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Decomposition-based modern metaheuristic algorithms for multi-objective optimal power flow – A comparative study

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ABSTRACT

This article presents multi-objective variants of two popular metaheuristics, namely, the artificial bee colony algorithm (ABC) and the teaching learning based optimization algorithm (TLBO). Both of them are used to solve an optimal power flow problem. The proposed multi-objective variants are based on a decomposition approach, where the multi-objective optimization problem is decomposed into a number of scalar optimization sub-problems which are simultaneously optimized. The proposed algorithms are tested on the IEEE 30-bus system with different objectives. In addition, an algorithm based on fuzzy set theory is used to select the best committed solution. The proposed approaches are compared with others metaheuristic algorithms available in the specialized literature. Results indicate that the proposed approaches are highly competitive and also able to generate a well-distributed set of non-dominated solutions for the optimal power flow problem.

1. Introduction

The optimal power flow (OPF) problem has a significant importance in the power system's operation, planning, economic scheduling, and security. It is a non-linear con strained optimization problem, where the solution attains the control variables optimal adjustment, while at the same time satisfying equality and inequality constraints related to the equipments' rating, in order to optimize a certain objective function.

In general, the optimal power flow problem may include several objective functions, possibly in conflict with each other. Such kind of optimization problem has a set of possible solutions (named Pareto optimal set), which represent the best commitment among the objectives (Stadler, 1988). Two major solution approaches may be identified:

(1) The first approach is based on conventional methods. Such as Gradient-based Methods, Non-Linear Programming (NLP), Quadratic Programming (QP), Linear Programming (LP) and Interior Point Methods (Lee et al., 1985; Momoh et al., 1999a, b), the Weighting Method (Kuo et al., 2005), and the ε-Constraint Method (Hsiao et al., 1994).
(2) The second approach is based on the use of metaheuristic algorithms such as the Differential Evolution (DE) (Abido and Al-Ali., 2012), the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Jeyadevi et al., 2011; Deb et al., 2002), Particle Swarm Optimization (PSO) (Abido, 2011), Harmony search algorithm (Sivasubramani and Swarup, 2011), and the Hybrid Evolutionary Programming Technique (Alawode et al., 2010).

Conventional methods are based on an estimation of the global minimum. However, due to difficulties of differentiability, non-linearity, and non-convexity, these methods may not guarantee to reach the global optimum (Yamille et al., 2008). Moreover, these methods exhibit some limitations, depending upon the type of problem, e.g., when the objective function is not available in algebraic form. Thus, metaheuristics (from which evolutionary algorithms is a particular subclass) have become a popular choice for solving complex optimization problems, due to their flexibility, generality, and ease of use. Additionally, most metaheuristics require little or no specific domain knowledge.

Modern multi-objective evolutionary algorithms (MOEAs) aim at generating a number of Pareto-optimal solutions as diverse as

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possible. Indeed, MOEAs need a density estimator that distributes solutions along the Pareto front (e.g., crowding distance, fitness sharing, niching). However, there is evidence that these methods cannot always provide good results, especially when dealing with complex multi-objective problems (MOP) (Zhang and Li, 2007; Li and Zhang, 2009).

Recently, a novel MOEA framework called the multi-objective evolutionary algorithm based on decomposition (MOEA/D) (Zhang and Li, 2007), has been proposed. MOEA/D decomposes a MOP into several single-objective optimization sub-problems with neighborhood relationship. In this way, a set of optimal solutions is achieved by minimizing each sub-problem instead of using the traditional Pareto ranking methods. This has given rise to a new generation of MOEAs. Nevertheless, the performance of MOEA/D in power system applications has not been fully investigated.

This paper proposes a modified artificial bee colony algorithm and a teaching-learning algorithm in the MOEA/D framework. The proposed approaches are used to solve an optimal power flow problem, with competing objectives.

In order to minimize the total fuel cost, the active power losses and a voltage stability index (Kessel and Glavitsch, 1986), the proposed algorithms estimate the following optimal values: (i) the generators' voltage magnitudes; (ii) generators' active power outputs, (iii) transformers' tap settings; (iv) the compensating value for shunt elements (reactors/capacitors). In addition, an algorithm based on fuzzy set theory is used to select the best committed solution.

The effectiveness of the proposed approaches is demonstrated and compared with respect to a MOEA based on decomposition, which is representative of the state-of-the-art in the area: MOEA/D-DRA (Zhang et al., 2009). Results are also compared with respect to the NSGA-II (Deb et al., 2002), which remains as the most popular Pareto-based MOEA. The methods are applied on an IEEE 30-bus test system. Additionally, results reported in the open research (Abido and Al-Ali., 2012; Sivasubramani and Swarup, 2011) are also included for a comparative study.

The rest of the paper is organized as follows. Section 2 presents some basic background. In Section 3, the general framework of the proposed approaches is summarized. Section 4 presents the problem formulation and the method based on fuzzy theory for choosing the best committed solution. Simulation results and a comparative study are presented in Section 5. Finally, our conclusions are provided in Section 6.

2. Preliminaries

2.1. Multi-objective optimization

A multi-objective optimization problem (MOP) is formulated as follows:

$$\text{Min } F(x) = \{f_1(x), \dots, f_m(x)\}$$
$$\text{Subject to } x \in \Omega \qquad (1)$$

where x is the vector of decision variables, and Ω is the feasible region within the decision space. $F: \Omega \rightarrow \Re^m$ is defined as the m objective functions mapping.

In multi-objective optimization, the goal is to find the best possible trade off among the objectives since, frequently, one objective can be improved only at the expense of worsening another. To describe the concept of optimality for problem (1) the following definitions are provided.

Definition 1. Let $x, y \in \Omega$, such that $x \neq y$, we say that x dominates y (denoted by $x \prec y$) if and only if, $f_i(x) \le f_i(y)$ for all $i = 1, \dots, m$.

Definition 2. Let $x^* \in \Omega$, we say that x^* is a Pareto optimal solution, if there is no other solution $y \in \Omega$ such that $y \prec x^*$.

Definition 3. The Pareto Optimal Set ($\overrightarrow{PS}$) is defined by $\overrightarrow{PS} = \{x \in \Omega | x \text{is Pare to Optimal Solution}\}$, while its image $\overrightarrow{PF} = \{F(x) | x \in \overrightarrow{PS}\}$ is called the Pareto Optimal Front.

2.2. Decomposition of a multi-objective optimization problem

There are several approaches for transforming a MOP into a number of scalar optimization problems, which have been described in detail in (Miettinen., 1999). Usually, these methods use a weighting vector to define a scalar function and, under certain assumptions (e.g., the minimum is unique, the weighting coefficients are positive, etc.), a Pareto optimal solution is achieved by minimizing such function. In this paper, the weighted *Tchebycheff* approach is used to decompose the MOP. In this approach, the scalar optimization problem is stated as (Miettinen., 1999):

$$\text{Minimize} \quad g(x|w, z^*) = \max_{i \in \{1,\dots,m\}} \{w_i |f_i(x) - z_i^*|\}$$
$$\text{Subject to} \quad x \in \Omega \qquad (2)$$

where $w = (w_1, \dots, w_m)$ is a weighting vector and $w_i \ge 0$ for all $i = 1, \dots, m$. $\sum w_i = 1$ and vector $z^* = (z_1^*, \dots, z_m^*)$ represents the reference point, i. e., $z_i^* = \min \{f_i(x) | x \in \Omega\}$, $i = 1, \dots, m$, where m is the number of objective functions.

For each Pareto-optimal solution x^* there exists a weighting vector w such that x^* is the optimal solution of (2), and each optimal solution is a Pareto-optimal solution for (1). Therefore, it is possible to obtain different Pareto optimal solutions using different weighting vectors w.

2.3. Modified artificial bee colony

The first framework of the Artificial Bee Colony (ABC) was introduced by Karaboga in 2005 as a new swarm intelligent technique inspired by the foraging behavior of a honey bee swarm (Karaboga, 2005). In ABC, a colony of artificial bees consists of three groups of bees: employed bees, onlooker bees, and scout bees. In the algorithm, the position of a food source represents a possible solution to the optimization problem, and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. Each food source is exploited by only one employed bee. In other words, the number of employed bees is equal to the number of food sources existing around the hive (number of solutions in the population). The employed bee whose food source has been abandoned becomes a scout.

Akay and Karaboga (Akay and Karaboga, 2012) proposed some modifications to the standard ABC algorithm in order to improve the convergence rate. The pseudo-code of the modified ABC algorithm proposed by Akay and Karaboga can be summarized in the following way (Akay and Karaboga, 2012):

```
1: Initialization
2: Evaluation
3: Cycle=1
4: Repeat
5:     Employed bees phase
6:     Calculate probability for Onlookers
7:     Onlooker bees phase
8:     Scout bee phase
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