Information Sciences xxx (2014) xxx–xxx

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Testing the performance of teaching–learning based optimization (TLBO) algorithm on combinatorial problems: Flow shop and job shop scheduling cases

Adil Baykasoğlu [a,*], Alper Hamzadayi [a], Simge Yelkenci Köse [a,b]

[a] Dokuz Eylül University, Faculty of Engineering, Department of Industrial Engineering, Buca, İzmir, Turkey
[b] Ministry of Science, Industry and Technology, Directorate General for Safety and Inspection of Industrial Products, Cankaya, Ankara, Turkey

A R T I C L E I N F O

Article history:
Received 17 March 2012
Received in revised form 23 January 2014
Accepted 9 February 2014
Available online xxxx

Keywords:
Teaching–learning based optimization
Flow shop scheduling
Job shop scheduling
Makespan
Meta-heuristic
Combinatorial optimization

A B S T R A C T

Teaching–learning based optimization (TLBO) algorithm has been recently proposed in the literature as a novel population oriented meta-heuristic algorithm. It has been tested on some unconstrained and constrained non-linear programming problems, including some design optimization problems with considerable success. The main purpose of this paper is to analyze the performance of TLBO algorithm on combinatorial optimization problems first time in the literature. We also provided a detailed literature review about TLBO's applications. The performance of the TLBO algorithm is tested on some combinatorial optimization problems, namely flow shop (FSSP) and job shop scheduling problems (JSSP). It is a well-known fact that scheduling problems are amongst the most complicated combinatorial optimization problems. Therefore, performance of TLBO algorithm on these problems can give an idea about its possible performance for solving other combinatorial optimization problems. We also provided a comprehensive comparative study along with statistical analyses in order to present effectiveness of TLBO algorithm on solving scheduling problems. Experimental results show that the TLBO algorithm has a considerable potential when compared to the best-known heuristic algorithms for scheduling problems.

1. Introduction

Teaching–learning based optimization algorithm (TLBO) has been proposed recently by Rao et al. [46,49] based on an inspiration from the teaching–learning process of human beings. The TLBO algorithm is based on the effect of influence of a teacher on the output of the learners in a class. Rao et al. [46] presented the first serious application of this population based meta-heuristic optimization algorithm on mechanical design optimization problems with reporting success. Almost simultaneously, the same authors [49] tested the effectiveness of the TLBO algorithm on many non-linear optimization benchmark problems with different characteristics. In their subsequent study, Rao and Kalyankar [47] employed the TLBO algorithm for parameter optimization of two advanced machining processes, namely "electrochemical machining process" and "electrochemical discharge machining process". They compared their results with other advanced optimization techniques such as genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), harmony search (HS), and artificial bee colony algorithm (ABC). It was observed that TLBO algorithm requires only 20–30 iterations for

* Corresponding author. Tel.: +90 232 3017600; fax: +90 232 3017608.
E-mail address: adil.baykasoglu@deu.edu.tr (A. Baykasoğlu).

http://dx.doi.org/10.1016/j.ins.2014.02.056
0020-0255/© 2014 Elsevier Inc. All rights reserved.

convergence to the optimal solution. The algorithm outperformed GA and SA in all of the examples in terms of accuracy of solution. The results obtained by TLBO also show slight superiority over those obtained by using PSO, HS, and ABC algorithms. In another study, Rao and Patel [48] applied the TLBO to thermodynamic optimization of plate-fin heat exchanger with reporting success. Moreover, the TLBO is also used for clustering the data vectors and compared to classical K-means algorithm and particle swarm optimization based clustering algorithm [62]. In a similar way, Amiri [2] applied the TLBO for solving clustering problems. Then, the results obtained from the TLBO were compared with the results of ant colony optimization algorithm, genetic algorithm, simulated annealing, particle swarm optimization, and K-means algorithm. Naik et al. [34] employed the TLBO for solving the "initial centers selection problem" for both fuzzy c-means and hard c-means clustering algorithms. Their approach consists of two stages. In the first stage, the TLBO was used for exploring the search space of the given dataset to find out the near optimal cluster centers. Then, the best cluster centers found were used as initial cluster centers for the c-means algorithms to perform clustering. Nayak et al. [35] developed an approach for power systems to optimize a fuzzy controller based on a simple function, and an improved TLBO was used for tuning the gains of the fuzzy controller. Most recently, Togan [66] employed the TLBO algorithm for discrete optimization of planar steel frames. They reported that the TLBO is a powerful optimization method when compared to genetic algorithm, ant colony optimization, harmony search, and improved ant colony optimization for their problem. Rao and Kalyankar [53] applied the TLBO for the parameter optimization of "ultrasonic machining process", "abrasive jet machining process" and "wire electrical discharge machining process". They compared the results obtained from the TLBO with the results previously generated by using genetic algorithm, simulated annealing, artificial bee colony algorithm, particle swarm optimization, harmony search, and shuffled frog leaping.

There are also some attempts for employing the TLBO to solve multiple objective optimization problems. Rao and Patel [50] employed the TLBO for optimum operating conditions of combined Brayton and inverse Brayton cycles determination by taking multi-objectives into consideration. Hosseinpour et al. [26] proposed a modified multiple objective TLBO algorithm for the placement of automatic voltage regulators in power distribution systems. Krishnanand et al. [29] and Niknam et al. [37] proposed multi-objective TLBO algorithms for solving environmental/economic dispatch problem and dynamic economic emission dispatch problems, respectively. Rao and Patel [54] modified the basic TLBO algorithm by introducing the concept of number of teachers, adaptive teaching factor, and self-motivated learning. Afterwards, they applied the modified TLBO algorithm to the multi-objective optimization of a two-stage thermoelectric cooler by considering two conflicting objectives: cooling capacity and coefficient of performance. In their subsequent study, Rao and Patel [55] employed the modified TLBO algorithm to the multi-objective optimization of heat exchangers by considering two conflicting objectives, namely effectiveness and total cost.

In more recent studies, Crepinšek et al. [12] and Waghmare [70] presented some notes and critiques about the TLBO algorithm. They reported three important potential mistakes related to the TLBO algorithm and presented some experimental results for constrained and unconstrained benchmark functions. Contrary to the opinions expressed by Crepinšek et al. [12] related to the fact that the TLBO is not a parameter-less algorithm, Waghmare [70] explained that the TLBO is an algorithm-specific parameter-less algorithm; and many of the comments made by Crepinšek et al. [12] about the TLBO algorithm were addressed by Rao and Patel [52].

TLBO seems to have some potential for solving non-linear programming and engineering design optimization problems based on the review of the publically available papers. However, its performance is not yet tested on complex combinatorial optimization problems. It is a well-known fact that the main motivation behind the development of the most of the meta-heuristics procedures is to provide effective solutions for combinatorial optimization problems. Based on this motivation, we decided to test the performance of the TLBO algorithm on two very well-known and complex combinatorial optimization problems, namely flow shop and job shop scheduling problems.

Scheduling is one of the most important problems in the field of production management and is mainly concerned with finding sequences of jobs on given machines that minimizes maximum completion time of a sequence or makespan. Some widely studied scheduling problems have been included in general flow shop scheduling (FSSP) and job shop scheduling problems (JSSP). In the FSSP, all jobs pass through all machines in the same order, whereas machine orderings can be different for each job in the JSSP. The difficulty experienced in the scheduling problems is to find the best possible schedule from a number of schedules [3]. Searching possible solution space, the computational time for algorithms to find a best possible schedule increases exponentially with job-machine size. Hence, the FSSP and the JSSP belong to the set of problems classified as NP-hard problems [21,4,19,17]. In the relevant literature, FSSP and JSSP have been studied for many years, and many heuristics have been developed for these problems. Johnson's rule [28], Palmer's slope index [40], CDS rule [11], NEH heuristic [36], and iterated greedy algorithm [59] are very well known heuristic methods developed for FSSPs. Heuristic methods get the solutions by considering pre-defined rules unsuitable for every environment. Therefore, many exact and meta-heuristic algorithms have been proposed in the field of production scheduling, such as branch and bound algorithm of Brah and Hunsucker [9], dynamic programming approach of Sönmez and Baykasoğlu [64], Taillard's tabu search method [65], Ogbu and Smith's simulated annealing algorithm [38], Reeves's genetic algorithm [56], Lian et al.'s particle swarm optimization algorithm [32], Kuo et al.'s hybrid particle swarm optimization algorithm [30], Wang et al.'s [71] and Pan et al.'s [42] hybrid discrete differential evolution algorithms, and Pan et al.'s discrete artificial bee colony algorithm [41]. There are various reviews for the FSSP such as Dudek et al. [14], Reisman et al. [58], Ruiz and Maroto [60], Hejazi and Saghafian [24], and Hooda and Dhingra [25]. They provided a detailed survey and comparison of various methods. For JSSPs, many heuristic, exact and meta-heuristic algorithms have also been proposed, such as shifting bottleneck procedure of Adams et al. [1]; Brucker et al.