Toward Teaching-Learning-Based Optimization Algorithm for Dealing with Real-Parameter Optimization Problems

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***Abstract*—A latest optimization algorithm, named Teaching-Learning-Based Optimization (simply TLBO) was proposed by R. V. Rao et al, at 2011. Afterwards, some improvements and practical applications have been conducted toward TLBO algorithm. However, as far as our knowledge, there are no such works which categorize the current works concerning TLBO from the algebraic and analytic points of view. Hence, in this paper we firstly introduce the concepts and algorithms of TLBO, then survey the running mechanism of TLBO for dealing with the real-parameter optimization problems, and finally group its real-world applications with a categorizing framework based on the clustering, multi-objective optimization, parameter optimization, and structure optimization. The main advantage of this work is to help the users employ TLBO without knowing details of this algorithm. Meanwhile, we also give an experimental comparison for demonstrating the effectiveness of TLBO on 5 benchmark evaluation functions and conclude this work by identifying trends and challenges of TLBO research and development.**

Keywords*—*Teaching-Learning-Based Optimization; clustering; multi-objective optimization

I. INTRODUCTION

Teaching-Learning-Based Optimization (TLBO) is firstly proposed by R. V. Rao et al in 2011 [1] for handling the optimization of mechanical design problems by considering the influence of a *teacher* on *learners*. Like other nature-inspired algorithms, e.g., genetic algorithm (GA) [2] and particle swarm optimization (PSO) algorithm [3], TLBO is also a population-based method and uses a population of solutions to proceed to the global solution. The population is considered as a group or class of learners. Generally speaking, the process of TLBO can be divided into two different parts, i.e., *teacher Phase* and *learner Phase*. The teacher phase means learning from the teacher and the learner phase means learning by the interaction among the different learners.

The basic philosophy of TLBO method can be gave by observing the following Fig. 1 and Fig. 2. Assume there are two different teachers, i.e., T_1 and T_2, which teach a subject with the same content to the same merit level learners in two different classes. Fig. 1 shows the distribution of marks obtained by the learners of two different classes evaluated by the teachers. Curves 1 and 2 represent the marks obtained by the learners taught by teacher T_1 and T_2 respectively. A normal distribution is assumed for the obtained marks, but in actual practice it can have skewness. The normal distribution is defined as the following Eq. (1):

$$f\left(\mathrm{X}\right)=\frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \tag{1}$$

where σ^2 is the variance, μ is the mean and x is any value for which the normal distribution function is required.

It is seen from Fig. 1 that curve-2 represents better results

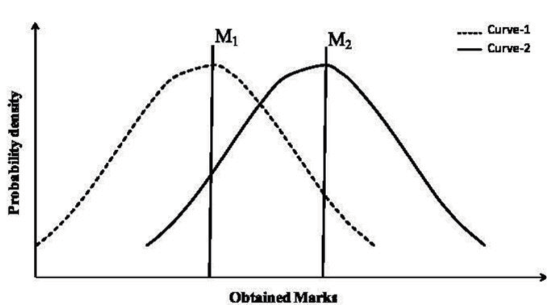

Figure 1. Marks obtained by learners taught by two different teachers[1]

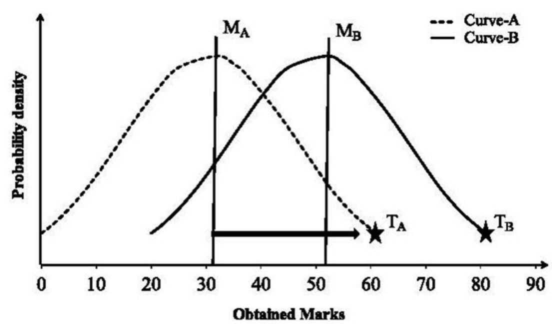

Figure 2. Model for distribution of marks obtained for a group of learners[1]

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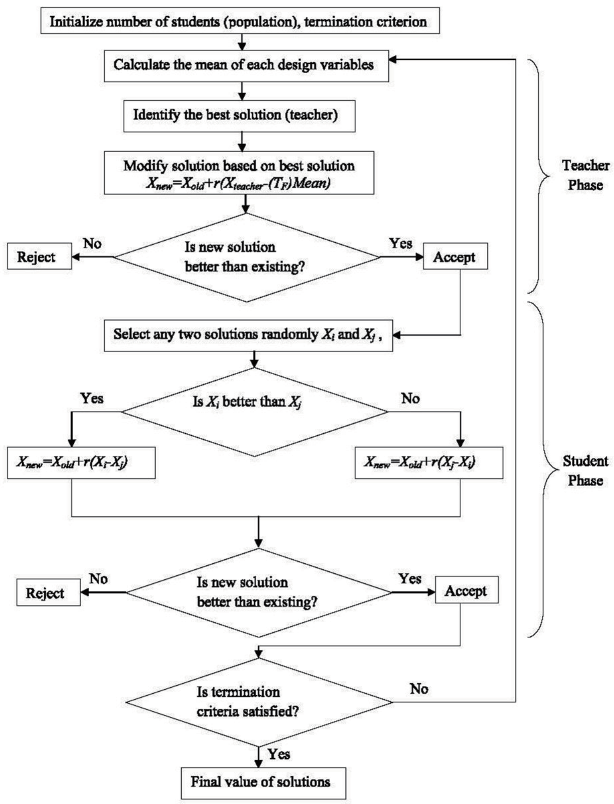

Figure 3. The flowchart of TLBO algorithm[1]

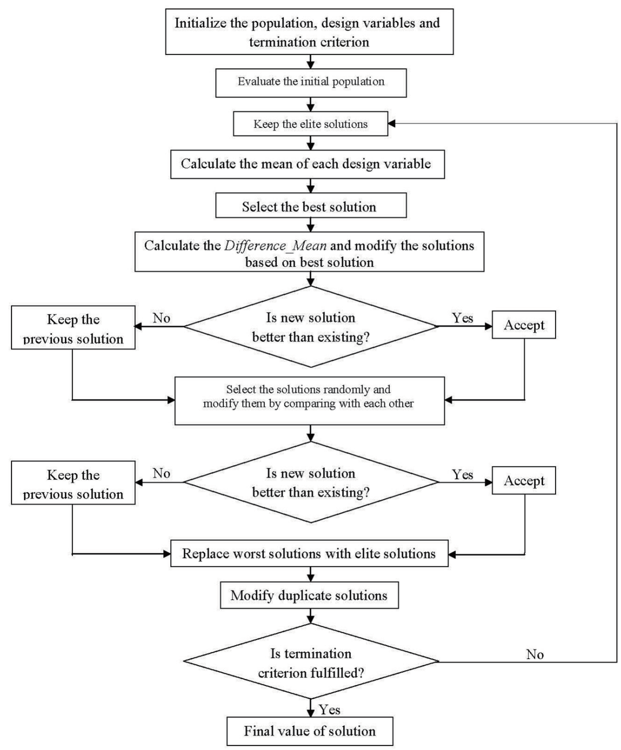

Figure 4. The flowchart of Elitist TLBO algorithm[11]

than curve-1 and so it can be said that teacher T_2 is better than teacher T_1 in terms of teaching. The main difference between both the results is their mean (M_1 for Curve-2 and M_1 for Curve-1), i.e. a good teacher produces a better mean for the results of the learners. Learners also learn from interaction between themselves, which also helps in their results.

Based on the above teaching process, a mathematical model is prepared and implemented for the optimization of a unconstrained non-linear continuous function with TLBO. Fig. 2 shows a model for the marks obtained for learners in a class with curve-A having mean M_A. The teacher is considered as the most knowledgeable person in the society, so the best learner is mimicked as a teacher, which is shown by T_A in Fig. 2. The teacher tries to disseminate knowledge among learners, which will in turn increase the knowledge level of the whole class and help learners to get good marks or grades. So a teacher increases the mean of the class according to his or her capability. In Fig. 2, teacher T_A will try to move mean M_A towards their own level according to his or her capability, thereby increasing the level of learners to a new mean M_B. Teacher T_A will put maximum effort into teaching his or her students, but students will gain knowledge according to the quality of teaching delivered by a teacher and the quality of students present in the class. The quality of the students is judged from the mean value of the population. Teacher T_A puts effort in so as to increase the quality of the students from M_A to M_B, at which stage the students require a new teacher, of superior quality than themselves, i.e., in this case the new teacher is T_B. Hence, there will be a new curve-B with new teacher T_B.

R. V. Rao et al. demonstrated that TLBO can obtain the better optimization performance in many fields, e.g., the constrained mechanical design optimization problems [1], unconstrained and constrained real-parameter optimization problems [4], and continuous non-linear large scale problems [5], in comparison with other optimization algorithms [6-10]. Then, a number of improvements and applications concerning TLBO have been proposed sequentially. In this paper, we want to give a detailed categorization to the current works concerning TLBO from the algebraic and analytic points of view.

II. TLBO Algorithm and Its Improved Version

A. TLBO Algorithm

Fig. 3 give the flowchart of TLBO algorithm [1]. By explaining Fig. 3, we give the implementation of TLBO algorithm for optimization as follows:

1) Define the optimization problem and initialize the optimization parameters: Initialize the population size (P_n), number of generations (G_n), number of design variables (D_n), and limits of design variables (U_L, L_L). Define the optimization problem as:

$$\begin{aligned}&\text{minimize } f(X)\\&\text{Subject to } X_i \in x_i = 1, 2, \cdots, D_n\end{aligned}$$

where $f(X)$ is the objective function, X is a vector for design variables such that $L_L \leq x_i \leq U_L$.

2) Initialize the population: Generate a random population according to the population size and number of design variables. For TLBO, the population size indicates the number of learners and the design variables indicate the subjects (i.e. courses) offered. This population is expressed as follows:

$$\text{population} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1D} \\ x_{21} & x_{22} & \cdots & x_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ x_{P_n,1} & x_{P_n,2} & \cdots & x_{P_n,D} \end{bmatrix}.$$

3) Teacher phase: Calculate the mean of the population column-wise, which will give the mean for the particular subject as $M_{*,D} = [m_1, m_2, \cdots, m_D]$. The best solution will act as a teacher for that iteration $X_{teacher} = X_{f(X)=\min}$. The teacher will try to shift the mean from $M_{*,D}$ towards $X_{*,teacher}$ which will act as a new mean for the iteration. So, $M_{new,D} = X_{teacher,D}$. The difference between two means is expressed as $\text{Difference}_{*,D} = r\left(M_{new,D} - T_F \times M_{*,D}\right)$, where, the value of T_F is selected as 1 or 2. The obtained difference is added to the current solution to update its values using $X_{new,D} = X_{old,D} + \text{Difference}_{*,D}$. Accept X_{new} if it gives better function value.

4) Learner phase: As explained above, learners increase their knowledge with the help of their mutual interaction. The mathematical expression is explained as follows:

$$\begin{cases} X_{new,i} = X_{old,i} + r_i\left(X_i - X_j\right) & \text{if } f\left(X_i\right) < f\left(X_j\right) \\ X_{new,i} = X_{old,i} + r_i\left(X_j - X_i\right) & \text{if } f\left(X_i\right) \geq f\left(X_j\right). \end{cases}$$

5) Termination criterion: Stop if the maximum generation number is achieved; otherwise repeat from Step *Teacher phase*.

B. Elitist TLBO Algorithm

Elitist TLBO algorithm [11] is also proposed by R. V. Rao in 2012. Fig. 4 give the flowchart of Elitist TLBO algorithm [11]. The concept of *elitism* is utilized in the original TLBO algorithm to identify the effect on exploration and exploitation capacity of TLBO algorithm, where during every generation the worst solutions are replaced by the elite solutions. In Elitist TLBO, the duplicate solutions are modified by mutation on randomly selected dimensions of the duplicate solutions before executing the next generation. Moreover, the effect of the common controlling parameters of the algorithm, i.e., population size, number of generations and elite-size on the performance of the algorithm are also investigated by considering different population sizes, number of generations and elite sizes.

C. A Note on TLBO Algorithm

Črepinšek et al. [12] gave an fairly experimentally investigation to the performance of TLBO and their findings have revealed three important mistakes regarding TLBO: 1) at least one unreported but important step; 2) incorrect formulae on a number of fitness function evaluations; and 3) misconceptions about parameter-less control. And, Črepinšek et al. [12] found that unfairly experimental settings and conditions were used to conduct experimental comparisons (e.g., different stopping criteria).

III. Clustering with TLBO

Satapathy and his collaborators in their works [13] and [14] demonstrated that TLBO can be successfully applied to deal with the clustering. They investigated how to use TLBO help k-means clustering [15] and fuzzy c-means clustering [16] to find the better cluster-centers. In [13], The TLBO approach was compared against classical K-means clustering and PSO clustering. From the simulation results it is observed that TLBO may have a slow convergence but it has stable convergence trend much earlier compared to other two algorithms and better clustering results. Then, in [14], TLBO algorithm was used to overcome cluster centers initialization problem in fuzzy c-means clustering, which is very important in data clustering since the incorrect initialization of cluster centers will lead to a faulty clustering process. The experimental results reflected that TLBO algorithm can work globally and locally in the search space to find the appropriate cluster-centers.

IV. Multi-objective Optimization with TLBO

Multi-objective optimization in automatic voltage regulator [17], power flow problem [18], heat exchanger [19], and thermoelectric cooler [20] can also be solved with TLBO. In [17], [18], [19], and [20], the authors gave the comprehensive and systematic discussions regarding how to use TLBO to optimize the practical applications. Niknam et al. in [17] paper proposed a new multi-objective optimization algorithm based on modified teaching-learning-based optimization (MTLBO) algorithm in order to solve the optimal location of automatic voltage regulators (AVRs) in distribution systems at presence of distributed generators (DGs). Nayak et al. in [18] presented a non-domination based sorting multi-objective teaching-learning-based optimization algorithm, for solving the optimal power flow (OPF) problem which is a nonlinear constrained multi-objective optimization problem where the fuel cost, Transmission losses and L-index are to be minimized. Rao et al. in [19] used a modified version of the TLBO algorithm to solve the multi-objective optimization of heat exchangers. Maximization of heat exchanger effectiveness and minimization of total cost of the exchanger are considered as the objective functions. Meanwhile, Rao et al. in [20] also proposed a modified version of the TLBO algorithm which is introduced and applied for the multi-objective optimization of a two stage thermoelectric cooler (TEC). Maximization of cooling capacity and coefficient of performance of the thermoelectric cooler are considered as the objective functions.

V. Parametric and Structural Optimization with TLBO

Rao and Kalyankar in [21] used TLBO algorithm to optimize the process parameters for selected modern machining processes which are nowadays widely used by manufacturing industries in order to produce high quality precise and very complex products. The main feature of modern machining processes is large number of input parameters which may affect the cost and quality of the products are involved.

TABLE I
COMPARATIVE RESULTS OF THE SUCCESS PERCENTAGE AND MEAN NUMBER OF FUNCTION EVALUATIONS[5]

	GA		ANTS		BA		GEM		TLBO	
Funct.	Succ.%	Mean no. of FE	Succ.%	Mean no. of FE	Succ.%	Mean no. of FE	Succ.%	Mean no. of FE	Succ.%	Mean no. of FE
1	100	10160	100	6000	100	868	100	746	100	676
2	100	5662	100	5330	100	999	100	701	100	649
3	100	2488	100	1688	100	526	100	258	100	243
4a	100	10212	100	6842	100	631	100	572	100	541
4b	—	—	100	7505	100	2306	100	2289	100	1082
5	—	—	100	8471	100	28529	100	82188	100	2563
6	100	15468	100	22050	100	7113	100	423	100	308

Selection of optimum machining parameters in such processes is very important to satisfy all the conflicting objectives of the process. Toğan in [22] presented a design procedure employing the TLBO algorithm for discrete optimization of planar steel frames. The total weight of the frame structures subjected to constraints in the form of strength and displacement requirements imposed by the American Institute for Steel Construction Load and Resistance Factor Design is considered as the objective function.

VI. A SIMPLE EXPERIMENTAL COMPARISON

In this section, a simple discussion about the experimental comparison for genetic algorithm (GA), ant colony system (ANTS), bee algorithm (BA), grenade explosion method (GEM) and TLBO is given. The experimental comparison is conducted based on 5 benchmark evaluation functions as employed in [5]. TABLE I summarizes the comparative results of the success percentage and mean number of function evaluations for GA, ANTS, Bee Colony, GEM and TLBO. From TABLE I, it can be seen that for all the considered benchmark functions, TLBO requires less number of mean function evaluations with very high consistency of 100% success. This experiment shows that TLBO is effective in terms of the computational effort and the consistency. Due to the better performance of TLBO on dealing with the problems with high dimensions, this method will be used for the engineering design applications.

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