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An effective teaching-learning-based cuckoo search algorithm for parameter optimization problems in structure designing and machining processes

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ABSTRACT

The optimum selection of parameters is great important for the final quality of product in modern industrial manufacturing process. In order to achieve highly product quality, an effective optimization technique is indispensable. In this paper, a new hybrid algorithm named teaching-learning-based cuckoo search (TLCS) is proposed for parameter optimization problems in structure designing as well as machining processes. The TLCS combines the Lévy flight with teaching-learning process, then evolves with a co-evolutionary mechanism: for solutions to be abandoned in the cuckoo search will perform Lévy flight to generate new solutions, while for other better solutions, the teaching-learning process is used to improve the local searching ability of the algorithm. Then the proposed TLCS method is adopted into several well-known engineering parameter optimization problems. Experimental results show that TLCS obtains some solutions better than those previously reported in the literature, which reveals that the proposed TLCS is a very effective and robust approach for the parameter optimization problems.

1. Introduction

There are a lot of optimization problems in modern manufacturing environment. For instance, in the structure designing and machining processes, the final product quality is sensitive to the combination of different processing parameters. In addition, the operational cost and the productivity are also highly depended on the selection of these processing parameters. Therefore, in order to obtain highly product quality, an effective optimization approach is needed.

However, it is very complicated to obtain the suitable parameters for the structure designing and machining process. Firstly, many design variables as well as the complex constraints make the determination of parameters difficult. Besides, a number of additional aspects such as knowledge of designing should be considered when achieving an optimum processing parameters. What's more, the nonlinearity results in a multimodal landscape optimization problem and traditional techniques are no longer suitable for the problem, thus new global optimization methods must be designed.

Since meta-heuristic algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO) are more effective than the traditional gradient techniques [1–3]. And many kinds of parameter optimization problems are solved by these evolutionary algorithms. Zarei et al. [4] presented a harmony search (HS) algorithm to determine the optimum cutting parameters for a multi-pass face-milling, while Shunmugam et al. [5] used GA for a selection of optimal conditions in a multi-pass face-milling. Liu et al. [6] proposed a modified GA based optimization of milling parameters. Vijayakumar et al. [7] proposed a new optimization technique based on the ant colony optimization (ACO) for solving multi-pass turning optimization problems. Rao and Pawar [8] used various advanced optimization algorithms such as ACO, PSO, and simulated annealing (SA) to optimize of process parameters of multi-pass milling process.

In order to improve the performance of algorithms, many evolutionary methods had been modified or hybridized with other optimization techniques. Yildiz [9] had hybridized an artificial immune algorithm with a hill climbing local search algorithm to solve optimization problems. Wang et al. [10] presented a hybrid of GA and SA algorithms (GSA) to select the optimal machining parameters for multi-pass milling process. Baskar et al. [11] used a memetic algorithm based on the GA and hill climbing algorithm for the selection of optimal parameters. Melo et al. [12] proposed

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an investigating multi-view differential evolution for solving constrained engineering design problems.

Although some improvements for parameter problems have been achieved, the further investigation need studied due to the complexity of conflicting objective and multiple constraints. Therefore, there has been a growing interest in applying new approaches to solve these problems in recent years. The cuckoo search (CS) was recently proposed by Yang and Deb [13], the algorithm is based on the obligate brood parasitic behavior of some cuckoo species in combination with the Lévy flight behavior of some birds and fruit flies. And it has been introduced for solving structural optimization and machining parameters optimization problems [14,15]. Another algorithm, teaching-learning-based optimization (TLBO) that has been recently developed by Rao et al. [16], is also wildly applied in many kinds of parameter optimization problems. However, these two new algorithms are also limited in several aspects of optimization problems [17].

We have proposed an effective hybrid algorithm named teaching-learning-based cuckoo search (TLCS) for continuous optimization problems lately [17]. In order to extend its applications range, it has been modified and applied for constrained optimization problems. Thus, in this paper, the proposed TLCS is used to solve the parameter optimization problems and the performance of the method is analyzed by comparing with other approaches.

The rest of this paper is organized as follows: Section 2 provides a basic framework of the proposed TLCS. Experimental results based on several typical engineering parameter optimization problems and comparisons with previously reported results are presented in Section 3. Section 4 presents a discussion and conclusions of the TLCS.

2. The proposed TLCS

2.1. The framework of TLCS

In the proposed hybrid algorithm, the main idea is to combine the good search ability of CS and the fast convergence rate of TLBO, the proposed algorithm mainly includes two parts, for solutions to be abandoned in the CS will perform Lévy flight to generate new solutions. And for other solutions, we use the TLBO to enhance the local search ability of CS. Thus, the algorithm becomes more practical for a wider range of applications but without losing the attractive features of the original CS and TLBO.

The framework of the TLCS is as shown in Fig. 1.

For the proposed TLCS, it has strong global search ability along with a fast convergence rate [17], and the method could suitable for a broad spectrum of problem domains. As in the framework, two important ways for updating the solutions in the population are Lévy flight and the teaching-learning process. The two key procedures are presented in the following sections.

2.2. Lévy flight

Cuckoo search (CS) is a new meta-heuristic search algorithm, based on cuckoo bird's behavior [13,14]. The algorithm is inspired by the reproduction strategy of cuckoo.

In CS, when generating new solutions x^{t+1} for cuckoo i, a Lévy flight is performed:

$$x_i^{t+1} = x_i^t + \alpha \oplus \ Lévy(\lambda) \tag{1}$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem. The product $\oplus$ means entry-wise multiplications. Lévy flights essentially provide a random walk while their random steps are drawn from a Lévy distribution for large steps.

$$Lévy(\lambda) \sim u = t^{-\lambda}, \quad 1 < \lambda \le 3 \tag{2}$$

which has an infinite variance with an infinite mean.

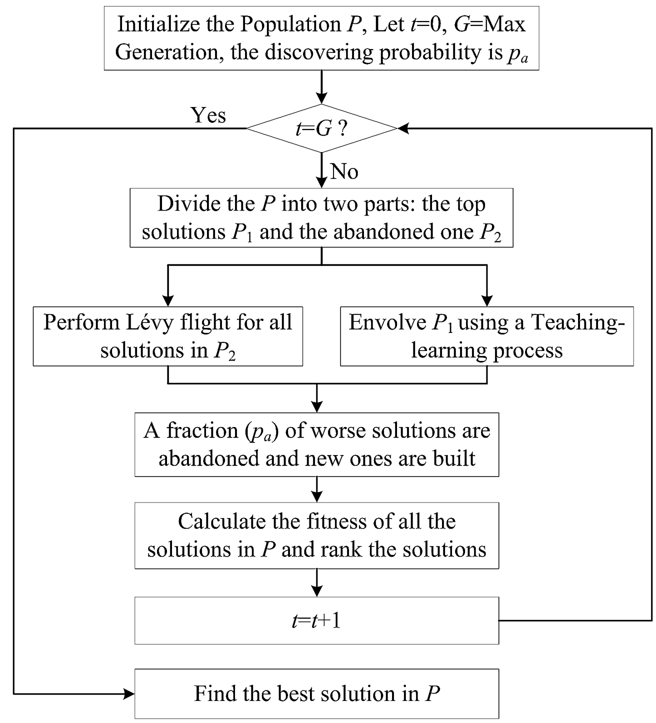

Fig. 1. The framework of the proposed TLCS.

2.3. Teaching-learning process

TLBO is a population based method. The algorithm mimics the teaching-learning ability of teacher and learners in a classroom [18]. The working of TLBO is divided into two parts, 'Teacher phase' and 'Learner phase'. Working of both the phase is explained below.

2.3.1. Teacher phase

It is first part of the algorithm where learners learn through the teacher. During this phase a teacher tries to increase the mean result of the classroom from any value M_i to his or her level (i.e. T_A). And the difference between the existing mean and new mean is given by:

$$Difference\_Mean_i = r_i(M_{new} - T_F M_i) \tag{3}$$

where T_F is the teaching factor which decides the value of mean to be changed, and r_i is the random number in the range [0, 1]. Value of T_F can be either 1 or 2 which is a heuristic step and it is decided randomly with equal probability as:

$$T_F = round[1 + rand(0, 1)\{2 - 1\}] \tag{4}$$

Based on this *Difference_Mean*, the existing solution is updated according to the following expression:

$$X_{new,i} = X_{old,i} + Difference\_Mean_i \tag{5}$$

2.3.2. Learner phase

It is second part of the algorithm where learners increase their knowledge by interaction among themselves. A learner interacts randomly with other learners for enhancing his or her knowledge. A learner learns new things if the other learner has more knowledge than him or her. Mathematically the learning phenomenon of this phase is expressed below.