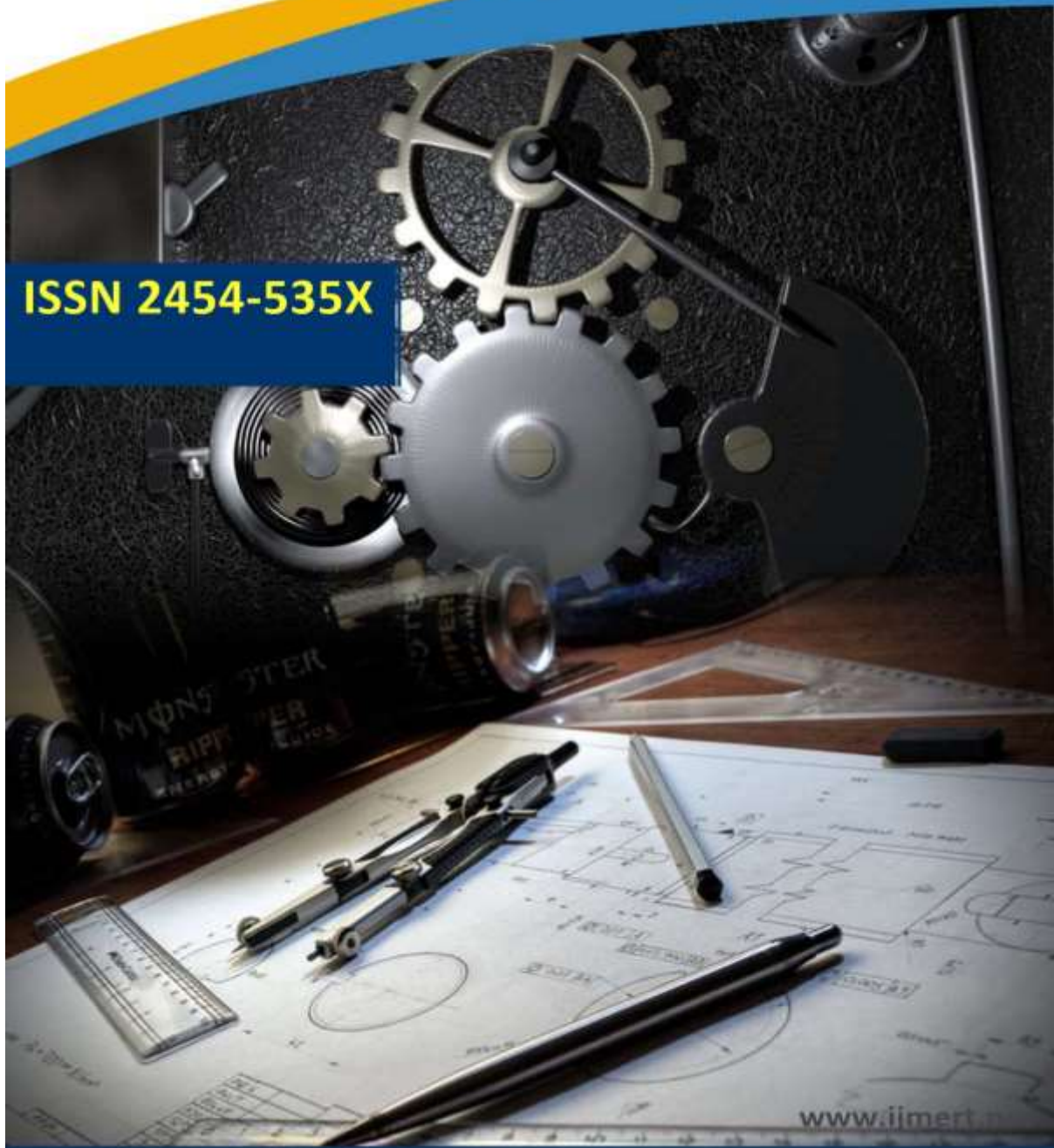




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Mechanical component layout optimization by using a richer toolkit of learning-based and differential operator-based optimization techniques

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Abstract:

The TLBO method (training-learning based primarily optimization) is used to optimize mechanical components. This website contains extensive background and current information about TLBO. Similar to previous methods, using a large number of responses may lead to a global optimal solution. Better solutions may be found in TLBO with the help of differential operators. The method's effectiveness in resolving common optimization problems is tested using an open coil helical spring and then a hollow shaft. The answer was a unanimous "yes." According to simulation data (mechanical components), current optimization algorithms fail to discover better alternatives as efficiently as the suggested approach.

INTRODUCTION

The capacity of a closed coil helical spring may be reduced using the standard methods. Graphs were employed to find a solution to certain limitations in a "hollow shaft" scenario. Using geometric programming, Reddy and his team were able to minimize the belt-pulley drive's weight. This is why optimization is a common topic of discussion among engineers while creating new mechanical systems. When trying to find the best configuration for a mechanical system, there are many variables and limitations to consider [4-6]. It is common practice not to optimize the whole system, but rather to concentrate on improving particular parts or intermediary assemblies. It is significantly simpler to optimize a centrifugal pump that does not have a motor or seals. In engineering calculations, it is common practice to use analytical or numerical techniques to estimate the function's extrema. The usage of common optimization techniques may fall short when developing complicated systems. A large number of design variables that have complex (nonconvex) and nonlinear impacts on the objective function to be optimized for are typical of real-time optimization issues. To succeed, we need to choose a global or local maximum that suits our needs. Optimisation is always the priority, regardless of the situation. The effectiveness of mechanical parts must not be sacrificed under any circumstances. When machine parts are optimized, production rates are increased and material costs are decreased [9-12]. This allows for maximum use of optimization strategies.

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High levels of output are maintained. Numerous suggestions for enhancing projects may be found in published works. Both direct and gradient methods may be used to investigate a topic. While function values are all that's needed for a direct search, the gradient information is necessary for gradient-based algorithms to determine the overall search direction and endpoint. The limitations of traditional optimization approaches will be further upon below. For a long time, these issues have been addressed using only conventional approaches. Newer, more varied approaches to tackling optimization issues may be more efficient if existing strategies are limited in some way. Using standard approaches (such gradient methods), it is not feasible to get globally optimum values. Therefore, mechanical engineers should maintain their focus on tried-and-true optimization strategies. Since they outperform deterministic methods, their popularity has increased [13–16]. The most common approach is the genetic algorithm (GA), a kind of evolutionary optimization. Complex problems with numerous variables and restrictions may have near-optimal solutions. It's important to remember how challenging it may be to find the optimal values for population size, crossover frequency, and mutation frequency. The algorithm's efficiency might be affected by adjusting its settings. PSO takes use of social and cognitive traits in addition to inertia. You may observe a similar drive to increase the population of bees in ABC [17]. Spectators, workers, and spies. A huge number of improvisations and a high rate of harmonic memory are necessary for HS to be successful. Developing novel, non-parametric optimization techniques is essential to keeping a successful algorithm up and running. Keep this in mind when you read the paper. Teaching-learning-based optimization (TLBO) is a technique created by Rao and his team. some of my fellow employees (TLBO). The principles of natural instruction and learning form the basis of this self-improving algorithm. Existing optimization methods like GA have been shown to be inferior to PSO, HS, DE, and hybridPSO. Differential mechanism and hybrid TLBO strategies are proposed in this research. We're going to start by searching TLBo. The final result will be calculated using the precise approach (SQP). Mathematical expressions Closed-coil, hollow-shaft, belt-pulley-driven helical springs are the focus of this section. The usage of [9] GA for optimisation often leads to issues.

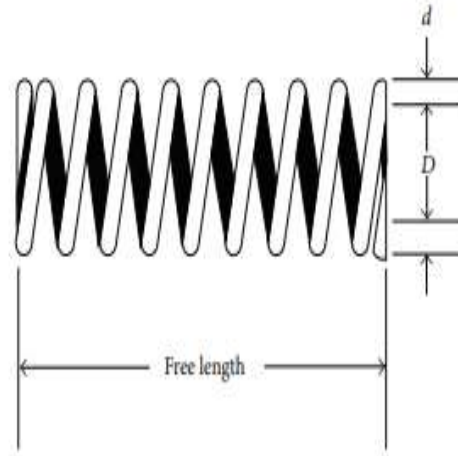


Figure 1: Schematic representation of a closed coil helical spring.

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

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

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

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

Where

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

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:

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

where G is equivalent to 808543.6 kgf/cm² shear modulus

The maximum working load deflection is determined by

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

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.

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

Thus, the constraint is given by

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

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:

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

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.

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

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:

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

where δ_w is made equal to 3.175 cm.

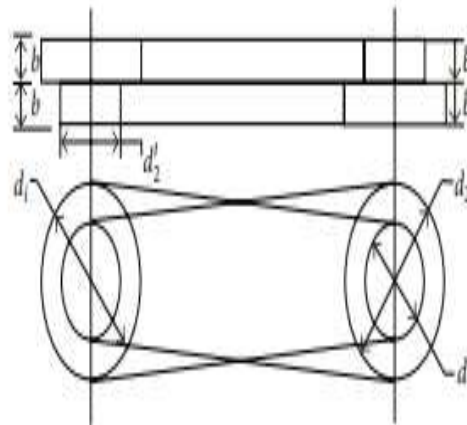


Figure 2 depicts a hollow shaft schematically. As a result of optimization, the following ranges are maintained:

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

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 $\times$ length $\times$ density

$$= \frac{\pi}{4} (d_o^2 - d_i^2) L \rho. \quad (16)$$

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

$$W_s = 0.326 d_o^2 (1 - k^2). \quad (17)$$

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, $\theta \geq TL/GJ$.

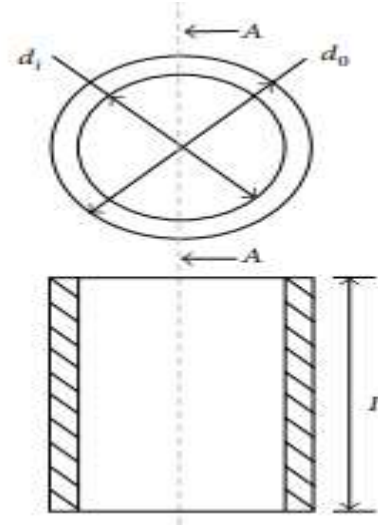


Figure 3: Schematic representation of a belt-pulley drive.

Constrained by substituting values of $[(/32)d_o^4 (0(1-k^4))]$, $[(1-k^4)]$ and $[(/32)d_o^4 (0(1-k^4))]$, one obtains the constraints as a result of substituting the values of, T , G , and J .

$$d_o^4 (1 - k^4) - 1736.93 \geq 0. \quad (20)$$

The critical buckling load (T_{cr}) is given by the following expression:

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

The critical buckling load (T_{cr}) is given by the following expression:

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

T_{cr} , 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

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

The ranges of variables are mentioned as follows:

$$\begin{aligned} 7 &\leq d_o \leq 25, \\ 0.7 &\leq k \leq 0.97. \end{aligned} \quad (23)$$



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..

$$W_p = \pi \rho b [d_1 t_1 + d_2 t_2 + d_1^1 t_1^1 + d_2^1 t_2^1] \quad (24)$$

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 $t_1 = 0.1d_1$, $t_2 = 0.1d_2$, $t_1^1 = 0.1d_1^1$, and $t_2^1 = 0.1d_2^1$ and replacing d_1 , d_2 , d_1^1 , and d_2^1 by N_1 , N_2 , N_1^1 , and N_2^1 , respectively, and also substituting the values of N_1 , N_2 , N_1^1 , and N_2^1 , ρ (to 1000, 250, 500, 500) 7.2×10^{-3} kg/cm³, respectively, the objective function can be written as

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

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

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

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

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

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

Assuming $T_2/T_1 = 1/2$, $P = 10$ hp and substituting the values of T_2/T_1 and P , one gets

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

Or

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

Assuming

$$d_2 N_2 < d_1 N_1 \quad (31)$$

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

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

Substituting $\sigma_b = 30$ kg/cm² $t_b = 1$ cm, $N_2 = 250$ 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

$$b d_2 - 381.97 \geq 0 \quad (35)$$

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

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

Or

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

The ranges of the variables are mentioned as follows:

$$\begin{aligned} 15 &\leq d_1 \leq 25, \\ 70 &\leq d_2 \leq 80, \\ 4 &\leq b \leq 10. \end{aligned} \quad (38)$$



Optimization Procedure

When faced with complexity, traditional search and optimization algorithms fall short in a variety of ways. Attempts to address many issues at once become increasingly challenging. The traditional approach often zeroes down on a select few variables. This limits its ability to deal with a wide range of problems. Because of their limited ability to see the big picture, parallel computing systems can only profit from more sophisticated approaches. It is challenging to get additional benefits from classical algorithms because of their sequential structure. More and more organizations are regularly using advanced methods of search and optimization. Computer simulations and genetic algorithms are employed to find optimal solutions to optimization problems.

Optimisation based on educational theory Ragsdell, Phillips, and David Edward created the first classroom implementation of teaching-learning-based optimization (TLBO). This technique is comparable to others that took their cue from nature in that it employs a population of potential answers. The method takes into account the courses' elective selections as one of its components. One way to evaluate a student's understanding is to calculate the objective function value of each feasible solution, factoring in the design considerations. Consult a fitness expert to help your school reach its goal of having a high percentage of physically fit students. Each student (X_i) develops an own answer to the same optimization issue faced by the population as a whole. The TLBO system mandates a certain number of courses for both students and teachers. For this D-dimensional number, the real-valued vector X_i stands in. During the procedure's Teacher and Learner Phases, humans might be replaced by algorithms if the latter's new answer is superior to the former's. As long as the algorithm is active, the process will continue to repeat itself. During the Teacher Phases, a candidate will rise to the position of best teacher ($X_{teacher}$). In order to improve the typical performance of new people (X_i), the strategy takes use of the present mean (X_{mean}) of those involved. In order to emphasize a particular area of interest (dimension), the averages of all students in this generation are shown here. Using Equation (39), a teacher may recreate a student's talents and knowledge. Stochastic purposes are served by random variables in the equation: There may be one or two TFs to stress the value of selecting high-quality students. In this context, r may take on values between 0 and 1.

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

When a student (X_i) is in the Learner Phase, he or she strives to increase their knowledge by learning from an unrelated student (X_{ii}). If X_{ii} is superior than X_i , X_i will gravitate toward X_{ii} (40). As a result, it will be relocated away from X_{ii} (41). Student X_{new} 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.

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

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

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.

	ith individual						
Dimension		Z_{i1}	Z_{i2}	Z_{i3}	Z_{i4}	Z_{i5}	$Z_i - Z_j$
		Z_{j1}	Z_{j2}	Z_{j3}	Z_{j4}	Z_{j5}	$Z_{i1} - Z_{j1}$
		Z_{j1}	Z_{j2}	Z_{j3}	Z_{j4}	Z_{j5}	$Z_{i2} - Z_{j2}$
		Z_{j1}	Z_{j2}	Z_{j3}	Z_{j4}	Z_{j5}	$Z_{i3} - Z_{j3}$
		Z_{j1}	Z_{j2}	Z_{j3}	Z_{j4}	Z_{j5}	$Z_{i4} - Z_{j4}$
		Z_{j1}	Z_{j2}	Z_{j3}	Z_{j4}	Z_{j5}	$Z_{i5} - Z_{j5}$

Figure 4: Differential operator illustrated.

For a long time, it has been referred to the "refuelling chasm." When compared to the traditional TLBO algorithm, the DTLBO has three key distinctions [4].



After determining the nearest members of each class by distance sensing, this system uses the potentials of all students to steer a student's new place. A student's status might be updated for each dimension using a different student as an example, rather than the same student again. Using the suggested equation (42), it is feasible for students to gain insight from one another's experiences and perspectives. Positions are updated by randomly selecting a student's neighbor in all three dimensions (care must be taken to prevent repeats). This also greatly enhances the original TLBO's capacity to thoroughly explore difficult optimization issues without rushing to a solution. DTLBO is faster than TLBO in locating the global optimum. Unlike KH, which updates all students simultaneously, a differential operator that just updates the basic TLBO provides a superior answer for each individual student. This is a very condescending stance to take. Premature convergence was a problem with the original TLBO design. In order to prevent a premature convergence and improve the original TLBO system's exploratory potential when all students' positions are updated simultaneously, a differential guiding system is implemented. The differential mechanism is described by an equation (42).

$$Z_i - Z_j = (z_{i1} \ z_{i2} \ z_{i3} \ \dots \ z_{in}) - (z_{p1} \ z_{p2} \ z_{p3} \ \dots \ z_{pn}), \quad (42)$$

where

z_{i1} is the first element in the n dimension vector Z_i ;

z_{in} is the n th element in the n dimension vector Z_i ;

z_{p1} is the first element in the n dimension vector Z_p ;

p is the random integer generated separately for each z , from 1 to n , but $p \neq i$.

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	46.6673	46.6803	12	3
PSO	46.6752	46.5217	46.6254	18	17
AB	46.6241	46.525	46.6033	15	13
TLBO	46.524	46.322	46.4998	22	2
DTLBO	46.4322	46.3012	46.3992	24	22

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.

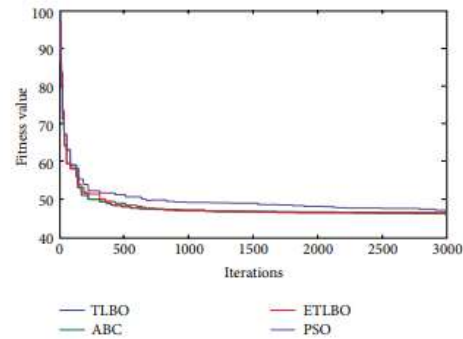
It is in this part that the results and recommendations are outlined. In this part, simulated experiments are used to tackle three of the aforementioned optimization difficulties. TLBO is compared to four nature-inspired optimization techniques (PSO, GA) that are commonly employed in the area for this 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	45.5392	NA	NA	NA
GA	46.6812	46.6673	46.6823	12	3
PSO	46.6752	46.5202	46.6254	18	17
ABC	46.6241	46.5315	46.6833	25	23
TLBO	46.5294	46.3221	46.4996	22	2
ETLBO	46.4372	46.3012	46.3942	24	22

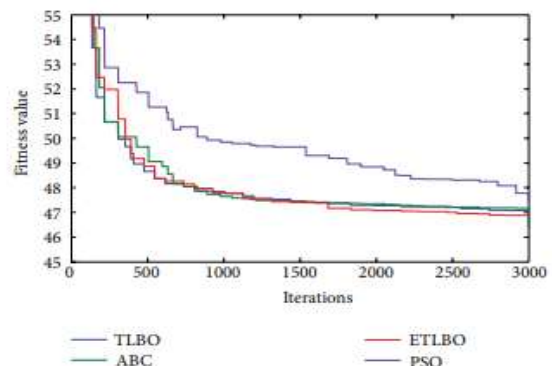


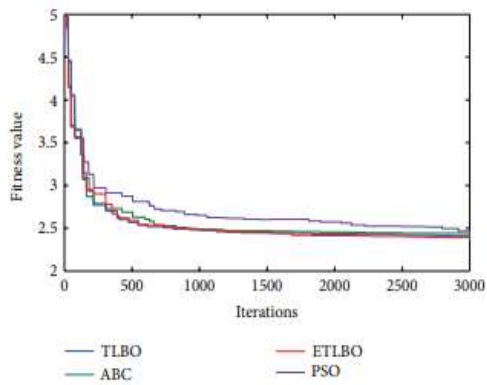
Figure 6: Convergence (magnified) plot of the various methods for Case 1.

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.

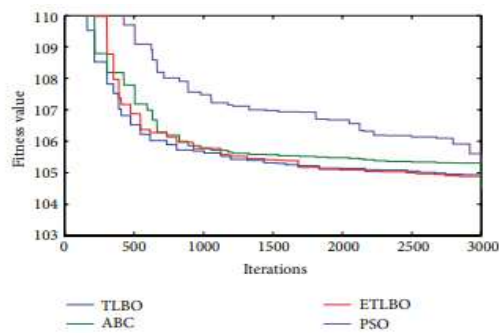
**Figure 8: Convergence plot of the various methods for Case 3.**

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_2^1), 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

$dmin$: 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	104.4235	104.4456	2.1	1.9
ABC	104.5002	104.419	104.4456	3.1	2.9
TLBO	104.4124	104.3907	104.4222	2.9	2.8
ETLBO	104.3992	104.3886	104.3942	3.3	3.1

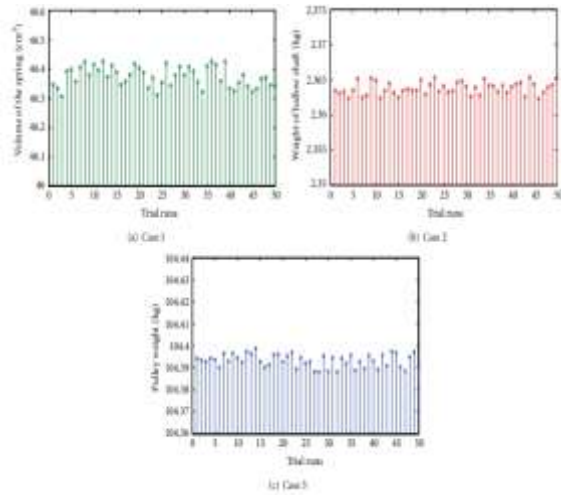


Figure 9: Final cost of the optimization obtained for all test cases using DTLBO method.

N_2 : rpm of the second pulley

N_{12} : rpm of the fourth pulley

N_c : Number of active coils

N_p : 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

t_1 : Thickness of the first pulley, cm

t_{11} : Thickness of the third pulley, cm

t_2 : Thickness of the second pulley, cm

t_{12} : Thickness of the fourth pulley, cm

T : Twisting moment on shaft, kgf-cm

F_{max} : Maximum working load, kgf

F_p : Preload compressive force, kgf

G : Shear modulus, kgf/cm

J : Polar moment of inertia, cm⁴

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, cm³

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/cm³
 σ : Allowable tensile stress of belt material, kg/cm³.

CONCLUSION

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

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