A Collaborative Learning Model in Teaching-Learning-Based Optimization: Some Numerical Results

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Abstract. By mimicking the learning process of human in real-life, teaching-learning-based optimization algorithm (TLBO) is proposed for global optimization. Since then, it has been widely and effectively used in kinds of fields. As a swarm intelligent optimization method, TLBO has the virtue of fewer algorithm-parameters adjusting, easy to implement, and good convergence. However, there exist no advising directions in the learning phase, which may result in a decrease of local search ability of the TLBO when solving complex problems. In this paper, a collaborative learning model (CLM) which modified learner phase and novel self-studying phase is proposed to enhance both the global and local searching ability. In CLM method, a collaborative pattern or competitive pattern is probability chosen by learners in the learner phase. To efficiently conduct learners, in the self-studying phase, teacher updates his/her position according to neighborhood information adaptively. We perform the CLM method on a series of real-world resource allocation problem in multi-cell networks. Experimental results indicate that the CLM method is able to achieve more satisfactory or at least comparable solutions on most real-world problems.

Keywords: Teaching-learning-based optimization · Collaborative learning · Neighborhood information · Resource allocation problem · Multi-cell network

1 Introduction

Global optimization problem which is defined as searching for the best solution to satisfy the given objective function among all possible feasible solutions arises frequently in every field of our real-world life [1]. Finding the global optima is often difficult especially in some complex problems since there may exist many

local optimal solutions. Furthermore, the derivative properties of some objective functions are hard or impossible to get when using analytic or numerical method. So plenty of intelligent algorithms which inspired by some natural situation or process are designed to overcome this shortage, such as genetic algorithm (GA) [2], simulated annealing (SA) [3], bat algorithm (BA) [4], particle swarm optimization (PSO) [5], harmony search (HS) [6] and so on.

Teaching-learning-based optimization (TLBO) is a population-based intelligent method which inspired by the learning process of a typical school studying scenario [7]. Recently, TLBO has been widely and effectively used for numerical functions and real-world optimization problems due to several appealing advantages (i.e., fewer and simple working parameters, easy to implement, fast convergence, etc.). Moreover, new learner or teacher phase and a set of other meta-heuristics have been incorporated into teaching-learning-based optimization to solve serials of discrete or mechanical problems [8–18]. In [9], a self-learning phase is involved to improve the weakly local search ability of classical TLBO.

In this paper, a collaborative learning model (CLM) that designed based on the TLBO framework is proposed for global optimization. In CLM method, there have three basic steps: the teacher phase, learner phase and self-studying phase. The teacher phase adopts the same operator as the original TBLO to undertake global searching mission. In learner phase, two learners are randomly chosen by the current learner, which learns through collaborative pattern or competitive pattern with a specified probability. In typical school teaching situation, teachers not only teach learners to improve their knowledge, but also upgrade own ability by self-studying or interaction simultaneously in order to give more effective guidance to the learners. So the self-studying concept is introduced in CLM, which utilize neighborhood information of the contemporary teacher to enhance the local search ability then conduct learners exploring more promising area. The performance of CLM is investigated on a series of resource allocation problems in multi-cell networks. The results indicate that the CLM can achieve more satisfactory or at least comparable solutions on most real-world problems [10–14].

The remainder of this paper is organized as follows: Sect. 2 presents a detailed description of the proposed CLM. Section 3 presents the experimental results and related analysis. Finally, Sect. 4 gives the concluding remarks.

2   The Collaborative Learning Model

In the classical TLBO, both the teacher phase and learner phase have good global searching ability. In the teacher phase, learners learn from the global optimal individual; and in the learner phase, the individual, which the current learner learns from is selected randomly. These may have the following drawbacks:

(1) Learning in the learner phase has no guiding direction;
(2) Too much emphasis in global performance causes weakly local searching ability.

To overcome these problems, novel learner phase and self-studying phase is proposed in CLM which are detailed as follows:

2.1 Learner Phase of CLM

As we all known, collaboration and competition are two typical models used in learning. Therefore, in the learner phase of CLM, two randomly selected individuals choose from the two modes with a certain probability for the learner to learn. In this work, a predefined probability P_L determines which learning mode will be adopted by a learner. The learning process is implemented as follows:

$$L_{i,new} = \begin{cases} L^1_{i,new}, & if\ rand \leq P_L\ (competition) \\ L^2_{i,new}, & otherwise(collaboration) \end{cases} \tag{1}$$

$$L^1_{i,new} = \begin{cases} L_{i,old} + r_1 * (L_{best} - L_{i,old}), & if\ L_{best}\ is\ better\ than\ L_i \\ L_{i,old} + r_1 * (L_{i.old} - L_{best}), & otherwise \end{cases} \tag{2}$$

$$L_{best} = \begin{cases} L_j, & if\ L_j\ is\ better\ than\ L_k \\ L_k, & otherwise \end{cases} \tag{3}$$

$$L^2_{i,new} = \begin{cases} L_{i,old} + r_2 * (L_j - L_k), & if\ L_j\ is\ better\ than\ L_k \\ L_{i,old} + r_2 * (L_k - L_j), & otherwise \end{cases} \tag{4}$$

Where L_j and L_k ($j \neq k \neq i$) are chosen by current ith learner randomly; r_1 and r_2 are randomly selected from range [0, 1]. Equations (2) and (3) is the competitive model, which indicates that the learner will learn from the better one between the two individuals. In the collaboration model shown as Eq. (4), the difference of the two individual is mainly considered when learning. Since this, by fully exploiting the information of the whole class, learning is always toward to a better direction.

2.2 Self-studying Phase of CLM

In general, in the process of the teacher teaching, they also interact with others or learn from themselves. The goal is to enhance their knowledge grade to give a better guide to learners in order to improve the overall performance of the class. In the proposed CLM method, to effectively enhance the local searching ability, position of the current teacher is updated by searching in the neighborhood area adaptively. The self-studying process is carried out as follows:

$$T_{new,j} = \begin{cases} T_{old,j}(g) + r_3 * TR, & if\ rand\ \leq P_{SL} \\ T_{old,j}(g), & otherwise \end{cases} \tag{5}$$

Where $T_{old,j}(g)$ and $T_{new,j}(g)$ are the jth component of the original and new teachers after local updating. g indicates the current iteration number, P_{SL} is a predefined mutation probability. r_3 is randomly selected from range [0, 1] and TR is selected at random in the reasonable value range.

It is worth noticing that, in the later iteration of the algorithm, searching generally focus on the local area, so the random step r_3 used in Eq. (5) can ensure a certain probability jump out of local optima when searching in the neighborhood. In each iteration, the executing number of the self-studying process is equivalent to the current iteration number g.
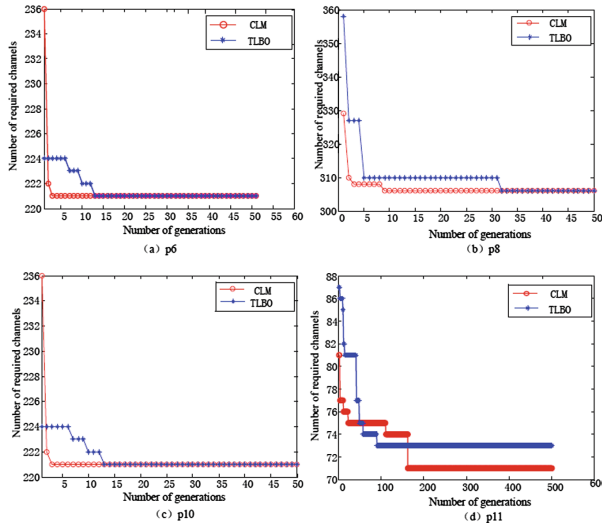

Fig. 1. Convergence curves of the CLM and TLBO on four benchmark problems.

3   Experimental Result

In this paper, we applied the CLM method to real-world resource allocation problem in multi-cell networks [19,20], and compared the results with TLBO and some related techniques [21,22]. The obtained comparison results indicate that the CLM method provides effective solutions when solving the optimal resource allocation problem. Detailed descriptions of the benchmark problem and resource allocation problem can be referred as [9,21,22]. A comparison results with TLBO and other two representative approaches [21,22] are presented in Table 1.

In this simulation, class size and maximum generations for TLBO and CLM are set to 100 and 500. In addition to demonstrating the coverage of the CLM, the comparison convergence curve of CLM and TLBO on two testing problems is illustrated (Fig. 1). From Fig. 1, it is clearly shown that the proposed CLM

has fast convergent speed than TLBO. For the easy problem p6, p8 and p10, the CLM can reach the global optima within 10 generations. For the complex p10, TLBO converge faster than CLM within 160 generations. However, in the later generations, CLM can jump out to find global optimal solutions while TLBO is still trapped into local optima.

Table 1. The comparison results of the eleven problems

Problem index	Lower bound	[21] Best	[22] Best	TlBO Best	CLM Best/Mean
1	381	381	382	381	381/381
2	427	463	449	463	445/460
3	533	533	534	533	533/533
4	533	533	533	533	533/533
5	221	221	222	221	221/221
6	221	273	268	274	268/274
7	309	309	309	309	309/309
8	309	309	312	310	309/309
9	21	73	73	73	73/73
10	309	309	312	310	309/309
11	71	79	74	75	71/71.1

4   Concluding Remarks

In this paper, a collaborative learning model (CLM) is proposed for global optimization. Different from TLBO, the CLM consists of three mainly phases: teacher phase, learner phase and self-studying phase. To efficiently guide learners toward to a better direction, a competitive learning model and collaborative learning model is probably chosen when leaning [23,24]. In addition, in the self-studying phase, each teacher updates his position adaptively using the neighborhood information, which is intended to enhance local search ability of the algorithm. Through collaborative learning by teachers and learners, global search ability and local search ability of the algorithm have been improved.

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