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Layout Optimization of Mechanical components employing an upgraded teaching-learning based completely Optimization set of rules using Differential Operator

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Abstract:

TLBO is a mechanical component optimization approach based on differential operators (training-learning based mainly optimization). There is a lot of information in this page on TLBO's beginnings and present status. You can employ a huge population of replies to arrive at a global solution in the same way as most other techniques. Differential operators are used to find better solutions in TLBO. An open coil helical spring is utilised first, followed by a hollow shaft, to evaluate the method's efficacy in solving typical optimization issues. There was a resounding "yes." Current optimization strategies fail to uncover better alternatives as effectively as the proposed strategy, according to simulation results (mechanical components).

INTRODUCTION

To diminish a closed coil helical spring's capacity, conventional procedures must be used. In a hollow shaft situation, graphs were used to solve a set of constraints. The weight of a belt-pulley drive was reduced by Reddy and his colleagues using geometric programming. For this reason, engineers often consider optimization while developing mechanical systems. There are several factors and constraints that must be taken into consideration while optimising a mechanical system [4–6]. Focusing on individual components or intermediate assemblies instead of optimising the whole system is a typical practise. Centrifugal pumps without motors or seals are much easier to optimise than pumps with these components. The extremes of a function are often estimated using analytical or numerical methods in engineering calculations. When designing complex systems, the use of traditional optimization methods may not be sufficient. Most real-time optimization problems include a high number of design variables with complicated (nonconvex) and nonlinear effects on the objective function that has to be optimised. In order for us to accomplish our goal, we must find an acceptable global or local maximum. Any given circumstance necessitates a focus on optimising. Mechanical components should not be compromised in any way in terms of efficiency. It is possible to boost production rates and lower material costs by optimising machine components [9–12]. Thus, optimization tactics may be used to their fullest extent.

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Production rates are kept high. In the literature, there are several ways to improve a project. To find information, you may use both direct and gradient techniques. Function values are adequate for a direct search, but gradient-based algorithms require the gradient information to identify the search's broad direction and target position. The disadvantages of classic optimization methodologies will be discussed in the following paragraphs. Traditional methods have been utilised for a long time to solve these problems. If present tactics are constrained in some manner, newer, more diversified methods may be more effective in solving certain optimization problems. It is impossible to get global optimal values using conventional techniques (such as gradient methods). So mechanical engineers must continue to use efficient and successful optimization methods. They've become more popular since they're more effective than deterministic approaches [13–16]. The genetic algorithm, a kind of evolutionary optimization, is the most often used method (GA). There may be a near-optimal solution to complex issues, even if they include many variables and constraints. Keep in mind the difficulties of determining ideal population size, crossover frequency, and mutation frequency numbers.. Changing the algorithm's parameters might impact its performance. PSO makes advantage of inertia, as well as social and cognitive characteristics. A similar emphasis on maximising the number of bees may be seen in ABC [17]. Bystanders, labourers, and scouts. HS's effectiveness depends on a high rate of harmonic memory and a large number of improvisations. Maintaining a successful algorithm requires constant innovation in the form of non-parametric methods of optimization. When reading this paper, bear this in mind.. Rao and his colleagues developed the teaching-learning-based optimization (TLBO) method. a few of my coworkers (TLBO). This self-improving algorithm is based on the concepts of natural teaching and learning. PSO, harmony search (HS), DE, and hybridPSO have been proved to be superior than existing optimization approaches such as GA in the past. In this study, a differential mechanism and hybrid TLBO approaches are suggested. First, we'll go through TLBo and see what we can find. Finally, the precise method (SQP) will be used to arrive at the final answer. Expressions in mathematics This section is devoted to the design of helical springs with closed coils, hollow shafts, and belt-pulley drives. In many cases, problems emerge because [9] GA is being used to optimise.

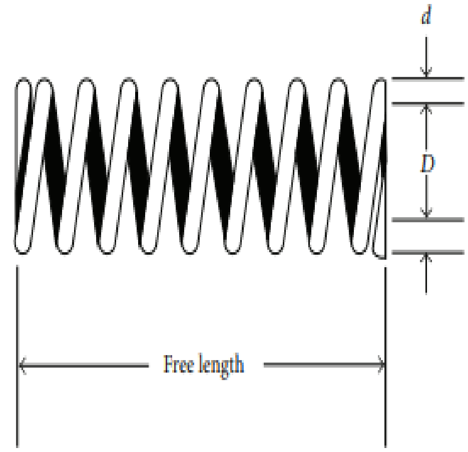

Figure 1: Schematic representation of a closed coil helical spring.

First of all, this is the situation (Closed Coil Helical Spring). Helical springs are often used for compressive and tensile stresses since the wire is coiled around itself (Figure 1). The cross-section of the wire used to build the spring might be round, square, or rectangular. Generally speaking, hydraulic springs may be used in compression and tensile designs, respectively. Torsional strain occurs when a spring wire is so tightly twisted that the plane containing each turn is practically perpendicular to the central axis (Figure 1). Shear stress is imposed on the helical spring when it is twisted to create a torque. Parallel or perpendicular stresses are applied to the spring. The problem of minimising the volume of a helical spring with a closed coil is a difficult one (Figure 1). It's possible to find a mathematical answer to this problem. When these conditions are met, the spring (U) may be lowered to its bare minimum volume. Consider

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

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:

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

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.

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

Thus, the constraint is given by

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

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:

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

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.

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

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.

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

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.

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

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

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

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:

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

where δw is made equal to 3.175 cm.

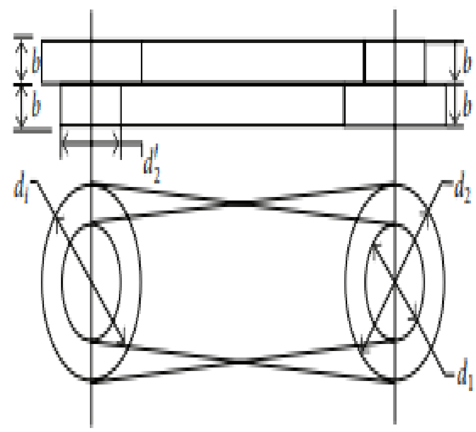

Figure 2 depicts a hollow shaft schematically. As a result of optimization, the following ranges are maintained:

$$\begin{aligned} 0.508 &\le d \le 1.016, \\ 1.270 &\le D \le 7.620, \qquad (15) \\ 15 &\le N_c \le 25. \end{aligned}$$

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 a rotating shaft is used to transport it from one area to another (Figure 2). Transmission and line shafts may be separated into two major groups for classification purposes. Transmission shafts provide electricity to the machinery. Machine shafts may be found in a very small number of machinery components on the whole. Crankshafts are among the most common machine shafts, however there are many more. Figure 2 schematically depicts a hollow shaft. An objective of the research is to lighten a hollow shaft.

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, $\theta \geq TL/GJ$.

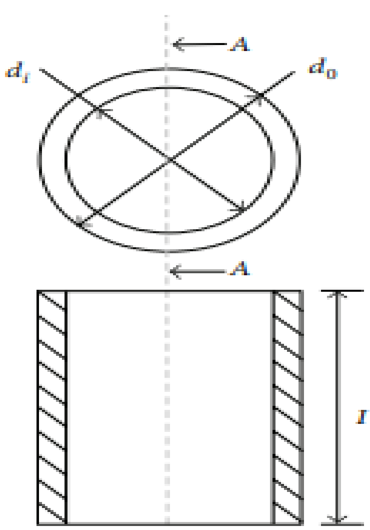

Figure 3: Schematic representation of a belt-pulley drive.

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:

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

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

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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

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

The ranges of variables are mentioned as follows:

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

It's number three in this scenario. (Optimal Belt-Pulley Drive Design) Power is transmitted from one belt to the next via a series of gears and pulleys, each of which rotates at a different pace (Figure 3). In manufacturing and fabrication, stepped flat belt drives are often used to carry modest amounts of power. The shaft and bearing are often affected by the pulley's weight. Shaft breakdowns are prevalent due to the weight of the pulley (Table 1). Flat belt drives must be minimal in weight in order to minimise shaft and bearing failure. Figure 3 depicts a schematic concept for a belt-pulley drive. What brought you here? An goal function is to keep the pulley's weight as low as possible..

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

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) $7.2 \times 10{-}3$ 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

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

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 $\sigma b = 30$ 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

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

Or

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

The ranges of the variables are mentioned as follows:

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

Optimization Procedure

Classical search and optimization algorithms have a number of shortcomings when dealing with complex situations. Solving many problems at the same time becomes more difficult. The conventional technique focuses on only a few subjects. Consequently, it is unable to cope with a broad variety of issues. Parallel computing systems cannot benefit from conventional techniques because they lack a global perspective and tend to converge on a locally optimal solution. Because of the sequential nature of classical algorithms, it is difficult to get extra advantages from them. The employment of new search and optimization techniques is becoming increasingly common. To solve optimization issues, genetic algorithms and computer simulations are used.

Optimization using principles of teaching and learning Teaching-learning-based optimization

(TLBO) was invented by Ragsdell, Phillips, and David Edward and was the first to be used in the classroom. Using a population of solutions, this method is similar to previous ones that were inspired by nature. Among the factors in the strategy's design are the classes' choices of study subjects. The objective function value of each conceivable solution, which takes into consideration the design aspects, may be used to measure a student's knowledge level. Work with a personal trainer to ensure the greatest number of individuals are properly fit (among all pupils). Despite the fact that the population as a whole is faced with the identical optimization problem, each student (Xi) comes up with a unique solution to it. In the TLBO system, the number of courses that students and instructors will take or teach is fixed. This D-dimensional integer is represented by the real-valued vector Xi. People may be replaced by algorithms if their new response is better than their previous one during the Teacher and Learner Phases of the procedure. It will keep repeating itself as long as the algorithm is running. The post of best teacher (Xteacher) is filled during the Teacher Phases. The method makes use of the current mean (Xmean) of those engaged in order to enhance the average performance of new individuals (Xi). All of the pupils in this generation's averages are shown here in order to highlight a specific area of concern (dimension). Students' abilities and knowledge may be reconstructed using Equation by the instructor (39). The equation uses random variables for stochastic purposes: There may just be a single or a couple of TFs to emphasise the importance of student quality. r's value ranges from 0 to 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 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.

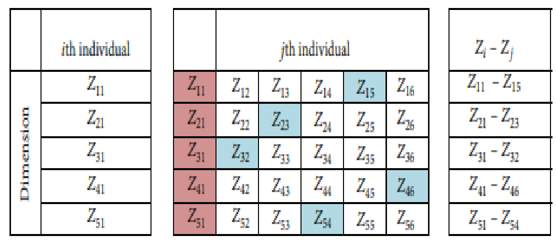


Figure 4: Differential operator illustrated.

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).

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

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

In the event of a problem, repeat steps 8 and 9 until all pupils have finished the exam (pairs).

There will be no duplication of applicants if the adjusted student strength is less than the initial student strength.

Return to step 4 to confirm that the termination conditions have been satisfied.

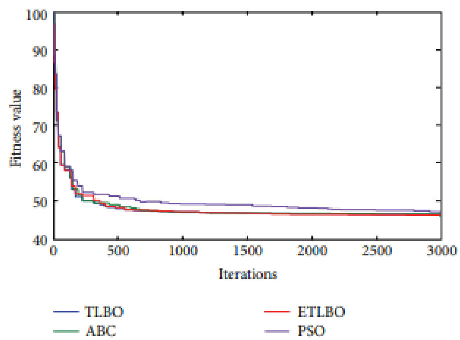
It is in this part that the results and recommendations are outlined. In this part, simulated experiments are used to tackle three of the aforementioned optimization difficulties. TLBO is compared to four nature-inspired optimization techniques (PSO, GA) that are commonly employed in the area for this research project. Each of the four methods may be examined in its original form. Inputs and outputs of an algorithm.

This strategy is based on evolutionary theory. The crossover likelihood in this scenario is 80 percent, whereas the mutation chance is just 10 percent. In this case, swarm optimization is used. For a particle size of 30 pixels, the generation number is 3000 when wmax is set to 1,11, and wmin is set to -0.73. A Beehive in a Box. This colony, which has been living for almost 3000 generations, consists of only 50 bees.

In order to become a better person, it is essential to both study and teach. The neighbourhood has seen more than 3000 generations come and go. Because the TLBO and the preceding algorithm have so little in common, this is the best option (Tables 2 and 3). Taking into account the algorithm's performance is a prerequisite for these optimization tactics. There are crossover probabilities, mutation rates, and selection procedures for GA, PSO, and ABC (the number of hired bees). The TLBO is OK as long as participants and iterations collaborate (Figures 5, 6, 7, and 8). Table 6 compares the GA findings to those that have been previously published. The table below shows the results of a 50-test evaluation of each method. GA provides the most accurate outcomes.

Table 3 shows the comparison between the GA results and published data. So, here's an example 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
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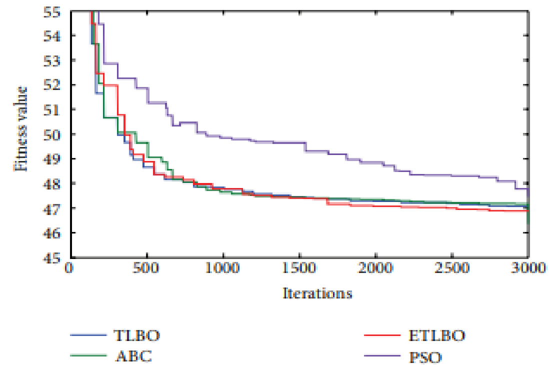

Figure 6: Convergence (magnified) plot of the various methods for Case 1.

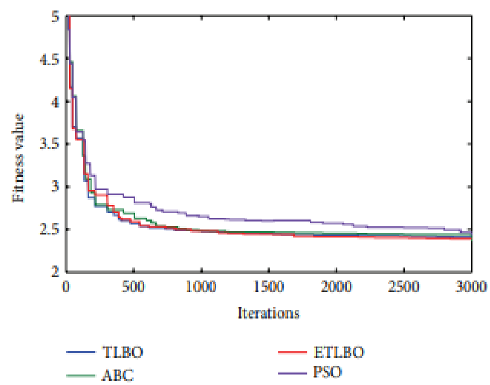

Figure 7 shows the different approaches' convergence rates and the number of function evaluations necessary for each method. A TLBO-based algorithm outperforms existing nature-inspired optimization approaches in terms of performance for the design issues studied. Although this study focuses on three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

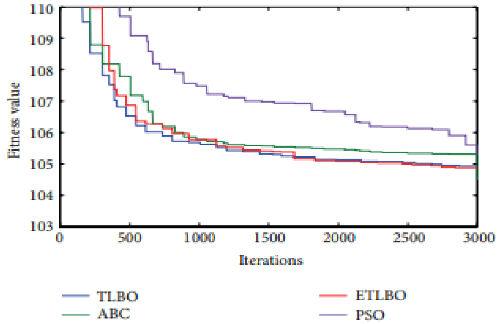

Figure 8: Convergence plot of the various methods for Case 3.

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

$dmin$: 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

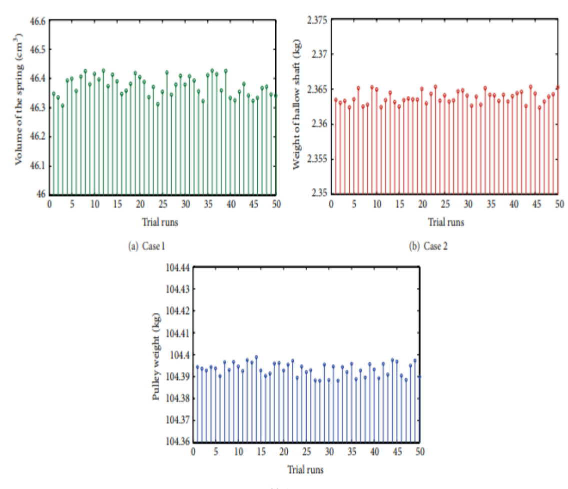

Figure 9: Final cost of the optimization obtained for all test cases using DTLBO method.

$N2$: 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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