Engineering Applications of Artificial Intelligence 39 (2015) 100–108

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

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

Solving optimal reactive power dispatch problem using a novel teaching–learning-based optimization algorithm

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ARTICLE INFO

Article history:
Received 23 February 2014
Received in revised form
26 November 2014
Accepted 2 December 2014
Available online 23 December 2014

Keywords:
Gaussian bare-bones teaching–learning-based optimization
Power systems
ORPD problem
Control variables

ABSTRACT

The paper presents a novel teaching–learning-based optimization (TLBO) algorithm, the Gaussian bare-bones TLBO (GBTLBO) algorithm, with its modified version (MGBTLBO) for the optimal reactive power dispatch (ORPD) problem with discrete and continuous control variables in the standard IEEE power systems for reduction in power transmission loss. The feasibility and performance of the GBTLBO and MGBTLBO algorithms are demonstrated for standard IEEE 14-bus and standard IEEE 30-bus systems. A comparison of simulation results reveals optimization efficacy of the GBTLBO and MGBTLBO algorithms over other well established other algorithms like bare-bones differential evolution (BBDE) and bare-bones particle swarm optimization (BBPSO) algorithm. Results for ORPD problem demonstrate superiority in terms of solution quality of the GBTLBO and MGBTLBO algorithms over original TLBO algorithm and other algorithm.

1. Introduction and literature review

Optimal reactive power dispatch (ORPD) problem is a useful tool in power energy management system. ORPD problem determines the optimal operating state of a power system by optimizing real power transmission losses while satisfying certain specified physical and operating constraints, with control variables such as the generator voltages, tap ratios of transformers and reactive power generation of volt-ampere reactive (VAr) sources. Since the voltage magnitudes is continuous variable whereas the transformer winding ratios and shunt capacitors/reactors, are discrete variables, the ORPD problem is considered as a non-linear multi-modal, large-scale, static optimization problem with a combination of the discrete and continuous control variables (Deeb and Shaidepour, 1990; Momoh et al., 1999; Quintana and Santos-Nieto, 1989).

Many classical optimization approaches such as quadratic programming (QP) (Lo and Zhu, 1991), linear programming (LP) (Aoki et al., 1988; Deeb and Shaidepour, 1988), interior point methods (IP) (Granville, 1994), predictor–corrector modified barrier approach (PCMBA) (de Sousa et al., 2009), gradient search (GS) (Yu et al., 1986), and a new approach called the modified barrier Lagrangian function (MBLF) (de Sousa et al., 2012), have been applied for solving ORPD problem. Also, an interior point method (IPM) is presented in Rider et al. (2004) for solving the optimal power flow (OPF) problem using IEEE 30, 57, 118, and 300 bus systems, and two realistic power systems, a 464 bus corresponding to the interconnected Peruvian system, and a 2256 bus corresponding to part (South-Southeast) of the interconnected Brazilian system were tested successfully. From the use literature survey for classical optimization approaches, it may be observed that these classical methods suffer from many drawbacks, such as excessive numerical iterations and insecure convergence properties. These approaches also suffer from the local optimality and resulting in large execution time and huge computations. These approaches are also incapable of handling nonlinear, discontinuous functions and constraints and problems having multiple local minimum points.

In recent decades, many optimization approaches ranging from conventional mathematical approaches to computational intelligence-based approaches have been proposed to deal with ORPD problem in the different power systems (Ghasemi et al., 2014a–2014e). Some of the proposed population-based methods such as examples of the progress which has been made in this field are improved evolutionary programming (IEP) (Yan et al., 2004), In Zhao et al. (2005) a multi-agent based particle swarm optimization (MAPSO) for the ORPD problem has been offered by Zhao, and simulated annealing particle swarm optimization (SA-PSO) (Mao and Li, 2008), self-adaptive real coded genetic algorithm (SARGA) (Subbaraj and Rajnaryanan, 2009) and seeker optimization algorithm (SOA) (Chaohua et al., 2009). In Wen and Yutian (2008) a fuzzy adaptive PSO (FAPSO) for reactive power and voltage control is used, and in Varadarajan and Swarup (2008) and Abou El Ela et al. (2011) differential evolution (DE) algorithm has been chose to constitute the core of the solution for

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http://dx.doi.org/10.1016/j.engappai.2014.12.001
0952-1976/

handling the ORPD problem. In another reported case, in Mahadevan and Kannan (2010) it offers another method based on comprehensive learning particle swarm optimization (CLPSO) for solving ORPD problem. Khazali and Kalantar (2011) are the application of a harmony search algorithm (HSA) for achieving optimal reactive power dispatch and voltage control by reaching a global optimization of a power system. Also in Roy et al. (2011, 2012), it demonstrated higher ability of biogeography based optimization (BBO) algorithm introduced to solve multi-constrained ORPD problem in power systems. Ramesh et al. (2012) addressed an application of modified NSGA-II (MNSGA-II) by incorporating controlled elitism and dynamic crowding distance (DCD) strategies in NSGA-II to solve multi-objective ORPD problem by minimizing real power loss and maximizing the system voltage stability. Devaraj and Roselyn (2010) presented an improved GA method to solve voltage stability enhance ORPD problem. Khorsandi et al. (2011) introduced the mixture of hybrid shuffled frog leaping algorithm and Nelder–Mead simplex search for optimal reactive power dispatch (SFLA-NM), as a solution for reactive power operational problems. Ramirez et al. (2011) proposed DE approach to solve optimal reactive power dispatch problem strategy that took care of steady state voltage stability implications. Zare et al. (2014) proposed a multi-objective modified bee swarm optimization (MOMBCO) for multi-objective probabilistic reactive power and voltage control in distribution networks using wind turbines, fuel cells, hydro turbines, static compensators and load tap changing transforms (Zare et al., 2014). Also, other methods, such as multiagent-based reinforcement learning (MASRL) (Xu et al., 2012), artificial bee colony optimization (ABC) algorithm (Ayan and Kılıc, 2012), gravitational search algorithm (GSA) (Roy et al., 2012), are presented for multi-objective probabilistic reactive power dispatch problem. Table 1 also summarizes population-based optimization techniques for solution of the ORPD problem.

However, the ORPD problem does possess the mentioned properties in itself. For these reasons, there is a significant need for reliable global approach for handling power system optimization problems. This paper presents a Gaussian bare-bones teaching–learning-based optimization (GBTLBO) algorithm and its modified version (MGBTLBO) for the ORPD problem with discrete and continuous control variables in the standard IEEE power systems. The original TLBO algorithm often converges to local optima (Niknam et al., 2012). In order to avoid this shortcoming, a new method is proposed to improve local search near the global best and a series of modifications is purposed in order to further enhance algorithm's rate of convergence for achieving a better solution quality. The numerical results obtained are found to be better than those already reported earlier by using other algorithms.

The rest of the presented study is categorized in four major parts, described as follows: Section 2 explains the typical formulation of an ORPD problem while Section 3 is dedicated to discussing the standard structure of the optimization algorithms, Section 4 of the paper covers optimization results and conducts comparison and performance analysis of the applied approaches used to solve the case studies of optimization problem on standard IEEE systems and last section of this article presents the conclusion of the implementation for the GBTLBO and MGBTLBO algorithms is presented.

2. Problem formulation ORPD problem

In general view, optimal reactive power planning problem determines the active power loss in the transmission network through optimal adjustment power system control parameters while satisfying equality and inequality constraints at the same time (Deeb and Shaidepour, 1990; Momoh et al., 1999; Quintana and Santos-Nieto, 1989).

The ORPD problem for can be mathematically formulated as follows (Zhao et al., 2005):

$$\text{Min } J(x,u) = P_{loss} = \sum_{k \in NTL} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{ij} \right) \quad (1)$$

$$\text{Subject to} : g(x,u) = 0 \quad (2)$$

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

Table 1
Summary of the proposed algorithms for solution of ORPD problem in literature.

Reference	Approach	Objective	Power system
Yan et al. (2004)	IEP	Power loss	IEEE 118-bus system and a realistic power system in Western China
Zhao et al. (2005)	MAPSO	Power loss	IEEE 30-bus and IEEE 118-bus
Mao and Li (2008)	SA-PSO	Power loss, voltage level and static voltage stability margin	IEEE 14-node system
Wen and Yutian (2008)	FAPSO	power loss, voltage deviation and the voltage stability index	IEEE 30-bus and IEEE 118-bus
Varadarajan and Swarup (2008)	DE	Power loss	IEEE 30-bus
Subbaraj and Rajnaryanan, 2009	SARGA	Power loss	IEEE 14-bus and IEEE 30-bus
Chaohua et al. (2009)	SOA	Power loss	IEEE 57-bus and IEEE 118-bus
Mahadevan and Kannan (2010)	CLPSO	Power loss and voltage profile	IEEE 30-bus and IEEE 118-bus
Devaraj and Roselyn (2010)	IGA	Voltage stability	IEEE 30-bus and IEEE 57-bus
Khazali and Kalantar (2011)	has	Power loss and voltage profile	IEEE 30-bus and IEEE 57-bus
Abou El Ela et al. (2011)	DE	Power loss, voltage profile, and voltage stability	IEEE 30-bus
Khorsandi et al. (2011)	SFLA-NM	Power loss	IEEE 30-bus, IEEE 57-bus and IEEE 118-bus
Ramirez et al. (2011)	DE	Voltage profile	IEEE 30-bus
Roy et al. (2011, 2012)	BBO	Power loss and voltage profile	IEEE 30-bus and IEEE 118-bus
Ramesh et al. (2012)	MNSGA-II	Power loss and voltage stability	IEEE 30-bus and IEEE 118-bus
Xu et al. (2012)	MASRL	Power loss	Ward–Hale 6-bus, IEEE 30-bus and IEEE 162-bus
Ayan and Kılıc (2012)	ABC	Power loss	IEEE 30-bus and IEEE 118-bus
Roy et al. (2012)	GSA	Power loss and voltage profile	IEEE 57-bus and IEEE 118-bus
Yang et al. (2012)	HDE	Power loss and voltage stability	IEEE 30-bus
Badar et al. (2012)	PSO	Power loss	IEEE 6-bus
Tehzeeb-Ul-Hassan et al. (2012)	FIPSO	Power loss	IEEE 30-bus and IEEE 118-bus
Niknam et al. (2013)	OSAMGSA	Power loss, voltage profile, and voltage stability	IEEE 30-bus