Information Sciences 327 (2016) 71–90

Contents lists available at ScienceDirect

Information Sciences

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

Balanced ranking method for constrained optimization problems using evolutionary algorithms

Max de Castro Rodrigues, Beatriz Souza Leite Pires de Lima*, Solange Guimarães

Civil Engineering Program, COPPE/Federal University of Rio de Janeiro, PO Box 68506, CEP 21945-970, Rio de Janeiro, RJ, Brazil

ARTICLE INFO

Article history:
Received 8 December 2014
Revised 29 July 2015
Accepted 9 August 2015
Available online 14 August 2015

Keywords:
Constrained optimization
Genetic algorithms
Constraint handling

ABSTRACT

This work presents a new technique to handle constraints in the solution of optimization problems by evolutionary algorithms – the Balanced Ranking Method (BRM). In this method the fitness function is based on two rankings, for feasible and infeasible solutions respectively. The rankings are merged according to deterministic criteria that consider the status of the search process and specific properties of the population. The focus of the BRM method is to comprise a constraint-handling technique (CHT) that is not coupled to the optimization algorithm, and thus can be implemented into different algorithms. The method is compared with other well-known CHTs that follow this same uncoupled approach, all implemented into a canonical Genetic Algorithm. Two well-known suites of benchmark functions and five engineering problems are used as case studies. The performance of the different CHTs is assessed by non-parametric statistical tests, including the Sign test and the Wilcoxon Signed-Ranks test. The results indicate that the BRM presents a good performance, being reliable and efficient, while maintaining its uncoupled characteristic leading to an easy implementation and hybridization with any search algorithm.

1. Introduction

The use of Evolutionary Algorithms (EA) and other heuristic methods to solve complex engineering optimization problems has been quite common in industry [4,24,27,28,36], due to the complexity of the objective function and to the significant amount of complex, nonlinear and problem-specific constraints.

Evolutionary methods were initially inspired by Darwin´s theory of natural selection; this is the case of the well-known Genetic Algorithm (GA) [18], probably the most widely acknowledged heuristic method. Several search methods based on EAs have been proposed to consider specifically the treatment of constraints [6,13,17,21,22,30], incorporating constraint handling techniques (CHTs) to manage the infeasible candidate solutions (ICS) that unavoidably arise along the evolutionary process. Ideally, such methods should be able to provide a larger number of feasible solutions: this is an important issue in real-world engineering problems, especially because the computational times required to perform multiple optimization runs might be impracticable.

Many CHTs currently available in the literature have been presenting good results; however they follow different approaches, each with its own target, and may present some disadvantages. The Stochastic Ranking method (SR) [30] compares adjacent solutions, and does not observe the population as a whole. Some methods, such as the Global Competitive Ranking (GCR) [31],

* Corresponding author. Tel.: +55 21999584046.
E-mail addresses: max.castro.rodrigues@gmail.com (M.d.C. Rodrigues), bia@coc.ufrj.br, beatriz@poli.ufrj.br (B.S.L.P. de Lima), sol@coc.ufrj.br (S. Guimarães).

http://dx.doi.org/10.1016/j.ins.2015.08.012

require parameters to adjust which is a troublesome issue. The Adaptive Penalty Method (APM) [22] is effective but may lose feasible solutions during the evolution. The ranking method of Ho and Shimizu [17] requires a low computational cost at the beginning of the procedure while searching for the feasible space, but may also lose feasible solutions during the evolution. Thus, one of the motivations of our work is to obtain a CHT that delivers an overall greater amount of feasible solutions, without parameters to adjust, while keeping the main qualities of the existing techniques.

Another desirable characteristic of a CHT is its versatility, that is, the ability to work uncoupled to the optimization algorithm, allowing its implementation along with any given evolutionary algorithm. In this context, a recent work [26] adopted an ensemble of four well-known uncoupled CHTs where each has its own population. The populations share all offspring taking advantage of the offspring diversity obtained by the CHTs. Another recent work [32] proposed an approach to balance feasible and infeasible solutions within the population throughout an alternative adaptive penalty function with a fuzzy controller-based parameter tuning.

In summary, our goal is to gather the many advantages of existing CHTs, by combining and enhancing ideas from previous methods, following the uncoupled characteristic and providing a larger number of feasible solutions. In this context, this work presents a new technique to handle candidate solutions in EAs: the Balanced Ranking Method (BRM). This method comprises an evolution of a former technique presented by the authors [29]. It adds new features to existing methods, enriching the domain of knowledge in this area, including the following aspects: Transformation of equality constraints into inequality constraints [6,30]; preference of a feasible candidate solution (FCS) over any ICS [6]; absence of adjustable parameters, the adaptive concepts behind the APM [22]; usage of ranking and searching for feasible space only while all individuals are infeasible [17]; and segregation of infeasible and feasible individuals [13]. The method is evaluated by experiments using the CEC2006 [23] and CEC2010 [25] benchmark functions, and also five engineering problems. Its performance is compared with five other CHTs [17,22,30,31,34] that follow this uncoupled approach, all implemented in the same canonic Genetic Algorithm to prevent biased results, adding credibility to the conclusions. Nonparametric statistical tests are used to compare the results: the Sign test [9,33] and the pairwise Wilcoxon Signed-Rank test [8,11,16].

2. Constrained optimization

This section summarizes some basic concepts regarding constrained optimization problems, and some of the methods currently available in the literature to deal with constraints in association with evolutionary methods.

The general form of a constrained optimization problem may be written as follows:

$$\begin{array}{lll} \text{Optimize} & f(\vec{x}), & \\ \text{Subject to} & g_j(\vec{x}) \le 0, & j = 1,\ 2, \ldots, q; \\ & h_j(\vec{x}) = 0, & j = q+1,\ 2, \ldots, m; \\ & x_i^{(\text{Low})} \le x_i \le x_i^{(\text{Up})} & i = 1,\ 2, \ldots, n. \end{array}$$

The goal is to optimize the objective function (OF), represented as $f(\vec{x})$. A solution $\vec{x}$ is a vector of n decision variables: $\vec{x} = (x_1, x_2, \ldots, x_n) \in \mathbb{R}^n$, with each decision variable x_i enclosed by a lower bound $x_i^{(\text{Low})}$ and an upper bound $x_i^{(\text{Up})}$ [7]. A decision variable space, or search space (S), is defined by the aforementioned bounds. In general, S consists of two disjoint subsets, one feasible ($\mathcal{F}$) and another infeasible (U). The infeasible space U is defined by m functions $g_j(\vec{x})$ and $h_j(\vec{x})$, i.e. the inequality and equality constraints, respectively. Candidate solutions (CS) in the $\mathcal{F}$ region are considered FCS while solutions $\vec{x}$ in U region are considered ICS.

Without special treatment, ordinary evolutionary methods could not be applied to constrained problems. Indeed, each year new CHTs are reported, giving birth to new ideas on the subject. These techniques can be classified either as direct, when only the FCS are considered, or as indirect, when both feasible and infeasible individuals are employed along the search [10].

The most common indirect method used in EAs is the penalty approach that penalizes infeasible solutions. Generally, the distance of a solution from the feasible region is used to compute the penalty amount. This distance may be defined as $\upsilon_j(\vec{x})$ for each constraint violation of candidate solution $\vec{x}$, as follows:

$$\upsilon_j(\vec{x}) = \begin{cases} \max\left\{0, g_j(\vec{x})\right\} & if\, 1 \le j \le q \\ \left|h_j(\vec{x})\right| & if\, q+1 \le j \le m \end{cases} \tag{1}$$

where $|h_j(\vec{x})|$, the absolute value of the equality constraint function, is frequently treated as an inequality within a definite interval of tolerance δ in the form of $\max\{0, |h_j(\vec{x})| - \delta\}$.

Although many works compute the penalty function differently [3,6,20,22], we may generalize the formulation of a penalty function, $p(\vec{x})$, and the commonly found evaluation function, eval$(\vec{x})$, as

$$p(\vec{x}) = C \sum_{j=1}^{m} [\upsilon_j(\vec{x})]^{\beta} \tag{2}$$