An Improved Teaching-Learning-Based Optimization Set of Rules for Component Layout Optimization with the Differential Operator

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Abstract:

TLBO is a differential operator-based technique to solving mechanical component optimization problems (training-learning based mainly optimization). This article goes into great detail on the origins and current state of TLBO. Like most other approaches to addressing an issue, you may use a large population of responses to arrive at the global solution. The TLBO features a strong differential operator to identify better solutions. To test the method's efficiency in addressing common optimization problems, an open coil helical spring is used initially, followed by a hollow shaft. affirmation was given. Simulation findings show that the suggested strategy outperforms current optimization techniques in terms of discovering better options (mechanical components).

INTRODUCTION

Conventional methods have to be used to reduce the capacity of a closed coil helical spring. Graphs were utilised to solve a set of constraints in a hollow shaft circumstance. Reddy and his colleagues used geometric programming to reduce the weight of a belt-pulley drive. Engineers often keep optimization in mind when designing mechanical systems since it is so important. A complicated objective function with numerous design variables and many restrictions is needed to optimise a whole mechanical system, on the other hand [4–6]. Instead of optimising the whole system, it's common practise to concentrate on optimising specific components or intermediary assemblies. Optimising centrifugal pumps without motors and seals is far simpler than doing it with pumps that have both a motor and a seal in place. Engineering calculations have typically used analytical or numerical methodologies to estimate the extremes of a function. Traditional optimization approaches may be useful in many cases, but they may fall short in increasingly complicated design circumstances. Typically, real-time optimization (design) issues include a large number of design variables that have a complex (nonconvex) and nonlinear effect on the objective function to be optimised.. We need an appropriate global or local maximum in order to achieve our desired function [7, 8]. In order to get the best possible outcome in any given situation, an optimization aim is needed. There should be no compromise on efficiency when it

comes to mechanical components. Machine components may be optimised to increase production rates and reduce material costs [9–12]. As a result, optimization strategies may be fully used.

output rates are maintained at a high level Several approaches for enhancing a project have been discussed in the literature. There are several ways to search for information, including direct and gradient approaches. Although the function value is sufficient for a simple direct search, gradient-based methods need the gradient information in order to establish the search's general direction and target location. In the following paragraphs, we'll discuss the drawbacks of traditional optimization approaches. Traditional procedures have been used for a long time to deal with these issues. Certain optimization issues may be better addressed using newer, more diverse ways if existing strategies have several constraints. In order to solve these issues, traditional approaches (such as gradient methods) are ineffective since they only identify local optimum values. This means mechanical engineers must continue to apply efficient and effective optimization techniques. Natural heuristic strategies have been more popular because of their superiority over deterministic optimization methods [13–16]. This evolutionary optimization approach, known as the genetic algorithm, is the most widely employed (GA). Complex problems with several variables and limitations might, nonetheless, have a near-optimal solution identified. The difficulty in identifying optimal values for factors like as population size, crossover frequency, and mutation frequency is an essential consideration to keep in mind.. The performance of the algorithm may be affected by adjusting its settings. Inertia, social and cognitive traits, and others are all used by PSO. Like ABC [17]'s stress on optimising the number of bees, this is comparable to ABC [17]. (workers, scouts, and bystanders). For HS to be effective it demands an abundance of improvisations and a high rate of harmony memory consideration. If you want your algorithm to work, you need to keep creating new optimization techniques that aren't dependent on parameters. This is something to keep in mind when reading this paper.. Teaching-learning-based optimization (TLBO) was established by Rao and colleagues lately (TLBO). Based on the principles of natural teaching and learning, this evolutionary algorithm is designed to improve itself over time. It has previously been shown that PSO, harmony search (HS), DE, and hybridPSO are better to other current optimization methods like GA. Hybrid methods for teaching-learning-based optimization (TLBO) and a differential mechanism are proposed in this paper. TLBO will be used as a starting point in the search process. Finally, the exact approach (SQP) will be employed for that area in order to arrive at the final answer. Mathematical expressions Designing helical springs with closed coils, hollow shafts, and belt-pulley drive difficulties occupy this part. A lot of issues arise as a result of [9] making use of GA as an optimization technique**.**

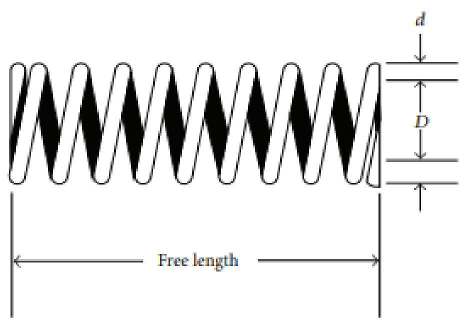

Figure 1: Schematic representation of a closed coil helical spring.

Yes, this is the first case (Closed Coil Helical Spring). For compressive and tensile loads, helical springs are often employed, since the wire is wrapped around itself (Figure 1). The wire used to make the spring might have a round, square, or rectangular cross-section. Hydraulic springs are most often employed in compression and tensile configurations. A spring wire that is twisted so tightly that the plane containing each turn is almost perpendicular to the central axis is referred to as having torsional strain (Figure 1). When the helical spring is twisted, it is subjected to shear stress. The spring is subjected to parallel or perpendicular stresses. Optimizing a helical spring that has a closed coil in order to minimise its volume is a complex task (Figure 1). The following is a mathematical solution to the issue. If the following criteria are satisfied, the volume of the spring (U) may be reduced to the bare minimum. Consider

$$U = \frac{\pi^2}{4}(N_c + 2) D d^2. \qquad (1)$$

Constraints on Stress. There must be a reduction in shear stress to the required level.

$$S - 8C_f F_{\max} \frac{D}{\pi d^3} \geq 0, \qquad (2)$$

Where

$$C_f = \frac{4C-1}{4C-4} + \frac{0.615}{C}, \quad C = \frac{D}{d}. \qquad (3)$$

Fmax and S are set to 453.6 kgf/cm2 and 13288.02 kgf/cm2, respectively, in this example.

Constraints on Configuration. The spring's free length cannot exceed the maximum value. You may get the spring constant (K) by multiplying by the expression:

$$K = \frac{G d^4}{8 N_c D^3}, \qquad (4)$$

where G is equivalent to 808543.6 kgf/cm2 shear modulus

The maximum working load deflection is determined by

$$\delta_l = \frac{F_{\max}}{K}. \qquad (5)$$

1.05 times the length of the solid is considered to be the spring length under the Fmax condition. In this way, the length of the statement is supplied.

$$l_f = \delta_l + 1.05 (N_c + 2) d. \qquad (6)$$

Thus, the constraint is given by

$$l_{\max} - l_f \geq 0, \qquad (7)$$

Lmax is 35.56 cm in this case. If the wire dia is less than the required minimum, it must also meet the following requirement:

$$d - d_{\min} \geq 0, \qquad (8)$$

where 0.508 centimetres is the minimum value of dmin. The coil's outside diameter must be less than the maximum allowed, and it must be less than that.

$$D_{max} - (D + d) \geq 0, \quad (9)$$

where Dmax is 7.62 cm. To prevent a spring from being too tightly coiled, the mean coil diameter must be at least three times the wire diameter.

$$C - 3 \geq 0. \quad (10)$$

The maximum deflection under preload must be less than the given value. Under preload, the deflection is represented as

$$\delta_p = \frac{F_p}{K}, \quad (11)$$

where the mass of Fp is 136.08 kg. The statement imposes the restriction.

$$\delta_{pm} - \delta_p \geq 0, \quad (12)$$

In this case, pm = 15.24 cm. The length of the combined deflection must be equal to the length of the combined deflection.

$$l_f - \delta_p = \frac{F_{max} - F_p}{K} - 1.05\left(N_c + 2\right) d \geq 0. \quad (13)$$

This restriction should be an equality, if you ask me. It is self-evident that the constraint function will always be zero at convergence. Preload to maximum load deflection must be the required value. An inequality restriction was put in place by these two because they wanted it to always equal zero. It has the following symbolism:

$$\frac{F_{max} - F_p}{K} - \delta_w \geq 0, \quad (14)$$

where δw is made equal to 3.175 cm.

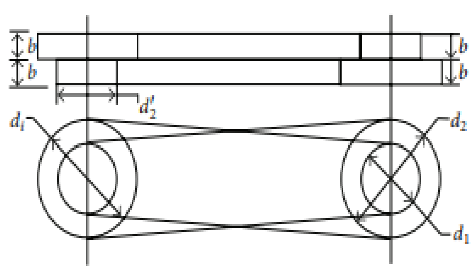

Figure 2 depicts a hollow shaft schematically. As a result of optimization, the following ranges are maintained:

$$0.508 \leq d \leq 1.016,$$
$$1.270 \leq D \leq 7.620, \quad (15)$$
$$15 \leq N_c \leq 25.$$

The task at hand may be classified as a constrained optimization problem since the objective function only has eight limitations. This is the second case (Optimum Design of Hollow Shaft). Power is transmitted from one location to another through a revolving shaft (Figure 2). For categorization reasons, transmission and line shafts may be divided into two main categories. Through a transmission shaft, the machines are supplied with power. For the most part, machine shafts can only be found in a limited number of machinery parts. There are many different kinds of machine shafts in use today, but crankshafts are among the most prevalent. A hollow shaft may be shown schematically in Figure 2. The study's stated goal is to reduce the weight of a hollow shaft.

Ws = cross sectional area × length × density

$$= \frac{\pi}{4}\left(d_0^2 - d_1^2\right) L\rho. \quad (16)$$

Substituting the values of L, ρ as 50 cm and 0.0083 kg/cm3 , respectively, one finds the weight of the shaft (Ws) and it is given by

$$W_s = 0.326 d_0^2 \left(1 - k^2\right). \quad (17)$$

It is subjected to the following constraints. The twisting failure can be calculated from the torsion formula as given below:

$$\frac{T}{J} = \frac{G\theta}{L} \quad (18)$$

or

$$\theta = \frac{TL}{GJ}. \quad (19)$$

Now, θ applied should be greater than TL/GJ; that is, $\theta \geq TL/GJ$.

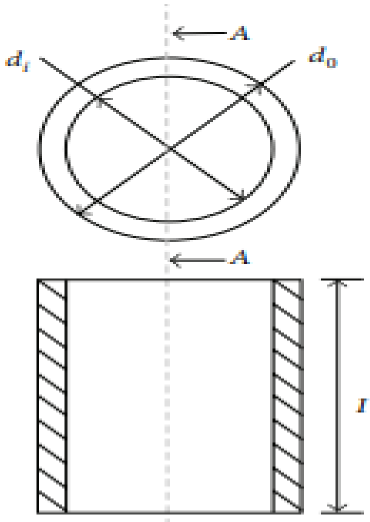

Figure 3: Schematic representation of a belt-pulley drive.

Constrained by substituting values of [(/32)d4 (0(1–k4)]], [(1–k4)] and [(/32)d4 (0(1–k4)], one obtains the constraints as a result of substituting the values of, T, G, and J.

$$d_0^4\left(1-k^4\right)-1736.93 \geq 0. \tag{20}$$

The critical buckling load (Tcr) is given by the following expression:

$$T_{cr} \leq \frac{\pi d_0^3 E(1-k)^{2.5}}{12\sqrt{2}(1-\gamma^2)^{0.75}}. \tag{21}$$

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Tcr,, and E are set at 1.0 105 kg-cm, 0.33, and 2.0 105 kg/cm2, respectively, such that the constraint may be represented as follows

$$d_0^3 E(1-k)^{2.5}-0.4793 \leq 0. \tag{22}$$

The ranges of variables are mentioned as follows:

$$7 \leq d_0 \leq 25, \quad 0.7 \leq k \leq 0.97. \tag{23}$$

In this case, it's number 3. (Optimum Design of Belt-Pulley Drive). Pulleys that rotate at different speeds or at the same rate as the shaft they're connected to use the belts to transmit power from one to the next (Figure 3). Stepped flat belt drives are often employed in manufacturing and fabrication operations to transport small quantities of electricity. It is common for the weight of the pulley to effect the shaft and bearing. Because the pulleys are so heavy, shaft failures are common (Table 1). In order to avoid shaft and bearing failure, flat belt drives must be light in weight. Figure 3 shows a belt-pulley drive schematic design. The reason for your visit. Keeping the weight of the pulley as low as feasible is an objective function.

$$W_p = \pi\rho b\left[d_1t_1 + d_2t_2 + d_1^1t_1^1 + d_2^1t_2^1\right]. \tag{24}$$

Table 1: Comparison of the results obtained by GA with the published results (Case 1).

Optimal values	Results obtained by GA	Published result
Coil mean dia, cm	2.3397870400	2.31140000
Wire dia, cm	0.6700824800	0.66802000
Volume of spring wire, cm^3	46.6653438304	46.53926176

Assuming $t1 = 0.1d1$, $t2 = 0.1d2$, $t\ 1\ 1 = 0.1d1\ 1$, and $t\ 1\ 2 = 0.1d1\ 2$ and replacing $d1$, $d2$, $d1\ 1$, and $d1\ 2$ by $N1$, $N2$, $N1\ 1$, and $N1\ 2$, respectively, and also substituting the values of $N1$, $N2$, $N1\ 1$, and $N1\ 2$, ρ (to 1000, 250, 500, 500) 7.2 × 10−3 kg/cm3 , respectively, the objective function can be written as

$$W_p = 0.113047d_1^2 + 0.0028274d_2^2. \tag{25}$$

It is subjected to the following constraints. The transmitted power (P) can be represented as

$$P = \frac{(T_1-T_2)}{75}V. \tag{26}$$

Substituting the expression for V in the above equation, one gets

$$P = (T_1-T_2)\frac{\pi d_p N_p}{75\times 60\times 100}, \tag{27}$$

$$P = T_1\left(1-\frac{T_2}{T_1}\right)\frac{\pi d_p N_p}{75\times 60\times 100}. \tag{28}$$

Assuming $T2/T1 = 1/2$, $P = 10$ hp and substituting the values of $T2/T1$ and P, one gets

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$$10 = T_1\left(1-\frac{1}{2}\right)\frac{\pi a_p N_p}{75\times 60\times 100} \quad (29)$$

Or

$$T_1 = \frac{286478}{d_p N_p}. \quad (30)$$

Assuming

$$d_2N_2 < d_1N_1, \quad (31)$$

And considering (26) to (28), one gets

$$\sigma_b b t_b \geq \frac{2864789}{d_2 N_2}. \quad (32)$$

Substituting σb = 30 kg/cm2 tb = 1 cm, $N2$ = 250 rpm in the above equation, one gets

$$30b \times 1.0 \geq \frac{28864789}{d_2 250} \quad (33)$$

Or

$$b \geq \frac{381.97}{d_2} \quad (34)$$

Or

$$bd_2 - 81.97 \geq 0. \quad (35)$$

Assuming that width of the pulley is either less than or equal to one-fourth of the dia of the first pulley, the constraint is expressed as

$$b \leq 0.25 d_1 \quad (36)$$

Or

$$\frac{d_1}{4b} - 1 \geq 0. \quad (37)$$

The ranges of the variables are mentioned as follows:

$$15 \leq d_1 \leq 25,$$
$$70 \leq d_2 \leq 80, \quad (38)$$
$$4 \leq b \leq 10.$$

Optimization Procedure

When confronted with complicated settings, classical search and optimization algorithms suffer from a variety of drawbacks. To tackle several issues with one solution gets more complex. There are just a few topics addressed in the traditional method. As a result, it's limited in its ability to deal with a wide range of problems. Because they lack a global viewpoint and tend to converge to a locally optimum solution, classical approaches cannot be applied successfully in parallel computing systems. The sequential structure of classical algorithms makes it difficult to get additional benefits from them. Search and optimization strategies that haven't been used before are becoming more prevalent. Optimization problems are addressed using genetic algorithms and simulated annealing.

Optimization Using teaching-learning principles Ragsdell, Phillips, and David Edward pioneered the teaching-learning-based optimization (TLBO) approach in the classroom. This algorithm, like earlier ones inspired by nature, makes use of a population of solutions to get the best possible result. The strategy's design variables are the classes' selections of topics to study. A student's level of knowledge may be assessed using the objective function value of each possible solution, which takes into account the design elements. Hire a fitness instructor if you want to get the most people fit (among all pupils). Each student (Xi) in the population faces the same optimization issue, but they all come up with different solutions to it. For students and teachers in the TLBO system, the amount of courses they'll be taking or teaching is predetermined. The real-valued vector Xi designates this integer, which has a dimension of D. If a person's new answer is better than their prior one throughout the Teacher and Learner Phases of the process, an algorithm may be able to replace them. For as long as the algorithm is running, it will keep repeating itself. During the Teacher Phases, the best teacher (Xteacher) obtains the position. For the purpose of attempting to raise the average performance of additional persons, the algorithm utilises the present mean (Xmean) of those involved (Xi). Mean values of all students in this generation are shown here to reflect a particular concern area (dimension). The teacher uses Equation to reproduce all of the students' skills and knowledge (39). Random variables are employed in the equation for stochastic purposes: The teaching factor (TF) might be one or two to emphasise the significance of student quality. r may have a value between 0 and 1.

$$X_{\text{new}} = X_i + r \cdot \left(X_{\text{teacher}} - \left(T_F \cdot X_{\text{mean}} \right) \right). \qquad (39)$$

When a student (Xi) is in the Learner Phase, he or she strives to increase their knowledge by learning from an unrelated student (Xii). If Xii is superior than Xi, Xi will gravitate toward Xii (40). As a result, it will be relocated away from Xii (41). Student Xnew will be allowed into the general population if he or she improves his or her grades by following (40) or (41). There is no limit on how many generations the algorithm may go through. Consider.

$$X_{\text{new}} = X_i + r \cdot \left(X_{ii} - X_i \right), \qquad (40)$$

$$X_{\text{new}} = X_i + r \cdot \left(X_i - X_{ii} \right). \qquad (41)$$

When solving restricted optimization issues, infeasible persons must be dealt with effectively to identify which individual is superior. Deb's restricted handling approach [4] is used by the TLBO algorithm for comparing two persons, according to [14–17]. A fitter person (one with a higher fitness function value) is preferable if both people are available. (ii) The feasible person is favoured over the infeasible one if only one can be achieved. The person with the less violations (a value determined by adding up all of the normalised constraint violations) is selected if both persons are infeasible. Operator for a differential equation. Using the best knowledge collected from other students, all students may develop new search space locations. We enable the learner to learn from the exemplars until the student stops improving for a specified amount of time in order to guarantee that the student learns from excellent examples and to limit the time lost on bad guidance.

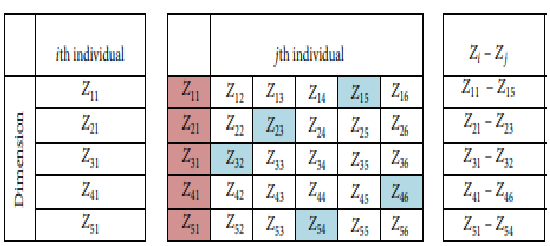


Figure 4: Differential operator illustrated.

For many generations, it has been known as the "refuelling chasm." There are three major differences between the DTLBO algorithm and the classic TLBO algorithm [4]. Using the potentials of all students to guide a student's new position after sensing distance is used to identify the closest members of each student, this methodology employs this method. Instead of using the same students as examples for all dimensions, different students might be utilised to update a student's status for each dimension. It's possible for students to learn from one another's dimensions using the equation proposed (42). updating a student's position by picking their next-door neighbour randomly in each of three dimensions (with a vigil that repetitions are avoided). Additionally, this significantly improves the original TLBO's ability to adequately investigate complex optimization problems while avoiding premature convergence. Finding the global optimum using DTLBO is more efficient than with TLBO. A better solution for each student is provided by using a differential operator that just updates the fundamental TLBO instead of updating all students at once as in KH. This seems to be a snooty attitude on their part. The first design of the TLBO had an issue with premature convergence. Due to the fact that all students' locations are updated simultaneously, a differential guiding system is used in order to avoid a premature convergence and enhance the exploration possibilities of the original TLBO system. Equation explains the differential mechanism (42).

$$Z_i - Z_j = \left(z_{i1} \;\; z_{i2} \;\; z_{i3} \;\; \cdots \;\; z_{in} \right) - \left(z_{\rho 1} \;\; z_{\rho 2} \;\; z_{\rho 3} \;\; \cdots \;\; z_{\rho n} \right), \qquad (42)$$

where

$zi1$ is the first element in the n dimension vector Zi;

zin is the nth element in the n dimension vector Zi;

$z\rho 1$ is the first element in the n dimension vector Zp;

ρ is the random integer generated separately for each z, from 1 to n, but $\rho = i/$.

Figure 4 depicts the differential selection of the neighbouring student (34). To put it another way, this means the problem dimension is 5 and the population size is 6. As soon as a new student is detected, the locations of all nearby students will be updated (as illustrated in Figure 4) using the detecting distance. Preventing early convergence and exploring a large promising region are the primary goals of this step prior to the run phase of the project.

The Pseudocode for the Simplified TLBO Algorithm.

An algorithm that uses the differential operator scheme may be improved as follows.

In this stage, the population, the range of design variables, and the number of iterations are all established.

In order to get a truly random sample, use the design factors.

The new students may be used to assess the fitness aspect of the programme.

The mean value of each design variable should be determined by performing the aforementioned calculation.

Determine the best course of action for the teacher based on the children's fitness level. The differential operator approach may be used to fine-tune the teacher.

The teacher's mean, which was obtained in step 4, should be used to adjust all of the other students' scores.

Preliminary Stage

Students who have been adjusted in steps 6 and 7 will be used to assess the fitness function in this stage.

Compare the degree of physical fitness of two different pupils. Students with higher fitness values should be subjected to differential operator analysis. Don't waste your time with those that aren't qualified. Substitute the student's fitness level and its design variable for the student's current fitness level.

Table 2: Best, worst, and mean production cost produced by the various methods for Case 1.

Method	Maximum	Minimum	Mean	Average time (min)	Minimum time (min)
Conventional	NA	46.5392	NA	NA	NA
GA	46.6932	46.6653	46.6821	3.2	3
PSO	46.6752	46.5212	46.6254	1.8	1.7
ABS	46.6241	46.5115	46.6033	2.5	2.3
TLBO	46.5214	46.3221	46.4998	2.2	2
DTLBO	46.4322	46.3012	46.3192	2.4	2.2

As a precaution, repeat steps 8 and 9 until the test is completed by all students (pairs).

If the amended student strength is smaller than the original student strength, there will be no duplication of candidates.

Ensure that the termination requirements are met by returning to step 4.

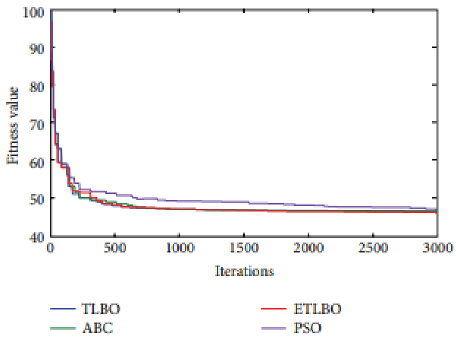
The findings and conclusions are presented in this section. Three of the aforementioned optimization challenges are addressed via simulated experiments in this section. For the purpose of this research, we compare the TLBO method to the four nature-inspired optimization strategies (PSO, GA) that are often used in the field. There is an original version of each of the four approaches that may be viewed. An algorithm's inputs and outputs.

Based on evolutionary principles, this method is This example uses a 100-person sample, and the crossover probability is at 80%, while the mutation chance is at 10%. Optimization by use of a particle swarm. When the particle size is 30 pixels and the wmax and wmin values are set to 1,11 and 0,73, the generation number is 3000. Boxed Beehive. There are just 50 bees in this colony, which has been around for almost 3000 generations.

The greatest approach to become better is to do both learn and teach. More than 3000 generations have passed through the neighbourhood. Since there isn't much of a difference between the TLBO and the previous algorithm (Tables 2 and 3). For these optimization strategies, the algorithm's performance must be taken into consideration. GA, PSO, and ABC (number of hired bees) all need crossover probability and mutation rate and selection procedure. As long as participants and iterations work together, the TLBO is OK (Figures 5, 6, 7, and 8). Table 6 shows comparisons between GA results and previously reported data. Each approach was put to the test 50 times, and the results are displayed in the table below. GA provides the most precise results.

As shown in Table 3, published data has been compared to the GA findings. Here we have the second example.

Optimal values	Results obtained by GA	Published result
Outer dia hallow shaft, cm	11.0928360	10.9000
Ratio of inner dia to outer dia	0.9699000	0.9685
Weight of hallow shaft, kg	2.3704290	2.4017



As an example, the claimed results in Figure 5 are somewhat more accurate than the actual findings. The settings that are chosen have an impact on the GA's performance. A lot more study may be done on the GA parameters even though they've been well studied in the past (Tables 4 and 5). The suggested method was able to produce the optimal values in 50 unique trials for each of the three scenarios investigated. In the conclusion, a belt-pulley drive's weight minimization, a hollow shaft's weight minimization, and a closed coil helical spring's volume minimization were all analysed in this study. Teaching-learning optimization (TLBO) is explained and assessed for several performance metrics, such as best fitness, mean solution, and average number of solutions, in order to address the above-mentioned issues.

For the second case, the manufacturing costs are shown in Table 4 for the best, worst, and average approaches.

Method	Maximum	Minimum	Mean	Average time (min)	Minimum time (min)
Conventional	NA	46.5392	NA	NA	NA
GA	46.6932	46.6653	46.6821	3.2	3
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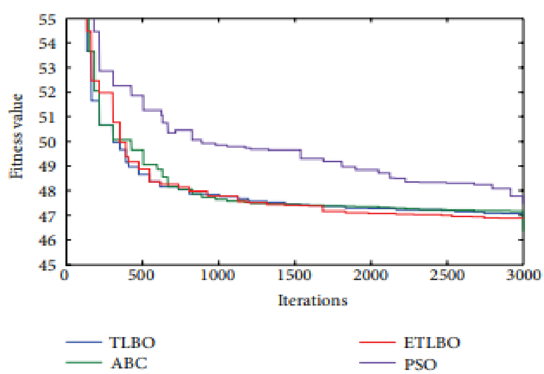

Figure 6: Convergence (magnified) plot of the various methods for Case 1.

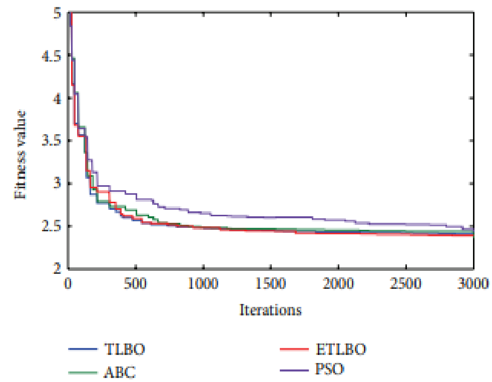

Figure 7 shows the different approaches' convergence rates and the number of function evaluations necessary for each method. A TLBO-based algorithm outperforms existing nature-inspired optimization approaches in terms of performance for the design issues studied. Although this study focuses on three basic mechanical component optimization issues, with a minimal number of constraints, this suggested technique may be applied to additional engineering design challenges, which will be examined in a future study.

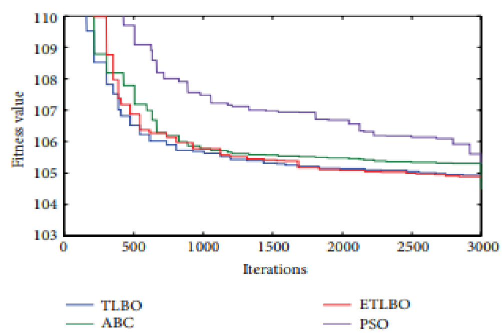

Figure 8: Convergence plot of the various methods for Case 3.

Table 5: Comparison of the results obtained by GA with the published results (Case 3).

Optimal values	Results obtained by GA	Published res
Pulley dia (d_1), cm	20.957056	21.12
Pulley dia (d_2), cm	72.906562	73.25
Pulley dia ($d^1{}_1$), cm	42.370429	42.25
Pulley dia ($d^1{}_2$), cm	36.453281	36.60
Pulley width (b), cm	05.239177	05.21
Pulley weight, kg	104.533508	105120

Nomenclature

b: Width of the pulley, cm

C: Ratio of mean coil dia to wire dia

d: Dia of spring wire, cm

dp: Dia of any pulley, cm

$d1$: Dia of the first pulley, cm

$d1\ 1$: Dia of the third pulley, cm

$d2$: Dia of the second pulley, cm

$d1\ 2$: Dia of the fourth pulley, cm

di: Inner dia of hollow shaft, cm

$d0$: Outer dia of hollow shaft, cm

$d$min: Minimum wire dia, cm

D: Mean coil dia of spring, cm

Dmax: Maximum outside dia of spring, cm

E: Young's modulus, kgf/cm2

Table 6: Best, worst, and mean production cost produced by the various methods for Case 3.

Method	Maximum	Minimum	Mean	Average time (min)	Minimum time (min)
Conventional	NA	105.12	NA	NA	NA
GA	104.6521	104.5335	104.5441	4.6	4.2
PSO	104.4651	104.4215	104.4456	2.1	1.9
ABS	104.5002	104.4119	104.4456	3.1	2.9
TLBO	104.4224	104.3987	104.4222	2.9	2.8
DTLBO	104.3992	104.3886	104.3912	3.3	3.1

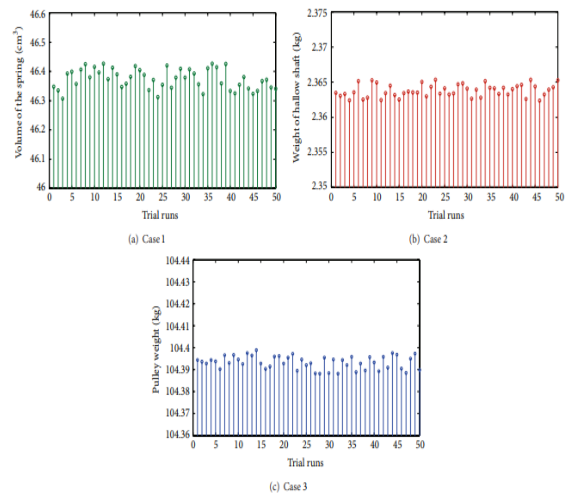

Figure 9: Final cost of the optimization obtained for all test cases using DTLBO method.

$N2$: rpm of the second pulley

$N12$: rpm of the fourth pulley

Nc: Number of active coils

Np: rpm of any pulley

P: Power transmitted by belt-pulley drive, hp

q: Any nonnegative real number

S: Allowable shear stress, kgf/cm2

tb: Thickness of the belt, cm

$t1$: Thickness of the first pulley, cm

$t11$: Thickness of the third pulley, cm

$t2$: Thickness of the second pulley, cm

$t12$: Thickness of the fourth pulley, cm

T: Twisting moment on shaft, kgf-cm

Fmax: Maximum working load, kgf

Fp: Preload compressive force, kgf

G: Shear modulus, kgf/cm
J: Polar moment of inertia, cm^4
k: Ratio of inner dia to outer dia
K: Spring stiffness, kgf/cm
l_f: Free length, cm
l_{max}: Maximum free length, cm
L: Length of shaft, cm
N_1: rpm of the first pulley
N_1^1: rpm of the third pulley
W_s: Weight of shaft, kg
W_p: Weight of pulleys, kg
V: Tangential velocity of pulley, cm/s
U: Volume of spring wire, cm^3
u: A random number
T_1: Tension at the tight side, kgf
T_2: Tension at the slack side, kgf
T_{cr}: Critical twisting moment, kgf-cm.

Greek Symbols

β: Spread factor
γ: Poisson's ratio
γ_1: Cumulative probability
δ: Perturbance factor
δ_p: Deflection under preload, cm
δ_{max}: Maximum perturbance factor
δ_{pm}: Allowable maximum deflection under preload, cm
δ_w: Deflection from preload to maximum load, cm
δ_1: Deflection under maximum working load, cm
θ: Angle of twist, degree
ρ: Density of shaft material, kg/cm^3
σ: Allowable tensile stress of belt material, kg/cm^3.

CONCLUSION

The authors do not have any conflict of interests in this research work.

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