

Comments on “A note on multi-objective improved teaching-learning based optimization algorithm (MO-ITLBO)”

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ABSTRACT

A note published by Chinta et al. (2016) [Chinta, S., Kommadath, R. & Kotecha, P. (2016) A note on multi-objective improved teaching–learning based optimization algorithm (MO-ITLBO). *Information Science*, 373, 337-350.] reported some impediments in implementation of MO-ITLBO algorithm. However, it is observed that their comments are based on incorrect understanding of TLBO, ITLBO and MO-ITLBO algorithms. Their raised issues are thoroughly addressed in this paper and it is proved that MO-ITLBO algorithm has no lacunae.

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1. Introduction

The real world optimization problems consist of many objectives that need to be optimized, simultaneously. Unlike single objective optimization problems (SOOPs) there is no single solution to multi-objective optimization problems (MOOPs). Therefore, in MOOPs the attempt is always towards finding the set of Pareto-optimal solutions. Obtaining the Pareto-optimal set of solutions is theoretically a challenging task and, therefore, has attracted the attention of many optimization researchers.

A number of population based metaheuristic multi-objective optimization algorithms have been proposed by researchers (Zhou et al., 2011). However, a major issue in implementation of population based metaheuristic optimization algorithms is the tuning of common control parameters and algorithm-specific parameters which increases the burden on the user. Teaching-learning-based optimization (TLBO) algorithm was proposed by Rao et al. (2011) as a algorithm-specific parameter-less algorithm. The TLBO algorithm has been applied widely by the researchers in various disciplines of engineering (Rao, 2016a; Rao, 2016b).

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Different multi-objective versions of TLBO algorithm have been also developed by researchers (Li et al., 2014; Zou et al., 2013; Medina et al., 2014; Yu et al., 2015; Sultana & Roy, 2014, Rao et al., 2016). Rao and Patel (2014) applied the multi-objective improved teaching-learning based optimization (MO-ITLBO) algorithm to solve the multi-objective benchmark functions of CEC 2009 and showed its effectiveness. Later, Patel and Savsani (2016) proposed the same work but with the addition of Friedman's rank test.

Recently, Chinta et al. (2016) published a note on the MO-ITLBO algorithm by Rao and Patel (2014) published in *International Journal of Industrial Engineering Computations* and Patel and Savsani (2016) in *Information Sciences*. The authors feel that there are impediments in the implementation of MO-ITLBO algorithm. However, it is observed that the issues raised by Chinta et al. (2016) are evolved out of misunderstandings regarding the working of MO-ITLBO algorithm. Chinta et al. (2016) raised many questions on the work of Rao and Patel (2014) and Patel and Savsani (2016). However, it seems that neither Rao nor Patel was involved in the review work of Chinta et al. (2016) nor their opinions were sought. This paper aims to address the note of Chinta et al. (2016) thoroughly and to prove that MO-ITLBO algorithm has no lacunae.

2. Comments on the note of Chinta et al. (2016)

The comments on the note of Chinta et al. (2016) on various steps of MO-ITLBO algorithm such as selection of teacher; assigning learners to teachers; teacher phase; learner phase; external archive; adaptive teaching factor and exploration factor; removal of duplicate solution; updating population members; computational time; number of variables; random seed; runs and plots; code and notations and schematic diagram of MO-ITLBO algorithm are addressed in the following sub-sections.

2.1 Selection of teachers

This step includes determination of (i) the chief teacher and (ii) the teacher for each group. Chinta et al. (2016) reported difficulties in the implementation of these two steps due to misunderstanding of the working of MO-ITLBO algorithm. The replies to the note of Chinta et al. (2016) on the working of MO-ITLBO algorithm are as follows.

2.1.1 Determination of chief teacher

In MOOPs, as a solution improves in terms of one objective it may deteriorate in terms of the other objectives, if the objectives are mutually conflicting in nature. In the case of MO-ITLBO algorithm, a user can select any solution which is best in terms of any objective chosen randomly out of the multiple objectives as the 'chief teacher' of the class. If a particular solution is the best with respect to one objective, either of the three cases are possible (1) the solution may be best with respect to other objective(s) also or (2) the solution may be poor with respect to other objective(s) or (3) the solution may be the best with respect to some objectives and poor with respect to some other objectives. In either of the three cases the particular solution is capable of improving the result of the class in terms of whichever objective it is superior. Therefore, the 'chief teacher' can be easily decided by considering the value of objective function of the solutions in the population in any one of the objective chosen randomly out of the multiple objectives.

It is implicit that this approach of deciding the 'chief teacher' by considering the value of the objective function of the solutions in any one of the objective chosen randomly out of the multiple objectives ensures good diversity, as all the solutions in the class get a fair chance of improving in different objectives in every iteration. The same concept was used by Rao and Patel (2014) and Patel and Savsani (2016) for selection of teacher, and therefore, it is not required to explicitly specify a separate strategy for selection of teacher in the MO-ITLBO algorithm. The statement of Chinta et al. (2016) that "*Under*

these circumstances, the article does not provide any strategy to determine the best solution which is crucial for the working of the algorithm” is not meaningful. In general, it is adequate to say that one of the solutions which is the best with respect to any of the objectives chosen randomly out of the multiple objectives can be treated as the ‘chief teacher’ of the class.

Furthermore, the strategy 1A.1 suggested by Chinta et al. (2016) is completely different from the approach used by Rao and Patel (2014) and Patel and Savsani (2016). The strategy 1A.2 proposed by Chinta et al. (2016) for the selection of ‘chief teacher’, is not new and is the same as the approach used Rao and Patel (2014) and Patel and Savsani (2016). In strategy 1A.3 Chinta et al. (2016) mentioned that *“One of the anonymous reviewers of this article has suggested another strategy....”*. This statement shows that strategy 1A.3 is suggested by an anonymous reviewer and is not an original idea of Chinta et al. (2016). Also strategy 1A.3 is completely different from the approach used by Rao and Patel (2014) and Patel and Savsani (2016).

2.1.2 Determination of group of teachers

Rao and Patel (2014) had given a pseudo-code for ‘determination of group teachers’ in Fig. 1. In Fig. 1, the term $f(.)$ is written in general sense and $f(.)$ may represent any objective out of the multiple objectives. However, to maintain consistency, it is implicit that $f(.)$ in Fig. 1 of Rao and Patel (2014) represents the same objective which was previously chosen randomly out of the multiple objectives for determination of the ‘chief teacher’ in section 2.1.1. In this context, the phrase ‘closeness of the solutions’ can only mean closeness of objective function value of the solutions corresponding to the particular objective which is represented by $f(.)$. There is no need of any explicit explanation on ‘closeness of the solutions’. Therefore the statement of Chinta et al. (2016) that *“the article does not explicitly provide any strategy to determine ‘closeness’ in the context of multiple objectives”* is incorrect.

Assuming that the user of MO-ITLBO is well aware about the preliminaries of multi-objective optimization, Rao and Patel (2014) and Patel and Savsani (2016) had implicitly specified the strategy for closeness measure. Furthermore, Chinta et al. (2016) described two strategies (1B.1 and 1B.2) for forming groups and selection of teachers for the groups. These two approaches suggested by Chinta et al. (2016) in their paper are completely different from the approach of Rao and Patel (2014) and Patel and Savsani (2016).

2.2 Assigning learners to teachers

In the pseudo-code given by Rao and Patel (2014) in Fig. 1 for selection of teachers of the groups and distributing students to different groups the term $f(.)$ was written in general sense and $f(.)$ may represent any objective out of the multiple objectives. However, to maintain consistency, it is implicit that $f(.)$ in Fig. 1 of Rao and Patel (2014) represents the same objective which was previously chosen randomly out of the multiple objectives for determination of the ‘chief teacher’ in section 2.1.1.

Now, based on the objective function value $f(.)$ the selection of teachers for the groups and distribution of solutions to these groups can be done following the pseudo-code given by Rao and Patel (2014). Therefore, pseudo-code provided by Rao and Patel (2014) is self-explanatory and there is no need to provide any explicit strategy for selection of teachers for groups and assignment of students to various groups in the context of MOOPs. Thus, the statement of Chinta et al. (2016) that *“Despite the critical nature of this step, the article does not provide any details about the strategy used for assignment of students to various groups in the context of MOOP”* is incorrect. The approach of Rao and Patel (2014) and Patel and Savsani (2016) for selecting the teachers of the groups and assigning solutions to these groups is correct and undisputable in the context of MOOPs.

2.3 Teacher phase

The teacher phase of MO-ITLBO algorithm involves (i) Calculating the mean result of each group of learners in each subject (ii) Utilizing the adaptive teaching factor for calculating the difference mean of that group (iii) updating the learners according to *learning through tutorial phase*. The comments of Chinta et al. (2016) regarding the implementation of *teacher phase* of MO-ITLBO algorithm are addressed as follows.

2.3.1 Modifying student

In the MO-ITLBO algorithm the solutions are modified according to the '*learning through tutorial*' phase using Eq. (4a) and Eq. (4b) given by Rao and Patel (2014) or Eq. (6a) and Eq. (6b) given by Patel and Savsani (2016). In the case of two competing solutions $X_{j,i}^h$ and $X_{j,i}^k$ a decision is required to be made as to which solution will share knowledge with the other. In single objective optimization the solution which has a better objective function value shares knowledge with the solution with poor objective function value. The same is reflected in the above equation. The above equation can also be applied to MOOPs, as it is, because in the case of MOOPs also if a solution $X_{j,i}^h$ is better than a solution $X_{j,i}^k$ in terms of any one objective $f(.)$, irrespective of the other objective(s), then solution $X_{j,i}^h$ is capable of sharing knowledge with solution $X_{j,i}^k$ because solution $X_{j,i}^h$ may improve solution $X_{j,i}^k$ in terms of $f(.)$ irrespective of whether solution $X_{j,i}^h$ is superior, inferior or equally good with respect to solution $X_{j,i}^k$ in terms of the remaining objectives.

The Eq. (4a) and Eq. (4b) are written by Rao and Patel (2014) in general terms and term $f(.)$ means any one objective chosen randomly out of the multiple objectives. However, the solutions $X_{j,i}^h$ and $X_{j,i}^k$ may be compared by considering the objective function value of any one objective and it is implicit that it should be chosen randomly from among the multiple objectives to ensure diversity. It is clear that the Eq. (4a) and Eq. (4b) of Rao and Patel (2014) are very much applicable to the multi-objective optimization scenario. Therefore, the statement of Chinta et al. (2016) that "*In context of MOOP, it is possible that the student h and the student k are non-dominated and thus it is not clear as to which of the above mathematical expression would be applicable in such a scenario*" is not correct. Furthermore, Chinta et al. (2016) suggested two strategies (3A.1 and 3A.2) for modifying the solutions in teacher phase. However, both the strategies (3A.1 and 3A.2) suggested by Chinta et al. (2016) in their paper are very different from the approach used by Rao and Patel (2014) and Patel and Savsani (2016).

2.3.2 Updating student

Chinta et al. (2016) stated that "*One of the anonymous reviewers have pointed out that in multi-objective perspective, 'if the result has improved' can be interpreted as a solution that is 'totally dominating', i.e., a solution which is better in all objectives. Hence it is necessary to clarify whether 'if the results have improved' corresponds to a non-dominated solution or a totally dominating solution*".

If X^{mod} is the modified solution and X^k is the old solution, then the phrase '*if the result has improved*' can be interpreted as X^{mod} has improved at least in terms of one objective. From the basic concept of dominance it can be inferred either X^{mod} totally dominates X^{old} , or X^{mod} and X^{old} both are non-dominated with respect to each other. In such case, following the philosophy of TLBO algorithm, it is obvious that, if X^{mod} totally dominates X^{old} then X^{mod} replaces X^{old} . Furthermore, Rao and Patel (2014) mentioned that "*The MO-ITLBO algorithm uses a fixed size archive to maintain the good solutions obtained in every iteration. The ε - dominance method is used to maintain the archive (Deb et al. (2005))*". Therefore it is clear that, in a scenario where X^{mod} and X^{old} both are non-dominated, then "*population acceptance*

procedure” and *“archive acceptance procedure”* suggested by Deb et al. (2005) is followed by Rao and Patel (2014) and Patel and Savsani (2016). As the paper (Deb et al., 2005) was well cited by Rao and Patel (2014) and Patel and Savsani (2016) and there is no ambiguity in this regard.

The points mentioned in the above discussion are basic and explicit discussion on such points is not necessary. Therefore, the statement of Chinta et al. (2016) that *“However, the article does not discuss as to how MO-ITLBO handles a scenario in which X^{mod} and X^k are non-dominated solutions”* is not meaningful.

2.3.3 Adaptive factor

In the basic TLBO algorithm the teaching factor (T_F) is chosen heuristically either 1 or 2 which mimics the scenario that a student is either unable to learn anything from the teacher or learns everything from the teacher. In actual teaching-learning scenario the teaching factor will not be always at its extreme values (i.e. 1 or 2) but varies in between (1 and 2) also in a continuous manner. This means that the teaching factor can also be a decimal fraction between 1 and 2. The students may learn in any proportion from the teacher. Therefore, in the ITLBO algorithm (Rao & Patel, 2013) and MO-ITLBO algorithm (Rao & Patel, 2014; Patel & Savsani, 2016) the value of teaching factor is fixed adaptively, in every iteration, using Eq. (1a) and Eq. (1b).

$$(T_F)_{s,i} = \left(\frac{f(X^k)}{T_s} \right)_i \quad \text{if } T_s \neq 0 \quad (1a)$$

$$(T_F)_i = 1 \quad \text{if } T_s = 0 \quad (1b)$$

where $f(X^k)$ is the result of any learner k associated with the group ‘ s ’ and T_s is the result of the teacher of the same group at iteration i .

In a multi-objective scenario, it is implicit that in the MO-ITLBO algorithm, the objective function value $f(X^k)$ corresponding to the objective which was previously chosen for identifying the teachers of the groups must be used to determine the teaching factor T_F to maintain consistency. Therefore, there is no need to separately specify the objective function value that should be used to determine the teaching factor in multi-objective scenarios. Thus, the statement of Chinta et al. (2016) that *“The article does not clearly specify the objective function value that should be used to determine the teaching factor”* has no meaning.

2.3.4 Updating teacher

It is very clear from the Fig. 2 and Appendix-A provided by Rao and Patel (2014) that selection of ‘chief teacher’ and selection of ‘other teachers’ (i.e. teachers for the groups) is performed before the commencement of the teacher phase. After the solutions are modified in the teacher phase all the groups are updated by considering the newly modified values of the solutions, this step is clearly shown in Appendix A provided by Rao and Patel (2014). Since all the groups are updated after the teacher phase it is obvious that the teachers for the updated groups have to be freshly selected. The approach used by Rao and Patel (2014) for selection of teachers for the groups is implicit and has already been discussed in section 2.1.2. Therefore, the statements of Chinta et al. (2016) that *“The article does not clearly describe whether the modified member (who might be superior to all others in the group at the end of the teacher phase) becomes the new teacher for the learner phase of the group or does the current teacher continue to be the teacher for the learner phase”* is not meaningful.

2.4 Learner phase

In the MO-ITLBO algorithm the solutions are modified according to the ‘*Self-motivated learning*’ phase using the following equation given by Rao and Patel (2014) and Patel and Savsani (2016).

$$X'_{j,i} = \left[X_{j,i}^p + r_i (X_{j,i}^p - X_{j,i}^q) \right] + \left[r_i (X_{j,i}^s - E_F X_{j,i}^p) \right], \quad \text{if } f(X^p) < f(X^q) \quad (2a)$$

$$X'_{j,i} = \left[X_{j,i}^p + r_i (X_{j,i}^q - X_{j,i}^p) \right] + \left[r_i (X_{j,i}^s - E_F X_{j,i}^p) \right], \quad \text{if } f(X^q) < f(X^p) \quad (2b)$$

It is obvious that Eq. (2a) and Eq. (2b) mentioned above are applicable even if solution p and solution q are non-dominated with respect to each other because if solution p is non-dominated with respect to solution q , then it implies that solution p is better than solution q at least in terms of one objective, assuming that solution p and solution q are not the duplicate solutions. Therefore, solution p can share its knowledge with solution q with respect to the particular objective(s) in which it is better than solution q which may improve solution q in those particular objective(s). The same is true if solution q is non-dominated with respect to solution p . Thus, there is no need to explicitly specify any strategy to handle multi-objective optimization scenarios. Therefore, the statement of Chinta et al. (2016) that “*However, the article does not provide any strategy to handle such circumstances*” is not meaningful.

Chinta et al. (2016) provided two strategies (4.1 and 4.2) to handle MOOPs. However, both the strategies suggested by Chinta et al. (2016) are very different from the approach used by Rao and Patel (2014) and Patel and Savsani (2016). Furthermore, Chinta et al. (2016) did not provide any logical explanation as to how strategies (4.1) and (4.2) can effectively improve the quality of the Pareto-front and the performance of the algorithm.

It has already been proved in section 2.3.2 that the strategy suggested by Rao and Patel (2014) and Patel and Savsani (2016) to handle newly modified solution is effective in the multi-objective optimization scenarios and does not suffer from any drawback. Therefore, the statement of Chinta et al. (2016) that “*However, this strategy also suffers from the same drawbacks that had been explained for updating the students in the teacher phase*” is incorrect.

2.5 External archive

It is clear that a user can select the value of ε based on their own discretion following the guideline given by Deb et al. (2005). In their work, the aim of Rao and Patel (2014) and Patel and Savsani (2016) was to show the effectiveness of MO-ITLBO algorithm in solving MOOPs and encourage other researchers to apply MO-ITLBO algorithm to their respective MOOPs. A value of ε which is suitable for the MOOPs considered by Rao and Patel (2014) and Patel and Savsani (2016) may not be suitable for other MOOPs. Researchers can set the value of ε by means of trial and error and try to identify the value of ε which best suits their MOOP.

Chinta et al. (2016) could have used the same procedure in order to set the value of ε in solving the MOOPs of CEC 2009. Finally, it can be said that the absence of exact value of ε used by Rao and Patel (2014) and Patel and Savsani (2016) does not stop the users from applying MO-ITLBO to their own MOOPs because the methodology to select the value of ε is well documented in the literature and the relevant paper was also cited by Rao and Patel (2014) and Patel and Savsani (2016).

2.6 Adaptive teaching factor and exploration factor

MO-ITLBO algorithm is a metaheuristic optimization algorithm. The algorithm automatically selects the value of E_F randomly either 1 or 2. Selection of E_F in MO-ITLBO algorithm is a heuristic step and requires no user intervention. Therefore, in order to preserve the heuristic nature of the algorithm it is not

reasonable to convert each and every heuristic step into an adaptive step. Thus, Rao and Patel (2014) and Patel and Savsani (2016) allowed the algorithm to randomly choose the value of E_F either 1 or 2. Therefore, the statement of Chinta et al. (2016) that “...the articles do not provide any reason for fixing the value of the exploration factor using ($E_F = \text{round}(1+r_i)$)” is not meaningful.

Furthermore, Rao and Patel (2014) and Patel and Savsani (2016) provided one application by selecting the E_F randomly either 1 or 2. However, if someone wants to determine the value of E_F adaptively, then he/she may do so and check its effect on the performance of the algorithm.

2.7 Removal of duplicate solutions

Rao and Patel (2014) clearly stated that “The total number of function evaluations in the proposed algorithm is = $\{2 \times \text{population size} \times \text{number of generations}\} + \{\text{function evaluations required for the duplicate elimination}\}$ ”.

It is absolutely clear from the above equation that a complete duplicate removal process was employed by Rao and Patel (2014). Further, Rao and Patel (2014) explicitly took into account the number of function evaluations spent by MO-ITLBO algorithm for duplicate elimination in the above equation given for calculating the maximum objective function evaluations required by MO-ITLBO algorithm. In the opinion of Mernik et al. (2015) such an approach for deciding the ‘function evaluations required for duplicate removal’ is imprecise, seems to be biased and invalid. However, previous researchers had used algorithms such as GA, SA, PSO, ACO, ABC, DE, ES, NSGA, SPEA, NSGA-II, VEGA, etc. but did not mention about function evaluations required for duplicate removal by those algorithms for solving optimization problems. In fact, the previous researchers had not even considered the concept of function evaluations required for duplicate elimination. Actually, there may not be any such need (Rao, 2016b).

Mernik et al. (2015) attempted to invalidate the approach followed by Rao and Patel (2012) for computing the function evaluations required for duplicate removal. However, Mernik et al. (2015) themselves did not compute any function evaluations required for duplicate elimination while describing certain misconceptions in comparing different versions of ABC algorithm. In general, the function evaluations required by well-known algorithms is calculated as (population size \times no. of generations), however, the function evaluations required by TLBO algorithm is calculated as (2 \times population size \times no. of generations).

Therefore, the statement of Chinta et al. (2016) that “As the duplicate removal step requires evaluation of objective function which in turn governs the termination of the algorithm, it is necessary to explicitly know whether the duplicate removal step is included in MO-ITLBO algorithm” raises some questions regarding their understanding of the working of metaheuristic optimization algorithms, in general, and their understanding of MO-ITLBO algorithm, in particular.

2.8 Updating population members

The flowchart for MO-ITLBO in Fig. 2 given by Rao and Patel (2014) and the demonstration of TLBO and ITLBO algorithms in Appendix A given by Rao and Patel (2014) clearly depicts that the complete class of learners first undergoes teacher phase and subsequently the entire class of learners undergoes learner phase, therefore the reporting of MO-ITLBO algorithm in Rao and Patel (2014) and Patel and Savsani (2016) and actual implementation of MO-ITLBO algorithm are consistent and free from any discrepancies. Thus the statement of Chinta et al. (2016) that “This issue also exists in MO-ITLBO algorithm and it is not explicitly specified if a member of the group undergoes teacher phase followed by the learner phase or if the entire group completes the teacher phase before undergoing the learner phase” is not correct.

2.9 Computational time

The steps such as number of teachers concept, adaptive teaching factor, tutorial training and self-motivated learning are introduced in the ITLBO and MO-ITLBO algorithms in order to enhance the exploration and exploitation capabilities of the algorithm (Rao and Patel, 2014) as compared to the basic TLBO algorithm.

Undoubtedly, the inclusion of these new steps will increase the computational effort and computational time required by the algorithm per iteration. However, with the improved exploration and exploitation capability the ITLBO algorithm and MO-ITLBO algorithm may require fewer number of iterations to search the space and may converge at the global optima within a few number of function evaluations. This may reduce the overall computational effort and the overall computational time required by the ITLBO algorithm and MO-ITLBO algorithm. Thus the statement of Chinta et al. (2016) that “... *the amount of computational time required in ITLBO algorithm could be higher than the base TLBO*” may not be true.

In general, the optimization researchers calculate the number of objective function evaluations required by any algorithm as $N_G \times N_c$, where N_G is the number of generations and N_c is the class size. The number of function evaluations required by TLBO algorithm is calculated as $2 \times N_G \times N_c$ (Rao, 2016b). However, Chinta et al. (2016) calculated the objective function evaluations required by TLBO and ITLBO algorithms as $N_c \times (1 + 2 \times N_G)$ which is unusual, if not incorrect.

2.10 Number of variables

It was clearly mentioned by Rao and Patel (2014) that the computational challenge provided by CEC 2009 competition had been considered in their work. CEC 2009 competition requires the participants to demonstrate the performance of their algorithm with 30 variables. Rao and Patel (2014) had already mentioned that “*The detailed mathematical formulations of the considered test functions are given in Zhang et al. (2009)*”. In that mathematical expression it is clearly mentioned that $n = 30$ (i.e. number of variables equal to 30).

Furthermore, Rao and Patel (2014) and Patel and Savsani (2016) compared the results of MO-ITLBO algorithm with a number of other algorithms which had considered the same challenge provided by CEC 2009. Therefore, it is clear that the number of variables used by Rao and Patel (2014) and Patel and Savsani (2016) was the same as that defined by CEC 2009. Thus the statement of Chinta et al. (2016) that “*The article does not seem to specify the number of variables used in the benchmark problems*” is incorrect.

2.11 Random seed

In the metaheuristic optimization algorithms it is unhealthy to use the same set of random numbers or a predefined set of random numbers in every simulation run of the algorithm. Using a constant random seed results in selection of random numbers from the same random number series and the same sequence of random numbers is followed. This may increase the tendency of the algorithm to converge at the same Pareto-front in different independent runs.

It is obvious that a researcher would not tend to use a fixed or predefined value of random seed. The random seed itself should be chosen randomly in every simulation run of the algorithm in order to allow the algorithm to work liberally and converge at the true Pareto-front in a probabilistic manner. Therefore, there must not be any user intervention as far as selection of random seed is concerned.

Hence, in order to allow liberal functioning of MO-ITLBO algorithm, Rao and Patel (2014) and Patel and Savsani (2016) might not have used a fixed or predefined set of random seed. Thus the statements of Chinta et al. (2016) that *“Thus it would have been beneficial if the article had specified the seed (and their selection for multiple runs) and the algorithm that was used to generate the random numbers”* is not meaningful.

2.12 Runs and Plots

It is quite obvious that Fig. 3 and Fig. 4 of Rao and Patel (2014) are for the run in which the MO-ITLBO algorithm had shown its best performance and there is no need of misinterpretation in this regard. The previous researchers had also attempted the same problems and reported the Pareto fronts without mentioning the particular run number. It was implicit that those plots were for the run in which those algorithms had shown their best performance. Thus, the statement of Chinta et al. (2016) that *“However, it is not clear as to which of the 30 runs have been plotted....”* is not meaningful.

2.13 Code

A demonstration of TLBO and ITLBO algorithms on Rastrigin function was given by Rao and Patel (2014) as Appendix A in their paper. Readers can make use of the demonstration to develop their own code suiting to their application. Furthermore, many new algorithms and the improved versions of existing algorithms have been proposed by various researchers and are available in the literature. The codes of all the versions of those algorithms are not public. It is not necessary that the code of every version is to be made public. Once the pseudo-code, flowchart and/or steps of the algorithm are explained in the paper then the peers are expected to understand the same instead of looking or searching for the public code.

2.14 Notations and schematic diagram of MO-ITLBO algorithm

Fig. 3 to Fig. 6 provided by Rao and Patel (2014) are only to enable the readers to visualize the true Pareto-front and the Pareto-front obtained by MO-ITLBO algorithm. The true performance of the MO-ITLBO algorithm was shown based on the mean and standard deviation of the values of IGD measure obtained over 30 runs of MO-ITLBO algorithm. The performance of MO-ITLBO algorithm was not judged based on Fig. 3 to Fig. 6. Therefore, detailing the font size of the symbols used in Fig. 3 to Fig. 6 is a trivial issue.

3. Additional Comments

- It is observed that Chinta et al. (2016) commented on several trivial issues in the work of Rao and Patel (2014) and Patel and Savsani (2016). However, Chinta et al. (2016) themselves committed basic mistakes in their paper. For example, in their work, Chinta et al. (2016) incorrectly cited Rao and Patel (2014) as Rao et al. (2014); and Patel and Savsani (2016) as Patel et al. (2016) throughout their paper. Thus, it makes unworthy of looking into the trivialities in the works of Rao and Patel (2014) and Patel and Savsani (2016).
- It must be noted that the results shown by Chinta et al. (2016) in Fig. 1 to Fig. 4 are obtained by using their self-proposed variants (variant 1 and variant 2) of the improved TLBO algorithm and the results are not of MO-ITLBO algorithm proposed by Rao and Patel (2014) and Patel and Savsani (2016). Rao and Patel (2014) had shown the results of application of MO-ITLBO algorithm for the unconstrained functions and constrained functions of CEC 2009 and proved the effectiveness of the algorithm. The two variants imagined by Chinta et al. (2016) are inferior to the MO-ITLBO algorithm and there is no point in questioning the effectiveness of MO-ITLBO based on the imagined versions. It is surprising to see the statement of Chinta et al. (2016) that *“Nevertheless, this exercise has been reported on the insistence of an anonymous reviewer to*

emphasize on the lacunae of the information provided in the MO-ITLBO and its impact". Rao and Patel (2014) need not be blamed if someone has not properly understood the working of MO-ITLBO algorithm. This means that Chinta et al. (2016) had not understood the MO-ITLBO algorithm and they had imagined two variants and tried those variants on CEC 2009 functions and had reported inferior results. Had Chinta et al. (2016) applied MO-ITLBO algorithm with correct understanding then the results, shown by Rao and Patel (2014) and Patel and Savsani (2016), would have been obtained by the authors. It is not meaningful to propose two variants (due to misunderstanding about the working about MO-ITLBO algorithm) and then to comment about MO-ITLBO algorithm.

- Just for the sake of publication the authors must not resort to pessimistically persuade the readers. It is worth contemplating that, many papers may not be explicit, however, it is not justifiable to speculate upon or write a note on all such works. Furthermore, the interest of the reviewers in encouraging such works is also questionable. Chinta et al. (2016) had mentioned that *"Nevertheless, this exercise has been reported on the insistence of an anonymous reviewer to emphasize on the lacunae of the information provided in the MO-ITLBO algorithm...."*. It is unfortunate that reviewers, instead of reviewing the paper assigned to them, resort to the practice of insisting the authors to propose these variants and to emphasize on "lacunae" of the information provided in MO-ITLBO. It reflects that the authors had resorted to write the extended note due to the insistence of an anonymous reviewer.
- Chinta et al. (2016) had presented the results of the two variants assumed by them (because of misunderstanding about the MO-ITLBO algorithm) for only unconstrained benchmark functions UF1 to UF10 of CEC 2009. But they had not reported any results of the constrained functions CF1 to CF10 of CEC 2009 that were reported in Rao and Patel (2014) and Patel and Savsani (2016). The reasons for not attempting CF1 to CF10 were not provided by Chinta et al. (2016).
- Many multi-objective versions of TLBO algorithm were reported by the researchers (Li et al., 2014; Zou et al., 2013; Medina et al., 2014; Yu et al., 2015; Sultana and Roy, 2014, Rao et al., 2016) and many explanations were implicit in those versions and those versions had provided good results. The codes of all those algorithms are not public. It is not necessary that the code of every version is to be made public. Once the pseudo-code, flowchart and/or steps of the algorithm are explained in the paper, the peers are expected to understand the same instead of looking or searching for the public code.
- Although many multi-objective versions of TLBO algorithm are available it is surprising that Chinta et al. (2016) chose to write a note only on MO-ITLBO algorithm and proposed two variants of MO-ITLBO algorithm and reported dissatisfactory performance of the two variants on multi-objective benchmark functions of CEC 2009.
- It is not clear whether Chinta et al. (2016) had contacted Rao and/or Patel before jumping to write a note on their work. The authors should have contacted Rao and/or Patel in the case of difficulty in understanding the working of MO-ITLBO algorithm for clarification of doubts. Furthermore, it is not clear whether Rao and/or Patel were given any reviewing opportunity to present their side.

4. Conclusions

The MO-ITLBO algorithm was proposed by Rao and Patel (2014) and has shown superior performance in solving multi-objective constrained and unconstrained benchmark problems of CEC 2009 as compared to the other optimization algorithms. The "issues" raised by Chinta et al. (2016) do not have any

meaningful base and are unfounded. Chinta et al. (2016) have simply speculated on the works of Rao and Patel (2014) and Patel and Savsani (2016). Such tendency to write notes just due to misunderstanding of the concepts may be discouraged by the Journals. Furthermore, the reviewers need to play a constructive role while reviewing the papers instead of insisting the authors to search and report the “lacunae”.

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