) [29], League Championship Algorithm (LCA) [30], Group Search Optimization (GSO) [31] and many others. Surveys of various metaheuristics used to solve the OPF problem are presented in [6,32,33].

However, due to the variability of objectives where different functions can be considered for modeling the OPF problem, no algorithm can be considered as the best in solving all OPF problems. Therefore, there is always a need for a new algorithm that can solve some of the OPF problems efficiently.

The Colliding Bodies Optimization (CBO) is a new nature inspired metaheuristic which is based on the law of collision between two bodies. The CBO has been developed by Kaveh and Mahdavi [34]. Moreover, Kaveh and Ghazaan [35] proposed an Enhanced CBO referred to as ECBO. The ECBO uses memory to save some best solutions and a mechanism to escape from local optima.

The aim of this paper is to develop an Improved CBO algorithm referred to as ICBO for solving OPF problems. In order to justify the development of ICBO, its performances are compared to CBO, ECBO and other well-known optimization algorithms.

The main contributions of this paper can be summarized as follows:

1. Development of an improved version of the CBO algorithm.
2. Implementation of ICBO, CBO, ECBO and other well-known optimization algorithms for solving realistic OPF problems.
3. Implementation of a complete set of tests in order to assess optimization algorithms using different OPF problems, test systems, objective functions and constraints.
4. Resolution of the OPF problem using practical constraints like prohibited zones and using non-smooth objective functions by including valve point effect and multi-fuels options for a more realistic OPF.
5. Resolution the OPF problem considering security constraints for more challenging conditions.
6. Implementation of a new comparison method based on best and average values.
7. Utilization of nonparametric statistics for the validation of the comparative method.

The remainder of this paper is organized as follows. In Section 2, the OPF problem is formulated. In Section 3, the proposed ICBO algorithm along with the standard and enhanced versions of the CBO are described. The applications and results are presented in Section 4. Finally, the conclusions are drawn in Section 5.

2. Problem formulation

As previously mentioned, generally, the objective of the OPF problem is to identify or adjust a set of control variables that optimize predefined power system objectives while satisfying system and practical constraints [36,37]. In this paper, two formulations of the OPF are considered. These are the classical OPF formulation and the security constrained optimal power flow (SCOPF) formulation.

2.1. Classical OPF formulation

The classical OPF problem can be formulated as follows [25,30]:

$$\begin{aligned} & \text{Minimize } F(\mathbf{x}, \mathbf{u}) & (1) \\ & \text{Subject to } g(\mathbf{x}, \mathbf{u}) = 0 & (2) \\ & \text{and } h(\mathbf{x}, \mathbf{u}) \leq 0 & (3) \end{aligned}$$

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

2.2. SCOPF formulation

The SCOPF (the preventive approach) problem can be formulated as follows:

$$\text{Minimize } F(\mathbf{x}_0, \mathbf{u}_0) \quad (4)$$

$$\text{Subject to } g_k(\mathbf{x}_k, \mathbf{u}_0) = 0 \quad k = 0, \dots, c \quad (5)$$

$$\text{and } h(\mathbf{x}_k, \mathbf{u}_0) \leq 0 \quad k = 0, \dots, c \quad (6)$$

where $\mathbf{x}_0, \mathbf{u}_0$ is the state and the control variables of the base case, respectively. $\mathbf{x}_k, \mathbf{u}_k$: the state and the control variables of the k th post-contingency state, respectively. c is the number of contingencies considered.

2.3. Control variables

The set of control variables in the OPF problem formulation are:

- P_G : active power generation at PV buses except the slack bus.
- V_G : voltage magnitudes at PV buses.
- T : tap settings of transformers.
- Q_C : shunt VAR compensation.

Hence, \mathbf{u} can be expressed as:

$$\mathbf{u}^T = [P_{G_2} \dots P_{G_{NG}}, V_{G_1} \dots V_{G_{NG}}, Q_{C_1} \dots Q_{C_{NC}}, T_1 \dots T_{NT}] \quad (7)$$

where NG, NT and NC are the number of generators, the number of regulating transformers and the number of VAR compensators, respectively.

It is worth mentioning that, transformer tap settings and shunt devices settings are discrete in nature. In many works reported in literature addressing the OPF, these settings are considered as continuous variables for simplicity. Then, the discrete variables are set to their nearest discrete value after the optimization has been done. The results have shown that this approach leads to acceptable results without incurring the exponential complexity as reported by [38]. This last approach is adopted in this paper.

2.4. State variables

The set of state variables for the OPF problem formulation are:

- P_{G1} : active power generation at slack bus.
- V_L : voltage magnitudes at PQ buses or load buses.
- Q_G : reactive power output of all generator units.
- S_l : transmission line loadings (or line flow).

Hence, \mathbf{x} can be expressed as:

$$\mathbf{x}^T = [P_{G_1}, V_{L_1} \dots V_{L_{NL}}, Q_{G_1} \dots Q_{G_{NG}}, S_{l_1} \dots S_{l_{nl}}] \quad (8)$$

where NL and nl are the number of load buses and the number of transmission lines, respectively.

Download English Version:

<https://daneshyari.com/en/article/6904551>

Download Persian Version:

<https://daneshyari.com/article/6904551>

[Daneshyari.com](https://daneshyari.com)