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Comparative Analysis of TLBO Algorithms

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Abstract

In this paper a detailed analysis has been made over the Teaching Learning based Optimization Algorithm, about its implementation application and the modifications that has been made to improve the performance of the algorithm in various environments. TLBO is an optimization algorithm similar to Particle Swarm Optimization, or some time it can be termed as the improved version of the PSO. Nature provides inspiration to computer scientists in many ways. One source of such inspiration is the way in which natural organisms behave when they are in groups. Consider a swarm of ants, a swarm of bees, a colony of bacteria, or a flock of starlings

Keywords: —Teaching Learning Based Optimization Algorithm, Particle Swarm Optimization, Swarm Intelligence, Nature Inspired Algorithms.

1 INTRODUCTION

WARM intelligence comes from swarming behaviors of groups of organisms. Group living enables organisms to solve problems that are difficult or impossible for single individuals to resolve. So, swarm intelligence can be seen as a mechanism which individuals can use to overcome some of their own cognitive limitations. Swarm intelligence claims the ability to manage complex systems of interacting individuals through minimal communication with only local neighbors to produce a global emergent behavior. They typically do not follow commands from a leader, or some global plan. These special features make swarm intelligence play important roles in many engineering applications such as formation control of multi-robot system, massive distributed sensing using mobile sensor networks, combat using cooperative unmanned aerial vehicles, flocking, etc. Also, for several decades, many researchers have been devoted much efforts to such systems, which can be roughly divided into three groups: 1) biological researchers, which are the first groups to make the early efforts to study swarm behavior; 2) Artificial algorithm researchers, which have done important work on swarming topology; 3) engineering application researchers, which have increased much interest on swarming engineering such as multi-robot, air vehicles, sensor network, etc. All three groups of researchershave greatly advanced the swarm intelligence by delivering
large number of significant results in the recent decades. Optimization has always been a ancient topic. A large number of scholars and researchers have made much contribution in this field. With the rapid development of the science technology, various of complex optimization problems come out in our daily life. Specially, some resources allocation, energy utilization, economy cost programming, large scale industrial system design and network running generally become compand optimization problems. We are hardly to find a reasonable soution in a limited time for these real-world optimization problems with non-differentiable, non-linear, large scale and multi-constraint. How to settle these new problems is a challenge. Some classic optimization methods such as steepest descent, Newton's method, liner programming, conjugate gradient method, dynamic programming, quasi-Newton method are can not satisfy the demand of accuracy and time. Therefore, it is necessary to find a new optimization path for the real-world optimization problems. Recently, Heuristic optimization algorithms such as the genetic algorithm (GA), ant colony algorithm (ACA), particle swarm optimizing algorithm (PSO) and the differential evolution algorithm (DE) based on imitating some natural phenomena or process have been successfully applied to many real-world optimization problems. Compared with traditional optimization algorithm, Heuristic optimization algorithm has its advantages of intelligence, wide applicability, parallelism and global search ability, and that is the motivation of all researcher's study heuristic optimization algorithm.

2 LITERATURE REVIEW

Intelligence optimization algorithms are a class of heuristic optimization algorithms, which contain genetic algorithm, tabu search algorithm, and simulated annealing algorithm, and so on. In recent years, with the rapid development of human's understanding on the self-organization behavior of certain animals,

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some swarm intelligence algorithms, such as particle swarm optimization [1], ant colony optimization [2], and cloud drops algorithm [3] have been proposed. Moreover, they have been applied to solve some practical problems, for example routing design [4].

Teaching-Learning-Based Optimization (TLBO) is a novel intelligence algorithm proposed by Rao etc in 2010 [5]. It achieves optimization by simulating the teaching process and learning process. It not only has a good performance, but also is simple for having only one parameter, namely the number of learners. TLBO is getting attention and widely employed in practical optimization problems [6].

To simulate the teaching and learning process more accurately and improve performance, researchers proposed some improvement strategies. In [7], an elitist strategy is introduced and the best learners are chosen as the elitist solutions to replace the least learners in each iteration. In [8], a feedback process is introduced after learning process to maintain the diversity of learners and improve the ability of global search. In [9], multiple teachers are set to speed up convergence, learning process is adaptively adjusted and self- driven learning is added to improve the ability of global search. The above strategies improve the quality of solution or convergence speed. However, on the one hand, they evaluate after updating all dimensions of a solution. In fact, each dimension of a solution can be seemed as one course of a learner and it is feasible to evaluate after not updating all dimensions of solutions, for the independence among courses. Meanwhile, for multi-dimensional functions, due to the interference phenomena among dimensions, the scheme of evaluating after updating all dimensions of a solution influences the quality of solution and convergence speed. On the other hand, these strategies introduce new parameters and destroy the simplicity of TLBO.TLBO has two main phases. The first one is "Teacher Phase" and the second one is "Learner Phase". The former means learning from the teacher and the latter means learning through the interaction between learners [5]. The detailed process is described as follows:

Step 1: Define the optimization problem and initialize the optimization parameters.

Step 2: Initialize the population.Step 3: Teacher phase.

Step 4: Learner phase.

Step 5: Terminate the algorithm if the maximum generation number is achieved, otherwise repeat from Step 3.

TLBO is similar to other swarm intelligence algorithms, for example ant colony optimization (ACO). Learners are similar to ants, and learners' learning behavior is similar to the moving behavior of ants. The teacher phase in TLBO is similar to the pheromone attraction in ACO. The teacher is similar to the current optimal ant, and each learner learns from the teacher, which makes the whole population converge to the optimal solution quickly, and speed up the convergence rate. The learner phase in TLBO is similar to the local heuristic in ACO, and learning between different learners maintains the diversity of population, avoids premature convergence, and strengthens the global search ability.

Teaching-Learning-Based Optimization (TLBO) mimicking the process of teaching-learning, has been developed by Rao, et.al [10]. TLBO has been proposed to obtain optimum solution for continuous optimization problems with less computational effort [11]. Like other nature inspired population-based algorithm, TLBO is a population-based algorithm which imitates the natural phenomena of knowledge dissemination within a school room circumstance, where students learn from teachers firstly and then communicate with schoolmates. TLBO demonstrates an excellent performance for a large number of nonlinear and multimodal numerical optimization functions. It seems to be a rising star among a number of meta-heuristics with relatively competitive performance [12]. Due to its simple structure, easy-to-implement feature, high efficiency and robustness, TLBO has been actively researched and applied in many fields including: mechanical design [12], planar steel frames [13], Data clustering [14], economic load dispatch problem [15], reactive power dispatch [16], short-term hydrothermal scheduling problem [17, 18], etc.

As it is well-known, the standard swarm intelligent algorithm-particle swarm optimization (PSO) is simple yet powerful in solving global optimization [19]. PSO consists of two key rules: velocity updating and position updating. Note that the procedure of the teaching phase of TLBO algorithm is similar to the velocity updating of PSO algorithm. Considering employed the position updating operation to enhance the global searching capability of TLBO algorithm, which is reasonable and effective.

The optimization problem has long been an interest research topic due to its wide application in real-world scenarios, including large-scale optimization, multi objective optimization, big data, feature selection, and so on [20, 21]. Inspired by natural and physical phenomena, evolutionary algorithms (EAs) are booming because nature-inspired mechanisms can be transformed into search mechanisms, which can be effectively implemented to improve the solution search ability for optimization problem [22]. For example, genetic algorithm (GA) [23], differential evolution (DE) [24], and derandomized evolution strategy with covariance matrix Adaptation (CMA-ES) [25] use an evolutionary mechanism. Chemical Reaction Optimization (CRO) [26], fireworks algorithm (FA) [27], and gravitational search algorithm (GSA) are implemented by a physics-based mechanism. Particle Swarm Optimization (PSO) [29], Artificial Bee Colony (ABC) [30], and Whale Optimization Algorithm (WOA) [31] employ a swarm intelligence mechanism. Brain storm optimization (BSO) [32], and Teaching-Learning-Based Optimization (TLBO) [33] involve a human-related mechanism.

TLBO, proposed by Rao et al. in 2011 [33], is a population based heuristic optimization algorithm which does not require any algorithm-specific parameters. This method simulates the traditional classroom teaching process. The whole optimization process includes teacher phase and learner phase. In the teacher phase, each student learns the outstanding performance, which is a differential vector related to the teacher. In the learner phase, each student learns from other students in a random way. TLBO has been proved of competitive exploration and exploitation capability during the optimization process. However, many experimental studies indicate that it is still possible to get trapped in a local optimum. To address such an issue, researchers have introduced many strategies into TLBO [34], such as initialization techniques, adaptive parameters, learning strategies, etc. The variants of TLBO can be roughly categorized into the following three groups.

1. Improvements of parameters. For example, Satapathy et al. [35] employed an adaptive weight in TLBO to improve the learning ability of each student. Bulbul and Roy [36] introduced two adaptive control parameters into TLBO. The teaching control parameter is dynamically adjusted according to fitness values of learners, while the learning control parameter is adaptively adjusted according to the current generation and the maximum generation. This mechanism can effectively improve the exploration ability and the exploitation ability of the algorithm. Sleesongsom and Bureerat [37] proposed a new TLBO variant. In the proposed algorithm, a self-adaptive strategy is employed to justify the population sizes for the teaching and learning reproduction. Shukla et al. [38] proposed an improved TLBO with adaptive exponential distribution inertia weight. The new inertia weight with linear increasing and nonlinear decreasing strategy can increase the learning capacity of the learners. Moreover, the logistic-map is used to generate uniformly distributed populations to enhance the quality of the original population.
2. Improvements of optimization mechanisms. For example, Zhang et al. [39] proposed a TLBO algorithm with a logarithmic spiral strategy and triangular mutation rule (LNTLBO). In the teacher phase, a logarithmic spiral strategy can accelerate convergence speed. Moreover, a triangular mutation is used to enhance the abilities of exploration and exploitation in the learner phase. Peng et al. [40] proposed a collective information- based TLBO (CIBTLBO). The information of the top learners and the neighborhood information of each learner are used to help learners learn in the teacher phase and the learner phase, respectively. Chen et al. [41] proposed a novel TLBO with generalized opposition-based learning strategy (GOTLBO). Generalized opposition-based learning strategy can enhance the convergence speed by retaining the fitter one from an individual to its opposite in the population. Xu et al. [42] proposed a dynamic-opposite learning TLBO (DOLTLBO). A new dynamic-opposite learning strategy is employed to overcome premature convergence. Zou et al. [43] proposed a novel TLBO with dynamic group strategy (DGSTLBO). All learners were divided into groups of equal number based on the Euclidean distance. The quantum-behaved learning strategy or the learning method was used to improve the knowledge level of learners. Cheng and Prayogo [44, 45] proposed a novel fuzzy adaptive TLBO variant (FATLBO) to enhance the efficiency of the learning process. More precisely, a fuzzy logic system was employed to adjust the probability rate based on the status monitor. Then, it can be determined whether a learner uses teaching phase or learning phase. Zou et al. [46] proposed a new two- level hierarchical multi-swarm cooperative TLBO variant (HMCTLBO) to increase the diversity of the population. Chen et al. [47] proposed a variant of TLBO with multi-classes cooperation and simulated annealing operator (SAMCCTLBO) to improve the learning ability of learners and the diversity of the whole class. A variant of TLBO which uses a variable population size in the form of a triangle form (VTTLBO) is proposed in [48] to decrease the computing cost of basic TLBO and optimize the parameters of artificial neural network.
3. Hybrid TLBO algorithms. Zhang et al. [49] proposed a novel hybrid algorithm which hybrids TLBO and neural network algorithm (NNA). The proposed algorithm makes the best of the excellent global optimization ability of NNA and the fast convergence rate of TLBO by dynamic grouping mechanism. Shao et al. [50] proposed a hybrid discrete optimization approach based on teaching- probabilistic learning mechanism. A population reconstruction operation was used to alleviate premature convergence. The neighborhood search strategies with the speed-up methods were employed to improve the quality of learners. Qu textitet al. presented a novel TLBO memetic algorithm [51]. In the proposed algorithm, the multi-meme learning based on meta-Lamarckian was utilized to enhance the promising refined region, and conservation of information was used to enrich learning behaviors so as to improve the exploitation ability. Turgut and Coban [52] developed a hybrid TLBO-DE algorithm. In TLBO- DE, an ensemble of mutation strategies including DE/best/1 and DE/best/2 was introduced to replace the learning method. Moreover, chaotic sequences generated by the Logistic map were employed to improve the global search ability and speed up the convergence of the algorithm.

3 CONCLUSION

From the above studied theory about the teaching learning based optimization algorithm there have been many attempts to improve the performance and the usability of the algorithm forthe real world implementation in various applications.

The major applications are found in electrical engineering, mechanical design, thermal engineering, manufacturing engineering, civil engineering, structural engineering, computer engineering, electronics engineering, physics, chemistry, biotechnology and economics. This paper presents a review of applications of TLBO algorithm and a tutorial for solving the unconstrained and constrained optimization problems.

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