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A Survey of Application and Classification on Teaching-Learning-Based Optimization Algorithm

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ABSTRACT Teaching-Learning-based Optimization is an optimization technique which does not require any algorithm-specific parameters and is popular for its less computational cost and high consistency. Therefore, it has achieved great success application by the researchers in various disciplines of engineering. It works on the philosophy of teaching and learning which is used to solve multi-dimensional, linear and nonlinear problems with appreciable efficiency. Recently the basic TLBO algorithm is improved to enhance its exploration and exploitation capacities and the performance. However, there is less surveys on TLBO algorithm recent advances and its application. In this paper, the successful researches of TLBO algorithm of the past decade are surveyed. Firstly, the available intelligent optimization algorithms were reviewed. Then the application fields of TLBO and the improved TLBO were discussed and analyzed. Furthermore, some representative TLBO methods were classified into three main groups: 1) Improvement of teaching process; and 2) Fusion with Other Optimization Methods; and 3) Weight Methods and Others. Finally, our viewpoints were shared on the open issues and challenges in TLBO as well as research trends in the future.

INDEX TERMS TLBO algorithm, optimization, global optimization, swarm intelligent optimization.

I. INTRODUCTION

From a mathematical point of view, optimization theory is to study how to find the optimum in the state space. Generally, the optimization theory is divided into two categories: local optimization and global optimization (as shown in Figure 1). The local optimization algorithm is mainly used to solve convex or single-peak problems. The basic idea is to accept only better state and reject deteriorating state in the process of state transition, such as stochastic gradient descent(SGD), sequence alignment(SA) method, newton method, conjugate gradient method, Lagrange method, mountain climbing method, and so on. 2). Global optimization algorithm involves the concepts of biological evolution, artificial intelligence, mathematical and physical sciences, nervous system and statistical mechanics, so it is called heuristic optimization algorithm too. It is mainly used to solve non-convex or multi-modal problems. The basic idea is to use intuition or experience to select effective methods, instead of seeking answers in a systematic and definite way. Local optimization algorithm cannot be used to solve multi-modal problem because it is easy to fall into local optimal solution, while heuristic optimization algorithm can avoid falling into local optimal solution prematurely and search global optimal solution by using experience. Heuristic optimization is widely used in physics, chemistry, computer, engineering and other fields, because it can find the optimal solution in the global scope and solve Np-Hard problems. Heuristic optimization algorithms generally include evolutionary algorithms (EA), swarm intelligence (SI) algorithms, and other algorithm based on natural phenomena.

Evolutionary Algorithms are random search algorithms that draw on biological natural selection and natural heritage mechanism, which include differential algorithm (DA), genetic algorithm (GA), artificial immune algorithm (AIA), Evolutionary Planning (EP) algorithm,

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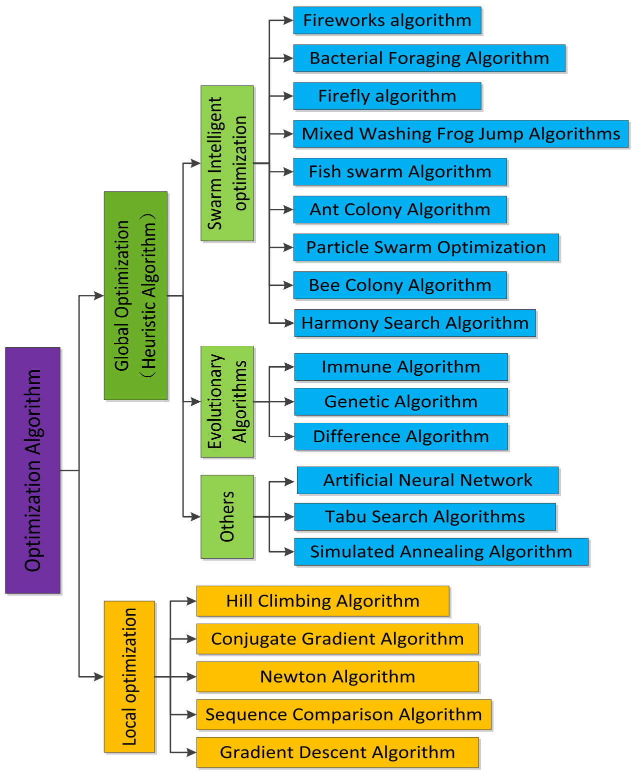

FIGURE 1. **Optimal algorithm and classification.**

Evolutionary Strategy (ES) algorithm. Evolutionary Algorithm is a robust method that can adapt to different environments and problems. In most cases it can obtain satisfactory and effective solutions. Swarm Intelligent optimization algorithms mainly simulate swarm behavior of insects, herds, birds and fishes. These swarms search for food in a cooperative way, and each member of the swarm constantly keeps changing the search pattern according to the learning the experience of its own and other members. Swarm Intelligent optimization algorithms include genetic algorithm(GA), particle swarm optimization(PSO) algorithm, ant colony optimization(ACO) algorithm, artificial bee colony (ABC) algorithm, artificial fish swarm algorithm (AFSA), mixed frog leaping algorithm (SFLA), fireworks algorithm (FWA), bacterial foraging optimization (BFO) algorithm, firefly algorithm (FA), etc. The prominent feature of swarm intelligence optimization algorithm is searching cooperatively and intelligence, so as to find the optimal solution in the solution space. There are some other optimization algorithms which simulate different natural processes, such as simulated annealing (SA) algorithm, which is based on the similarity between the annealing process of solid materials and the combinatorial optimization problem. Tabu search (TS) algorithm is to find a part of the local optimal solution, consciously avoid it (but not completely isolated), thereby obtain more search intervals. Harmony Search (HS) simulates the principle of music playing. Artificial Neural Network (ANN) is simulation of human brain thinking. All these heuristic algorithms are based on the random feasible initial solution, and use the strategy of iterative improvement to approximate the optimal solution to the problem. In addition to the common parameters such as population size, genetic algebra, each heuristic algorithm has its own specific parameters. These parameters play an important role in the algorithm, and their setting directly affects the efficiency of the algorithm.

Rao *et al.* [1], [2] proposed the teaching-learning-based optimization (TLBO) algorithm which is one of the modern heuristic optimization algorithms. Its principle is to simulate the processes of teacher's teaching to students and student's learning in traditional classroom teaching. According to this algorithm, students obtain knowledge not only from the lecture delivered by a teacher but also from their mutual interaction. Comparing to other heuristic algorithms, the TLBO algorithm is simple, easy to be described and implemented. Moreover, the TLBO algorithm has less parameters and high accuracy, good convergence performance and good robustness on optimization problems. Therefore it had attracted great attention from experts and scholars in the past few years. The TLBO algorithm has not only been greatly improved, but also been widely used. Rao [3], and Kumar and Gayathri [4] had given a review of TLBO algorithm, where they focus on the applications for the unconstrained and constrained problem, pay little attention to the algorithm improved and important works proposed in recently years. Since there are still many technical challenges on TLBO optimization method, various ideas and techniques have been provided to solve the optimization problem in recent years. The paper focuses on summarizing these latest works in improvement and application of TLBO optimization method, the concerns of which are different from previous related reviews. The major contributions to this paper are briefly summarized as follows:

- The paper aims to provide a survey on recent progress and application in TLBO algorithm. It does rarely find in previous work, which is beneficial to the beginners to get familiar with TLBO algorithm.
- The paper gives taxonomy of TLBO algorithm. The improvement on different TLBO algorithm is expounded, which are helpful for readers to understand and apply the TLBO algorithm.
- The paper describes the application fields, solutions to TLBO and some meaningful findings. All of these are helpful for understanding the TLBO algorithms, and are expected to benefit both practical applications and future research.

The rest of this paper is organized as follows: Firstly, an overview of basic TLBO algorithm is given in Section 2. Then, the application of teaching and learning optimization algorithm in recent years is listed in Section 3. Next, in Sections 4, the existing TLBO algorithms are classified and the application examples of them are illustrated in detail. Discussion and prospects of the future trends for TLBO algorithm are made in Section 5. Finally, the conclusion is summarized in Section 6.

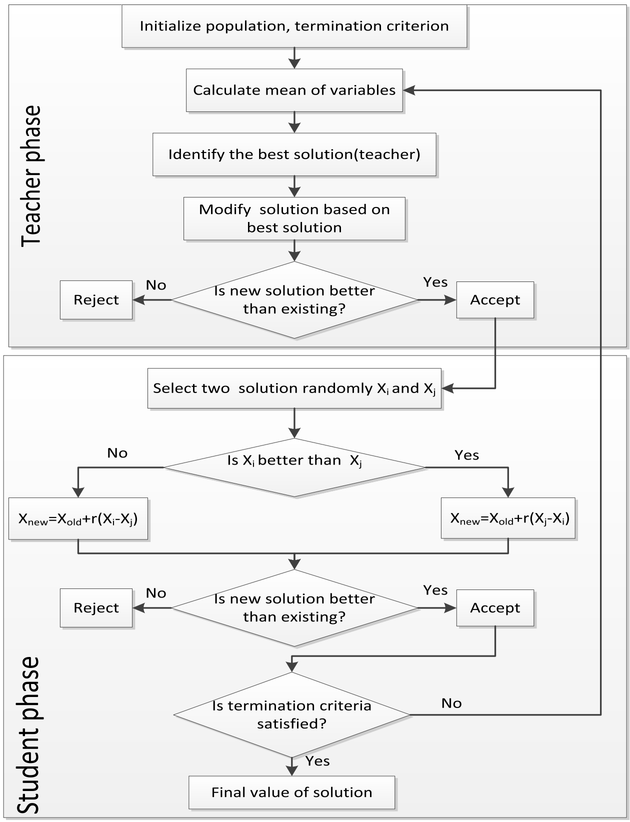

FIGURE 2. Flow chart for TLBO.

II. THE BASIC TLBO

The basic TLBO algorithm procedure inspired by the traditional teaching process, generally it is divided into two fundamental parts. One part is teacher phase and the other part is learner phase. In the teacher phase, students are considered as the population, the different subjects are regarded as the different design variable parameters of the optimization problem, and the mean value of subject are considered as the fitness of optimization problem. Teacher tries to upgrade the mean value of class in the subject taught by him/her to his/her level. In the learner phase, students increase their knowledge level by interaction themselves. A student can increase his knowledge by learning randomly with other students. If a student has a higher level of knowledge than other students, other students can acquire new knowledge from him to increase their own level of knowledge. Figure 2 presents flow chart of the basic TLBO algorithm. Firstly, students increase their knowledge levels by their teacher in teacher phase. And then, students improve their knowledge level by mutual learning in learner phase. If the variable does not meet the requirements of the termination criteria, then return to the teacher phase to start learning again.

III. SURVEY OF APPLICATION OF TLBO ALGORITHMS

TLBO algorithm is a relative new metaheuristic optimization tool, and the report of its application appears in more application fields. In the section, some new literatures are listed to show their application and development in TLBO algorithm.

As show in table 1, the application field and correlation algorithm are described through three columns. In the first column, there is the area of application of related TLBO algorithm; the second column described the typical application-related method; the last column showed the origin of the algorithms, i.e. relevant references. As the table 1 shown, there are over 100 TLBO algorithms and their modified versions which have been extended to function optimization problems, engineering optimization, multi-objective optimization, parameters identification, clustering, and other fields.

As the table 1 shown, TLBO algorithm and its modified versions are applied in various fields. In power system, the basic TLBO or modified TLBO combined with the characteristics of power system to deal with various optimization problems of power system. In medical field, the TLBO algorithm is applied to adjuvant therapy, detection and prediction of various parts of human body. With the development of information technology, more and more TLBO algorithm and its variants are used in network, power flow, image processing, data mining, mobile robot navigation, etc. Thus it can be seen that, TLBO algorithm has become popular in many fields and solved many optimization problems.

IV. CLASSIFICATION OF TLBO IMPROVED ALGORITHMS

In the traditional teaching procedure, the teaching and learning process follows the general teaching activities, where learners learn from their teacher to improve his/her knowledge in class. After class, one leaner learn from the other leaner. According to the phenomenon, the basic TLBO algorithm simulates the process: learning from teacher, learning from other learner, i.e. teacher phase and learner phase. In order to improve the performance of the basic TLBO algorithm, there are more and more improved methods which are mainly modified in the following three aspects.

- Improvement in Teaching Process. Fig. 2 presents the flow of basic TLBO algorithm. Where, all students (leaners) learned from teacher or other student. But now with the advancement of information technology, students can learn by themselves through internet, mobile phone, or other electronic devices. With the advancement of teaching reform, the learning styles are changing, and the students can learn by grouping and cooperation. MOOC and flip teaching are also popular with teaching. All of these have led to great changes in students' learning process. So, reforming the teaching process of basic TLBO algorithm became the fashionable improvement measure.
- Fusion with Other Optimization Methods. Fig.1 shows many existing optimization methods, as useful optimization tools their optimization capabilities may be strong in some areas and weak in others. In the process of research and application, these algorithms are fused to enhance or compensate each other for better robustness. For these, a lot of work had been done to modify the basic TLBO algorithm through hybrid optimization to enhance or improve its performance.

TABLE 1. Application of TLBO.

Area of Application	Typical algorithm	Refere -nce
AHP	Modality of TLBO is used to get the optimal judgment values of comparison matrix and to get the minimum consistency ratio (CR)	[5]
	TLBO is used to AHP	[6]
Flood Disaster	Enhance TLBO with elitism and chaotic behavior.	[7]
Human Genome	CPGTLBO: The clustering approach is used to detect CpG island candidates. TLBO was used to accurately predict CpG islands among promising CpG island candidates.	[8]
Distributed Generation	Discrete TLBO(DTLBO) is used to distributed generation.	[9]
Shop Scheduling	HDTPL, HDTLM: hybrid discrete teaching-learning is used.	[10, 11]
	TTLB include teachers'self-learning, interactive learning and teaching, and neglect learners' interactive learning, TTLB is used to solve shop scheduling problem.	[12]
	TLBO is used to solve flexible job shop scheduling problem	[13]
	A hybrid meta-heuristic based on probabilistic teaching-learning mechanism (mPTLM) is used to solve no-wait flow shop scheduling problem	[14]
	TLBO and JAYA algorithms are used to solve flexible flow shop problem (FFSP)	[15]
	Two-stage TLBO(2S-TLBO) is used to solve flexible job-shop scheduling problem	[16]
Multi-objective optimal	MO-ITLBO is used to solve muti- objective optimization.	[17]
	Proposed a novel hybrid TLBO and PSO with circular crowded sorting (CCS) to solve muti-objective optimization.	[18, 19]
	A modified TLBO is used to solve the multi-objective optimal power flow problem.	[20]
	Multi-objective TLBO(MOTLBO) is proposed, where it adopts the concept of non-dominant sorting and the computer mechanism of congestion distance.	[21]
Energy Demand Estimation	Standard GSA searches the optimum points in the global space and the standard TLBO finds the best solution in the local space.	[22]
Power System	A new phase named ‘‘chaotic phase’’ is added in TLBO to solve power system stabilizers design problem	[23]
	TLBO is used to solve the fault location problem in power system	[24]
	TLBO based proportional–integral (PI) controllers are used to the wind turbine system.	[25]
	Smart line search and TLBO(SLS-TLBO) is used to optimize the power system stabilizer.	[26]
	TLBO and 2-DOF PID controller are used for automatic Generation Control	[27]
	The hybrid differential evolution(DE) and TLBO (DE–TLBO) is used to optimize optimal H_∞ and PID.	[28]
	Two binary TLBO methods is used to solve the unit commitment problem	[29]
	TLBO based PIDD controller is used for AGC of power system.	[30]
	Clustered adaptive TLBO (CATLBO) is used to solve the non-smooth and non-convex generator fuel cost characteristics	[31]
	TLBO is used in economical operation of a power system for accurate estimation of	[32]

TABLE 1. ***(Continued.)*** **Application of TLBO.**

	coefficients of fuel cost function in thermal power plants.	
	TLBO is used to adjust the controller’s parameters and possible signal delay of a double stage conventional damping controller for Contribution of Tidal Power Generation System	[33]
	MTLBO is used to optimize DG scheduling, capacitor sizing, and reconfiguration	[34]
	Bit shift operator based TLBO(BSTLBO)is used to reconfigure distribution system and find the optimal placement and sizing	[35]
	TLBO -based global MPPT is used to track global MPP of PVPS under PSC	[36]
	Clustered adaptive teaching learning based optimization (CATLBO) is proposed to optimal energy and spinning reserve (SR) scheduling	[37]
	TLBO is used for reactive power planning	[38]
	TLBO is used to solve economic emission load dispatch problems	[39]
Structural Problems	Modifications of TLBO are used to solve structural problems, where the three modify are: status monitor, FATLS and remedial operator.	[40]
0-1 Knapsack Problem	HSTL (harmony search algorithm based on teaching-learning) is used to solve 0-1 knapsack problems	[41]
Commodity Futures Index Forecasting	The SVM–TLBO hybrid regression model is used to forecasting.	[42]
	DR-SVM-TLBO: combining SVM–TLBO with dimensional reduction (DR) techniques is used.	[43]
Symmetric Key Cryptosystems	Using TLBO to build strong S-Box meeting preset standards in symmetric key cryptosystems.	[44]
Complex Genetic Diseases	TLBO-based Mutagenic Primer Design (TLBOMPD) is used for mismatch polymerase chain reaction（PCR）primer design.	[45]
Functional Link ANN (FLANN)	By using the learning ability of TLBO and GDL, the optimal weight set of FLANN model is obtained.	[46]
Path Generation	Adapting self-adaptive population based TLBO (SAP-TLBO) to find the optimum parameters of a four-bar linkage.	[47, 48]
	TLBO and other optimization algorithm are used in path generation, and compared.	[49, 50]
Economic Load Dispatch	Improved Teaching-learning-based Optimization Algorithm is proposed to solve economic load dispatch problems.	[51]
Assembly Sequence	TLBO is used to solve assembly sequence problem.	[52]
Two-sided Assembly Line	Hybrid teaching-learning based optimization (HTLBO) is used to solve the stochastic two-sided assembly line balancing problem.	[53]
	Decoding Algorithm with TLBO is used to solve the two-sided assembly line balancing problem (TALBP).	[54]
	Improved TLBO is used to obtain the Pareto-optimal set in multi-objective two-sided assembly line.	[55]
ANN	Neighborhood search with TLBO(NSTLBO) is applied to ANN.	[56]
	Elitist teaching learning based optimization (ETLBO) is used to optimization of the process variables in ANN prediction.	[57]
	VTTLBO is proposed to optimize the parameters of ANN.	[58]

TABLE 1. *(Continued.)* **Application of TLBO.**

Electrical Discharge Machining	Two-stage ((SVM-TLBO)-(PLM-TLBO pseudo PARETO)) optimization is used in Electrical Discharge Machining (EDM).	[59]
Super Scattering Plasmonic Nanodisk	Binary TLBO algorithm is proposed to design an array of plasmonic nanodisks in order to achieve maximum scattering coefficient spectrum.	[60]
Neural Network Training	Compact Real-valued TLBO(cTLBO) is reduce the algorithm memory size requirement of neural network training.	[61]
	Modified TLBO is used to optimum structure of neural network in data mining.	[62]
Resource Allocation	ETLBO is used to solve the two dimensional discrete combinatorial optimization problems.	[63]
Engineering Problems	A hybridization of TLBO and BA (TLBBO) is used to solve the problem of structural geometry and size optimization.	[64]
Structural Health Monitoring	TLBO hybridized with AIS is used to damage detection.	[65]
Synthesizing the Crank-rocker Mechanism	TLBO is used to solve nonlinear optimization problem about design of artificial human knee joint.	[66]
Solar Air Heater	TLBO and ETLBO are used in design optimization of a smooth flat plate solar air heater.	[67]
Robot Manipulator	TLBO and ETLBO are used in design optimization of robot manipulator.	[68]
Primer Design	TLBO with elite strategy is used in natural PCR-RFLP primer design.	[69]
Wireless Sensor Networks	TLBOR is used to solve discrete problem of WSN routing.	[70]
	Modified Distance Vector Hop algorithm using TLBO (MDV-TLBO) is used in WSN.	[71]
	The IDV-Hop using TLBO technique is used to minimize the localization error.	[72]
Image Processing	TLBO is used to segment and analysis brain tumor by brain MR images.	[73]
Hydro-thermal System	Hybrid Differential Evolution (DE) with TLBO algorithm is proposed to solve the multi-objective short-term optimal hydro-thermal scheduling.	[74]
Visual Tracking	Hybrid sine–cosine algorithm (SCA) with TLBO is proposed to solve visual target tracking problem.	[75]
Cloud Manufacturing	Hybrid HTLBO is used for optimal service composition.	[76]
Distribution Systems	TLBO is used for optimizing inspection and repair of distribution systems.	[77]
Welding Process	TLBO is used for welding parameters optimization.	[78]
FIR Hilbert Transformer	TLBO is used for minimax design of linear phase FIR digital Hilbert transformers.	[79]
Truss Structures	Modified sub-population TLBO is proposed for the shape and size optimization of trusses with multiple natural frequency constraints.	[80]
	School-based optimization (SBO) is used to solve the shape and size optimization problem.	[81]
	TLBO is proposed for the truss topology optimization.	[82]
	Modified subpopulation TLBO is proposed for the truss topology optimization.	[83]

TABLE 1. *(Continued.)* **Application of TLBO.**

Power Flow	TLBO is used to solve multi-objective power flow problem.	[84]
Community detection	Discrete variant of TLBO (DTLBO) is used to community detection problem.	[85]
Heat Exchanger	Modified TLBO is used in heat exchangers.	[86]
Thermo-acoustic Devices	TLBO is used in thermo-acoustic devices.	[87]
Power Dispatch	Quasi-opposition based learning (QOBL) is introduced into TLBO algorithm.	[88]
	TLBO is used in power dispatch based on FACTS device "STATCOM".	[89]
Multi-pass Turning	TLBO is used in multi-pass turning.	[90]
Multiuser Detection (MUD)	TLBO-TSI(two-stage initialization) is used to minimize a penalty function.	[91]
Electric Energy Demand	The ANN with TLBO is used in electric energy demand.	[92]
Energy Commodity Futures Index	DR- SVM-TLBO is use to optimize forecast to supports improved investment decisions.	[93]
Automatic Heliostat Aiming	A preliminary parallel version of TLBO is used to search-space large exploration.	[94]
LC Filter	TLBO is used to optimize design of LC filter.	[95]
Congestion Management	In the ITLBO, the learning phase is divided into: Learning from fellow mates and Self-learning mechanism.	[96]
Power Generation	TLBO is used to solve congestion management problem.	[97]
Fuel Cell	TLBO and DE is used to estimate unknown Simulation proton exchange membrane fuel cell model parameters.	[98]
Satellite Image Compress	TLBO is proposed to compress satellite image.	[99]
Power Distribution	A bit-relocate-based TLBO is used in static primary power distribution.	[100]
Trajectory Optimization	Combined TLBO with variable neighborhood search (VNS) is used to optimal trajectory planning for robotic manipulators.	[101]
	A hybrid modified teaching-learning-based particle swarm (HMTL-PSO) is proposed to solve trajectory optimization.	[102]
Carbon Fiber Reinforced Polymer (CFRP)	HS and TLBO is used to optimize fitness function developed by MPCI nonlinear regression model.	[103]
	TLBO is used to assess optimal machining environment.	[104]
Computer Numerically Controlled (CNC) Turning	TLBO is used to optimize surface roughness in CNC turning of aluminum alloy.	[105]
Configuration for Cyber-network	Graph Theory (GT)Structure and TLBO are used in optimizing configuration of cyber network.	[106]
Suspension System	Heat transfer search (HTS) and TLBO are used to minimize the vertical acceleration of sprung mass.	[107]
Shunt Faults in Power System	MATLBO is used to optimize relay coordination problem.	[108]
Modern Machining Processes	TLBO is applied for the process parameter optimization of selected modern machining processes.	[109]

TABLE 1. *(Continued.)* **Application of TLBO.**

Power Management	TLBO is applied to power management in a microgrid.	[110]
Component-based Software Systems	ANN-based TLBO is used to predict the quality of the software components.	[111]
CAD models	Sampling-TLBO (S-TLBO) is proposed for the automatic search and generation.	[112]
Random Forest	TCTLBO is used for the signal sorting model based on weighted random forest.	[113]
Heating, Ventilating, and Air conditioning (HVAC)	The improved TLBO to solve optimal chiller loading(OCL)problems.	[114]
Kerf Deviations	TLBO is applied to optimize various cutting parameters.	[115]
MRI Images	TLBO based FLANN adaptive filter is used to suppress noise.	[116]
RCPSP	TLBO is applied for multiskill resource constrained project scheduling problem (MS-RCPSP).	[117]
Hybrid System	TLBO is used to solve minimum cost with maximization of EC and HDI.	[118]
Mobile Robot Navigation	TLBO-based ANFIS is proposed to solve navigational problem.	[119]
Power Flow	TLBO is used to solve optimizing power flow problem.	[120]
FACTS	Multi-Objective Modified TLBO(MOMTLA)is presented to coordinate the FACTS controller parameters.	[121]
image processing	TLBO algorithm was modified and used in image processing image enhancement.	[122]
Dental Age	Fuzzy Neural Network - Based TLBO(FNN-TLBO) is proposed to estimate dental age.	[123]
Photovoltaic System	An ITLBO is proposed for maximum power point trackers.	[124]
Gene Expression Profiles	A Selective Ensemble Method Based on TLBO is proposed to optimize dimensions and noise of Gene Expression Profiles.	[125]
Radial Distribution Systems	TLBO is used in optimal allocation of Distributed Generations.	[126]
Budget Allocation of Government	OFS–TLBO–SVR hybrid model is proposed to optimal budget allocation.	[127]
Structural Design	Observer-TLBO is proposed to optimize structural design.	[128]
Profit Based Unit Commitment(PBUC)	Improved-TLBO is applied PBUC problem.	[129]
Data Mining	Modified TLBO is used in data clustering.	[130]
Polypropylene Composites	TLBO is explored and used in optimize performance measures associated with polypropylene composites.	[131]
Pairwise Testing	Fuzzy Adaptive TLBO is present and used in pairwise testing.	[132]
Fused Deposition Modeling	Non-dominated Sorting TLBO (NSTLBO) is proposed to solve optimization of the FDM process.	[133]
Mechanical Design	TLBO based on Hadoop is used in distributed computing.	[134]
Data Classification	ETLBO is combined with Jordan Pi-sigma neural network (ETLBO- JPSNN) for real-world data classification.	[135]
IIR Filter	Multi-objective TLBO is used to the design IIR digital filters.	[136]

TABLE 2. **Classify of TLBO.**

Category	Typical algorithm
Improvement of Teaching Process	[2],[136],[137],[138],[139],[128],[140],[141], [142], [143], [144], [145],[146],[147]
Fusion of Multiple Optimization Methods	[148],[149],[150],[151],[152],[153],[154],[155],[156],[157],[158]
Weight Method and Others	[159],[160],[161],[162],[163],[164],[165]

•Weight Methods and Others. In addition to the above two categories, in the updating process of teacher and learner phase, weight or factor are introduced to increase optimizing ability and improving convergence. There are some other improved TLBO algorithms which introduced new framework.

On the basis of discussion above, typical algorithms of the TLBO in terms of different categories are summarized in Table 2.

A. IMPROVEMENT IN TEACHING PROCESS

The basic TLBO algorithm consists of two parts: teacher phase and learner phase. In teacher phase, students learn from teachers. In learner phase, students gain knowledge from their classmates. However, in reality, student can learn by themselves online, on mobile phones, or other device. The teaching method also tends to be self-regulated learning and teacher-assisted flip-flop teaching, group learning. Based on the above teaching reform, experts and scholars have improved the basic TLBO method.

In [136] the collaborative learning model(CLM) is proposed. Where it modified the learner phase of basic TLBO and increased the self-study phase, to enhance the local and global search ability. Collaboration learning and competition learning are introduced in learner phase. P_L denotes a predefined probability which decides to adopt collaboration learning or competition learning. In equations (1) $L^1_{i,new}$ is the ith learner randomly in competitive learning, in which the learner learns from the better one between two individuals. $L^2_{i,new}$ is the ith learner randomly in collaboration learning, in which differences between two individuals are considered. The class is considered as a whole, learning level is increasing.

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

In self-studying phase, in order to increase the local searching ability effectively, the neighborhood area is used to update the position of teacher, as shown in equation (2).

$$T_{new,j}(i) = \begin{cases} T_{old,j}(i) + r \cdot TR, & if\ rand \leq P_{SL} \\ T_{old,j}(i), & otherwise \end{cases} \tag{2}$$

where $T_{old,j}(i)$ and $T_{new,j}(i)$ are knowledge level of former and new teachers in j subject after updating. i is the iteration number. P_{SL} is a predefined mutation probability. r is a random number in [0, 1]. TR is a random number.

In autonomous teaching-learning based optimization algorithm(ATLBO) [137], the teaching process is divided into three stages: teacher phase, mutual learning phase and self-learning phase. In teacher phase, the random number r is replaced by $r \cdot G_i(t)$. The modified equation is shown as follows:

$$G_i(t) = G_i(t-1) \cdot \alpha^{-(f(X)-f_{min}+\varepsilon)/(f_{max}-f_{min}+\varepsilon)} \tag{3}$$

where f_{max} and f_{min} are the maximum and minimum fitness values respectively, $\alpha \in (1, 2)$ is the difficulty factor. The learner is updated as follow:

$$X_i(t) = X_i(t-1) + r_i \cdot G_i(t) \cdot (X_{teacher}(t) - T_F \cdot M(t-1)) \tag{4}$$

In mutual learning phase, Gaussian random $N(\mu, \delta)$ is used to update his/her knowledge level, the equation as follow:

$$X_i(t) = N\left(\frac{X_{best}(t-1)+X_i(t-1)}{2}, \frac{X_{best}(t-1)-X_i(t-1)}{2}\right) \tag{5}$$

where X_{best} is the best individual of one group. If $f(X_i(t)) < f(X_i(t-1))$, $X_i(t-1)$ will be replaced with $X_i(t)$, otherwise, remain the $X_i(t-1)$. In self-learning phase, the chaos mapping of ants is used.

In [2], before each generation optimization, the ETLBO algorithm chooses the N best individuals as elite solutions to the population. After each "teaching and learning" optimization of the population, the worst N individuals in the new population are replaced by the elite solution. At the same time, in order to avoid duplicate individuals after replacement, a duplicate deletion of population is needed. The deletion strategy is when there is a duplicate individual in the population it is needed to change one of them.

During traditional teaching-learning, learners learn by themselves or discussing with their classmate except for the teacher, so Rao and Patel [138] modified the basic TLBO algorithm as follow. Firstly, the teaching factor is replaced by formula (6).

$$(T_F)_i = \begin{cases} \left(\dfrac{X_{total-k}}{X_{total-k\cdot best}}\right)_i, & \\ \quad if\ X_{total-k\cdot best,i} \neq 0 & k = 1, 2, \cdots, n \\ 1, & \\ \quad otherwise & \end{cases} \tag{6}$$

where $X_{total-k}$ is the result of any learner of kth subjects at ith iteration, and $X_{total-k\cdot best}$ is the result of the best one at the ith iteration of kth subjects. Secondly, the self-motivated learning and the learning through tutorial are considered in learner phase.

For most of heuristics optimization algorithm, exploration and exploitation ability are two fundamental strategies in the search space. An improved TLBO algorithm (I-TLBO) is provided in [139] to enhance global optimization performance by balancing exploration and exploitation ability. Here the self-feedback learning phase and mutation and crossover phase are introduced into the basic TLBO. Firstly, learners make an effort to improve their knowledge level from the teachers, after that they improve their knowledge level by themselves in self-feedback phase, and then they gain knowledge from partner in learner phase. The self-feedback learning phase is between teacher phase and learner phase. At the end, the mutation and crossover phase is designed to improve the exploration ability.

In [128] the learners are split into groups according to their knowledge level, each group is assigned a teacher. The teaching factor is modified as follow:

$$T_F = \frac{f(x)}{\min(f(x))} \tag{7}$$

where $f(x)$ is the objective function of costing. In fact, the learners may be enhancing their knowledge level by tutorial or self-motivated learning. For the reason, the tutorial learning brings into the teacher phase, and the self- motivated learning brings into learner phase.

To overcome slow convergence rate and avoid trapping in local optimum in the basic TLBO, the LNTLBO [140] (TLBO algorithm with a logarithmic spiral strategy and a triangular mutation rule)is proposed. In the teacher phase, a logarithmic spiral strategy combined with the original search method to accelerate convergence speed and enhance the exploitation capacity.

$$X_i^{iter+1} = dist_{i-T} \cdot e^{\beta\theta} \cdot \cos(2\pi\theta) + X_{teacher}^{iter} \tag{8}$$

where $dist_{i-T} = |X_i^{iter} - X_{teacher}^{iter}|$ is the distance of the ith learner and the teacher, $\theta = 2\left(1 - \frac{iter}{MaxIter}\right) - 1$. With the increase of iterations the θ decreases linearly. $\beta = 1$. $iter$ and $MaxIter$ are the current iteration and the maximum number of iteration, respectively. The learner phase is divided into case 1 and case 2. In case 1, the learners X_j^{iter}, X_i^{iter} and X_1^{iter}, X_2^{iter} are all random vector to maintain the population diversity, they satisfy $X_1^{iter} \neq X_2^{iter} \neq X_j^{iter} \neq X_i^{iter}$.

If $f(X_j^{iter}) < f\left(X_i^{iter}\right)$ then

$$X_i^{iter+1} = X_i^{iter} + rand \cdot \left(X_1^{iter} - X_2^{iter}\right) \tag{9}$$

In case 2, a new triangle mutation rule is introduced, that is to utilize the convex combination vectors and the difference between the three random vectors to enhance search abilities. The model describe as follow:

$$\begin{aligned} X_i^{iter+1} = X_c^{iter} &+ F_1 \cdot \left(X_{best}^{iter} - X_{worst}^{iter}\right) \\ &+ F_2 \cdot \left(X_{best}^{iter} - X_{better}^{iter}\right) + F_3 \cdot \left(X_{better}^{iter} - X_{worst}^{iter}\right) \end{aligned} \tag{10}$$

where $f(X_j^{iter}) > f\left(X_i^{iter}\right)$, F_1, F_2 and F_3 are all random mutation factors in range [0, 1]. X_{worst}^{iter}, X_{better}^{iter} and X_{best}^{iter} are the best, better and worst randomly selected vectors, respectively. And they satisfy:

$$X_{worst}^{iter} \neq X_{better}^{iter} \neq X_{best}^{iter} \neq X_j^{iter} \neq X_i^{iter}$$
$$X_c^{iter} = \lambda_1 \cdot X_{worst}^{iter} + \lambda_2 \cdot X_{better}^{iter} + \lambda_3 \cdot X_{best}^{iter}$$

where λ_i are the weights, and must satisfy:

$$\lambda_i \geq 0, \sum_{i=1}^{3} \lambda_i = 1, \quad \lambda_i = \frac{p_i}{\sum_{i=1}^{3} p_i},$$

where $p_1 = 1, p_2 = rand\,(0.75, 1)\,, p_3 = rand(0.5, p_2)$. $i = 1, 2, 3$.

CLTLBO (closed-loop teaching-learning-based optimization) [141] is a closed-loop TLBO. In teacher phase, the teacher helps learner to improve their knowledge level, the learner feedback the learning situation to their teachers. After mastering the learning situation of students, teachers take corresponding measures to improve the learners' knowledge level. Thus, the feedback information for a closed-loop system is constituted. In learner phase, learners learn each other by group, and the BSO (Brain storm optimization) is introduced to learn by interacting and discussing together.

ICTLBO [142] (Improved constrained teaching–learning-based optimization) is proposed for the constrained optimization problem. In teacher phase, according to the Euclidean distance, the population P is partitioned into k subpopulation, each size of subpopulation is NS. Therefore the updating process is as follows:

$$X_{i,new,k} = X_{i,old,k} + rand \cdot (X_{teacher} - T_F \cdot SubMean_k) + rand \cdot \left(X_{r1,k} - X_{r2,k}\right), \quad k = 1 \tag{11}$$
$$X_{i,new,k} = X_{i,old,k} + rand \cdot (X_{teacher} - T_F \cdot SubMean_k) + rand \cdot \left(X_{SubBest,k-1} - X_{r2,k}\right), \quad k \geq 2 \tag{12}$$

where $SubMean_k$ is the mean knowledge of kth subpopulation, $X_{SubBest,k-1}$ is the best learner of the (k − 1) subpopulation, $r_1 \neq r_2 \neq i, X_{r1,k}$ and $X_{r2,k}$ are the random learner in kth subpopulation. In leaner phase, in order to maintain diversity and increase the search ability, the follow formula is used.

$$X_{j,new} = X_{j,old} + rand \cdot \left(X_l - X_j\right) + rand \cdot (X_{r1} - X_{r2})\ if\ (X_l) <_c f\left(X_j\right) \tag{13}$$

$$X_{j,new}^d = \begin{cases} X_{j,old}^d & if\ rand_1 \leq rand_2 \\ X_{r1}^d + \phi^d \cdot \left(X_{r2}^d - X_{r3}^d\right) & otherwise \end{cases} \quad if\ f\left(X_j\right) <_c f\left(X_l\right) \tag{14}$$

where $r1 \neq r2 \neq r3 \neq j \neq l$, they are all learners, $rand_1$ and $rand_2$ are all random in [0,1], ϕ^d is a uniformly distributed random real number within [−1, 1]. Here, X_l is better than X_j and expressed as $f\,(X_l) <_c f\left(X_j\right)$.

TLBO-FL(Teaching Learning Based Optimization with Focused Learning) [143] is used for the case where learners have not improved their knowledge level by teacher phase, they have to improve their knowledge level by learner phase. In teacher phase, the teacher is allowed randomly to improve his/her knowledge level; the learner improves their knowledge according to basic TLBO. In learner phase, the learner interacts with one better partner and the other inferior partner. The mathematical model is as follow:

$$X_j^{new} = X_j + r\left(X_j^{partner1} - X_j\right) + r'\left(X_j - X_j^{partner2}\right) \quad \forall j = 1, \cdots D \tag{15}$$

where $X_j^{partner1}$ and $X_j^{partner2}$ are the better and inferior partner.

In [144] DGSTLBO(teaching–learning-based optimization algorithm with dynamic group strategy), the learners are divided into small groups by Euclidean distances to increase the diversity, and the dynamic group learning is allowed in each group. In teacher phase, the learner learns from the teacher and the mean of the corresponding group. The updating of learner X follows as:

$$newX = X + r \cdot (Teacher - TF \cdot groupMean) \tag{16}$$

In learner phase, the probability P_c expresses the number of learners that adopt the quantum behavioral learning [166], it is set for learners. The r is the random number in the range [0, 1] for each learner. If r is smaller than P_c, using the basic TLBO to update learner, otherwise using the quantum behavioral learning as follows:

$$tempX = \varphi \cdot groupTeacher + (1 - \varphi) \cdot Teacher \tag{17}$$

$$newX = \begin{cases} tempX + \beta\,|groupMean - X| \cdot \ln\left(\frac{1}{u}\right) & if\ k < 0.5 \\ tempX - \beta\,|groupMean - X| \cdot \ln\left(\frac{1}{u}\right) & if\ k \geq 0.5 \end{cases} \tag{18}$$

where $Teacher$ and $GroupTeacher$ are the best learners in the class and in the group, respectively. $groupMean$ is the mean of learner X in the group. φ, u, k are vectors in the range [0, 1].

DRLTLBO [145] (TLBO algorithm with differential and repulsion learning) includes teacher phase, learner phase and self-learning phase. In teacher phase, differential learning is used to enhance the diversity of the population [167], the update process is as follows:

$$newX_i = u \cdot newX_i^1 + (1 - u) \cdot newX_i^2 \tag{19}$$
$$newX_i^1 = X_i + r_i \cdot (X_{Teacher} - T_F \cdot X_i^{NMean}) \tag{20}$$
$$newX_i^2 = X_{ri1} + F \cdot (X_{ri2} - X_{ri3}) \tag{21}$$

where $newX_i$ is the knowledge level of ith learner, u is the hybridization factor in the range [0, 1]. $X_{Teacher}$ and X_i^{NMean} are the knowledge level of best learner and the mean knowledge level respectively. Definition of r_j and T_F is the same as TLBO. $ri1$, $ri2$, $ri3$ are the mutually exclusive integers in [1, P]. P is the population size. $X_{ri1}, X_{ri2}, X_{ri3}$ are the position of three learners. F is a mutation scaling factor.

The learner phase is divided into learner phase with repulsion learning and self-learning phase. In repulsion learning, if $rand(\cdot) < P_c$, the local learning method is shown as follow:

$$newX_i = \begin{cases} X_i + r_{i1} \cdot \left(X_i^{NTeacher} - X_j\right) + r_{i2} \cdot \left(X_i - X_{ji}\right) \\ \quad if \ \ (X_i) < f\left(X_{ji}\right) \\ X_i + r_{i1} \cdot \left(X_i^{NTeacher} - X_j\right) + r_{i3} \cdot \left(X_{ji} - X_i\right) \\ \quad otherwise \end{cases} \tag{22}$$

If $rand(\cdot) < P_c$, the repulsion learning method is used as follow:

$$newX_i = X_i + r_{i1} \cdot \left(X_i^{NTeacher} - X_i\right) + r_{i2} \cdot \left(X_i - X_i^{worst}\right) \tag{23}$$

In self-learning phase, it is remembered the history positions. If the fitness value of the learner i is not changed in n continuous iteration, the knowledge level of the j-th subject of i-th learner $X_{i,j}$ will be updated as follow:

$$newX_{i,j} = X_{i,j} + rand \cdot \left(X_{i,j}^{Mean} - X_{i,j}\right) \tag{24}$$

where $X_{i,j}^{Mean}$ is the history mean knowledge level of the j-th subject of i-th learner.

$$X_{i,j}^{Mean} = \sum_{g=1}^{m} X_{i,j}^{g} \tag{25}$$

where g is the number of iteration in m, which is the number of successive iterations.

TLFBO(Teaching-learning-feedback-based Optimization) [146] added a feedback phase after the learning phase to increase the converging speed. The optimal value of the basic TLBO is used as teacher to evaluate the learning result and select teacher (expressed as the current teacher). The difference between the two teachers was recorded as a judgment group to supervise everyone in the class, the produce described as follows:

$$St_i^{new} = St_i^{current} + l_1 \cdot \omega \cdot D_{last} + l_2 \cdot \omega \cdot D_{current} \tag{26}$$

$$D_{last} = Tr_i^{last} - St_i^{current} \tag{27}$$

$$D_{current} = Tr_i^{current} - St_i^{current} \tag{28}$$

$$\omega = (G_{total} - G_{current}/G_{total}) \tag{29}$$

where ω is the weight, $l_1 and l_2$ are the feedback weights of the two selected teacher, defined in range [0, 1], and $l_1 + l_2 = 1$. G_{total} is the predefined number of iteration, $G_{current}$ is the current number of iteration. The differences D_{last} and $D_{current}$ of learner and the two teachers are used to update the knowledge level of the population.

In ITLBO [147], random weighed differential vector is varied in the range (0.5, 1) by using the relation $0.5 \cdot (1 + rand)$. So, in the teaching phase updating of learners can be described as follow:

$$newX_i = X_i + 0.5 \cdot (1 + rand) \cdot (X_{teacher} - T_F \cdot X_{mean}) \tag{30}$$

In the learner phase, updating of learners can be described as follow:

$$newX_i = \begin{cases} X_i + 0.5 \cdot (1 + rand) \cdot (X_i - X_r) \\ \quad if \ \ (X_i) < f\,(X_r) \\ X_i + 0.5 \cdot (1 + rand) \cdot (X_r - X_i) \\ \quad otherwise \end{cases} \tag{31}$$

B. FUSION WITH OTHER OPTIMIZATION METHODS

In order to improve the performance of various optimization methods and their optimization strategies, experts and scholars integrate various optimization methods to make up for and improve their optimization capabilities and enhance their search and convergence capabilities. In recent years, in order to improve the robustness of the basic TLBO algorithm, the method combining TLBO with other common optimization methods has been widely used.

In [148], Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton method is blended into the basic TLBO algorithm to enhance local searching ability. In which, the basic TLBO is used to perform global search and BFGS quasi-Newton method is used for local refinement. The experimental results show that the search performances of TLBO-BFGS are better than GA, PSO. In [149], the simultaneous perturbation stochastic approximation (SPSA) and basic TLBO algorithm are combined to enhance local search ability and balance the ability of global exploration and local exploitation. Where SPSA goes on local optimization, TLBO performs the global optimization. Reference [150] proposed an ECTLBO to enhance TLBO performance by error correction strategy and Cauchy distribution, where Cauchy distribution is used to expand the searching space and error correction is utilized to precise optimization. In teacher phase and learner phase, random number r is replaced by Cauchy distribution Cauchy(0,1), which solved effectively for accuracy, improved ability of anti-jamming and self-adjustment.

In [151], experience information (EI) and differential mutation are mixed into basic TLBO, called EI-TLBO. The EI achieved before the current iterative learning process can be regarded as the learner's learning direction and trend information, where the ring-neighborhood topology is used to improve the search capability. In addition, differential mutation that based on distance and information is adopted to make better the diversity of populations throughout the evolutionary process.

In order to improve the global optimization capability of basic TLBO, the PSO is introduced [152], in which the main change in teacher phase is that the new knowledge level of the ith learner is determined by the old knowledge level, the mean knowledge level, and the teachers' knowledge level of current generation. The updating of learners can be described as follow:

$$X_{i,new} = X_{i,old} + r_1\left(X_{teacher} - T_F X_{gmean}\right) + r_2\left(X_{teacher} - X_{i,old}\right), \tag{32}$$

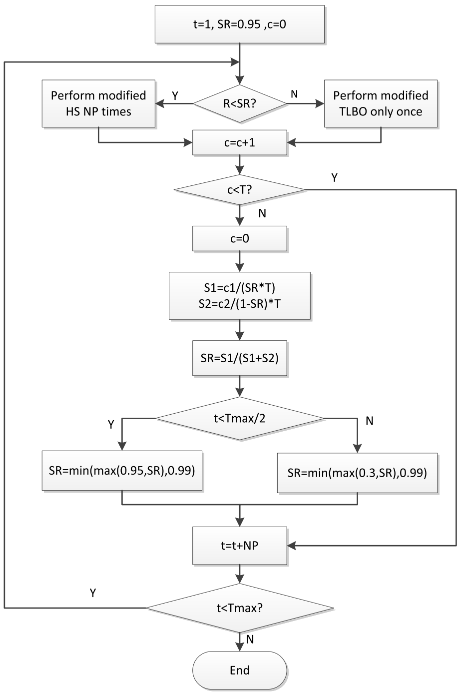

FIGURE 3. The flow chart of HSTLBO.

where r_1, r_2 are the random number in the range [0, 1], T_P is a random number (1 or 2).

A hybrid optimization algorithm HSTLBO(HS and TLBO) [153] is proposed, the flow chart as show in Fig.3. In this revised TLBO, only teacher phase or learner phase are randomly selected for learning. Each subject $M(i)$ is selected from the ith subject of all learners randomly, and a part of dimensions of X_{new} is generated by learning from teachers or other learners, while other dimensions are inherited from X_{old} directly. As a consequence, the learner's learning of the subject is to select the excellent learners of the subject from the population to study.

In HS algorithm, selection probability (SR) is expressed by formula (33). Where D is the number of notes in a harmony, t is the current iteration times, T is the cycle length for recalculating the SR. SR is adjusted dynamically according to t, c_1 and c_2 are The times of updating old solutions successfully of HS/ TLBO in the tth iteration. $Tmax$ is the maximum evaluation times of objective function.

$$SR = min\left[\frac{100}{D} - \left(\frac{100}{D} - \frac{30}{D}\right) \cdot \left(\frac{t}{T}\right), 1\right] \tag{33}$$

In [154], HTLBO_HS (Hybrid TLBO with Harmony Search) is proposed, where the HTLBO_HS modified the teacher phase and learner phase. In teacher phase, the harmony search is used to optimize the current best learner. If there is new learner better than the best, then replace the best.

$$X_i^{new} = \begin{cases} X_i^{old} + rand_{1,i} \cdot \left(X^{new} - T_F \cdot X^m\right), \\ \quad if\ f(X^{new}) \le f(X^{best}) \\ X_i^{old} + rand_{1,i} \cdot \left(X^{best} - T_F \cdot X^m\right), \\ \quad otherwise \end{cases} \tag{34}$$

In order to balance the exploitation and exploration capability, the local searching method is described as formula:

$$X_i^{new} = X_i^{old} + (2 \cdot rand - 1) \cdot \left(X_i^{A_m} - X^{worst}\right) \tag{35}$$

where $X_i^{A_m}$ is the mean of A learner, X^{worst} is the worst learner.

In learner phase, the two groups are selected to compare, the better one generated the new learner, described as follows:

$$X_i^{new} = \begin{cases} X_i^{old} + rand \cdot \left(X^{A_{m1}} - X^{A_{m2}}\right), \\ \quad if\ f(X^{A_{m1}}) \le f(X^{A_{m2}}) \\ X_i^{old} + rand \cdot \left(X^{A_{m2}} - X^{A_{m1}}\right), \\ \quad otherwise \end{cases} \tag{36}$$

where $X^{A_{m1}}$ and $X^{A_{m2}}$ are the mean of the two small groups respectively.

In SAMCCTLBO [155] (A variant of teaching–learning-based optimization algorithm (TLBO) with multi-classes cooperation and simulated annealing operator), the population is divided into groups and select the best learner as the teacher for each group. In teacher phase, the way updating the teacher's position is the same as in basic TLBO, and the way updating learners is simulated annealing. In learner phase, the way updating the learner's position is the same as in the basic TLBO. After some iteration, all the learners are integrated and regrouped again. Until $T_k = \lambda \cdot T_{k-1}$ and the terminal condition is satisfied. Otherwise, go on teaching and learning.

In TPLPSO [156](Teaching and peer-learning PSO), there have the teacher phase and the peer-learning phase. In teacher phase, PSO is adopted to update each learner's velocity V_i and position X_i, evaluated and compared the X_i(the learner i's personal position) with the P_i(the learner i's personal best position). If $f(X_i) < f(P_i)$, X_i then replaces P_i, update and compare X_i and P_g(the population's best position). If $f(X_i) < f(P_g)$, X_i then replaces P_g. Thus, the learner becomes more knowledgeable than the teacher. And the identity of the learner and the teacher exchanged. Where, f_c is introduced, when the learner replace the teacher successfully, $f_c = 0$, else $f_c = f_c + 1$. In the peer-learning phase, each learner can choose an exemplar P_e. Each exemplar candidate k is determined by weight W_k.

$$W_k = \frac{f_{\max} - f(P_k)}{f_{\max} - f_{\min}}, \quad \forall k \in [1, K] \tag{37}$$

where $f_{\max}$ and $f_{\min}$ are the maximum and minimum personal best fitness values of the exemplar candidates, respectively. k is the number of exemplar candidates. The exemplar candidate with lower fitness is assigned to larger W_k that means it much more be the exemplar. Since the exemplar learner is selected through a probabilistic, there will be the two possible results ($f(P_{ei}) < f(P_i), f(P_{ei}) > f(P_i)$). For the two results, two kinds of velocity are updating as follows.

$$V_i = \begin{cases} \omega V_i + cr_1 \left(P_{ei} - X_i\right), & if\ f\left(P_{ei}\right) > f(P_i) \\ \omega V_i - cr_2 \left(P_{ei} - X_i\right), & if\ f\left(P_{ei}\right) < f(P_i) \end{cases} \tag{38}$$

where c is the acceleration coefficient and $c = 2$. r_1 and r_2 are random numbers in the range of [0,1]. Position updating of learner X_i is similar as the teacher phase. In addition, the stagnation prevention strategy (SPS) is used to prevent falling into the local optima. P_{gd} is one of dth dimension learner P_g, its initial value is randomly selected, it is affected by a normal distribution.

$$P_{gd}^{per} = P_{gd} + sgn(r_3) \cdot r_4 \cdot (X_{\max,d} - X_{\min,d}) \tag{39}$$

where P_{gd}^{per} is the affected P_{gd}, $X_{max,d}$ and $X_{min,d}$ are the lower an upper bounds of d dimension space. r_3 and r_4 follow the uniform distribution and normal distribution respectively. In the normal distribution $N \sim (\mu, \sigma^2)$, $\sigma = R$.

$$R = R_{\max} - (R_{\max} - R_{\min}) \frac{fes}{FE_{\max}} \tag{40}$$

where $R_{\max} = 1$, $R_{\min} = 0$, fes is the number of FEs consumed. $FE_{\max}$, $FE_{\min}$ is the maximum and minimum FEs.

The TLBO-TSI(TLBO with two-stage initialization (TSI) [157]) consists of TSI and TLBO. Firstly, TSI [168] method is used to initialize variable, the population is generated as follow:

$$X_{i,j} = X_i^{min} + rand \cdot \left(X_j^{max} - X_j^{min}\right) \tag{41}$$

where, $i = 1, 2, \cdots, ps$; $j = 1, 2, \cdots, nva.ps$ is the population size, nva is the variables. X_j^{max} and X_j^{min} are the minimum and maximum values of jth variable. Find out the overall average value of each variable and store it. Repeat this process n times until obtaining the $n \times nva$ matrix, then execute the basic TLBO.

In [158], a new algorithm ABC-TLBO is proposed. The bee period is modified to carry out exploration process and the bee period of bystanders is modified to controls the exploration process, so as to achieve a better balance between exploration and exploitation. In the employed bee phase, a new search strategy combining direction-guided search and differential evolution cross-search is designed to improve the diversity of the population and accelerate the convergence rate. In the bystander bee phase, in order to enhance ABC's development ability, a search method based on personalized teaching and learning is adopted.

C. WEIGHT METHODS AND OTHERS

Here, weight or factor or the new frames are introduced into the basic TLBO to accelerate the convergence speed, improve the performance, enhance learning ability, etc. Weight or factors are used mainly in updating process in both teacher phase and learner phase.

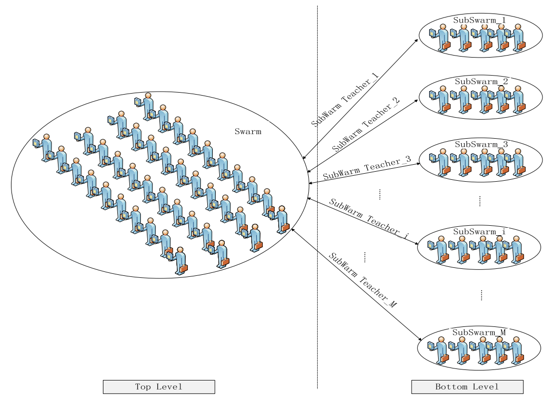

FIGURE 4. The structure of the two-level hierarchy for HMCTLBO.

According to the real teaching process, [159] proposed the MTLBO, where it introduces inertia weight in equation(42) to balance the exploration and the exploitation ability.

$$W = \omega_{start} - (\omega_{start} - \omega_{end}) \cdot \frac{iter}{MaxIter} \tag{42}$$

The inertia weight descends linearly from ω_{start} to ω_{end}. The updating machine is shown in formula (41).

$$X_{new,i} = \begin{cases} X_{old} \cdot W + \left(X_{best} - X_{old,i}\right) \cdot rand, \\ \quad if\ f\left(X_{old,i}\right) < f(X_{mean}) \\ \left(X_{old,i} + (rand - 0.5) \cdot 2 \cdot \left(X_{mean} - X_{old,i}\right)\right) \\ \cdot \sin\left(\frac{\pi}{2} \cdot \frac{iter}{MaxIter}\right) + diff \cdot \cos\left(\frac{\pi}{2} \cdot \frac{iter}{MaxIter}\right), \\ \quad if\ f\left(X_{old,i}\right) > f(X_{mean}) \end{cases} \tag{43}$$

where, $\sin\left(\frac{\pi}{2} \cdot \frac{iter}{MaxIter}\right)$ and $\cos\left(\frac{\pi}{2} \cdot \frac{iter}{MaxIter}\right)$ are the inertia weights to increase the convergence speed.

In HMCTLBO (hierarchical multi-swarm cooperative TLBO) [160], the detail of the two-level hierarchical multi-swarm cooperative TLBO described as Fig.4.

The population divided into M subpopulation with same size, each subpopulation selected the best learner by the teacher phase and the learner phase at bottom level. Then the best learners combine into the swarm of the top. Here, Gaussian sample learning is used to update the learner.

$$X_{j,new} = N\left(\frac{X_{j,old} + teacher}{2}, \left|teacher - X_{j,old}\right|\right) \tag{44}$$

where $N(\cdot)$ is a Gaussian distribution. If *mod(iteration, period)==0*(*iteration* is the number of iterations, *period* is the regrouping period), execute random regrouping. Otherwise, using LHS (Latin hypercube sampling) [169] method to search subspace.

In the real world, teacher often want their student to acquire all their knowledge as soon as possible. In reality, a student often forgets part of his existing knowledge because of the biological phenomena in his brain. Owing to the forgetfulness of people and other personal factors, only a few people can achieve this goal. According to the phenomenon, ''weight'' is introduced the TLBO, such as [161] and [162].

In NIWTLBO [161] (nonlinear inertia weighted teaching-learning-based optimization algorithm) a nonlinear inertia weighted factor is proposed to control the memory rate. And the dynamic inertia weighted factor is proposed to replace the random number in teacher phase and learner phase. The nonlinear inertia weighted factor described as follows.

$$\omega = 1 - \exp\left(\frac{-iter^2}{2 \cdot \left(\frac{MaxIter}{8}\right)^2}\right) \cdot (1 - \omega_{\min}) \tag{45}$$

where, $iter$ is the number of iterations, $MaxIte\ r$ is the maximum of $iter$, $\omega_{\min} \in [0.5, 1]$ is the minimum of ω. In teacher phase the new learner described as follows.

$$X_{i,k,j}^{new} = \omega \cdot X_{i,k,j}^{old} + r_i' \cdot (X_{i,teacher,j} - T_F \cdot M_{i,j}) \tag{46}$$

In the learner phase, the new learners can be expressed by using equation:

$$X_{i,k,j}^{new} = \begin{cases} \omega \cdot X_{i,k,j}^{old} + r_i' \cdot \left(X_{i,k,j} - X_{i,q,j}\right), \\ \quad if\ f\left(X_{i,total\_k}\right) < f\left(X_{i,total\_q}\right) \\ \omega \cdot X_{i,k,j}^{old} + r_i' \cdot \left(X_{i,q,j} - X_{i,k,j}\right), \\ \quad if\ f\left(X_{i,total\_k}\right) < f\left(X_{i,total\_q}\right) \end{cases} \tag{47}$$

where, r_i' is the dynamic inertia weighted factor.

$$r_i' = 0.5 + \frac{rand(0,1)}{2} \tag{48}$$

In WTLBO(Weighted Teaching Learning-Based Optimizer) [162] a parameter known as ''weight'' is introduced into the procedure, here the ω is described as follows:

$$\omega = \omega_{\max} - \left(\frac{\omega_{\max} - \omega_{\min}}{\max iteration}\right) \times i \tag{49}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of weight factor ω. i is the number of current iteration. *maxiteration* is the maximum number of allowable iterations. In the teacher phase the updating formula is:

$$newX_i = \omega \cdot X_i + r \cdot (X_{teacher} - T_F \cdot X_{mean}) \tag{50}$$

In the learner phase the updating formula is:

$$newX_i = \begin{cases} \omega \cdot X_i + r \cdot \left(X_i - X_j\right) & if\ f\left(X_i\right) < f(X_j) \\ \omega \cdot X_i + r \cdot \left(X_j - X_i\right) & otherwise \end{cases} \tag{51}$$

In [163] DAEDTLBO (Dynamic Self-adaptive and elitist Dynamic Random Search TLBO), Dynamic Learning Factor λ is introduced to adjust the influence of knowledge level of learners on their own state updating, In the teacher phase the updating formula is:

$$newX_i = \lambda \cdot X_i + r \cdot (X_{teacher} - T_F \cdot X_{mean}) \tag{52}$$

$$\lambda = (\lambda_{start} - \lambda_{end}) \cdot iter/iter_{max} \tag{53}$$

where $\lambda \in [\lambda_{\max}, \lambda_{\min}]$. In order to improve the convergence speed, the probability-based DRS (Dynamic Random Search) algorithm is implemented for individual teachers. Teachers perform DRS (dynamic random search) [170] to enhance the exploration of the optimal individual's surrounding space.

In ATLBO [164], a weight factor W is included in both teacher phase and learner phase. A team leader concept is introduced, which denote the position of best learner. In the learner phase, the former best learners act as team leader, who is changed in each iteration until the results are not available in the global solution. The weight factor decreases linearly with time.

$$W = W_{max} - w \tag{54}$$

$$w = (W_{max} - W_{min}) \cdot (T_{max} - t)/T_{max} \tag{55}$$

where, W_{max} and W_{min} are the maximum and minimum value of W. t and T_{max} are the current iteration number and max iteration number of allowable iterations respectively. The updating of teacher phase as follows:

$$newX_i = W \cdot X_i + r \cdot (newX_{mean} - T_F \cdot X_{mean}) \tag{56}$$

In the learner phase, the updating formula can be described as:

$$newX_i = \begin{cases} W \cdot X_i + r \cdot \left(X_i - X_j\right) + r \cdot (X_{best} - X_i) \\ \quad if\ f\left(X_i\right) < f(X_j) \\ W \cdot X_i + r \cdot \left(X_j - X_i\right) + r \cdot (X_{best} - X_i) \\ \quad otherwise \end{cases} \tag{57}$$

In [165] FATLBO, three new strategies are proposed to enhance performance of TLBO: status monitor, fuzzy adaptive teaching–learning strategies (FATLS) and remedial operator. Status monitor is used to record the learning progress of students in the learner and teacher phase and to improve their knowledge level within a given iteration range. In FATLS, teaching rate (TR) and learning rate (LR) are two new parameters to express the probability rate of a student to enter teacher or learner phases, they are self-adjust according to the collected information from the status monitor. If $TR = 0.6$, each student has a 60% probability of entering the teacher phase, and 30% probability of skipping the teacher stage. Remedial operator is introduced to ensure students do not falling into local optimum.

According to the above description, the FATLBO method adjusts the TLBO framework, and adding remedial operator and status monitor. Other methods are to change different weights based on the basic TLBO.

V. DISCUSSION AND FUTURE TRENDS

TLBO algorithm is a relatively new algorithm. It has simple application, no specific parameters, and provides the best results in some function evaluation. It has a strong potential to solve optimization problems. TLBO algorithm has opened up a small world for itself in the field of optimization. However, there is still a gap between the most advanced TLBO algorithm and users' expectations, which means that the TLBO algorithm is still needed to study for some optimization problems. The future research opportunities for TLBO are discussed as follows.

A. SELECTION AND SETTING OF PARAMETERS

Generally, a set of appropriate parameters can greatly enhance the search and convergence ability of the optimization algorithm, the performance of the algorithm can be greatly improved too. Most heuristic optimization algorithm cannot avoid the trouble of setting reasonable parameters. As one of the heuristic optimization algorithms, TLBO algorithm is simpler and easier to implement, with few parameters compared with the other heuristic optimization algorithms. Its parameters are population size (NP), teaching factor (TF), and random factor. NP is a necessary parameter for any optimization algorithm. The size of NP greatly affects the efficiency of the algorithm. In the ordinary, NP is adjusted through many experiments until it can achieve satisfactory optimization effect. The random factor is a random number in range [0, 1], which can enhance the flexibility and anti-interference ability of the algorithm. In the basic TLBO, TF is either 1 or 2. This value does not make full use of the information contained in the population, which may lead to premature convergence or optimization failure of the algorithm to some extent. So that TLBO algorithm is easy to lose the diversity of the population, and difficult to search for the global optimal value.

In order to keep the diversity of population and make the TLBO algorithm to find the optimal solution quickly, it is an important problem to select and set a set of parameters. The setting of parameters will not only affect the efficiency of the algorithm, but also affect the accuracy of the algorithm to obtain the optimal solution. At the same time, the parameter setting is often determined by the actual problem. It is a time-consuming and laborious work to choose the appropriate parameter value in the case of the fitness surface of the uncertain problem. If there is a more qualitative understanding of the parameter selection law of TLBO algorithm, it will be of great help to the parameter selection of different problem domains.

B. REDUCE THE COMPLEXITY OF THE TLBO ALGORITHM

In order to improve the performance of TLBO algorithm, there are many modified TLBO algorithms in recent years. One of them is mixed other optimization algorithm with TLBO. Each optimization algorithm has its own advantages and disadvantages. According to the advantages and disadvantages of each algorithm, two or more algorithms are combined with TLBO to make up for each other's shortcomings, so as to better solve the optimization problem and enhance optimization ability of the basic TLBO algorithm. In addition to, different mechanisms are added to the basic TLBO algorithm to enhance its performance in some aspects, so as to improve the solution effect of the algorithm.

Of course, these modified algorithms improved the optimization capability of TLBO to some extent. But, the emergence of these improved algorithms leads to the increase of the overall complexity and the loss of the simplicity of the basic TLBO. How to ensure its own advantages and avoid premature convergence without affecting the simplicity and fast convergence of the TLBO algorithm is of great significance to the improvement of the robustness of the algorithm.

C. STRENGTHEN THEORETICAL BASIS RESEARCH

Unlike other heuristic algorithms, TLBO algorithm hasn't a good mathematical theoretical basis and the overall analysis method of the system. So, the behavior of TLBO algorithm cannot be analyzed thoroughly, and it can only be further understand from the experimental results, because there is no perfect mathematical theory derivation and analysis to prove its convergence. It also fails to provide a set of theoretical methods to strictly analyze the influence of parameter changes on the convergence of the algorithm. If a set of strict mathematical theory can be developed to evaluate the impact of parameter changes on algorithm performance in real time during the operation of the algorithm, and adjust the parameter values dynamically, higher algorithm performance can be obtained. To some extent, it also solves the problem of parameter control and adjustment.

Therefore, no matter in theory or in practice, there are still many problems in the current research need to be further studied and solved.

D. RESEARCH ON COMPLEX MULTI-MODAL PROBLEMS

In recent years, large-scale complex problems such as industrial design, system control, biomedical and social network analysis have emerged, most of the problems are ultra-high dimensional (more than 500 dimensional), non-linear, non-dimensional, multimodal NP hard optimization problems, which pose a huge challenge to high-performance computing technology. During the calculation of these practical optimization problems, it is not only required to find the global optimal solution in the feasible region, but also to search multiple global optimal solutions and meaningful local optimal solutions. It has become a continuous research field about how to construct an optimization algorithm that can search all global optimal solutions and as many local optimal solutions as possible. For continuous function optimization problems and combinatorial optimization problems with multimodal properties, the traditional search algorithms or other heuristic algorithm all have the problem of how to avoid being trapped in local optimum and find the global optimal solution. In contrast, TLBO algorithm is better in dealing with complex multimodal optimization problems.

However, like other heuristic optimization algorithms, TLBO algorithm will converge prematurely when solving some complex problems, that is to say, TLBO algorithm converges faster in the early convergence process. In the later optimization process, the population has gathered to the local minimum point before finding the global best point. If an effective mechanism can be adopted to make the TLBO algorithm escape from the local optimum, the TLBO algorithm can be further improved in dealing with multimodal problems.

E. RESEARCH ON THE HYBRID ALGORITHM

Each optimization algorithm has its own advantages. For many complex and hard to solve optimization problems in real life, using only one algorithm to solve the problem often fails to achieve the expected results. Therefore, how to combine two or more optimization algorithms with TLBO, and design a hybrid optimization algorithm with stronger optimization ability and wider optimization scope, has become a research hotspot in the field of intelligent optimization, and which has a very important research value and practical significance.

There are many hybrid algorithms to solve the multi-objective optimization problems, especially the constrained multi-objective optimization problems. Therefore, it is meaningful to apply the TLBO algorithm and other hybrid algorithms to the multi-objective optimization problems by using efficient constraint processing technology.

F. RESEARCH ON THE APPLICATION OF THE ALGORITHM

TLBO algorithm has been widely used in dynamic, constrained, uncertain, multidimensional and other complex optimization problems, involving different fields. In the world of machine learning, there are many problems with no optimal solution, or it takes a lot of computation to calculate the optimal solution. In the face of such problems, usually the idea of iteration is used to approach the optimal solution as much as possible. In deep learning, especially deep neural network training and prediction, large models often take days or even months of training time, and model optimization can greatly accelerate the training of deep learning models. Traditional machine learning will find ways to design objective functions and constraints, so that the objective functions are convex functions, so as to avoid non convex functions of the optimization process problem. However, even convex functions will encounter optimiza-tion problems. The optimization algorithms commonly used in machine learning are gradient descent method, Newton method, and other heuristic optimization algorithms, while TLBO algorithm is rarely used in them. So it is necessary to study the optimization methods of machine learning.

In addition, TLBO algorithm has excellent performance in dealing with continuous problems, while most of the problems in real life are discrete. However, there is little research on TLBO algorithm in dealing with discrete problems. Therefore, the methods and approaches to solve the discrete global optimization problems with TLBO algorithm optimization model need to be further studied.

VI. CONCLUSION

Swarm intelligence optimization algorithm, as a heuristic optimization algorithm, has been more and more developed and applied. Because it is not limited by the continuous and differentiable conditions of the optimization objective function, it shows better applicability and quickly becomes popular in the field of optimization. Compared with other swarm intelligence optimization algorithms, TLBO algorithm has many advantages, such as less parameters, simple algorithm, easy to understand, fast solution speed, high accuracy, and good convergence ability. It is widely used in solving optimization design and other problems.

This paper has given an overview of optimization algorithm, summarized numbers of TLBO algorithm and its applications. The different version TLBO algorithms are described briefly and classified into three groups: 1) Improvement on teaching or learning process, 2) Fusion with Other Optimization Methods, 3) Weight methods and others. According to TLBO algorithm performance and application, the TLBO algorithm is discussed and prospected. Although a lot of work has been done to improve the TLBO and its applications in different area, so far, some optimization problems have not been solved well. In order to better deal with optimization problems of various fields, there is still much work to be done.

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