International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A Review of an Optimization Technique: Teaching Learning Based Optimization

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ABSTRACT

Swarm intelligence (SI) is a natural phenomena that has now been replicated in artificial systems. When considering an ant colony, each individual ant has extremely little intelligence, such as travelling along a path with more pheromones, but the colony as a whole displays a sophisticated way of finding food or dealing with disasters. A decentralized or self-organized system's collective behavior is defined as swarm intelligence. These systems are made up of a large number of low-intelligence individuals who communicate with one another using simple rules. Although the individual is not very intelligent, and there is no central leader dictating how individuals behave, the entire system can only acquire holistic intelligence through the interaction of individuals. In general, no one has an overarching cognition; instead, they simply carry out their daily activities. The teaching-learning-based optimization (TLBO) algorithm is a population-based metaheuristic search algorithm that is inspired by the classroom teaching and learning process. In recent years, it has been successfully used to a variety of scientific and engineering applications. All learners have the same chance of receiving knowledge from others in the basic TLBO and most of its modifications. In the actual world, however, learners differ, and each learner's learning zeal differs, resulting in varying probabilities of information acquisition.

Index Terms—Swarm Intelligence, Particle Swarm Optimization, Teaching and learning Algorithm

INTRODUCTION

T LBO is a population-based MS algorithm that simulates a regular class's teaching and learning process. The population of solutions in the TLBO is a group of learners, and the fitness of the solutions is measured in outcomes or grades. The algorithm learns from the teacher and from the interaction between students to adaptively update each learner's grade in the class. The TLBO method is divided into two parts: the instructor phase and the learner phase. There are two types of stategies for locating the optimum in the optimization sector. The first refers to local search strategies that make use of domain searches. This type of optimization technique tends to generate a new point that is close to the current point. The second is about global approaches, which are based on domain search exploration. The TLBO algorithm was inspired by the Leaching-Learning process and was proposed by Rao et al. and Rao and Patel based on the effect of a teacher's influence on the output of learners in a class[1]. The algorithm replicates two basic types of learning: I learning from a teacher and (ii) learning from other students. TLBO is a population-based method in which a population of students (i.e. learners) is considered, and the many subjects available to the students are equivalent to the various design variables of the optimization problem. A learner's grades in each course are a potential answer to the optimization problem (value of design variables). The instructor is thought to be the finest answer for the entire population. Since its introduction in 2011, the TLBO algorithm has gotten a lot of attention. Researchers have developed numerous variations to increase the performance of the TLBO algorithm. Algorithm performance enhancement and algorithm application are the two primary categories that these versions fall into. However, one of the disadvantages of the TLBO and its derivatives is that they are prone to premature convergence, especially when dealing with nonlinear problems that require more local optimal solutions.

Literature Survey

In [2], teaching learning based optimization (TLBO) was used to solve a multi-objective optimization problem, while in [13], it was utilized to solve a constraint optimization issue. In various sectors, it has been discovered that TLBO performs better while addressing optimization problems. To estimate the cumulative number of failures, [4] introduced ANN based exponential encoding (NNEE) and ANN based logarithmic encoding (NNLE) models. The back propagation approach is used to train the network in all ANN-based models [4]. The ANN was trained using PSO, and the prediction accuracy was better than the ANN built using the back propagation approach. In this study, TLBO was used to train an artificial neural network (ANN) to forecast the cumulative number of software failures and to assess software reliability in terms of failures.

The facial emotion recognition survey can be found in [5], and the research implies that emotion recognition from humanoid face photos can be applied in emotional computing. The authors of [5] disassembled pipelines into primary components to look at advanced resolutions such face registration, dimensionality devaluation, visualization, and identification. The Active Appearance Model (AAM) was chosen as the appropriate method for FER in [6]. The AAM is a useful statistical structure for validating and classifying deformable compounds. To get the best FER results, the IEBM (Iterative Error Bound Minimization) methodology was utilized, which consistently produces precise FER and excellent face arrangement even when the first face finding used to create the required method was insufficient. The authors predicted an automated approach to analyze subtle fluctuations in FE in [7], which focused on mutually temporary (e.g., wrinkles and furrows) and enduring (e.g., eye and brow, mouth) facial characteristics in a closely forward image sequence (facial emotion). In [8, the authors proposed that square-centered Gabor structures in positions of digging out local systems had a higher enactment than point-centered Gabor structures. The authors cite a timeline outlook of the advancements prepared in FER, the attributes of an excellent scheme, the utilizations of instinctive FE recognizers, the datasets used, and the advances developed in positions of their calibration, as well as a comprehensive outline of the current state of the art in [9].

ANN (Artificial Neural Networks) were developed to identify grouping and recognizing duties in a wide range of situations. Deep Convolutional Neural Networks (DCNN), Linear Regression Classification [10], and other taxonomy approaches are employed to complete the FER. For emotion recognition, an adjustment on a compacted part of 117 milestones is used in [11]. In [12], a portrait is expected to follow a collection of facts in order to identify feelings as sequences. [13] presents a survey that stresses the seamless blend of in-depth learning portraits. A feeling perception portrait is suggested in [14] based on minimum–maximum likeness, which reduces interclass pixel mismatching challenges during categorization. FER's simple technique is offered by combining CNN (Convolutional Neural Network) and a few picture preparation tools. For facial expressions, [15] considers two prototypes: feature level combination and fuse decision level. By employing some pre-processing picture processes from a facial appearance and recognizing the FE, the authors were able to extract just seem definite structures; a convolutional network was utilized by using specific appearance attributes. On the CK+ dataset, they achieve a recognition accuracy of 90.9 percent. The authors of [16] proposed DeXpression, a Convolutional Neural Network-based facial emotion recognition algorithm that includes two FeatEx (Parallel Feature Extraction) blocks. The authors of [17] proposed a zero-bias Convolutional Neural Network that ignored the partialities of the convolutional layers; this zero-bias Convolutional Neural Network was skilled on FE data and achieved decent enactment on two emotion identification criteria.

Table 1: Contribution of Researchers

S.No.	Author	Contribution
1	Rao et al.	Introduction of the TLBO to solve the constrained mechanical design problems
2	Črepinšek et al.	A note on the TLBO
3	Rao and Patel	Introduction of Elitist TLBO for solving complex constrained optimization problems
4	Rao and Patel	Introduction of Improved TLBO for solving unconstrained optimization problems
5	Roy, Provas Kumar	TLBO for short-term hydrothermal scheduling problem
6	Niknam et al.	Introduction of modified TLBO for reserve constrained dynamic economic dispatch
7	Satapathy et al.	Introduction of Orthogonal TLBO based on orthogonal design
8	Baykasoğlu et al.	Testing of TLBO on combinatorial optimization problems: Flow Shop and Job Shop scheduling problems
9	Chen et al	Introduction of improved TLBO to solve global optimization problems
10	Umbarkar et al	Solving 0/1 Knapsack Problem Using Hybrid TLBO-GA Algorithm
11	Zou et al.	TLBO with learning experience of other learners and its application
12	Derakhshan et al.	The optimization of demand response programs in smart grids with TLBO
13	Chen et al.	TLBO with variable-population scheme and its application for ANN and global optimization
14	Rao, R. Venketa	Covering of all the aspects of the TLBO algorithm in detail in the form of a book
15	Rao, R. Venkata	Review of the TLBO and its application

Application of TLBO

The biggest advantage of TLBO is that it is simple and easy to implement, requires very few parameters to be tuned, and has a higher computational efficiency than traditional methods. it has been widely used in neural network design, function optimization, mechanical design optimization, power system reactive power optimization, economic dispatching problems, constant heat exchanger optimization, and travel route optimization. it has been widely used in neural network design, function optimization, mechanical setup optimization, power system reactive optimization, economic scheduling problem, fixed heat exchanger optimization, travel route optimization, etc. For example, To et al. used TLBo algorithm to optimize the design of planar steel frame[18], Rao R V et al. used TLBo algorithm to optimize constrained and unconstrained functions [18], Tuo Shouheng et al. used TLBO algorithm to optimize weights and thresholds in neural network [19], Basu et al. used TLBO algorithm to solve multiregion economic scheduling problem. Hua Jie et al. used the ITLBO algorithm to optimize the structure of biogas liquefaction heat exchanger[20]. He Hong et al. used an improved ITLBO algorithm to optimize tourist routes[20].Lata P et al. used TLBO to optimize the location and size of energy storage system to improve the reliability of radial power distribution system.Le, P.-N et al. used TLBO to improve the model recognition of robots and the calibration accuracy of neural network operators.Ummidivarapu TLBO was used to optimize the geometry of the sound horn and other shapes[21].

Conclusion

Though there have been many advancements made to the existing TLBO algorithm, all have been successfully implemented for an application of particular field, still the scope of TLBO hasn't reached its saturation even after 10 years of its existence, TLBO algorithm can be implemented in various fields, which are currently in news such as blockchain hash generation, cloud computing, data storage, and many more such industrial applications.

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