SELECTIVE TLBO

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Abstract: Teaching Learning Based Algorithm Optimization is one of the recent optimization algorithms which have outperformed most of the evolutionary and swarm intelligence-based optimization techniques. This paper discusses about an improved version of TLBO, called SPECIFIC TLBO [5][6]. The core difference in the TLBO and SPECIFIC TLBO lies in the idea of selectivity of candidates. This metaheuristic-based algorithm further involves addition of a new phase in TLBO. These alteration enables the algorithm to converge to the global solution at much faster convergence rate. The Specific TLBO - (STLBO) has been tested on well-known bench mark function and has been compared with TLBO, WTLBO and other evolutionary process.

Keyword -- bench mark function, convergence rate, fitness curve.

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1. INTRODUCTION

Optimization speaks of discovering one or more solutions which correspond to the extremities of one or more objectives. The need of finding such optimum solution comes from the need to plot minimums or maximums (local or global). When such optimization problem involves only one objective function they are defined as single objective optimization while those involving more than one objective function are referred as multi objective function.
The success of any optimization depends upon the convergence rate of the solution set rather than the iteration it takes to reach the global solution. TLBO outperforms ABC [2][3], PSO [4], GA [1] in the convergence time due to the fact that it does not need to tune any also algorithm specific parameters.
This work is an attempt to make TLBO perform better by improving its convergence rate as well as improving iteration count.

1.1 PROPOSED ALGORITHM

Specific TLBO (STLBO) differs from TLBO in two main aspects:
a. Selectivity of students in interactions.
b. Introduction of a new equation in LEARNER phase.
In terms of analogy, S-TLBO is based on the same analogy of a classroom environment where teacher is the most knowledgeable person and aims at teaching the students and improving their knowledge. The value of the objective function defines the marks scored by the individuals. The number of variables involved in the objective function resemble the number of subjects that the students study. The number of different values resemble the total number of students in the classroom.
Again, S-TLBO is divided into three phases on the basic of philosophy. They are:
1. Teacher Phase
2. Learner Phase
3. Introspection Phase

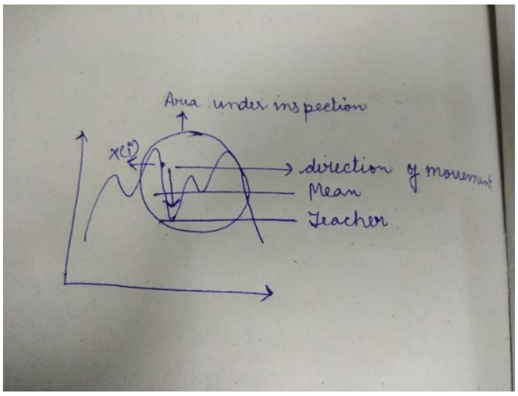
1. TEACHER PHASE
This phase is analogous to the initials of a classroom environment where a teacher teaches his students with no biasness with an aim to improve the average sum of the marks scored by them or simply improve the knowledge level of the class. The instructor is the most knowledgeable person in the closed system. Further, after the students learn the subjects, they collectively perform a group discussion for clarification of doubts and for introspection purpose. The teacher being the most knowledgeable person in the class, the learner who gets the best solution is often referred as the teacher.

Ideally in a group discussion, the entire class participates but in real world only the interested students participate in the group discussion and the others simply accept their statements. This can be seen in this following equation as mean. Mean resemble the conclusion of the group discussion in the classroom i.e., the average of the participated candidates.[7]

Y(i) = Y(i) + rand (0 1) *(teacher – mean*)

Here, Y(i) is the knowledge level of students initially
Rand (0 1) reflects the learning efficiency of student
Teacher reflects the best solution obtained
Mean* is the mean of the students involved in the discussion.
If the knowledge of individuals increases, they accept the teaching of the teacher and group discussion.

GRAPH



The direction of movement shows tendency to knowledge to flow in that direction.
The graphical representation is for a minimization problem.

2. LEARNER PHASE

Under this phase the students begin to interact among themselves in order to uplift their understanding level. As the iteration increases which resemble the number of exams the interaction level increases among the students until the saturation is reach. According to selectivity the number of students who wants to interact could be completely random.
Mathematically, this philosophy has been captured by the following equation.

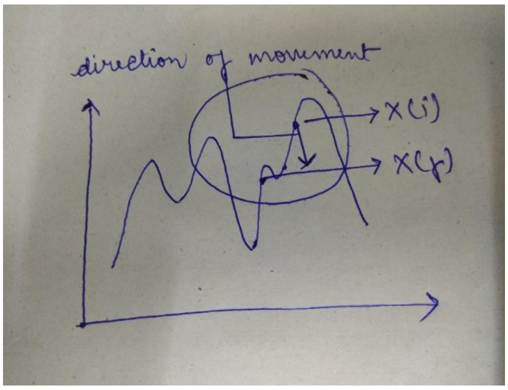
Y(i) = Y(i) + rand (0 1) *(Y(i) – Y(j)) if (i)<Y(j)

Or

Y(i) = Y(i) + rand (0 1) *(Y(j) – Y(i)) if Y(j) < Y(i)

The sign of (Y(i)- Y(j)) resemble the direction of flow of knowledge among two students.

GRAPH



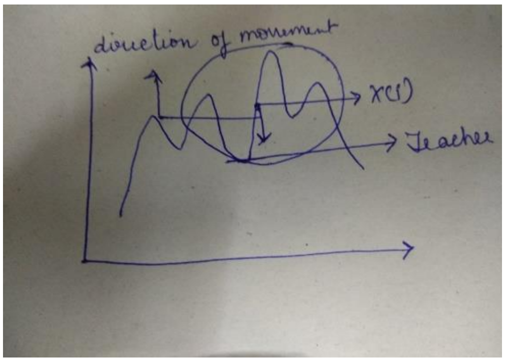
The direction of movement resembles the accepting of knowledge of a student from another student with better knowledge.
Again, the graph is plotted for a minimization statement.

3. INTROSPECTION

This is the phase where selective student from the class reach out to the teacher after the classes and interaction among students. This is done for clarification of doubts and better understanding.

The number of students interacting can be completely random.
Mathematically, it can be expressed by:
Y(i) = Y(i) + rand (0 1) (teacher – Y(i))

GRAPH



The direction of movement resembles interested students moving towards teacher that is clarification of their doubts directly by teacher.
Again, this graph is for a minimization statement.

1.1.1 ILLUSTRATION OF WORKING OF ALGORITHM

We have considered an unconstrainted benchmark function of Sphere to illustrate the working of S-TLBO algorithm. The objective function is to obtain the values of Y(i) that minimize the value of the Sphere
SPHERE FUNCTION:

$$\Sigma(y^2)$$

CONSTRAINTS:

$$-99 \leq y_i \leq 99$$

The known solution to this benchmark function is 0 for all *yi* values of 0.
To illustrtae the S-TLBO algorithm,

Let's consider the following assumptions: a population size of 5 (i.e., candidate solutions); two y_1 and y_2 design variables; and a termination condition of two iterations. The initial population is randomly generated within the variable range (Table1). Since it is a minimization function, the instructor is the lowest value of f(y).

Table 1:

Candidates	Y1	Y2	F(y)	
1	-5	18	349	
2	14	63	4165	
3	70	-6	4936	
4	-8	7	113	Teacher
5	12	-18	468	

We can see the best solution corresponds to candidate number 4 and is considered as teacher. Taking random no as 0.52 for y_1 and 0.49 for y_2.

TEACHER PHASE
Applying teacher phase eq we have:
Mean = y_1 = 83/5= 16.6, y_2 = 64/5= 12.8

Candidates	Y1	Y2	F(y)
1	-17.792	15.158	546.32
2	1.208	60.158	3620.44
3	57.208	-8.842	3350.93
4	-20.792	4.158	449.59
5	-0.792	-20.842	435.01

Updating Values, we get:

Candidates	Y1	Y2	F(y)	
1	-5	18	349	
2	1.208	60.158	3620.44	
3	57.208	-8.842	3350.93	
4	-8	7	113	Teacher
5	-0.792	-20.842	435.01	

LEARNER PHASE
Let 1st candidate interact with 4th, 2nd with 5th, 3rd with 1st, 4th and 5th don't interact.
Again, let $r1$=0.52 and $r2$= 0.49
Applying equation, we have new values as:

Candidates	Y1	Y2	F(y)	
1	-6.56	12.61	202.04	
2	0.168	20.468	418.96	
3	24.859	-21.994	1101.70	
4	-8	7	113	Teacher
5	0.792	-20.842	435.01	

Assuming out of the 5 candidate 1, 2, 3 interact in the group discussion. Applying equation and updating corresponding to teacher phase we have:

Candidates	Y1	Y2	F(y)	
1	-6.56	12.61	202.04	
2	0.168	20.468	418.96	
3	24.859	-21.994	1101.70	
4	-8	7	113	Teacher
5	0.792	-20.842	435.01	

INTROSPECTION PHASE
Now, the few interested students say 1st, 4th, 5th interact with the teacher for their doubt clarification.
Applying equation of introspection phase and updating value, we have
Again $r1$=0.52 and $r2$=0.49

Candidates	Y1	Y2	F(y)	
1	-7.308	9.861	150.64	
2	0.168	20.468	418.96	
3	24.859	-21.994	1101.01	
4	-8	7	113	
5	-4.54	-7.19	72.437	Teacher

SECOND ITERATION

Table 2:

Candidates	**Y1**	**Y2**	**F(y)**	
1	-7.308	9.861	150.64	
2	0.168	20.468	418.96	
3	24.859	-21.994	1101.01	
4	-8	7	113	
5	-4.54	-7.19	72.437	Teacher

We can see the best solution correspond to candidate number 5 and is considered as teacher. Taking random no as 0.52 for y_1 and 0.49 for y_2.

TEACHER PHASE

Applying teacher phase eq we have:

Mean = y_1 = 5.179/5= 1.03, y_2 = 8.145/5= 1.629

Candidates	**Y1**	**Y2**	**F(y)**	
1	-10.204	5.539	134.80	
2	-2.728	16.146	268.13	
3	-21.962	-26.315	1174.80	
4	-10.896	2.678	125.89	
5	-7.436	-11.511	187.79	

Updating Values, we get:

Candidates	**Y1**	**Y2**	**F(y)**	
1	-10.204	5.539	134.80	
2	-2.728	16.146	268.13	
3	24.859	-21.994	1101.01	
4	-8	7	113	
5	-4.54	-7.19	72.437	Teacher

LEARNER PHASE

Let 1st candidate interact with 5th, 2nd with 4th, 3rd with 1st. 4th and 5th don't interact. Again, let $r1$=0.52 and $r2$= 0.49. Applying equation, we have new values as:

Candidates	**Y1**	**Y2**	**F(y)**	
1	-13.149	-0.698	173.38	
2	-5.469	11.664	165.95	
3	5.094	-35.485	1285.13	
4	-8	7	113	
5	-4.54	-7.19	72.437	Teacher

Assuming out of the 5 candidate 1, 2, 3 interact in the group discussion. Applying equation and updating corresponding to teacher phase we have:

Candidates	**Y1**	**Y2**	**F(y)**	
1	-10.204	5.539	134.80	
2	-5.469	11.664	165.95	
3	24.859	-21.994	1101.01	
4	-8	7	113	

5	-4.54	-7.19	72.437	Teacher

INTROSPECTION PHASE

Now, the few interested students say 1st, 2nd, 4th interact with the teacher for their doubt clarification. Applying equation of introspection phase and updating value, we have

Again $r1$=0.52 and $r2$=0.49

Candidates	**Y1**	**Y2**	**F(x)**	
1	-7.258	-0.698	53.16	
2	-4.98	2.425	30.68	Teacher
3	24.859	-21.994	1101.01	
4	-6.200	0.046	38.44	
5	-4.54	-7.19	72.437	

EXPERIMENTAL EVALUTION

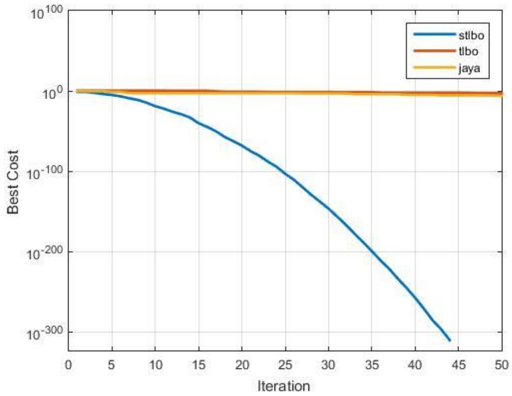
The initial thing we need is a fair time measurement to compare the algorithms' speeds. We cannot use the no. of iterations or generations as a time measure because the algorithms perform varying amounts of work in their inner loops and have varying population sizes. Therefore, rather than using the number of iterations as a measure of computation time, we opt to use the no. of fitness function evaluations (FEs). Because of the stochastic nature of the algorithms, the outcomes of two subsequent runs typically do not coincide.

As a result, I ran each algorithm several times independently using different random number generator seeds. We have collected several FEs for various algorithms to compare with STLBO. Nevertheless, we have set a cap of 50 FEs for STLBO.
Finally, I want to emphasise that MATLAB was used to implement all of the experiment codes.

SPHERE FUNCTION

$f(x)= \Sigma(x^2)$ $\qquad f_{min} =0$

STLBO VS TLBO



The above graphs have been plotted for 50 iterations and as we can see that the convergence of the graph for STLBO is better than the normal TLBO.
It should also be noted that the number of values updated for x and y is greater than that of TLBO. But it should be also kept in mind even in 500+ iterations TLBO fail to achieve such accuracy which is far more than the updated values of x.
The reason for a greater number of updated values is that during learner phase, as iteration i.e., number of exam/classes passes interaction increases and thus student interact with almost most of classmates and thus helping them to increase their knowledge.
STLBO puts a lot of weightages on interaction and passing of information. As interaction increases almost most of the information is available for each student and that is why it outperforms TLBO which limits number of interactions as 1.

CONCLUSION

An enhanced version of the fundamental Teaching-Learning-Based Optimisation (TLBO) technique is proposed in this study, and its performance is evaluated in comparison to that of the original TLBO and other evolutionary computation techniques, such as JAYA, PSO, and TLBO and its variants. The SELECTIVE-TLBO (STLBO) strategy that has been suggested is based on the concept of selectivity, which is expressed in students' interests. Additionally, individuals who are interested can speak with the teacher at the conclusion of the day to get their questions answered. The candidates' interactions may be entirely arbitrary. The suggested approach in our study makes the process easier and can produce better results than the basic TLBO algorithm, despite the fact that the addition of a parameter like selectivity and a new phase could seem to increase the complexity of the fundamentals of TLBO algorithm. The proposed STLBO is able to find the global optima results at a faster computation time. We need to conduct additional research to demonstrate how this method works with various benchmark functions and actual data clustering issues.

2. EQUATIONS

$$Y(i) = Y(i) + rand\ (0\ 1) * (teacher - mean*) \tag{1}$$

$$\begin{gathered} Y(i) = Y(i) + rand\ (0\ 1) * (Y(i) - Y(j))\ \text{if}\ Y(i) < Y(j) \\ \text{Or} \\ Y(i) = Y(i) + rand\ (0\ 1) * (Y(j) - Y(i))\ \text{if}\ Y(j) < Y(i) \end{gathered} \tag{2}$$

$$Y(i) = Y(i) + rand\ (0\ 1)\ (teacher - Y(i)) \tag{3}$$

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3. FIGURES

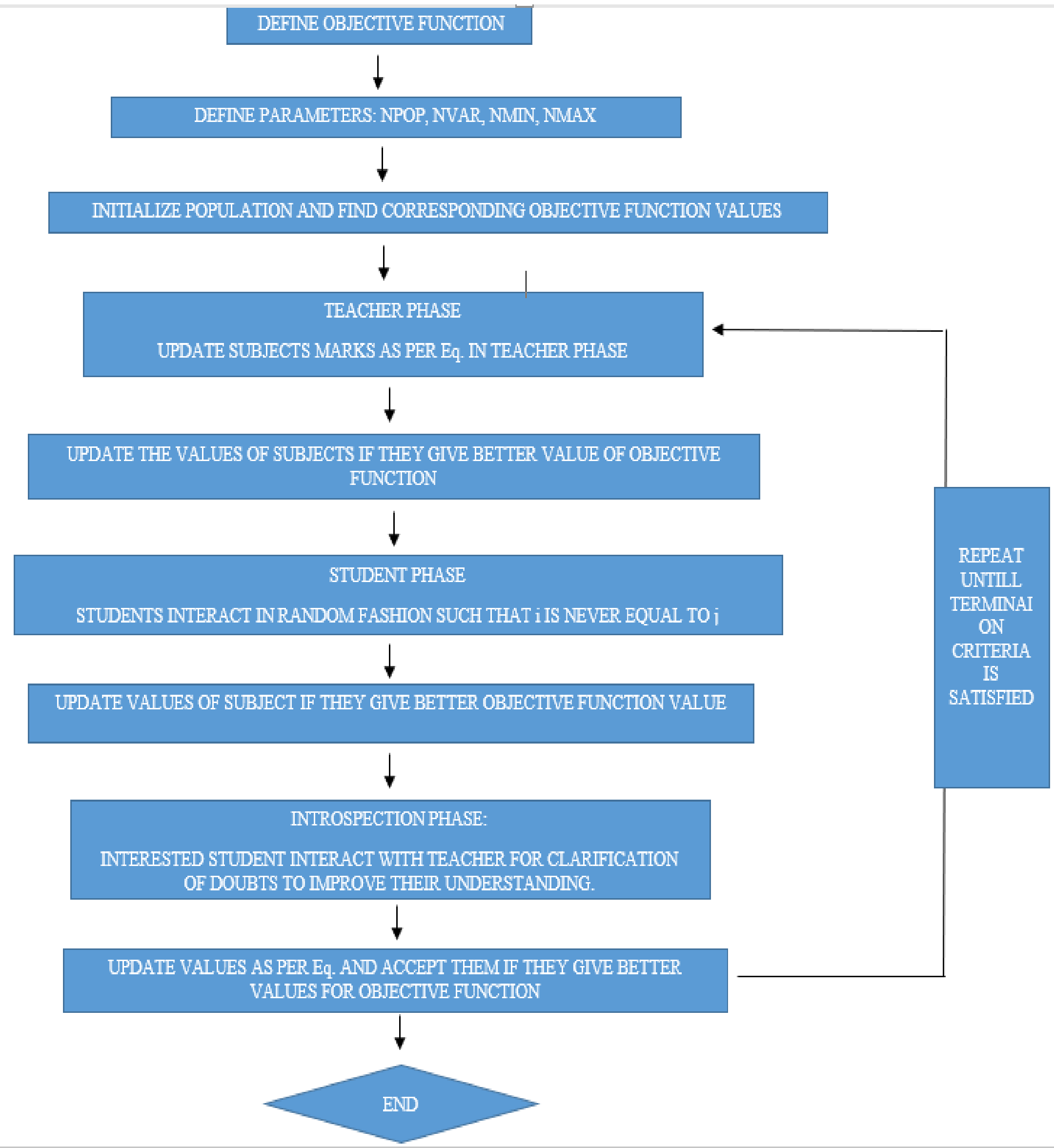

Figure 1. Flow Chart For STLBO.

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