Information Sciences 435 (2018) 240–262

Contents lists available at ScienceDirect

Information Sciences

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

Differential evolution with adaptive trial vector generation strategy and cluster-replacement-based feasibility rule for constrained optimization

Bin Xu[a,*], Xu Chen[b], Lili Tao[c]

[a] School of Mechanical Engineering, Shanghai University of Engineering Science, 201620, China
[b] School of Electrical and Information Engineering, Jiangsu University, Jiangsu 212013, China
[c] College of Engineering, Shanghai Second Polytechnic University, 201209, China

ARTICLE INFO

Article history:
Received 6 March 2017
Revised 3 January 2018
Accepted 7 January 2018
Available online 8 January 2018

Keywords:
Constrained optimization
Differential evolution
Adaptive strategy
Cluster
Feasibility rule

ABSTRACT

Constrained optimization problems (COPs) are common in many fields. To solve such problems effectively, in this paper, we propose a new constrained optimization evolutionary algorithm (COEA) named CACDE that combines an adaptive trial vector generation strategy-based differential evolution (DE) algorithm with a cluster-replacement-based feasibility rule. In CACDE, some potential mutation strategies, scale factors and crossover rates are stored in candidate pools, and each element in the pools is assigned a selection probability. During the trial vector generation stage, the mutation strategy, scale factor and crossover rate for each target vector are competitively determined based on these selection probabilities. Meanwhile, the selection probabilities are dynamically updated based on statistical information learned from previous searches in generating improved solutions. Moreover, to alleviate the greediness of the feasibility rule, the main population is divided into several clusters, and one vector in each cluster is conditionally replaced with an archived infeasible vector with a low objective value. The superior performance of CACDE is validated via comparisons with some state-of-the-art COEAs over 2 sets of artificial problems and 5 widely used mechanical design problems. The results show that CACDE is an effective approach for solving COPs, basically due to the use of adaptive DE and cluster-replacement-based feasibility rule.

1. Introduction

In real-world designs, many problems can be formulated as global numerical optimization problems with constraints. This type of problem is commonly known as a constrained optimization problem (COP), and it can be formulated as follows [28]:

$$\begin{array}{rl} \text{minimize} & f(x), x = [x_1, \ldots, x_i, \ldots, x_n]^T \in S \\ \text{subject to} & g_j(x) \le 0, (j = 1, 2, \ldots, p) \\ & h_j(x) = 0, (j = p+1, \ldots, q) \\ & a_i \le x_i \le b_i, (i = 1, 2, \ldots, n) \end{array} \tag{1}$$

* Corresponding author.
E-mail address: xubin@mail.ecust.edu.cn (B. Xu).

https://doi.org/10.1016/j.ins.2018.01.014

where x is the n-dimensional decision variable in the search region S defined by the lower boundary $a = [a_1, \ldots, a_n]^T$ and upper boundary $b = [b_1, \ldots, b_n]^T$. The functions $f(x)$, $g(x)$ and $h(x)$ are, respectively, the objective function, inequality constraint and equality constraint. When a solution simultaneously satisfies all the p inequality and $q - p$ equality constraints, it is called a feasible solution; otherwise, it is an infeasible solution. Those inequality constraints that satisfy $g_j(x) = 0$ at a feasible solution are called active constraints. All equality constraints are therefore considered as active constraints at any feasible solutions.

Evolutionary algorithms (EA) are population-based metaheuristic algorithms that use mechanisms inspired by biological evolution such as reproduction, mutation, recombination, and selection. The primary advantage of EAs over traditional mathematical methods is that they require only that the objective function be calculable; other properties, such as differentiability and continuity, are unnecessary. The current popular EAs include particle swarm optimization (PSO), differential evolution (DE), artificial bee colony (ABC), artificial immune system (AIS), and teaching-learning-based optimization (TLBO). Among all these EAs, DE is a simple yet powerful algorithm for global optimization over continuous spaces [29,39]. Until now, DE has been widely and successfully applied in various domains [5,15,41,49]. However, it must be emphasized that DE was originally proposed for unconstrained problems [33], while the main goal of a constrained optimization algorithm is to find the feasible global optimum. Thus, to solve COPs effectively via DE, the following two issues should be considered [35,42]: (1) developing an effective constraint-handling technique (CHT); and (2) designing a powerful search engine.

In many constrained optimization evolutionary algorithms (COEAs), the CHTs serve as the main criterion for comparing multiple solutions during the selection process [28], and many different CHTs have been proposed. According to the ways in which the constraints are addressed, the existing CHTs can be grouped into three categories: (1) penalty function-based methods; (2) superiority of feasible solutions-based methods; (3) multiobjective optimization-based methods. Penalty function-based methods are simple to implement; however, they have been criticized because they require a fine-tuned penalty factor. When the penalty factor is too large, feasible solutions can be found quickly, but will have low quality. In contrast, when the penalty factor is too small, the quality of solutions may be high with respect to the objective function, but they may also be infeasible. To avoid this limitation, dynamic factor settings or adaptive factor settings [1] are applied. Superiority of feasible solutions-based methods prefer feasible solutions over infeasible ones, and they are both simple and parameter-free. However, they suffer from premature convergence because of the excessive greediness of the rule. To alleviate this greediness to some extent, some modifications have been proposed, such as the stochastic ranking method [38], the alpha constrained method [35,41], and the individual replacement technique [43]. Multiobjective optimization-based methods first combine the objective function with overall constraint violations to form a new bi-objective optimization problem; then, they optimize the bi-objective optimization problem [44]. However, some deficiencies still exist, and solving multiobjective optimization problems is still a challenging and often time-consuming task.

In its early stages, DE with slight modifications was directly combined with multifarious CHTs, such as penalty function methods [1], superiority of feasible solution-based methods [41], multiobjective-based methods [18], and multiple CHTs [22]. As stated above, designing a powerful search engine for COPs is also challenging. To improve the search capability of basic DE, some improved DE variants have been studied. Increasing the diversity is one significant direction. Tasgetiren and Suganthan [40] divided the main population into smaller sub-populations and then allowed them to search in parallel. Meanwhile, these sub-populations exchanged information periodically. Gao et al. [10] divided the main population into two sub-populations based on the feasibility of vectors and let the feasible sub-population focus on minimizing the objective, while the infeasible sub-population on the overall constraint violation. Mezura-Montes et al. [30] proposed a new COEA named Diversity-DE by incorporating a diversity mechanism into DE. Iacca et al. [14] proposed a multi-strategy approach that coevolved aging particles for global optimization. This method combined two components with complementary algorithm logic. Poikolainen et al. [34] proposed a cluster-based population initialization technique for DE that used the K-means clustering algorithm to group the solutions into two sets based on Euclidean distance.

In addition to introducing diversity, DE approaches that utilize multiple strategies are also popular. Wang and Cai [42] proposed a new DE framework called $(\mu + \lambda)$DE, in which three trial vectors are created for each target vector using three different mutation operators. Later, to overcome drawbacks in $(\mu + \lambda)$DE, Jia et al. [16] proposed an improved version called ICDE, which uses a new mutation strategy and an archive-based adaptive tradeoff model. In addition to using multiple mutation strategies, Elsayed et al. [8] included multiple mutation and crossover strategies into DE for COPs.

More recently, designing adaptive DE for COPs has attracted considerable research attention. Brest et al. [4] proposed the jDE-2 algorithm, in which the parameters *F* and *CR* are self-adaptively controlled based on previous search information. Ao and Chi [2] used a new mutation operator that did not require the *F* parameter. Moreover, they adaptively controlled the *CR* parameter to enhance their algorithm's adaptive capacity. Elsayed et al. [7] proposed an improved algorithm framework that uses a mixture of different mutation operators with a self-adaptive strategy. Zhang and Rangaiah [49] proposed a COEA named SaDETL, in which the mutation strategies and parameters are self-adjusted based on previous learning experiences. In addition, SaDETL applies a taboo list to avoid revisiting already searched areas. Qian et al. [35] proposed SADE-αCD, which solves complex constrained multiobjective problems by using multiple mutation-strategy-based DE operators with self-adaptively controlled *F* and *CR*. Elsayed et al. [8] included multiple mutation and crossover operators in DE by determining a mutation and a crossover operator for each vector in the population using an adaptive learning process. Kong et al. [17] proposed an adaptive grouping DE (AGDE) for COPs, in which the population is dynamically divided into three sub-populations, each with its own mutation strategies. During the evaluation process, AGDE adjusts *F* and *CR* adaptively