

Teaching-learning-based artificial bee colony

Xu Chen¹, Bin Xu²

¹School of Electrical and Information Engineering, Jiangsu University, Zhenjiang 212013, Jiangsu, China;

²School of Mechanical Engineering, Shanghai University of Engineering Science, Shanghai 201620, China

Email: xuchen@ujs.edu.cn

Content

- 1 Introduction
- 2 A Short Introductions to TLBO and ABC
- 3 Proposed Algorithm: Teaching-learning-based Artificial Bee Colony
- 4 Experimental Results and Analysis
- 5 Conclusion



1 Introduction

■ **Problem**: continue function optimization

$$\min f(x)$$
s.t. $x_{min} \le x \le x_{max}$

Metaheuristic algorithms

- nature inspired optimization strategies
- received much attention regarding their potential as global optimization techniques



2 TLBO and ABC

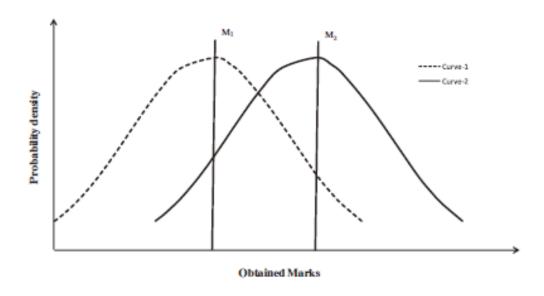
- Our paper focuses on two metaheuristic algorithms
 - □ Teaching-learning-based optimization (TLBO)
 - Inspired by the teaching and learning process of a class
 - Two operators: teacher phase and learner phase
 - Artificial bee colony (ABC)
 - Inspired by the intelligent foraging behavior of honey bees
 - Three kinds of bees: employed bees, onlooker bees, and scout bees



2.1 TLBO

- Teaching-learning-based optimization (TLBO)
 - □ **Two operators**: teacher phase and learner phase
 - □ **Teacher phase**: the teacher provides knowledge to the learners to increase the mean result of the class.

$$x_i^{new} = x_i^{old} + rand \cdot (x_{teacher} - T_F \cdot x_{mean})$$





2.1 TLBO

- **■** Teaching-learning-based optimization (TLBO)
 - □ Two operators: teacher phase and learner phase
 - Learner phase: each learner randomly interacts with other different learners to further improve his result

$$x_i^{new} = \begin{cases} x_i^{old} + rand \cdot (x_i - x_j), & if \ f(x_i) \leq f(x_j) \\ x_i^{old} + rand \cdot (x_j - x_i), & if \ f(x_j) > f(x_i) \end{cases}$$

Remark: In both teacher phase and learner phase, if x_i^{new} is better than x_i^{old} , then use x_i^{new} to replace x_i^{old} .



2.2 ABC

Artificial bee colony (ABC)

- Inspired by the intelligent foraging behavior of honey bees
- □ Three kinds of bees: employed bees, onlooker bees, and scout bees
- **Employed bees:** responsible for seeking out better food sources and passing quality information of the food sources to onlooker bees by dancing.
- Onlooker bees: select good food sources found by employed bees to further search for better food source.
- Scout bees: abandon the exhausted food sources, and regenerate a new food source.



Motivation

- TLBO: Good exploitation, poor exploration
- □ **ABC**: Good exploration, poor exploitation
- Design a hybrid metaheuristic algorithm based on TLBO and ABC.

Question

■ How to effectively combine TLBO and ABC?



- Teaching-learning-based Artificial Bee Colony (TLABC)
 - **Method**: Combine the search equations of TLBO with the search framework of ABC

- □ Three hybrid search phases
 - (1) **Exploration**: teaching-based employed bee phase
 - (2) **Exploitation**: learning-based onlooker bee phase
 - (3) **Restart**: generalized oppositional scout bee phase

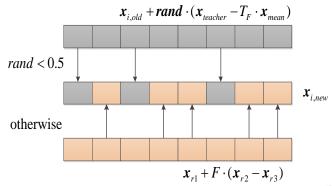


Teaching-based employed bee phase

- Exploration phase
- Each employed bee use an hybrid TLBO teaching strategy to update the position

$$= \begin{cases} x_{i,d}^{old} + rand_2 \cdot (x_{teacher,d} - T_F \cdot x_{mean,d}) & if \ rand_1 < 0.5 \\ x_{r1,d} + F \cdot (x_{r2,d} - x_{r3,d}) & else \end{cases}$$

Remark: The hybrid TLBO teaching strategy can improve the **exploration** of the original TLBO teaching strategy.





- Learning-based onlooker bee phase
 - Exploitation phase
 - Each onlooker bee select a solution based on the fitness

$$fit(\mathbf{x}_i) = \begin{cases} \frac{1}{1+f(\mathbf{x}_i)} & \text{if } f(\mathbf{x}_i) \ge 0\\ 1+|f(\mathbf{x}_i)| & \text{otherwise} \end{cases}$$

Use the TLBO learning strategy to update the position

$$x_i^{new} = \begin{cases} x_i^{old} + rand \cdot (x_i - x_j), & if \ f(x_i) \leq f(x_j) \\ x_i^{old} + rand \cdot (x_j - x_i), & if \ f(x_j) > f(x_i) \end{cases}$$



Generalized oppositional scout bee phase

- Restart phase
- Each exhausted solution re-initializes using a generalized opposition based learning (GOBL)

$$\boldsymbol{x}_{i} = \begin{cases} \boldsymbol{x}_{i}, & if \quad f(\boldsymbol{x}_{i}) \leq f(\boldsymbol{x}_{i}^{GO}) \\ \boldsymbol{x}_{i}^{GO}, & if \quad f(\boldsymbol{x}_{i}) > f(\boldsymbol{x}_{i}^{GO}) \end{cases}$$

where
$$x_i = (x_{i1}, \dots, x_{ij}, \dots, x_{iD}), \quad x_i^{GO} = (x_{i1}^{GO}, x_{i2}^{GO}, \dots, x_{iD}^{GO})$$

$$x_{ij}^{GO} = k \cdot (x_{min,j} + b_{max,j}) - x_{ij}$$



Framework of TLABC

Algo							
1	Initialization						
2	While the stop criterion is not satisfied						
3	Teaching-based employed bee phase;	Exploration					
4	Learning-based onlooker bee phase;	Exploitation					
5	Generalized oppositional scout bee phase;	Restart					
6 End While							
7	Output the best solution.						



13

Benchmarks

- □ CEC2014 test functions
- □ G1: unimodal functions (F01–F03);
- □ G2: simple multimodal functions (F04–F16);
- □ G3: hybrid functions (F17–F22);
- □ G4: composition functions (F23–F30).

Comparisons

- Four TLBO: TLBO, NIWTLBO, LETLBO and GOTLBO
- □ Four ABC: ABC, GABC, MABC and GBABC



Compared with TLBO algorithms

Table The win-draw-loss statistics results between TLABC and the compared TLBO algorithms based on Wilcoxon rank-sum test

TLABC vs TLBO		NIWTLBO	LETLBO	GOTLBO	
G1	3-0-0	3-0-0	3-0-0	2-1-0	
G2	9-2-2	9-2-2	7-3-3	8-3-2	
G3	3-2-1	3-0-3	3-1-2	2-3-1	
G4	5-2-1	3-2-3	6-2-0	1-2-5	
Total	20-6-4	18-4-8	19-6-5	13-9-8	

- (i) TLABC shows the best performance on the unimodal functions, simple multimodal functions and hybrid functions.
- (ii) On composition functions, GOTLBO shows the best performance, TLABC the second.



Compared with ABC algorithms

Table The win-draw-loss statistics results between TLABC and the compared ABC algorithms based on Wilcoxon rank-sum test

TLABC vs	ABC	GABC	MABC	GBABC
G1	3-0-0	3-0-0	2-1-0	3-0-0
G2	3-2-8	3-2-8	5-2-6	3-2-8
G3	5-0-1	5-0-1	3-0-3	3-3-0
G4	7-0-1	6-2-0	5-2-1	4-3-1
Total	18-2-10	17-4-9	15-4-11	13-8-9

- (i) TLABC shows the best performance on the unimodal functions, hybrid functions, and composition functions.
- (ii) For the simple multimodal functions, the performance of TLABC is not very satisfactory, but it also gets the best results on some multimodal functions.

Multiple-problem statistical comparison

Table Results of Multiple-problem Wilcoxon test between TLABC and the compared TLBO and ABC algorithms

Algorithm	R+	R-	p-value	α=0.05	α=0.1
TLABC vs TLBO	375	60	3.32E-04	Yes	Yes
TLABC vs NIWTLBO	318	117	2.91E-02	Yes	Yes
TLABC vs LETLBO	331	104	1.29E-02	Yes	Yes
TLABC vs GOTLBO	328	107	1.57E-02	Yes	Yes
TLABC vs ABC	331	134	4.27E-02	Yes	Yes
TLABC vs GABC	311	154	1.09E-01	No	No
TLABC vs MABC	284	181	≥0.2	No	No
TLABC vs GBABC	256	209	≥0.2	No	No

Multiple-problem statistical comparison

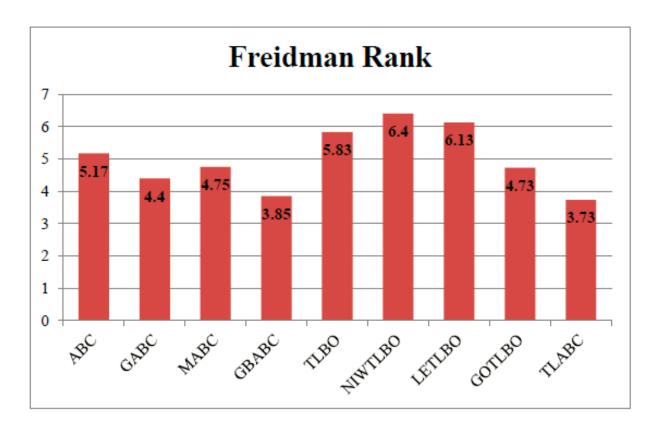


Figure Friedman rank of TLABC and the compared algorithms.



Convergence graphs

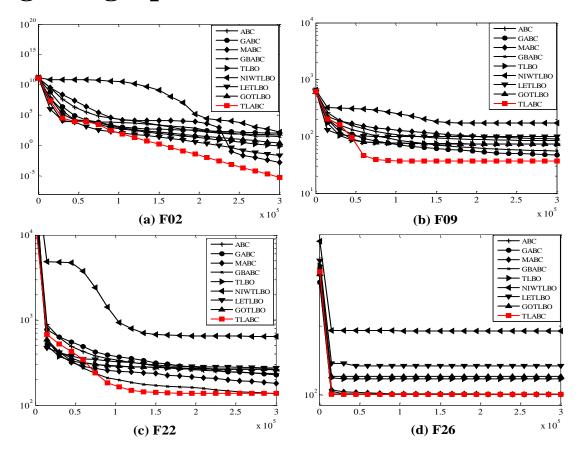


Figure Convergence graphs of TLABC and the compared algorithms on four typical functions

5 Conclusion

- A hybrid TLABC algorithm based on TLBO and ABC is proposed.
- TLABC combines good exploitation of TLBO and good exploration of ABC.
- TLABC provides a better balance between exploration and exploitation compared with the previous TLBO and ABC algorithms.
- TLABC is better than the compared TLBO and ABC algorithms on most of CEC2014 benchmark functions.



The End.

Thanks for Your Attentions.

