Design optimization of mechanical parts by use of a more complex suite of optimization algorithms founded on the differential operator and based on teaching-learning

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Abstract:

TLBO, or training-learning based optimization, is a method for optimizing mechanical components using differential operators. The history and current state of TLBO are extensively detailed on this page. Using a large population of answers is similar to previous methods in that it may lead to a worldwide solution. If you want better results with TLBO, you should employ differential operators. To test how well the approach works for tackling common optimization problems, an open coil helical spring is used first, and then a hollow shaft. It was unanimously "yes." Results from simulations show that existing optimization methods (including mechanical components) do not find superior alternatives to the suggested technique.).

1. INTRODUCTION

Traditional methods are required to reduce the capacity of a closed coil helical spring. Graphs were used to resolve a set of limitations in a hollow shaft scenario. Researchers Reddy and colleagues used geometric programming to make belt-pulley drives lighter. Engineers often think about optimization while creating mechanical systems because of this. When trying to find the sweet spot for a mechanical system, there are a lot of variables and limitations to think about [4-6]. Rather of maximizing the whole system, it is common procedure to concentrate on specific parts or intermediary assemblies. It is far simpler to optimize centrifugal pumps that do not have motors or seals. When doing calculations in engineering, it is common practice to use analytical or numerical techniques to estimate the function's extremes. Classical optimization techniques may not cut it when it comes to building complicated systems. In order to optimize the objective function, most real-time optimization problems include a large number of design variables that have complex, nonconvex, and nonlinear impacts. Our success depends on our ability to settle on a reasonable upper limit, either on a global or local scale. A focus on optimization is necessary in each given situation. In terms of efficiency, mechanical parts should not be slouched. Optimisation of machine components may increase production rates while decreasing material costs [9–12]. This allows for the maximum use of optimization strategies.

We maintain high production rates. Several methods for making a project better may be found in books and articles. Direct and gradient methods of information retrieval are also at your disposal. For a straight search, function values will do, but for gradient-based algorithms, the gradient data is necessary to determine the general direction and location of the search. In what follows, we'll talk about the problems with traditional optimization techniques. There has been an extensive history of using conventional approaches to address these issues. To solve certain optimization challenges, it may be more successful to use newer, more diverse ways if current strategies are limited in some way. The use of traditional approaches (such gradient methods) to get globally optimum values is not feasible. Therefore, mechanical engineers should stick to what has worked in the past: optimization. Their effectiveness surpasses that of deterministic techniques, which has led to their rising popularity [13–16]. As an evolutionary optimization technique, the genetic algorithm is by far the most popular choice (GA). Even with a lot of variables and limitations, a near-optimal solution could be possible to a complicated problem. A good population size, crossover rate, and mutation rate are all difficult to pin down. The algorithm's performance might be affected by adjusting its settings. PSO takes use of people's social and cognitive traits in addition to their inertia. You may see a similar focus on increasing the beehive count in ABC [17]. Observers, workers, and scouts. For HS to work, you need a lot of improvisations and a fast rate of harmonic memory. Updating an effective algorithm necessitates ongoing exploration of non-parametric optimization techniques. Keep this in mind while you read this article. The teaching-learning-based optimization (TLBO) approach was created by

Rao and his colleagues. (TLBO) a few of my colleagues. Natural learning and teaching are the foundations of an algorithm that improves itself. Earlier iterations of optimization methods like GA were outperformed by PSO, HS, DE, and hybridPSO. The research presented here proposes a hybrid TLBO strategy based on a differential mechanism. Our first order of business is to search TLBo for any relevant results. The last step in getting the answer is to apply the precise approach (SQP). Calculus expressions Hollow shafts, helical springs with closed coils, and belt-pulley drives are the focus of this section. When using [9] GA for optimization, issues often arise.

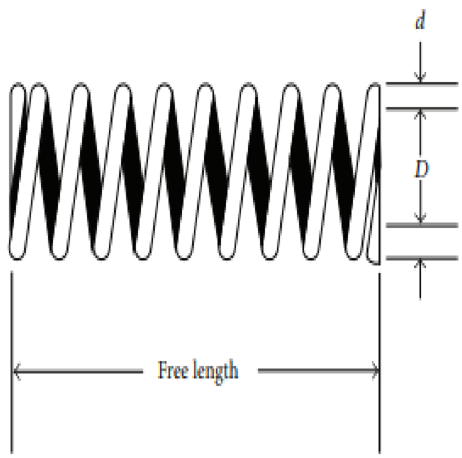

Figure 1: Schematic representation of a closed coil helical spring.

Here we have the scenario (Closed Coil Helical Spring) to begin with. The coiled wire of a helical spring is ideal for both compressive and tensile loads, as seen in Figure 1. The spring's wire may have a round, square, or rectangular cross-section. The two most common applications for hydraulic springs are compression and tensile designs. Figure 1 shows that torsional strain occurs when the twists in a spring wire are so tightly wound that the plane containing the turns is almost perpendicular to the central axis. When a helical spring is bent to produce a torque, it undergoes shear stress. The spring is subjected to tension in two directions: parallel and perpendicular. A helical spring with a closed coil presents a challenging task when trying to minimize its volume (Figure 1). There may be a mathematical solution to this issue. The spring (U) may be let down to its lowest possible volume after these requirements are fulfilled. Think about it

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

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:

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

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.

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

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.

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

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

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

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

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

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

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

If you ask me, this constraint should be equal. At convergence, the constraint function is guaranteed to be zero. Preloading to the maximum deflection of the load is essential. Because they intended it to always equal zero, these two placed an inequality limitation in place. The symbolism is as follows:

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

where δw is made equal to 3.175 cm.

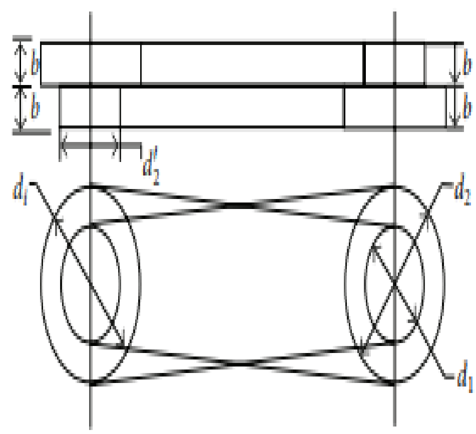

Figure 2 depicts a hollow shaft schematically. As a result of optimization, the following ranges are maintained:

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

With just eight constraints on the objective function, we may say that this is a restricted optimization problem. The second scenario is the Optimal Design of Hollow Shaft. To move it from one place to another, power is used in the form of a spinning shaft (Figure 2). For categorization reasons, transmission and line shafts may be divided into two main categories. Machines get their power via transmission shafts. In general, only a few of machine parts really use shafts. Although there are several other types of machine shafts, crankshafts are among the most prevalent. Figure 2 shows a schematic of a shaft with no interior. Finding a way to make a hollow shaft lighter is one of the research goals. Ws = cross sectional area × length × density

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

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

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

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

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

or

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

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

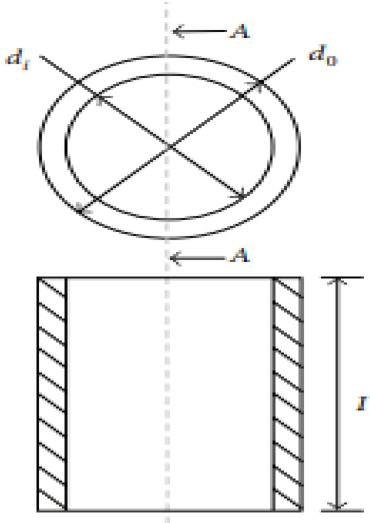

Figure 3: Schematic representation of a belt-pulley drive.

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.

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

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

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

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

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

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

The ranges of variables are mentioned as follows:

$$7\leq d_0\leq 25, \quad 0.7\leq k\leq 0.97. \qquad (23)$$

In this particular situation, it ranks third. (The Best Design for a Belt-Pulley Drive) Figure 3 shows the gears and pulleys that transfer power from one belt to another at varying speeds. For small loads, stepped flat belt drives are a common tool in the fabrication and manufacturing industries. The pulley's weight might have an impact on the shaft and bearing. The pulley's weight is a common cause of shaft breaks (Table 1). In order to keep shaft and bearing failure to a minimum, flat belt drives must be lightweight. Figure 3 shows a simplified diagram of a belt-pulley drive. Is this your first stop? Keeping the pulley's weight low is an objective function.

$$W_p=\pi\rho b\left[d_1t_1+d_2t_2+d_1^1t_1^1+d_2^1t_2^1\right]. \qquad (24)$$

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

$$W_p=0.113047d_1^2+0.0028274d_2^2. \qquad (25)$$

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

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

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

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

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

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

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

Or

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

Assuming

$$d_2 N_2 < d_1 N_1, \qquad (31)$$

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

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

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

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

Or

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

Or

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

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

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

Or

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

The ranges of the variables are mentioned as follows:

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

Optimization Procedure

When faced with complicated conditions, classical optimization and search algorithms suffer from a multitude of flaws. It becomes increasingly challenging to solve many issues simultaneously. Traditional methods limit their attention to a select few topics. This means it can't handle a wide range of problems. Traditional methods are ineffective for parallel computing systems because these systems converge on locally optimum solutions rather than taking a global view. It is challenging to derive additional benefits from classical algorithms due to their sequential structure. More and more, modern search and optimization strategies are being used. Genetic algorithms and computational modeling are used to address optimization challenges.

Optimization based on pedagogical concepts The first implementation of optimization in the classroom was the teaching-learning-based optimization (TLBO) developed by Ragsdell, Phillips, and David Edward. Much like earlier methods that drew inspiration from nature, this one uses a population of solutions. The courses' topic selections are one component of the strategy's framework. One way to evaluate a student's understanding is to look at the objective function value of all possible solutions, which factor in the design features. Collaborate with a personal trainer to make sure that all students are as fit as possible. Each student (Xi) finds their own unique solution to the optimization issue, even if the population faces the same challenge overall. There is a predetermined limit on the amount of classes that both students and teachers may take under the TLBO model. The real-valued vector Xi represents this number with D dimensions. If an algorithm's latest answer during the procedure's Teacher and Learner Phases is superior to its earlier one, humans may be substituted by algorithms. If the algorithm is still running, it will keep looping. While in the Teacher Phases, one might occupy the position of best teacher (Xteacher). The strategy takes use of the present average (Xmean) of the participants to improve the average performance of new people (Xi). In order to draw attention to a particular aspect, we have shown the averages of all students from this generation. Equation allows the educator to rebuild the students' talents and knowledge (39). A number of stochastic variables are used by the equation: To stress the significance of student quality, there could be just one or two TFs. You may find r between zero and one.

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

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.

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

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

When tackling constrained optimization concerns, infeasible individuals must be dealt with efficiently to establish which individual is better. Deb's constrained handling technique [4] is employed by the TLBO algorithm for comparing two individuals, according to [14–17]. A fitter individual (one with a higher fitness function value) is desirable if both persons are available. (ii) The feasible individual is preferred over the infeasible one if only one can be attained. The person with the least violations (a value derived by summing up all of the normalised constraint violations) is picked if both individuals are infeasible. Operator for a differential equation. Using the best information obtained from other students, all students may design new search space locations. We permit the learner to learn from the exemplars until the student stops progressing for a set length of time in order to ensure that the student learns from outstanding examples and to minimize the time wasted on substandard coaching.

Dimension	ith individual	jth individual						$Z_i - Z_j$
	Z_{11}	Z_{11}	Z_{12}	Z_{13}	Z_{14}	Z_{15}	Z_{16}	$Z_{11} - Z_{15}$
	Z_{21}	Z_{21}	Z_{22}	Z_{23}	Z_{24}	Z_{25}	Z_{26}	$Z_{21} - Z_{23}$
	Z_{31}	Z_{31}	Z_{32}	Z_{33}	Z_{34}	Z_{35}	Z_{36}	$Z_{31} - Z_{32}$
	Z_{41}	Z_{41}	Z_{42}	Z_{43}	Z_{44}	Z_{45}	Z_{46}	$Z_{41} - Z_{46}$
	Z_{51}	Z_{51}	Z_{52}	Z_{53}	Z_{54}	Z_{55}	Z_{56}	$Z_{51} - Z_{54}$

Figure 4: Differential operator illustrated.

Its name, the "refuelling chasm," has stuck for a long time. When compared to the original TLBO algorithm, the DTLBO method differs in three key respects [4]. Following the use of distance sensing to determine which students are physically nearest to one other, this system makes advantage of each student's capacity to direct their new position. You may use distinct students to update a student's status for each dimension instead of using the same ones for all of them. Using the suggested equation, pupils might potentially learn from one other's dimensions (42). shifting a student's standing by selecting a random neighbor in each of three dimensions (while keeping an eye out for repeats). Also, the original TLBO is now much better able to probe complicated optimization issues thoroughly without undergoing premature convergence because of this. It is more efficient to use DTLBO to find the global optimum than TLBO. Using a differential operator that updates the basic TLBO alone, rather than updating all students simultaneously as KH does, provides a better answer for every student. It seems like they're being pretentious. Problems with early convergence plagued the original TLBO design. The original TLBO method enhances exploration opportunities and prevents premature convergence by using a differential guiding system, which is necessary since all students' positions are updated concurrently. The differential mechanism is explained by the equation (42).

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

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 $\rho = i$/.

Fig. 4 displays the neighbouring student's differential selection (34). This suggests that the issue dimension is 5 and the population size is 6 As soon as a new student is located, the detecting distance is used to update the positions of all adjacent students (as shown in Figure 4). During this first phase of the project, the key focus is on avoiding early convergence and exploring a vast prospective area.

Simplified TLBO Algorithm Pseudocode.

The following changes may be made to a differential operator scheme-based algorithm.

During this phase, the target audience is identified, as are the range of design variables and the number of iterations to be used.In order to get a truly random sample, use the design factors.

The program's fitness level may be gauged by looking at the new pupils.

The aforementioned technique should be used to calculate the mean value of each design variable.

Children's fitness levels should be taken into account to help teachers choose the best course of action for them. The instructor may be fine-tuned using the differential operator technique.

Students' scores should be adjusted using the teacher's mean, which was calculated in step 4.

Preliminary Stage

Steps 6 and 7 students will be employed in this stage to evaluate the fitness function.

Look at how physically fit two distinct students are side by side. There should be differential operator analysis for students who have greater fitness levels. People who aren't qualified are a waste of time. In place of the student's current fitness level, use the design variable.

Table 2 summarises the best, worst, and average production costs 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

If an issue arises, go to steps 8 and 9 again until all students have completed the test in pairs.

If the number of adjusted students is lower than the number of original students, then no candidates will be considered again.

To verify that the requirements for termination have been met, go back to step 4.

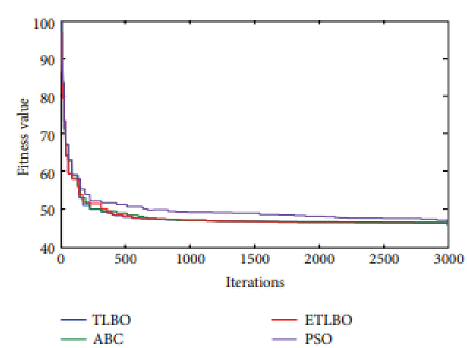
Here you can find the findings and suggestions presented. This section addresses three of the optimization challenges stated earlier by using simulated trials. This research effort compares TLBO to four extensively used optimization approaches in the domain that are influenced by nature: PSO and GA. It is possible to look at the four approaches in their raw form. Data that an algorithm takes in and uses as return.

According to evolutionary theory, this tactic will work. In this case, the mutation probability is low at 10%, whereas the crossover likelihood is high at 80%. This situation calls for swarm optimization. With wmax=1.11 and wmin=-0.73, the generation number for a particle size of 30 pixels is 3000. An Enclosed Beehive. There are only fifty bees in this colony, yet they have managed to survive for over three thousand generations.

It is vital to learn and teach if one wants to improve himself. More than three thousand generations have passed through the area. This is the optimal choice due to the lack of commonality between the TLBO and the previous algorithm (Tables 2 and 3). These optimization approaches require considering the algorithm's performance. For GA, PSO, and ABC (the quantity of bees recruited), there exist mutation rates, crossover probabilities, and selection techniques. So long as iterations and participants work together, the TLBO should be OK (Figures 5, 6, 7, and 8). In Table 6, we can see how the GA results stack up against the literature. The outcomes of each method's 50-test assessment are shown in the table below. GA provides the most precise results.

The GA findings are compared to the published data in Table 3. Here then is a case of the second kind.

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



For example, Figure 5 shows data that are somewhat more accurate than what was really found. When it comes to the GA's performance, the options you choose have an influence. Even though GA factors have been extensively researched in the past, there may be a lot more research to be done (Tables 4 and 5). A total of 50 unique experiments were conducted for each of the three situations to determine the best possible values. In the end, this research looked at how to reduce the weight and volume of a belt-pulley drive, a hollow shaft, and a closed coil helical spring. In order to overcome the aforementioned problems, TLBO is described and evaluated in terms of many performance measures, such as best fitness, mean solution, and average number of solutions.

An average method is provided in Table 4 along with expenses for all three extremes in the second scenario.

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
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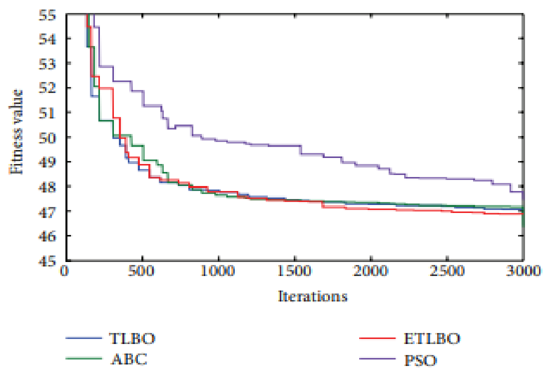

Figure 6: Convergence (magnified) plot of the various methods for Case 1.

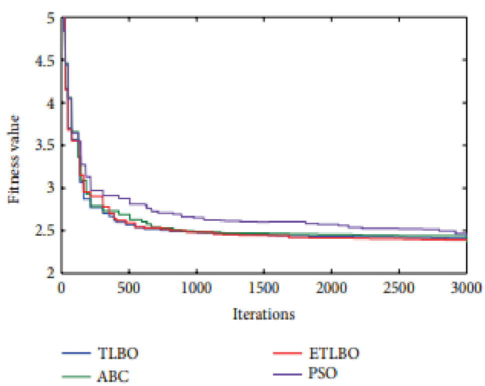

Figure 7 shows the different approaches' convergence rates and the number of function evaluations necessary for each method. A TLBO-based algorithm outperforms existing nature-inspired optimization approaches in terms of performance for the design issues studied. Although this study focuses on three 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.

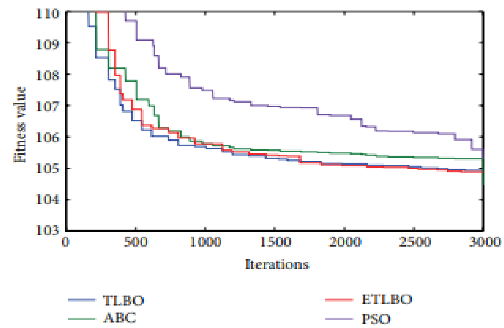

Figure 8: Convergence plot of the various methods for Case 3.

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

Optimal values	Results obtained by GA	Published result
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

$d11$: Dia of the third pulley, cm

$d2$: Dia of the second pulley, cm

$d12$: 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

$D\max$: 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

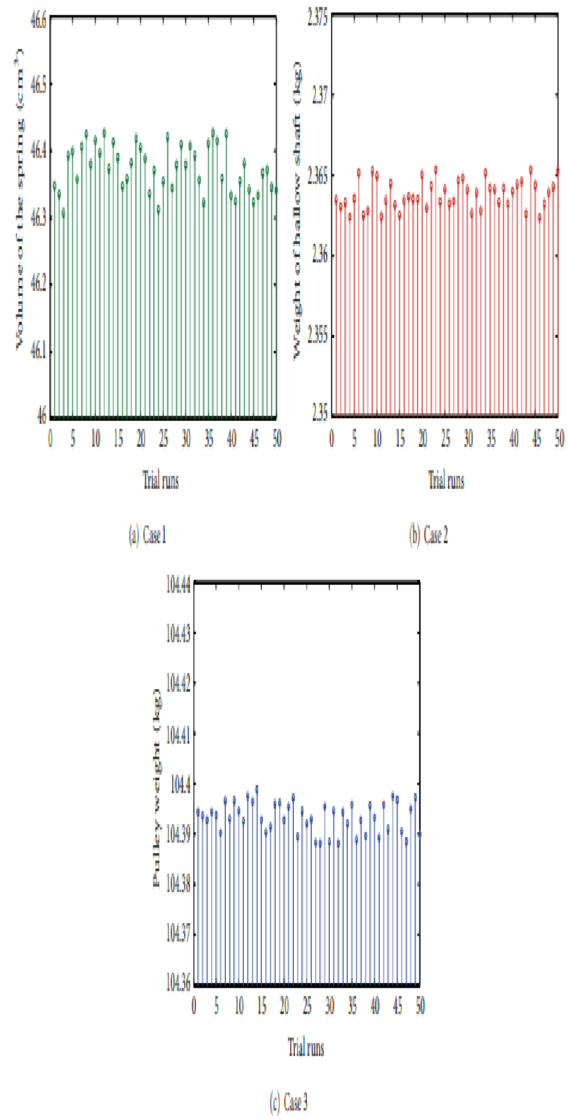

Figure 9: Final cost of the optimization obtained for all test cases using DTLBO method.

$N2$: rpm of the second pulley

$N1\ 2$: 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

$t\ 1\ 1$: Thickness of the third pulley, cm

$t2$: Thickness of the second pulley, cm

$t\ 1\ 2$: 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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