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Constrained optimization based on improved teaching–learning-based optimization algorithm

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A B S T R A C T

This paper proposes an improved constrained teaching–learning-based optimization (ICTLBO) method to efficiently solve constrained optimization problems (COPs). In the teacher phase of ICTLBO, the population is partitioned into several subpopulations, and the direction information between the mean position of each subpopulation and the best position of population guide the corresponding subpopulation to the promising region promptly. Information exchange between different subpopulations is used to discourage premature convergence of each subpopulation. Furthermore, in the learner phase, a new learning strategy is introduced to improve the population diversity and enhance the global search ability. Three different constraint handling methods are adopted for three situations, which are infeasible, semi-feasible, and feasible situations, during the evolution process. To evaluate the performance of ICTLBO, 22 benchmark functions presented in CEC2006 and 18 benchmark functions introduced in CEC2010 are chosen as the test suite. Moreover, four widely used engineering design problems are selected to test the performance of ICTLBO for real-world problems. Experimental results indicate that ICTLBO can obtain a highly competitive performance compared with other state-of-the-art algorithms.

1. Introduction

Most real-world optimization problems in science and engineering are subject to different types of constraints. These problems can be viewed as constrained optimization problems (COPs). The feasible region is reduced and the search processing is complex due to the presence of various constraints, making it difficult to solve COPs. Evolutionary algorithms (EAs), as a search and optimization technique inspired by nature, have been successfully used for solving optimization problems. Although the original versions of EAs lack a mechanism to tackle constraints, coupled with constraint handling techniques, EAs have gained extensive attention and have been broadly applied to solve COPs during the past decade [6,23,30,32].

Wang et al. [58] pointed out that constrained optimization EAs (COEAs) need to achieve two goals. The first goal is to land in or approach the feasible region promptly, while the second goal is to find the feasible global optimal solution. Thereby, COEAs should contain effective constraint handling techniques and powerful EAs to obtain competitive performance. Mezura-Montes and Coello [30] surveyed the most popular constraint handling techniques currently used in EAs, which are penalty functions, feasibility rules, multi-objective concepts, ensemble of constraint handling techniques, etc. In addition, the

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current popular EAs include particle swarm optimization (PSO) [8,20,51,52,57,69], differential evolution (DE) [49], artificial bee colony (ABC) [19,66], artificial immune system (AIS) [53], teaching–learning-based optimization (TLBO) [39,41], Jaya algorithm [46], etc. Numerous COEAs have been proposed by combining constraint handling techniques with EAs. Storn [50] suggested the constraint adaptation DE for the COPs. Huang et al. [17] presented a coevolution DE algorithm named Co-DE, which incorporated a coevolution model into DE and utilized two kinds of population to evolve solutions and penalty factors. Mallipeddi and Suganthan [24] proposed an ensemble of four constraint handling techniques with evolutionary programming to solve COPs, wherein each constraint handling method had its own population. Elsayed et al. [12] developed an algorithm framework that employed multiple search operators in each generation, which had been implemented with DE (SAMODE) for COPs. Wang et al. [59] put forward an adaptive tradeoff model with evolutionary strategy (ATMES) for COPs. A variety of tradeoff schemes in different search stages are implemented to obtain an appropriate tradeoff between objective function and constraint violations. Mezura-Montes and Cetina-Domínguez [31] reported a modified artificial bee colony algorithm (M-ABC) with four modifications related with the selection mechanism, scout bee operator, and equality and boundary constraints. Rao et al. [39] proposed the TLBO method for constrained mechanical design problems. Inspired by the fundamental principle of the vertebrate immune system, Zhang et al. [71] introduced an artificial immune system for solving COPs, where the population was classified into the feasible group, which focused on exploitation, and infeasible group, which facilitated exploration. Elsayed et al. [13] suggested a self-adaptive mix of PSO to improve the PSO performance in solving a wide range of COPs. Guedria [16] developed an improved accelerated PSO by introducing individual particles memories and two selected functions to solve constrained nonlinear optimization problems with various types of design variables. To accelerate the convergence rate of DE and achieve feasible solutions of COPs, Gong et al. [14] introduced the adaptive ranking mutation operator (ARMOR). In ARMOR, solutions were adaptively ranked according to the situation of the current population. Wei et al. [63] presented a new constrained DE framework with non-dominated sorting mutation operator by using fitness and diversity information to achieve a good balance between exploration and exploitation.

The TLBO algorithm [39,41], which simulates the teaching–learning process in a classroom, is a recently proposed population-based algorithm and has emerged as one of the simplest and most efficient techniques. It requires few parameters and performs well on many optimization problems. It has been improved and widely applied to a wide range of real-word optimization problems [45]. Rao and Patel [40] introduced the concept of elitism and developed the elitist TLBO (ETLBO) algorithm for COPs. Rao and Patel [44] then introduced the concept of number of teachers, adaptive teaching factor, tutorial training, and self-motivated learning to improve exploration and exploitation capacities. Zou et al. [73] employed dynamic group strategy, random learning strategy, and quantum-behaved learning strategy to maintain the TLBO algorithm's population diversity and discourage premature convergence. Satapathy Naik [48] proposed a modified TLBO by adding an extra term in the learner phase based on the concept of tutorial classes to enhance the convergence speed of TLBO. Chen et al. [4] introduced the producer-scrounger model into TLBO and developed the PSTLBO to decrease the computation cost. Afterwards, Chen et al. [3] developed a new improved TLBO algorithm by designing local learning and self-learning methods to upgrade the global performance of TLBO. In addition, a variant of TLBO with multi-classes cooperation and simulated annealing operator was also established by Chen et al. in 2015 [5]. Wang et al. [56] put forward an improved TLBO with neighborhood search to maintain the exploration ability of the population. Dokeroglu [11] cultivated a hybrid TLBO algorithm with robust tabu search to solve quadratic assignment problems. Xu et al. [64] proposed an effective TLBO by incorporating special local search operators into the search framework of TLBO to balance the exploration and exploitation capabilities. Ouyang et al. [35] developed a TLBO with global crossover (TLBO-GC), in which a perturbed scheme is introduced into the teacher phase to prevent the best solution from getting trapped in local optimal and a new global crossover strategy is incorporated into the learner phase to balance local and global search. Furthermore, the TLBO has been improved and extended to solve multi-objective problems [22,27,36,43,68,72], engineering optimization [42,54,65,67], and other fields
Q4 [1,10,38]. However, most of these previous works are noted to mainly focus on the unconstrained optimization problems, and few researches [39,40] have been done for the COPs. Moreover, in the teacher phase of the original TLBO, since all learners learn from the same direction information that is determined by the mean position of population with the best position of population, this leads the TLBO to be slow at the exploitation of the solutions. In addition, due to the limitation in the learning ability of learners in the learner phase, the population diversity is deteriorative as the searching process, thus TLBO can be trapped in a local optimal or cannot obtain feasible solutions when solving COPs, especially when the proportion of the feasible region is very small compared with the entire search space or when the optimum is located exactly on the boundaries of the feasible region.

Hence, this paper proposes an improved constrained teaching–learning-based optimization (ICTLBO) algorithm to enhance the performance of TLBO when solving COPs. In the teacher phase of ICTLBO, the population is clustered into a number of subpopulations, and the direction information of each subpopulation is determined by the mean position of corresponding subpopulation with the best position of population. With the help of different direction information, the population can approach the feasible region from different directions promptly, which can accelerate the convergence rate. In addition, information exchange among subpopulation is adopted to discourage premature convergence of each subpopulation. In the learner phase of ICTLBO, a new learning mechanism is introduced to improve the population diversity and facilitate the exploration ability in the promising search region. To obtain an appropriate tradeoff between objective function and constraint violations, three different constraint handling methods are adopted for three situations in the search process. To evaluate the performance of ICTLBO, 22 benchmark functions presented in CEC2006 [21] and 18 benchmark functions exhibited in CEC2010 [25] are selected as the test suite. Additionally, four constrained engineering design problems are also