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ENHANCED TEACHER-LEARNING BASED ALGORITHM IN REAL SIZE STRUCTURAL OPTIMIZATION

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Abstract. Space frame structures that are made up of a huge number of members are often used on a large scale, hence their accurate evaluation is important to achieve the optimal design. On the other hand, the use of space Frames and 3D truss structures has become more popular due to its time efficiency. Also, these types of structures can carry loads in long-span buildings and are used in large-scale structures such as halls, hangars, passenger stations, etc. In this study, a novel evolutionary algorithm, named ETLBO, has been proposed for the optimization of space frame design in real-size structures. Despite the existing methods in the literature, the ETLBO method can be used for large-scale space frame structures due to its high speed with sufficient accuracy. At first, four optimization algorithms Particle swarm optimization (PSO), Genetic Algorithm (GA), Differential Evolution (DE), and Teaching–learning-based optimization (TLBO) under structural problems have been evaluated. The results show that the TLBO algorithm performs better in solving problems and has been better in most problems than other algorithms. So, we have tried to improve this algorithm based on a machine learning approach and combination operators. Algorithm improvement is created by adding a crossover operation between the new solution and the best solution in the teacher phase. This change causes a sudden movement and escapes from the local minima for the algorithm. Enhanced algorithm results show that convergence speed and optimal response quality have improved. Finally, using this algorithm, several new practical examples have been optimized.

Keywords: large-scale structure, space frame structures, optimization, hybrid method.

Introduction

Optimization is a mathematical method to achieve optimal solutions in one or many objective functions. The other words, optimization algorithms are the process of searching for a vector in a given domain to make the best solution among a large number of possible feasible solutions. Optimization is used in many kinds of science and engineering fields.

The most important issue is selecting the right algorithm to find the best solution for optimization problems. The type of problem, the availability of algorithms, computational resources, and type of constraints are the main parameters to select the appropriate algorithms.

Metaheuristic algorithms are the common types of random search algorithms. Metaheuristic algorithms are often inspired by nature. Based on the source of inspiration, metaheuristic algorithms can be classified into different categories which the biology-inspired algorithms are one of them that generally use the biological behavior of animals as their models. Another source of inspiration for metaheuristic algorithms is science which is usually inspired by physics and chemistry. Moreover, art-inspired algorithms which are generally inspired by the creative behavior of artists such as architects and musicians have been successful for global optimization. Another source of inspiration is a social behavior that inspired algorithms to simulate social behavior to solve optimization.

During the 1960s, a novel kind of optimization method called genetic algorithms (GAs) (Holland, 1998) was put forward. These methods have been developed by idealizing the evolution theory. Since then, many other meta-algorithms have been introduced, such as particle swarm optimization (PSO) (Kennedy & Eberhart, 1995), differen-

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tial evolution (DE) (Price & Storn, 1997), Harmony search (HS) (Lee & Geem, 2005), Colliding bodies optimization (CBO) (Kaveh & Mahdavi, 2014), Imperialist competitive (IC) (Atashpaz-Gargari & Lucas, 2007), Teaching–learning-based optimization (TLBO) (Rao et al., 2011), Interior search algorithm (ISA) (Gandomi, 2014), Bat algorithm (BA) (Yang, 2010), Animal migration optimization (AMO) (Li et al., 2014), Krill herd (KH) (Gandomi & Alavi, 2012), Improved cat swarm optimization algorithm (Kumar & Singh, 2019), EMoSOA: a new evolutionary multi-objective seagull optimization algorithm (Dhiman et al., 2021), Sine-cosine optimization algorithm (Yıldız et al., 2020a), Seagull optimization algorithm (Panagant et al., 2020), Enhanced grasshopper optimization algorithm (Yildiz et al., 2021a), Political optimization algorithm (Yıldız et al., 2021c), Conceptual comparison of the ecogeography-based algorithm (Yıldız et al., 2021d), new Hybrid Taguchi-salp swarm optimization algorithm (Yıldız & Erdaş, 2021), Self-adaptive many-objective metaheuristic (Champasak et al., 2020), Biogeography-based optimization (BBO) (Simon, 2008), and Symbiotic Organisms Search (SOS) (Cheng & Prayogo, 2014).

In recent years some metaheuristic algorithms have been proposed to solve optimization problems, which have achieved better results in terms of computational and time complexity. One of the effective methods for generating new algorithms is hybrid algorithms. In general, the combination of algorithms is performed by combining their operators, and this combination can increase the efficiency of the new algorithms (Kaveh & Talatahari, 2009a; Mahi et al., 2015; Wang et al., 2016; Shahrouzi et al., 2017; Strauss et al., 2006, 2017, 2018; Zambon et al., 2017). In addition, Yildiz et al. (2021b), recently, proposed a new optimization approach based on a grasshopper optimization algorithm, and Nelder–Mead algorithm for demanding a high-speed and reliable answer.

Moreover, recently, metaheuristic algorithms have found various applications. Meng et al. (2021) have investigated the application of metaheuristic algorithms in reliability-based design optimization. Also, for reliability-based design optimization, Demirci and Yıldız (2019) proposed a new hybrid algorithm. In addition, these methods have been used in solving constrained mechanical design optimization problems (Gupta et al., 2021). These algorithms have also found much more specific applications such as optimum structural design of automobile brake components (Yıldız et al., 2020a), optimum shape design of automobile suspension components (Yıldız et al., 2020b), optimal structural design of vehicle components (Yıldız et al., 2020c, 2020d), optimal spur gear design (Abderazek et al., 2021), crashworthiness optimization (Aye et al., 2019; Karaduman et al., 2019) and automated design of aircraft fuselage stiffeners (Sarangkum et al., 2019). The other application of metaheuristic algorithms is population clustering. Many research focused on improving optimization algorithm to achieve better clustering (Kumar & Singh, 2018, 2019).

One of the important applications of optimization in civil engineering is the optimization of the skeleton weight of structures. In recent years, this issue has attracted the attention of many researchers. In some studies, the focus is on the optimization of frame structures (Talatahari et al., 2012b; Kaveh et al., 2019; Talaslioglu, 2019; Es-haghi et al., 2020), and in others, the focus is on space frame (3D truss) structures (Li et al., 2009; Eskandar et al., 2011; Talatahari et al., 2012a; Kaveh & Hosseini, 2014; Panagant et al., 2021).

Swarm intelligence (SI) is a type of artificial intelligence which introduce based on the collective behavior of decentralized, self-organized systems. Many optimization methods use this type of artificial intelligence, which is often inspired by the biological sciences. In optimization problems such as the machine learning (ML) approach, some data should be organized to a goal. ML helps systems reach a suitable response by using data, specific operators, and computer calculations. The explorer population in meta-heuristic optimization methods makes a data bank in each step. This data bank by using some operators reaches the best solution (Es-haghi et al., 2020).

Since space frame structures are commonly used in large-scale structures, their optimal evaluation usually takes a long time. Therefore, optimization algorithms of space frame structures must have high speed and accuracy to meet the design needs more effectively. In this paper, by examining the performance of TLBO, we have tried to improve its accuracy and efficiency. Therefore, some operators were added to the TLBO algorithm to achieve a more robust method for solving large-scale structures. The main objectives of the present study are:

- Provide a way to reduce the weight and cost of materials in the actual project;
- Weight optimization of real-size space frame structures;
- Using evolutionary algorithms in real-size structures' optimization;
- Upgrading existing optimization methods for use in large-scale space frame structures;
- Comparing existing optimization methods in terms of speed and accuracy in space-frames.

The structure of this paper is organized as follows. Section 1 describes the TLBO and enhanced TLBO (ETLBO) approach. The Structural optimization problems are presented in Section 2. Finally, the conclusion of our present work is given.

1. Preliminary

Many engineering phenomena can be expressed by governing equations and boundary conditions. The governing equations are often in the form of partial differential equations (PDE). A numerical technique for solving problems that are described by partial differential equations is the finite element method (FEM). By using the FEM method, the PDE of truss structures analysis will be solved in closed form and these equations can be shown in matrix form (Öchsner, 2020). In this paper, all examples are analyzed by matrix form.

This section describes the basics of two algorithms TLBO and enhanced TLBO and presents the performance of each algorithm to solve optimization problems.

1.1. Teaching-learning based optimization (TLBO)

TLBO algorithm is one of the most recently developed metaheuristics which has many similarities to evolutionary algorithms (EAs): randomly selected initial population, moving toward the best position (teacher and classmates), comparable to mutation operator in EA, and selection is regarding the comparison of two solutions in which the better one always survives (Rao et al., 2011).

TLBO is a population-based algorithm inspired by the learning process in a classroom which is similar to most other evolutionary optimization methods. The searching process consists of teacher and learner Phases. In the teacher phase, learners get knowledge from a teacher. After that, they will be learned by classmates in the learner phase. The best solution is considered as the teacher in the entire population.

1.2. Enhanced TLBO

In this section, an attempt has been made to provide an improved algorithm from TLBO by using the previous experiences and combining some effective operators in optimization problems, which provides higher convergence speed and higher accuracy. According to the previous section, the TLBO algorithm has two phases. In the first phase, the population is directed to the teacher who is the best member of the set, and in the second phase, each member moves to the member with higher fitness by randomly selecting two members of the set and evaluating their suitability. The combination of these two phases has led to extensive research and detailed exploration of this algorithm. Based on the experiences of the initial assessments, it is clear that algorithms that converge their population rapidly may be exposed to local minima, and ultimately the algorithm may not achieve the best possible response. To prevent this, new algorithms should be created to overcome local minimums. According to various experiments that have been performed on base algorithm operators in this study. The best operator to exit local minimums is the link operator, which is found in both the GA algorithm and the DE algorithm. Therefore, to improve the behavior of the algorithm, a combination of crossover operators has been created in the TLBO algorithm.

Introducing the steps created in the improved algorithm is as follows:

1) Select the primary population;
2) Performing the teacher phase and moving the population in the direction of the best solution;
3) The crossover between the new solution and the corresponding solution with the teacher (best solution);
4) Investigate the improvement of the result and replace it;
5) Do the learning phase and randomly select two members and move towards a better solution;
6) Population adjustment at the end of the step;
7) Repeat step 2 onwards until the end of the run.

As can be seen, the algorithm improvement is created by adding a crossover operator between the new solution and the best solution in the teacher phase. This makes it possible to always move suddenly and escape from the local minimum for the algorithm. The steps of the crossover operator in this study are as follows:

1) Select a random number between 1 and the size of the design variables;
2) Produce a new position from 1 to a random number based on the best solution;
3) Generate a new position from the random number to the last member of the variable vector based on the new solution in the teacher phase;
4) Evaluate fitness of the new solution.

The flowchart for enhanced TLBO is presented in Figure 1.

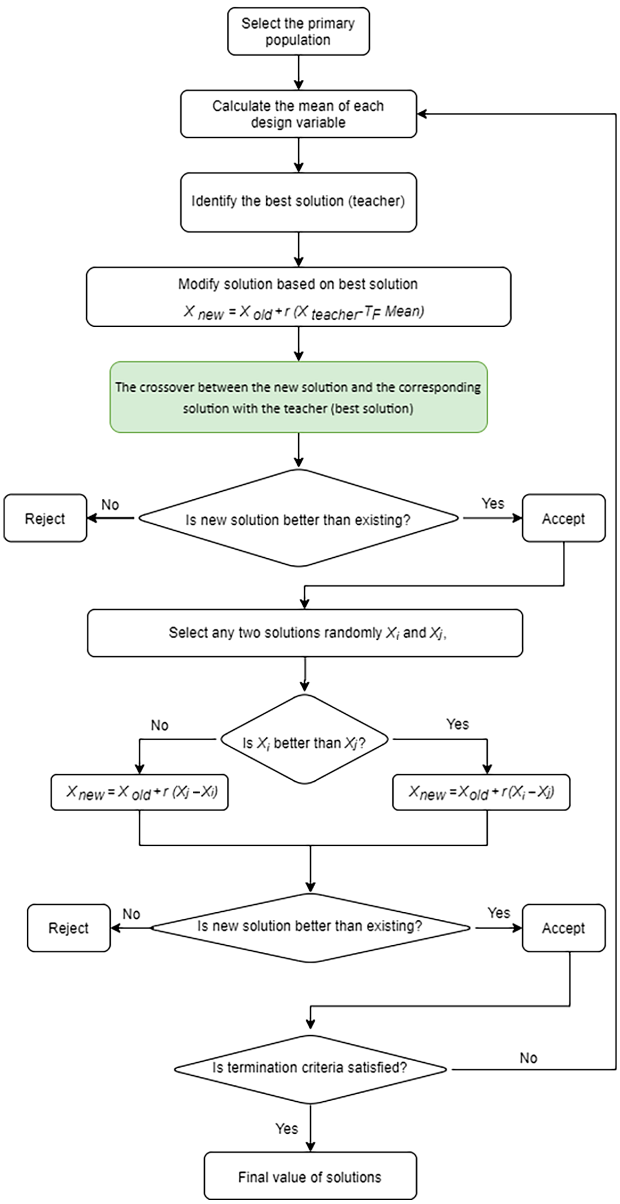

Figure 1. The flowchart for ETLBO

2. Structural optimization problems

In this section, four optimization examples are used, which include a new practical example. The four basic algorithms PSO, GA, DE, TLBO, and the proposed algorithm have been evaluated under these examples. The basic algorithms have been used in their original form. In all optimization solutions, the control parameters of PSO are considered equal to 1, 2, and 2, respectively, and the mutation probability of GA is considered equal to 0.1, and the other algorithms aren't control parameters.

The results have been compared with other research results of other well-known optimizers.

A Diversity Index, DI is also utilized via the following relation (Shahrouzi & Kaveh, 2015). It is further used to compare the convergence behavior of the algorithms:

$$DI = \underset{j}{mean}\left(\frac{SD_j}{U_j - L_j}\right), \quad (1)$$

where: L_j and U_j are the lower and upper bounds on every j^{th} design variable, respectively; meanwhile, SD_j stands for the Standard Deviation of the corresponding design variable among the population. *DI* is evaluated for the entire population at each iteration. It is desired that the diversity index be high at early iterations and decreases by the search progress as the population agents converge to the optimum. The *DI* trace vs. iterations varies for various algorithms and so can be employed for understanding the behavioral differences.

In all algorithm runs in this section, the number of populations equal to 50 have been used and the NFEs have continued until the best result has been reached.

2.1. 10-bar truss design

The 10-bar truss, shown in Figure 2, has been widely addressed by many researchers. The material density is 0.1 lb/in^3 (0.0272 N/cm^3) and the modulus of elasticity equals E = 10^4 ksi (68947.57 MPa). Stress limitation in compression and tension for each member is taken ±25 ksi (±172.37 MPa). Maximum nodal displacement in each direction is limited to ±2 in (±0.0508 m). A vertical load of 10^5 lb is exerted at nodes 2 and 4.

Table 1 compares the results of different algorithms in solving the 10-member example. As can be seen, the TLBO provides better results than other basic algorithms. Also, the proposed algorithm shows a better result than its basic algorithm (TLBO). As shown in Figure 3, the convergence rate in ETLBO has been faster in achieving the optimal solution.

According to Figure 4, the *DI* index is reduced rapidly in the ETLBO after a few iterations and its value in the ETLBO has always been less than the TLBO.

To closely evaluate the performance of the proposed algorithm, the results of other algorithms presented in the literature have been compared under the 10-bar truss example (see Table 2). The comparison results show that the ETLBO has better performance in convergence quality and convergence speed than other methods.

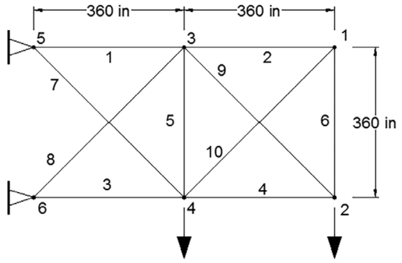

Figure 2. 10-bar truss

Table 1. Result of optimization algorithms 10-bar truss example

Variables (in^2)	PSO	GA	DE	TLBO	ETLBO
A1	30	30	30	30	33.5
A2	1.62	1.62	1.8	1.62	1.62
A3	30	30	26.5	22.9	22.9
A4	13.5	18.8	15.5	13.5	14.2
A5	1.62	1.62	1.62	1.62	1.62
A6	1.8	1.62	1.62	1.62	1.62
A7	11.5	13.9	11.5	7.97	7.97
A8	18.8	16	18.8	26.5	22.9
A9	22	19.9	22	22	22
A10	1.8	3.13	3.09	1.8	1.62
Weight (lb)	5581.8	5706.52	5593.4	5531.9	5490.74
SD	664.1	257	12.8	3.8	69.7

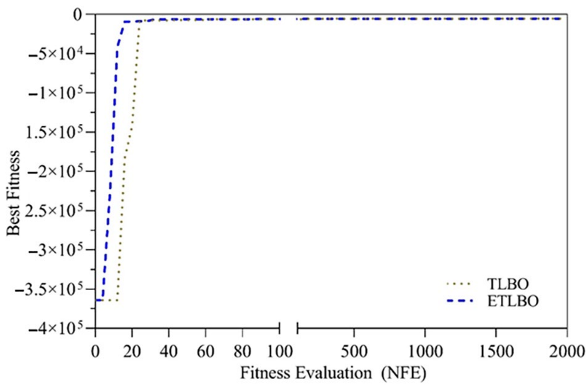

Figure 3. Convergence comparison of ETLBO vs. TLBO for the 10-bar truss example

2.2. 15-bar truss design

The 15-bar truss of Figure 5, has been studied by Li et al. (2009) and Sadollah et al. (2013), material density and elasticity modulus are 7800 kg/m^3 and E = 200 MPa, respectively. The allowable stress for each member of this structure equals ±120 MPa. Nodal displacements are confined within ±10 mm in any direction.

Discrete design variables are selected from the set {113.2, 143.2, 145.9, 174.9, 185.9, 235.9, 265.9, 297.1, 308.6, 334.3, 338.2, 497.8, 507.6, 736.7, 791.2, 1063.7} (mm^2). Concentrated loads of 35 kN are applied at the nodes 4, 6 and 8.

According to Table 3, the results obtained from the ETLBO and TLBO have been better than the other methods, but as can be seen in Figures 6 and 7, the convergence

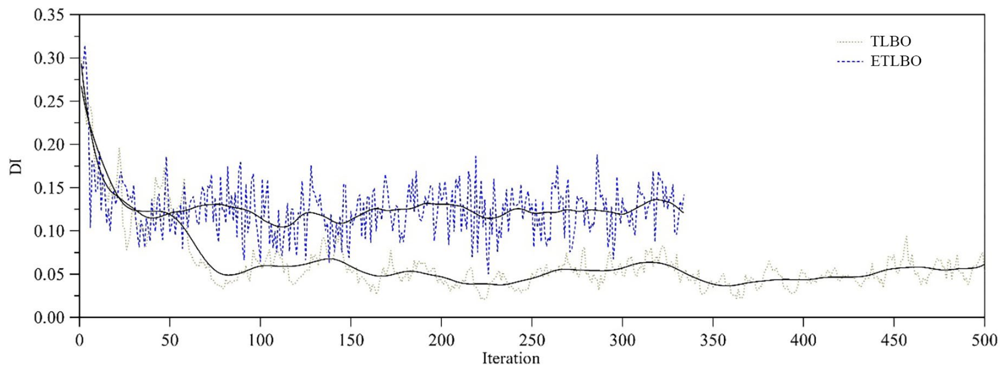

Figure 4. *DI* traces of ETLBO vs. TLBO for the 10-bar truss

Table 2. Comparison of results algorithm in literature for the 10-bar truss example

Variables (in^2)	GA (Rajeev & Krishnamoorthy, 1992)	PSO (Li et al., 2009)	PSOPC (Li et al., 2009)	HPSO (Li et al., 2009)	MBA (Sadollah et al., 2012)	ETLBO
Best weight (lb)	5613.8	5581.8	5593.4	5531.9	5507.7	5490.74
Mean (lb)	–	–	–	–	–	6239.3
SD	–	664.1	12.8	3.8	–	69.7
NFE (NFE-best)	–	50000 (15000)	50000 (15000)	50000 (12500)	20000 (3600)	20000 (1000)

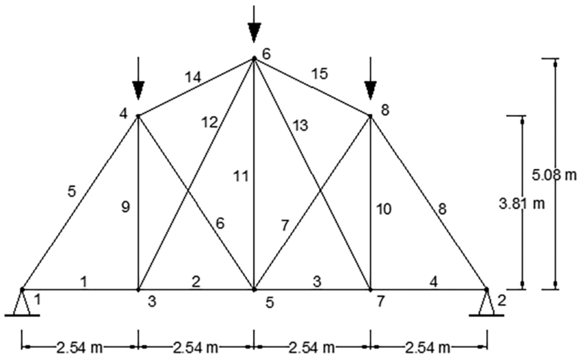

Figure 5. 15-bar truss

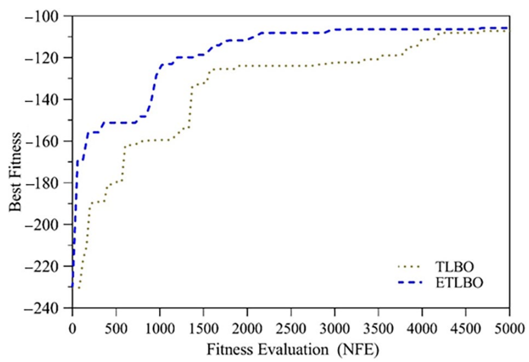

Figure 6. Convergence comparison of ETLBO vs. TLBO for the 15-bar truss example

speed of ETLBO is more than TLBO. Also, ETLBO accuracy is better than TLBO and the best result of ETLBO obtain in 4700 NFE.

Table 4 shows that the MBA and ETLBO have been converged in 2000 NFE and 4700 NFE respectively, while the other methods solved this example in a larger number of NFE. Therefore, ETLBO has shown good behavior in this example as well.

Table 3. Result of optimization algorithms 15-bar truss example

Variables (mm^2)	PSO	GA	DE	TLBO	ETLBO
A1	185.9	113.2	113.2	113.2	113.2
A2	113.2	113.2	113.2	113.2	113.2
A3	143.2	113.2	113.2	113.2	113.2
A4	113.2	113.2	113.2	113.2	113.2
A5	736.7	736.7	736.7	185.9	185.9
A6	143.2	113.2	113.2	113.2	113.2
A7	113.2	113.2	113.2	113.2	113.2
A8	736.7	736.7	73 6.7	185.9	185.9
A9	113.2	113.2	113.2	113.2	113.2
A10	113.2	113.2	113.2	113.2	113.2
A11	113.2	113.2	113.2	113.2	113.2
A12	113.2	113.2	113.2	113.2	113.2
A13	113.2	185.9	113.2	113.2	113.2
A14	334.3	334.3	334.3	334.3	334.3
A15	334.3	334.3	334.3	334.3	334.3
Weight (kg)	125.84	175.96	115.255	105.735	105.735
SD	20.36	25.78	11.39	10.79	0.5316

2.3. 582-bar tower truss design

As an example of a large-scale problem, a 582-bar truss of Figure 8 (80 m tower) is considered. This optimization problem has already been solved with discrete variables by Hasançebi et al. (2009), Kaveh and Talatahari (2009a, 2009b, 2010), Kaveh and Mahdavi (2014) and Shahrouzi et al. (2017). To keep the symmetry of the tower around x-and y-axes its members are considered in 32 groups for sizing. A single load case consisting of 5 kN in both x- and y- directions and a vertical force of 30 kN in the downward z-direction, is applied at every node of the tower.

Table 4. Comparison of results algorithm in literature for the 15-bar truss example

Variables (mm^2)	PSO (Li et al., 2009)	PSOPC (Li et al., 2009)	HPSO (Li et al., 2009)	MBA (Sadollah et al., 2012)	ETLBO
Best weight (kg)	108.84	108.96	105.735	105.735	105.735
Mean	–	–	–	–	106.115
SD	–	–	–	–	0.5316
NFE (NFE-best)	25000 (18700)	25000 (16000)	25000 (7500)	25000 (2000)	6000 (4700)

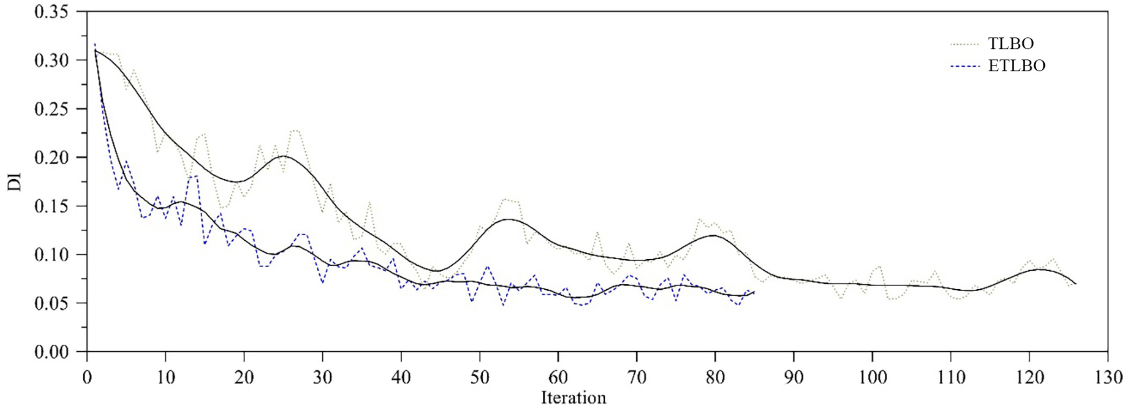

Figure 7. *DI* traces of ETLBO vs. TLBO for the 15-bar truss

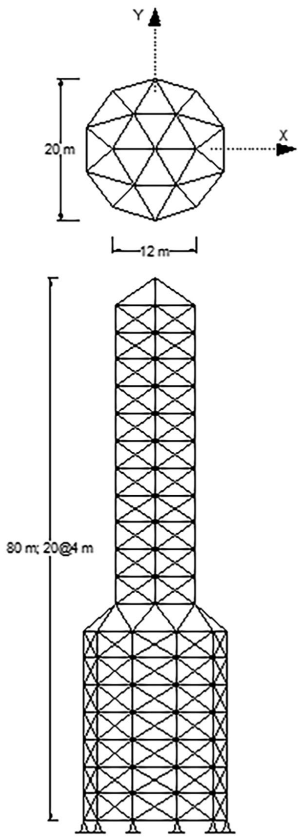

Figure 8. 582-bar tower truss

The tower is optimized for minimum volume while member cross-sections are selected from a list of AISC W-sections based on area and radius of gyration. The corresponding lower and upper bounds of section area are 39.74 cm^2 and 1387.09 cm^2, respectively. Nodal displacements are limited to 8.0 cm in each direction. The allowable tensile and compressive stresses are calculated due to the AISC_ASD provisions (American Institute of Steel Construction [AISC], 1989) as:

$$\sigma_i^+ = 0.6\,F_y \quad \text{for} \quad \sigma_i \geq 0; \tag{2}$$

$$\sigma_i^- = \begin{cases} \left[\left(1-\dfrac{\lambda_i^2}{2C_c^2}\right)F_y\right] / \left(\dfrac{5}{3}+\dfrac{3\lambda_i}{8C_c}-\dfrac{\lambda_i^3}{8C_c^3}\right) & \text{for} \quad \lambda_i < C_c \\ \dfrac{12\pi^2 E}{23\lambda_i^2} & \text{for} \quad \lambda_i \geq C_c \end{cases}, \tag{3}$$

whereas E (the modulus of elasticity) is 203893.6 MPa and F_y (the yield stress of steel) is taken 253.1 MPa. λ_i is the slenderness ratio ($\lambda_i = k\ L_i / r_i$) where L_i stands for the length of the i^{th} member and r_i is the corresponding minimal radius of gyration. $C_c = \sqrt{2\pi^2 E / F_y}$ denotes the slenderness measure by which the elastic and inelastic buckling regions are distinguished from each other. Furthermore, the maximum slenderness ratio λm for tension and compression members is limited to 300 and 200, respectively.

The 582-bar truss is a large-scale example, so it needs more iteration to achieve the optimal solution. Also, the large number of design variables and various analytical constraints make this example more complex.

Comparison of the results of the basic algorithms and the proposed method shows that the ETLBO algorithm has been efficient in this example as well. As shown in Table 5, The proposed algorithm has a better result than other algorithms and the optimal solution in this algorithm is 20.2382. In this example, the TLBO algorithm is the second algorithm with the optimal solution 20.9218.

Table 5. Result of optimization algorithms 582-bar truss example

Variables (cm^2)	PSO	GA	DE	TLBO	ETLBO
A1	39.74	45.68	39.74	39.74	39.74
A2	149.68	136.13	149.68	136.13	149.68
A3	45.68	53.16	53.23	53.23	56.71
A4	113.55	109.68	90.96	118.06	113.55
A5	45.68	45.68	45.68	45.68	39.74
A6	39.74	45.68	39.74	39.74	39.74
A7	90.97	92.90	128.38	92.90	92.90
A8	45.68	45.68	45.68	45.68	39.74
A9	39.74	92.90	39.74	39.74	47.35
A10	85.81	45.68	90.96	90.97	39.74
A11	45.68	45.68	49.35	39.74	39.74
A12	129.03	75.48	118.06	136.13	149.68
A13	140.65	56.71	143.87	144.52	165.16
A14	90.97	136.13	100.64	92.90	109.68
A15	143.87	143.87	115.48	149.68	155.48
A16	55.90	92.90	75.48	58.90	49.61
A17	39.74	155.48	101.93	118.06	123.23
A18	127.10	45.68	49.35	45.68	39.74
A19	45.68	39.74	39.74	39.74	39.74
A20	39.74	75.48	81.29	87.10	83.87
A21	75.48	45.68	45.68	39.74	39.74
A22	45.68	41.87	39.74	39.74	39.74
A23	39.74	58.84	41.89	47.35	39.74
A24	41.87	53.23	45.68	39.74	39.74
A25	45.68	39.74	39.74	39.74	39.74
A26	39.74	39.74	39.74	39.74	39.74
A27	39.74	45.68	45.68	39.74	39.74
A28	45.68	53.23	39.74	39.74	39.74
A29	39.74	68.39	39.74	39.74	39.74
A30	39.74	45.68	47.35	39.74	39.74
A31	45.68	39.74	62.64	39.74	39.74
A32	45.68	45.68	53.22	39.74	39.74
Volume (m^3)	32.3958	35.0607	28.8376	20.9218	20.2382
SD	7.450	12.32	5.345	2.553	1.6599

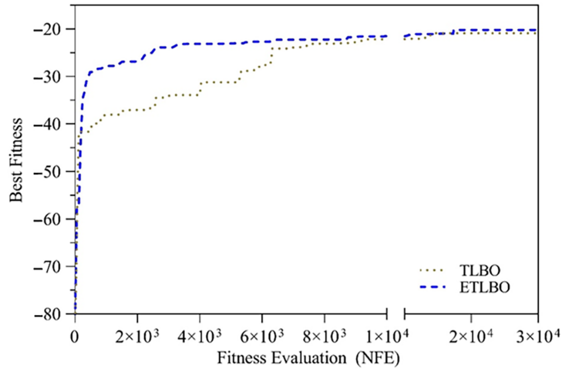

Figure 9. Convergence comparison of ETLBO vs. TLBO for the 582-bar truss example

Given that the initial population and the number of programs run for all algorithms have been the same, so we can see the better performance of ETLBO compared to other methods.

Figures 9 and 10 show the trend of fitness and *DI* index for the two algorithms ETLBO and TLBO, respectively. Examination of the two figures shows that the proposed algorithm focuses on the population after several iterations and performs a more accurate search. So, in the end, a more accurate solution has been reached.

A comparison of the results obtained from other studies with the results of the proposed algorithm is shown in Table 6. The accuracy of the optimal solution obtained from the ETLBO was higher than other algorithms. Other algorithms performed the best fitness in the lower NFE, but their results are less accurate than the ETLBO optimal solution.

2.4. 112-bar bridge truss design

The 112-bar bridge truss is a new practical example in this paper. The member groups, the geometric dimensions of the structure and supported nodes have been shown in Figure 11.

The material density of elements is 7850 kg/m^3 and the modulus of elasticity equals E = 203893.6 kPa. According to Figure 12, the structure is subject to a vertical load of 200 kN and a horizontal load of 30 kN. The bridge is optimized for minimum weight while member cross-sections are selected from a list of AISC W-sections based on area

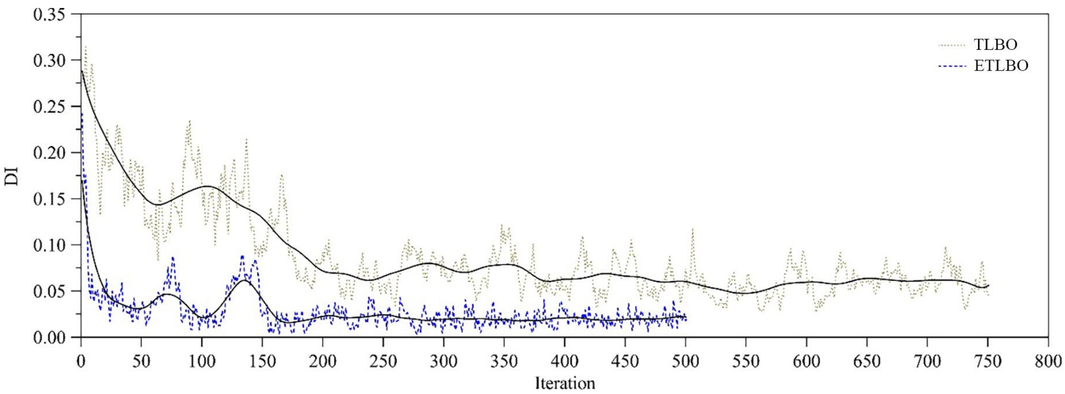

Figure 10. *DI* traces of ETLBO vs. TLBO for the 582-bar truss

Table 6. Comparison of results algorithm in literature for the 582-bar truss example

Variables (cm^2)	PSO (Hasançebi et al., 2009)	DHPSACO (Kaveh and Talatahari, 2009a, 2009b)	CBO (Kaveh & Mahdavi, 2014)	OTLBO (Shahrouzi et al., 2017)	ETLBO
Best volume (m^3)	22.3958	22.0607	21.8376	20.9835	20.9218
Mean					24.28
SD	–	–	–	–	1.6599
NFE (NFE-best)	50000 (17500)	17500 (8500)	20000 (17700)	50000 (15500(	30000 (22500)

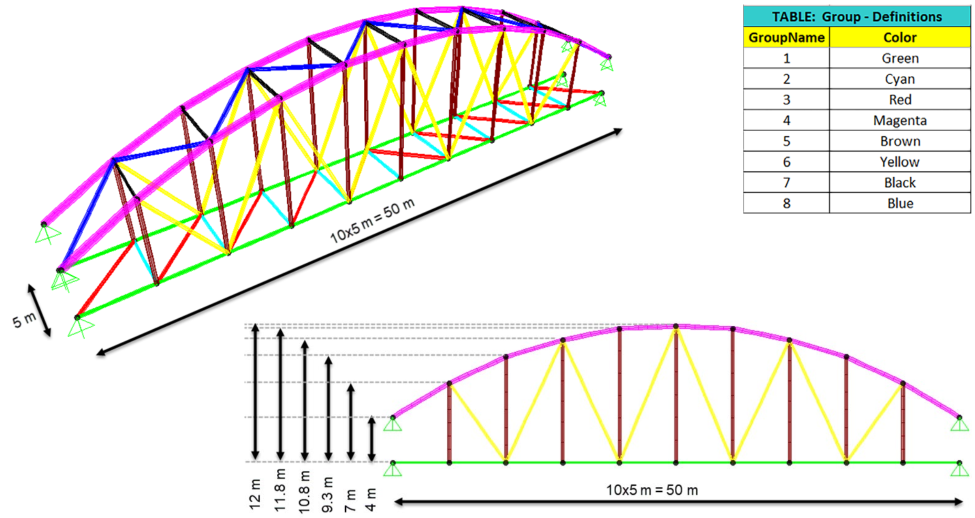

Figure 11. 112-bar bridge truss

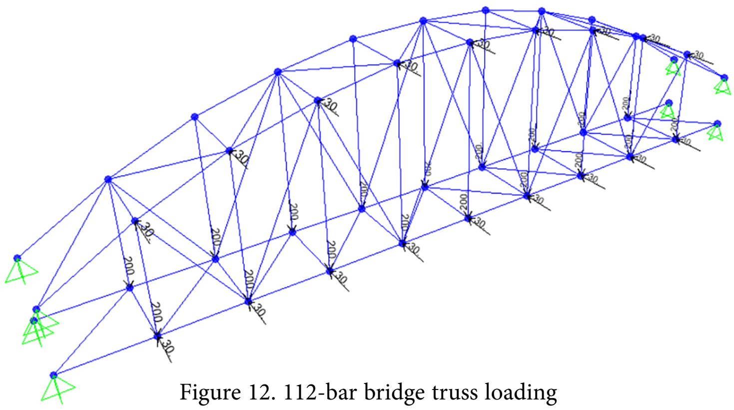

Figure 12. 112-bar bridge truss loading

and radius of gyration. The corresponding lower and upper bounds of section area are 22.84 cm^2 and 303.23 cm^2, respectively.

The allowable tensile and compressive stresses are calculated due to the AISC_ASD provisions (AISC, 1989). Maximum nodal displacement in each direction is limited to 0.05 m.

In this example, the population size of the algorithms is assumed to be 50 and the initial population is the same in both algorithms. The implementation of the algorithms is continued up to 30,000 NFE and its results are shown in Table 7. As can be seen, the ETLBO has reached the optimal solution of 35997.6 after 14800 NFE, while the TLBO has obtained its best solution in 22500 NFE, and it's equal to 41188. The mean and standard deviation of the results obtained from both algorithms show that the ETLBO has higher reliability than its basic algorithm.

The convergence trend of the two algorithms is compared in Figure 13. As can be seen, the convergence speed of the ETLBO is much higher than that of the TLBO and it has reached close to its optimal solution about 5000 NFE, while the TLBO has continued its initial convergence trend up to 20,000 NFE.

The *DI* index trend shows that the proposed algorithm has directed the population to the optimal solution in the initial iterations and has increased the accuracy of the result. While in the TLBO, due to higher population diversity, the convergence speed has been slow (Figure 14).

Table 7. Result of optimization algorithms 112-bar bridge truss example

Variables (cm^2)	TLBO	ETLBO
A1	49.35	47.3
A2	37.87	33.94
A3	22.84	22.84
A4	201.29	170.97
A5	22.84	22.84
A6	74.19	58.9
A7	22.84	22.84
A8	56.71	53.23
Best Weight (kg)	41188	35974.6
Mean Weight (kg)	44184	39241
SD	1649	2328
NFE (NFE-best)	30000 (22500)	30000 (14800)

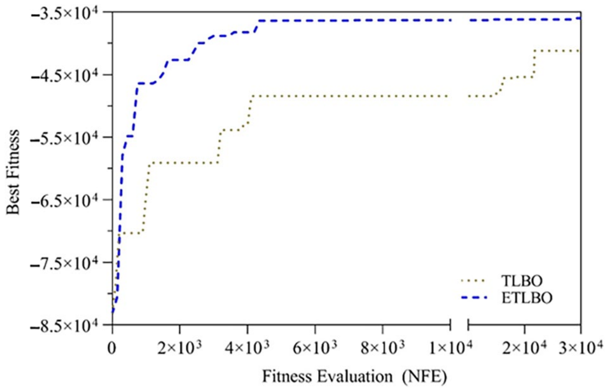

Figure 13. Convergence comparison of ETLBO vs. TLBO for the 112-bar truss example

2.5. 1152-bar double layer space frame roof

The sports complex roof is one of the most applications, of space frame structures. So, as a new optimization example, we designed a double-layer space frame that using in sports complexes' roofs. The structural geometry and support nodes have been shown in Figure 15. As can be seen, this structure has 314 nodes and 1152 bars.

In this example two load cases are applied to all nodes, the first one is dead load (DL) equal to 50 kgf/m^2 at the top layer and 15 kgf/m^2 at the bottom layer and the second one is snow load (S) equal to 150 kgf/m^2 at the top layer. The loading surface of each node is (3×3 m) 9 square meters, so the concentrated load of each node is obtained by multiplying the load by the loading surface. In optimization analysis, two load combinations 1.4DL and 1.2DL+1.6S have been considered.

The material density of elements is 7850 kg/m^3 and the modulus of elasticity equals E = 235359 kPa. The structure is optimized for minimum weight while members are selected from pipe-shaped members in Table 8.

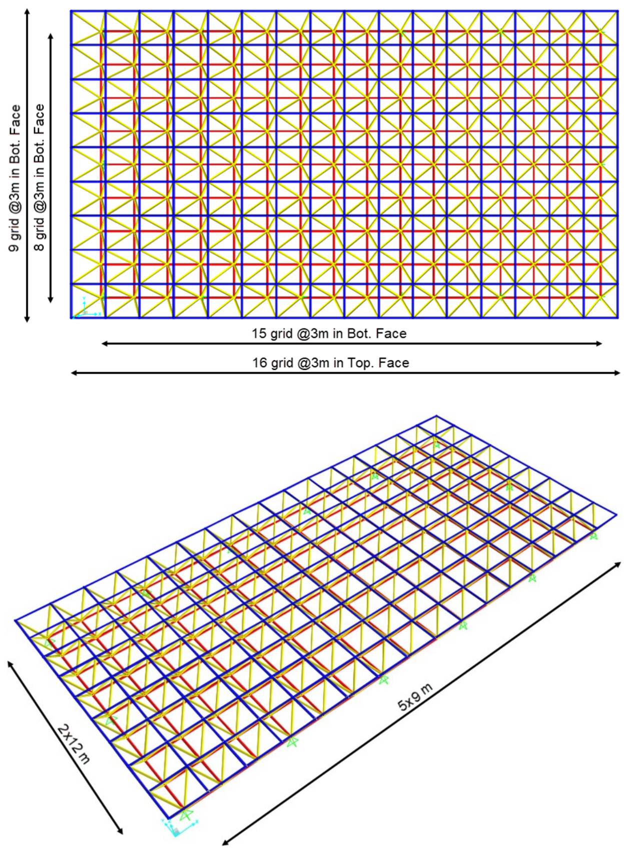

Figure 15. 1152-bar double-layer space frame roof

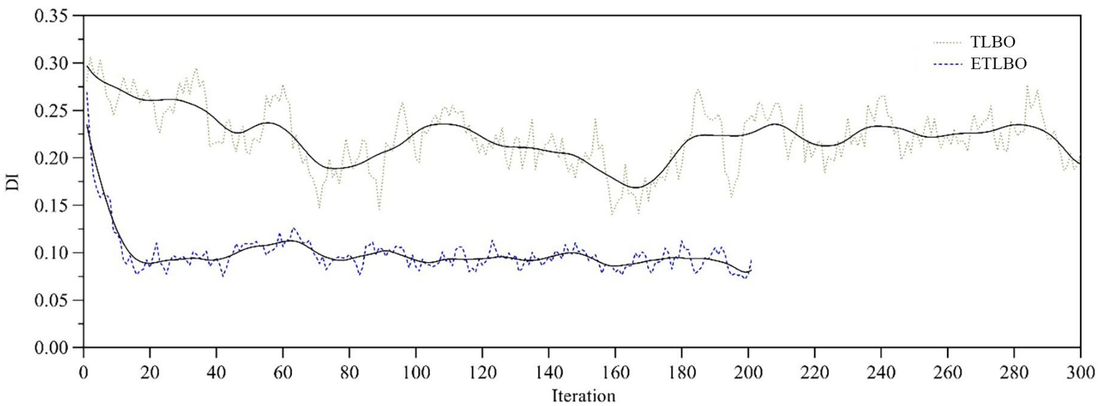

Figure 14. *DI* traces of ETLBO vs. TLBO for the 112-bar truss

Table 8. List of members in 1152-bar example

Pipe name	A (m^2)	The radius of gyration (m)
PIPE1.5 in	0.00042	0.01595
PIPE2 in	0.00054	0.02018
PIPE2.5 in	0.00073	0.02539
PIPE3 in	0.00087	0.02999
PIPE4 in	0.00125	0.03868
PIPE5 in	0.00206	0.04781
PIPE6 in-1	0.00244	0.05660
PIPE6 in-2	0.00299	0.05630

Table 9. Result of optimization algorithms in 1152-bar double layer space frame roof example

	TLBO	ETLBO
Best Weight (kg)	45764.88	38887.08
Mean Weight (kg)	51443.33	47322.45
SD	8136.79	4453.56
NFE (NFE-best)	5000 (2560)	5000 (3600)

The design constraints are imposed by LRFD–AISC (Load and Resistance Factor Design, American Institute of Steel Construction), and the maximum nodal displacement in each direction is limited to 0.1 m. Also, all members have been used as design variables. In this example, the implementation of the algorithms is continued up to 5,000 NFE.

In Figure 16, the Convergence trend of the two algorithms is shown. The Convergence trend in ETLBO shows that its fitness at often NFEs is more than the best fitness of TLBO.

According to Table 9, the best fitness of ETLBO and TLBO is equal to 38887.08 kg and 45764.88 kg, respectively, also the mean fitness of ETLBO is better than TLBO that indicates more reliability in ETLBO. For brevity in the context, the design variables value in ETLBO is provided in Appendix (Table A1).

As can be seen in Figure 17, the *DI* value does not significantly decrease along with runs, and the *DI* trend for the two algorithms has the same behavior because the number of design variables is high in this problem, as a result, the problem is more complicated.

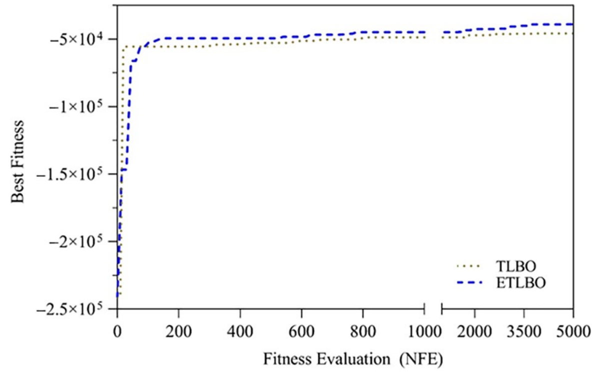

Figure 16. Convergence comparison of ETLBO vs. TLBO for the 1152-bar double layer space frame roof

Conclusions

The space frame structures are commonly used in large-scale structures and their optimal evaluation usually takes a long time. Therefore, optimization algorithms must have high speed and accuracy to meet the design needs more effectively in these problems. Thus, improving the behavior of optimization algorithms can help structural designers to achieve an optimal design. In this paper, by comparison of four basic algorithms have been tried to introduce the practical optimization algorithm to solve structural optimization. Based on the evaluation of these algorithms' results, a new algorithm was developed called ETLBO, in the proposed method, the crossover operator helps the TLBO process to efficiently perform the global exploration for rapidly attaining the feasible solution space and also helps to reach an optimal or near-optimal solution.

To compare the results of the algorithms, the values of the best fitness, mean fitness, and standard deviation of results along with convergence trend and DI index trend have been considered under the five examples consist of two new practical examples and three benchmark structural problems. Also, the results show, the proposed algorithm has a better solution and less standard deviation than the TLBO algorithm in most problems, and it achieves the best solution at fewer NFEs. Therefore, the proposed algorithm has performed better than other basic algorithms, and in terms of speed and accuracy of convergence compared to the results obtained from other

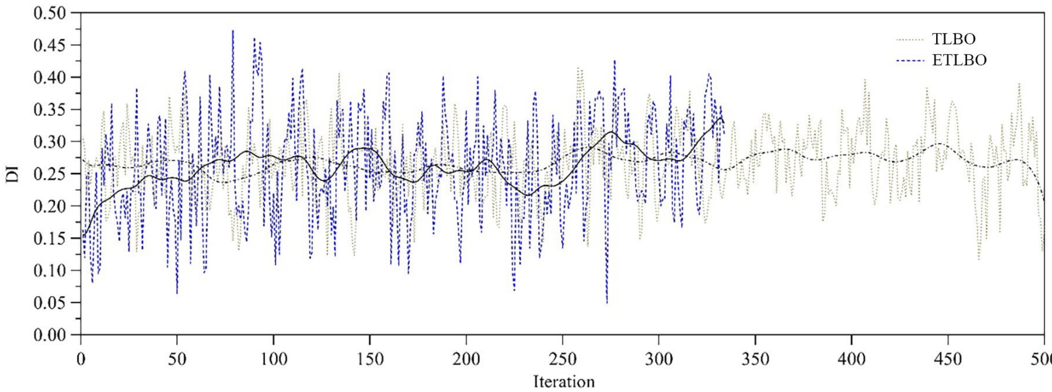

Figure 17. DI traces of ETLBO vs. TLBO for the 1152-bar double layer space frame roof

algorithms shows a significant improvement. Finally, due to the speed and accuracy of ETLBO algorithm, it can be used for the optimization of real-size space frame structures. For future works, it is suggested that the performance of ETLBO algorithm be examined for other problems that contain a huge number of variables, such as the optimization of real steel and concrete buildings.

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APPENDIX

Table A1. The design variables value in ETLBO

Numbers	Section	Frequency
(1119–1152)	PIPE1.5 in	34
(1–43), (212–357), 714, (771–937), (944–1070), (1099–1107), (1109–1112)	PIPE5.0 in	497
(44–77), (117–192), (382–399), (520–556), (564–596), (684–713), (1071–1098), 1108	PIPE4.0 in	257
(78–116), (358–381), (400–442), (462–519), (715–770), (938–943), (1113–1118)	PIPE3.0 in	232
(205–211), (443–461), (557–563), (597–683)	PIPE2.5 in	120
(193–204)	PIPE2.0 in	12