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Original Article

Design and Volume Optimization of High-Speed Helical Gear Pair by using Cohort Intelligence Algorithm

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Abstract *- Gears are the most fundamental unit for mechanical power transmission and play an important role in industrial applications. High-speed gearboxes are widely used in different applications, such as steam and gas turbines, pumps, compressors, etc. In this case study, a high-speed gearbox with a helical gear pair is considered using the DIN and AGMA standards, along with design factors including the face width, number of teeth on the pinion and gear, module, and helix angle. The DIN and AGMA standards are used to calculate the various gear geometry parameters, such as size and strength. A multivariable and constrained optimization problem is presented with a derived objective function. The volume minimization is performed using the cohort intelligence algorithm in MATLAB, and the results obtained are found to be satisfactory. Cohort intelligence is a modern technique that is applied for the optimization of different mechanical parts, systems, and processes. An optimized set of parameters models a helical gear pair in CAD software. The optimized design is then validated using FEA software, which shows that the stress value in the gear pair is below the allowable stress limit for the given material.*

Keywords *- Helical gear pair, Nature-inspired optimization algorithm, Cohort Intelligence Algorithm, Genetic Algorithm, Particle Swarm Optimization, and FEA.*

1. Introduction

Helical gear units are used as power transmission devices in various applications, such as generator units, compressors, pumps, gas turbines, and steam turbines. They enable smooth and quiet operation, increase load-carrying capacity, operate at faster speeds, and provide effective engagement, which enhances the speed of power transmission and maximizes efficiency. High-speed gearboxes are commonly used in industrial applications and power plants. This case study considers a high-speed gearbox for turbine generator applications. The layout of the high-speed gearbox is shown in Figure 1. A high-speed gearbox is primarily composed of a High-speed Shaft (HS) and a Low-speed Shaft (LS), both of which are supported by Drive End (DE) and Non-drive End (NDE) bearings. The turbine shaft is coupled to a high-speed shaft, and the generator shaft is coupled to a low-speed shaft. A helical gear pair transmits power from a high-speed shaft to a low-speed shaft. There is a demand for optimized gears with lower weight and volume to meet high-speed and industrial gearboxes' transmission requirements. Low-weight optimized gear can improve process efficiency while using less material and costing less to manufacture.

Nature-inspired optimization techniques, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), simulated annealing (SA), and Tabu search, have gained popularity due to their simplicity of implementation and rule-based functioning. GA operates on a population-based approach, which evolves using selection, crossover, and mutation operators. According to Deb [5] and Ray et al. [6], the effectiveness of GA depends on the quality of the population being evaluated, and it may require local improvement techniques to incorporate into it to reach close to the global optimal solution.

Swarm Intelligence (SI) is a decentralized, self-organizing optimization approach that takes inspiration from the social behavior of living organisms, such as insects, fishes, etc., that communicate with each other either directly or indirectly. PSO is a technique inspired by the social behavior of bird flocking and fish schools searching for food [7].

Similarly, ACO is based on the foraging behavior of ants, following the shortest path [8]. At the same time, the Bee Algorithm (BA) is modeled after the social behavior of honey bees finding food. However, it aims to optimize the use of the number of members involved in particular pre-decided tasks [9].

Cohort Intelligence (CI) is a novel Artificial Intelligence (AI) technique introduced by Kulkarni et al. [10], which draws inspiration from the self-supervised learning patterns exhibited by a group of individuals within a cohort.

Anand Kumar Gaurav and R. K. Ambikesh have taken care of business on the weight optimization of a helical gear pair using FEA [17]. Ketan Tamboli employed particle swarm optimization techniques to optimize the design of a heavy-duty helical gear pair. They formulated an optimization problem and obtained a solution using the particle swarm optimization algorithm in their research [19].

In this case study, the cohort intelligence algorithm is used for volume optimization of a helical gear pair. Cohort intelligence is a modern algorithm for optimization that takes inspiration from the self-supervised learning behavior of the candidates in a cohort. Based on previous research, it has been found that it is widely used for the optimization of different mechanical systems as well as processes. Compared to other algorithms like GA, PSO, ACO, etc., the cohort intelligence algorithm has fewer algorithm-centric settings, making it easy to operate. The user only needs to input an objective function with upper and lower bounds, and the algorithm takes less time to produce results.

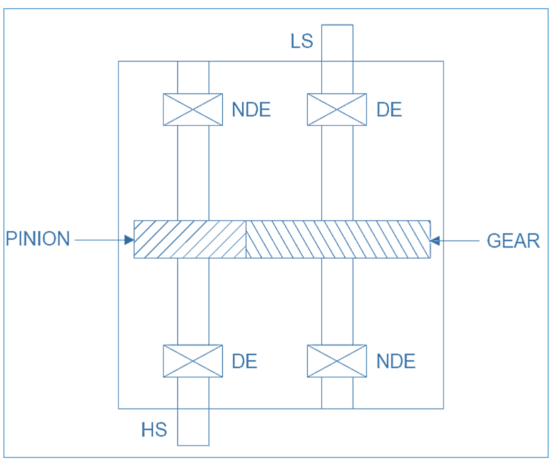

Fig. 1 Layout of High-Speed gearbox

1.1. Methodology

In this case study, the cohort intelligence algorithm is used for volume optimization of a helical gear pair. Cohort intelligence is a modern algorithm for optimization that takes inspiration from the self-supervised learning behavior of the candidates in a cohort. Based on previous research, it has been found that it is widely used for the optimization of different mechanical systems as well as processes. When compared to other algorithms like GA, PSO, ACO, etc., the cohort intelligence algorithm has fewer algorithm-centric settings, making it easy to operate. The user only needs to input an objective function with upper and lower bounds, and the algorithm takes less time to produce results.

2. Design of Helical Gear

The helical gear pair is designed for high-speed gearbox applications, and the following input parameters are considered:

1] Power Transmitted = 1270 KW; 2] Gear Ratio = 5.038; 3] Helix Angle =5 ˚ ; 4] Module = 4; 5] Pinion Speed = 7500 RPM; 6] Gear Speed = 1500 RPM.

Material of the gear pair is case hardening steels (18CrNiMo 7-6) according to DIN EN 10084 standard. Table 1 shows the properties of 18CrNiMo 7-6.

Table 1. Properties of 18CrNiMo 7-6 material

No	Parameter	Value
1	Density (kg/m^3)	7800
2	Poisson's Ratio	0.3
3	Modulus of Elasticity (GPa)	210
4	Shear Modulus (Gpa)	80
5	Yield Tensile Strength (Mpa)	780
6	Ultimate Tensile Strength (Mpa))	1200

Table 5 provides a summary of the key design parameters for a single-stage helical gear pair, which are based on DIN 3960 and AGMA 6011 J14 standards [2, 3]. Additional geometrical parameters and strength-based factors for the pinion and gear wheels are listed in Tables 6 and 7, respectively, provided in the Appendix. A helical gear pair is modelled in PTC Creo software, as shown in Figure 2.

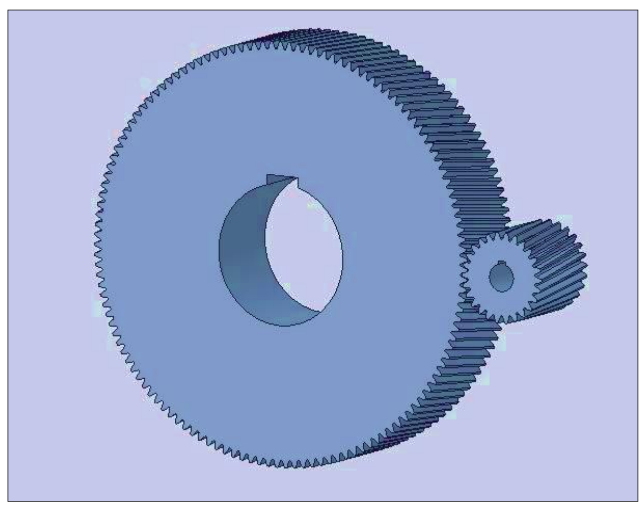

Fig. 2 CAD model of helical gear pair

3. Formulation of Mathematical Model

To achieve volume minimization for the helical gear pair, several design variables are considered, including the module ($m_{n,}$), face width (b), pinion teeth ($z_{1,}$), gear teeth (z_2), and helix angle (β). These parameters significantly impact the overall performance and efficiency of the gear pair, as well as its size and weight. Upper and lower bounds for each parameter are specified and summarized in Table 2.

3.1. Formulation of Objective Function

For the present case study, the volume of the cylindrical gear pair may be expressed as [19].

$$\text{Volume} = \frac{\pi}{4} * \left[\frac{m_n^2\, b}{\cos^2(\beta)}\,(z_1^2 + z_2^2)\right] \quad (1)$$

The objective function of the above system is represented in the below format,

$$f(x) = f(m_n, b, z_1, z_2, \beta)$$

$$f(x) = \frac{\pi}{4} * \left[\frac{m_n^2\, b}{\cos^2(\beta)}\,(z_1^2 + z_2^2)\right] \quad (2)$$

Table 2. Variable parameter of helical gear pair

No	Parameter	Lower Bound	Upper Bound
1	Module (m_n)	4	8
2	Face Width (b)	80	250
3	No of Teeth on Pinion (z_1)	23	52
4	No of Teeth on Gear (z_2)	110	280
5	Helix Angle (β)	5˚	14˚

3.2. Formulation of Constraints

The various strength factors for helical gear pairs include load distribution factors, safety factors for bending, safety factors for pitting, and safety factors for geometry, among others. Geometric constraints such as the number of teeth, face width, and helix angle are calculated and summarized in Tables 5, 6, and 7, respectively.

The mathematical model for the gear pair system is expressed below. The transverse contact ratio for helical gears is given by,

$$= \frac{1}{2\pi}[Z_1\{\tan(\theta_1) - \tan(\phi_w)\} - Z_2\{\tan(\theta_2) - \tan(\phi_w)\}] \quad (3)$$

For the present problem, the expression for transverse contact ratio for pinion and gear, respectively, may be expressed as,

$$\varepsilon_{\alpha 1} = \frac{z_1\left[\tan\left\{\cos^{-1}\left(\frac{d_{b1}}{d_{a1}}\right)\right\} - \tan\left[\cos^{-1}\left[\frac{\frac{m_n}{\cos(\beta)} * (z_1 + z_2)}{\frac{2a'}{\cos(\phi_t)}}\right]\right]\right]}{2\pi} \quad (4)$$

$$\varepsilon_{\alpha 2} = \frac{z_2\left[\tan\left\{\cos^{-1}\left(\frac{d_{b1}}{d_{a1}}\right)\right\} - \tan\left[\cos^{-1}\left[\frac{\frac{m_n}{\cos(\beta)} * (z_1 + z_2)}{\frac{2a'}{\cos(\phi_t)}}\right]\right]\right]}{2\pi} \quad (5)$$

3.2.1. Safety Factor for Pitting

The safety factor constraints for pitting in both the pinion and gear are calculated based on the elasticity, Poisson's ratio, transverse contact ratio, and contact stress of the pinion and gear.

$$[S_H]_1 = 1.2 - \frac{985.5}{189.65 * \sqrt{\frac{1}{\varepsilon_{\alpha 1} + \varepsilon_{\alpha 2}}} * \sqrt{\cos(\beta)} * \sqrt{\frac{1}{b}} * 1.06 * 48.55} \quad (6)$$

$$[S_H]_2 = 1.2 - \frac{1078.5}{189.65 * \sqrt{\frac{1}{\varepsilon_{\alpha 1} + \varepsilon_{\alpha 2}}} * \sqrt{\cos(\beta)} * \sqrt{\frac{1}{b}} * 1.06 * 48.45} \quad (7)$$

3.2.2. Safety Factor for Bending

The safety factor constraints for bending in both the pinion and gear are calculated based on various factors, including the life, size, and relative toughness of the gears and the dynamic load, load distribution, helix angle, reliability, application, and bending stress.

$$[S_F]_1 = 1.4 - \frac{392.5}{\frac{30390.31}{m_n * b} * \left[0.25 + \frac{0.75}{\varepsilon_{\alpha 1} + \varepsilon_{\alpha 2}}\right] * \left[1 - \frac{b\sin(\beta)}{\pi * m_n}\right] * 1.20 * 3.06} \quad (8)$$

$$[S_F]_2 = 1.4 - \frac{413.5}{\frac{30390.31}{m_n * b} * \left[0.25 + \frac{0.75}{\varepsilon_{\alpha 1} + \varepsilon_{\alpha 2}}\right] * \left[1 - \frac{b\sin(\beta)}{\pi * m_n}\right] * 1.20 * 3.06} \quad (9)$$

4. Constraints Handling Technique

Optimization algorithms inspired by nature are usually developed to handle unconstrained optimization problems. However, the majority of engineering problems in the real world are constrained optimization problems [14-22].

The static penalty function approach is a technique used to handle constraints in optimization problems. This approach converts a constrained optimization problem into an unconstrained one by adding a penalty function to the objective function. The penalty function assigns a penalty value to any solution that violates the problem constraints. A simple way to penalize infeasible solutions is to apply a constant penalty to any solution that violates the feasibility constraints. The penalty function for a problem with equality and inequality constraints can be added to form the pseudo-objective function $f_q(x)$ as follows.

$$f_p(x) = f(x) + \sum_{i=0}^{n} q_i * S * \{g_i(x)\}^2 + \sum_{j=0}^{n} B_j * S * h_j(x) \quad (10)$$

Here, $f_p(x)$ is the expanded penalized objective function S is a penalty for violating a constraint.

q_i = 1, if constraint *i* is violated.
q_i = 0, if constraint *i* is satisfied.
B_j = 1, if constraint *i* is violated.
B_j = 0, if constraint *i* is satisfied.

Let n be the number of inequality constraints, and m be the number of equality constraints in an optimization problem. If the constraint is violated, the value of the q_i will be one else; it will be zero. The penalty S can be chosen based on preliminary trials of the algorithm, and as the optimization algorithm progresses, the violation of constraints may decrease, and the penalty coefficient can be adjusted accordingly. Eventually, the algorithm may converge to the optimum value for the problem.

5. Volume Optimization by using Cohort Intelligence Algorithm

The Cohort Intelligence (CI) algorithm models the ability of candidates in a cohort to self-supervise and improve their independent behavior. Each candidate possesses unique qualities that determine their behavior, and in each learning attempt, they seek to improve their behavior through interaction and competition with their peers. As candidates learn from one another, their individual qualities converge to form a shared behavior for the entire cohort. This convergence occurs after a series of learning attempts, at which point the behavior of each candidate becomes saturated, resulting in a unified behavior for the entire cohort [10].

Figure 3 indicates the flow process through which the Cohort Intelligence (CI) algorithm applies its logic to the given condition. Consider a general constrained problem (in the minimization sense) as follows [13].

Minimize $\quad f(x) = f(x_1, \dots x_i \dots, x_N)$

Subject $\quad g_i(x) \leq 0, \quad i = 1, 2, \dots, n$

$h_j(x) = 0, \; j = 1, 2, \dots, m$

$\Psi_i^{lower} \leq \Psi_i^{upper}$

In the context of CI, the objective function $f(x)$ i.e., equation 1, is considered the behavior of an individual candidate in the cohort, and the variable $x=(x_1, \dots x_i \dots, x_N)$ i.e.,m_n, b, z_1, z_2, β are considered as qualities. The CI optimization procedure begins with the initialization of the number of candidates C, the sampling interval Ψ_i for each quality x_i=1, 2… N, learning attempt counter l=1, and setting up of static sampling interval reduction factor $r \in [0, 1]$, convergence parameter.

6. Finite Element Analysis

Finite Element Analysis (FEA) refers to the utilization of the Finite Element Method (FEM), a numerical technique, for simulating and analyzing physical phenomena. The optimized parameters for a helical gear pair are obtained from a cohort intelligence optimization algorithm after 1800 iterations. The CI algorithm is coded in MATLAB (R2021a) and runs on a Windows 10 platform with a 2 GHz Intel (R) Core (TM) i3-5005U CPU and 8 GB of RAM. The CAD modelling and FEA analysis of the optimized helical gear pair are conducted using PTC Creo and Ansys, respectively. Contact stress analysis is performed in Ansys to determine the contact stresses generated in the helical gear pair.

6.1. Modelling

PTC Creo is used to create a CAD model of an optimized helical gear pair, as shown in Figure 7. Then, for FEA analysis, a step file of an optimized helical gear pair from PTC Creo is imported to ANSYS.

6.2. Meshing

After importing the CAD model into Ansys, fine meshing is performed. As the helical gear pair is a solid component, 3D meshing is required, and tetrahedral elements are utilized for this purpose. At the contact point, a very fine mesh is applied. The mesh's total number of nodes and elements is 1,516,966 and 351,461, respectively.

6.3. Boundary Condition

The driven gear and driving pinion are subjected to a remote displacement, while a moment of 1.619×10^6 N mm is applied to the driving pinion under the boundary condition, as shown in Figure 8. Remote displacement is a type of boundary condition that can be applied to both displacements and rotations at any given location in space. It is commonly used to restrict a particular displacement or rotation to a required direction.

In this case, the remote displacement allows rotation of the driving pinion and driven gear in the X direction only while restricting rotation in the Y and Z directions. The tangential load acting on the gear pair and the reference diameter of the pinion are used to calculate the moment.

6.4. Post Processing

The post-processing phase involves estimating the Von Mises stress and total deformation. Contact stress is determined at the tooth contact point while bending stress is determined at the root fillet of the helical gear pair.

6.5. Convergence in FEA

The convergence is a crucial aspect of Finite Element Analysis (FEA) that involves achieving an accurate solution to Partial Differential Equations (PDEs) by refining the mesh or reducing the element size in the spatial domain. The mesh convergence process involves analyzing the impact of decreasing the element size on the accuracy of the solution. Generally, a finer mesh size yields a more precise solution because it provides a better sampling of the physical domain, enabling a more accurate representation of the design or product's behavior.

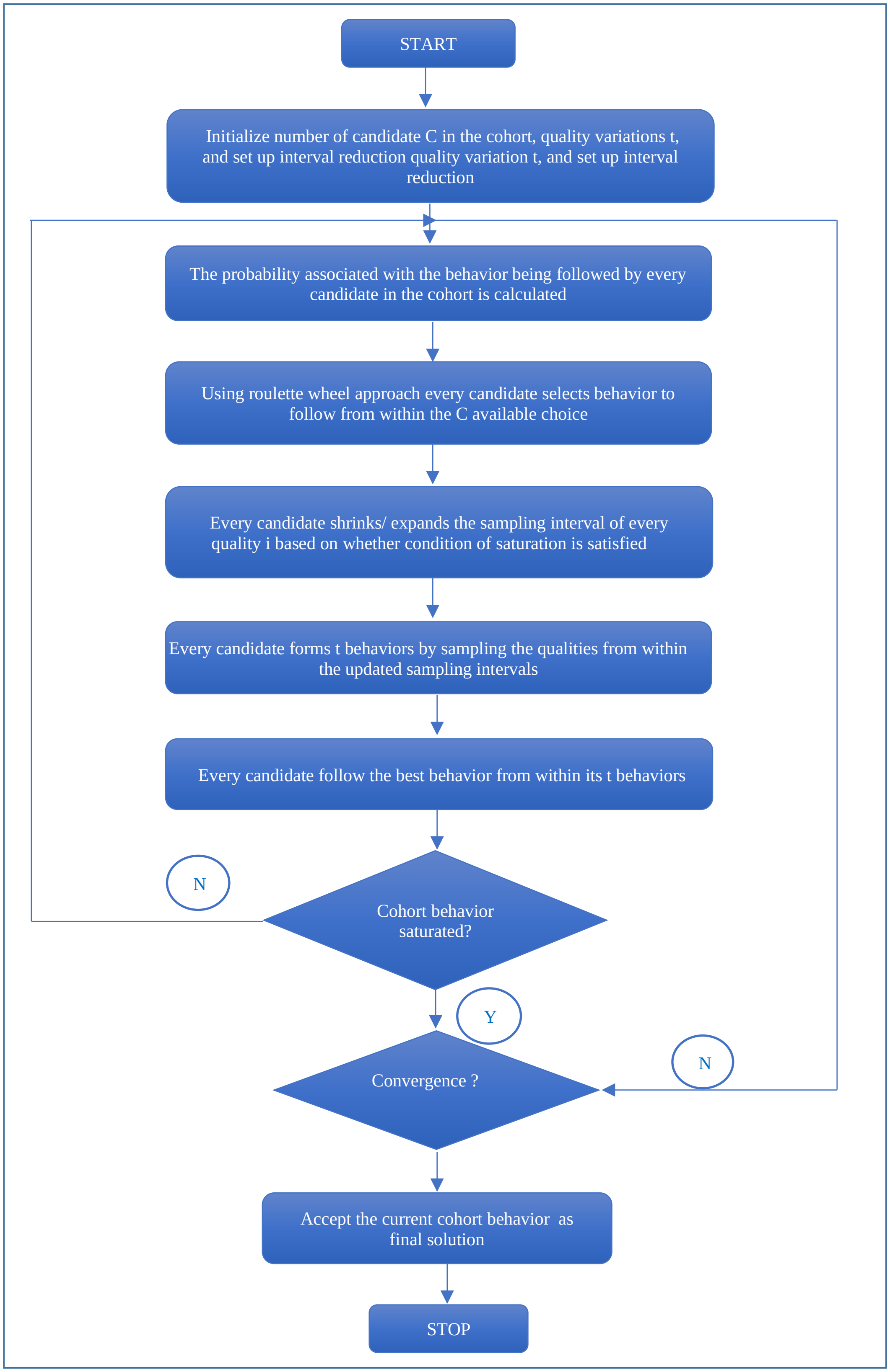

Fig. 3 Cohort Intelligence Algorithm (CI) flow chart [11]

Table 3. Comparison of CIA, GA and PSO results with design parameters of helical gear pair

No.	Parameter	Technique			
		Design Value	CIA	GA	PSO
1	Module (m_n)	4	4	4	4
2	Face Width (b)	130	110	110	110
3	No of Teeth on Pinion (z_1)	26	25	25	25
4	No of Teeth on Gear (z_2)	131	126	126	126
5	Helix Angle (β)	7°	8°	9°	9°
6	Volume (mm^3)	2.9578 X 10^7	2.325 X 10^7	2.345 X 10^7	2.345X10^7

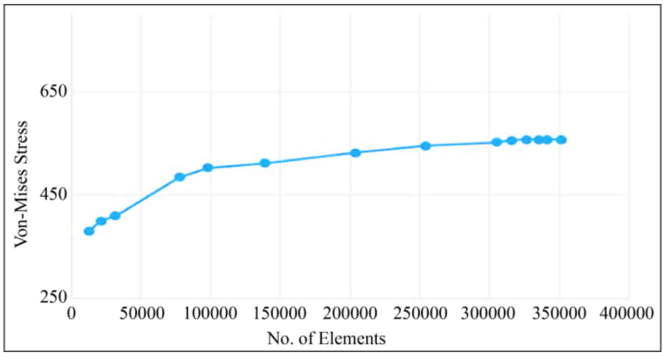

Fig. 4 Graph obtained from FEA for converging the solution

Figure 4 shows the convergence criteria used in the FEA for the analysis of an optimized helical gear pair. From the graph below, it is clear that the solution is converged, and von Mises stress is achieved at 351,461 number of elements.

7. Result and Discussion

The cohort intelligence algorithm (CIA) is a technique utilized to optimize the volume of a helical gear pair. To validate the effectiveness of CIA and compare the results, the optimization problem is also solved using the genetic algorithm (GA) and particle swarm optimization algorithm (PSO). The constraint considered is the safety factor for the pitting and bending of gear teeth. The CI, GA and PSO algorithm is coded in MATLAB (R2021a) and runs on a Windows 10 platform with a 2 GHz Intel (R) Core (TM) i3-5005U CPU and 8 GB of RAM.The results of the CI optimization algorithm are compared with the designed results, GA results, and PSO results, as presented in Table 3. From the above results, it is clear that CIA provides optimal results for a helical gear pair compared to GA and PSO. The optimal parameters of a helical gear pair obtained by the cohort intelligence optimization algorithm are m_n= 4, b=110 mm, z_1=25, z_2=126, β =8°.

The cohort intelligence optimization algorithm can produce better and more optimal results than the current design, GA, and PSO results by minimizing the volume of the helical gear pair with optimal values. After obtaining the optimized parameters, the helical gear pair is analyzed using Ansys software under the given boundary conditions. The FEA analysis yields the Von Mises stress and total deformation in the gear pair.

The results obtained from the finite element analysis for the designed gear pair are presented in Figures 5 and 6, while the FEA result for the optimized gear pair is presented in Figures 9 and 10.

Table 4 compares the analytical results and the FEA results for the optimized helical gear pair. The results obtained from the FEA analysis indicate that the contact stresses in the helical gear pair are within the permissible limits of the material, indicating that the assigned constraints are fully satisfied.

Table 4. Comparison of analytical and FEA results for optimized helical gear pair

No	Stresses	Analytical Value (Mpa)	FEA Value (Mpa)
1	Contact Stress	572.22	558.07
2	Bending Stress	176.4	168.52

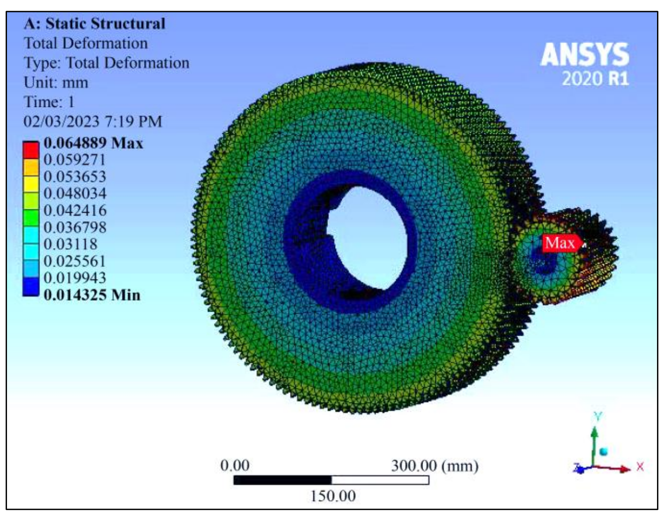

Fig. 5 Total deformation in designed gear pair

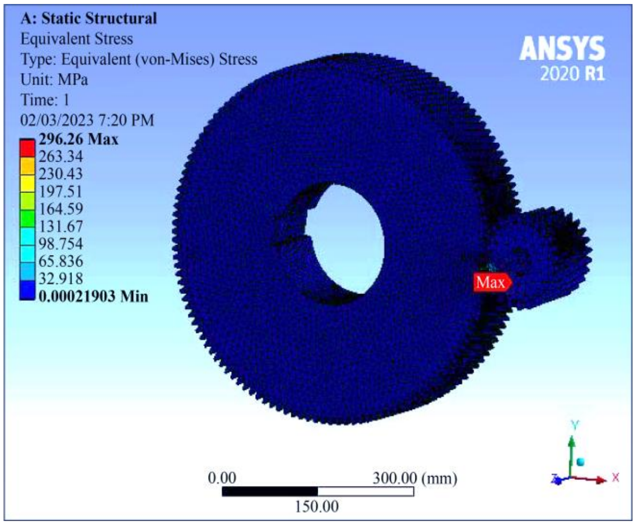

Fig. 6 Von-Mises stress in designed gear pair

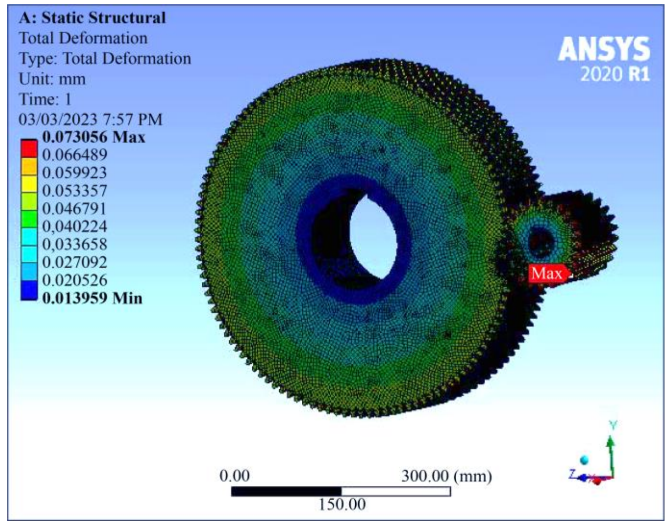

Fig. 9 Total deformation in optimized gear pair

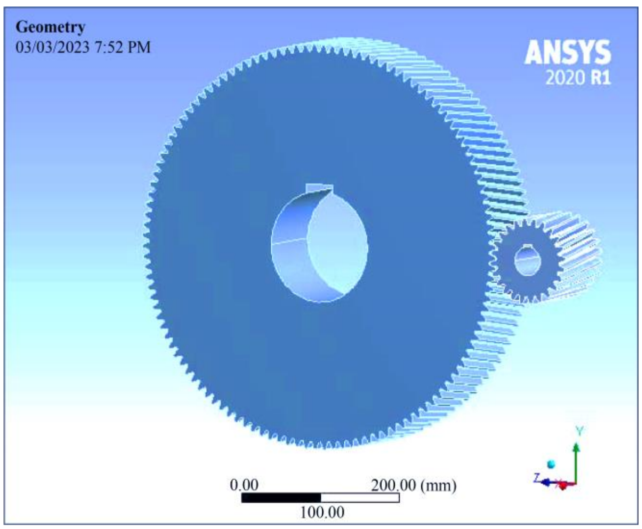

Fig. 7 CAD model of optimized gear pair

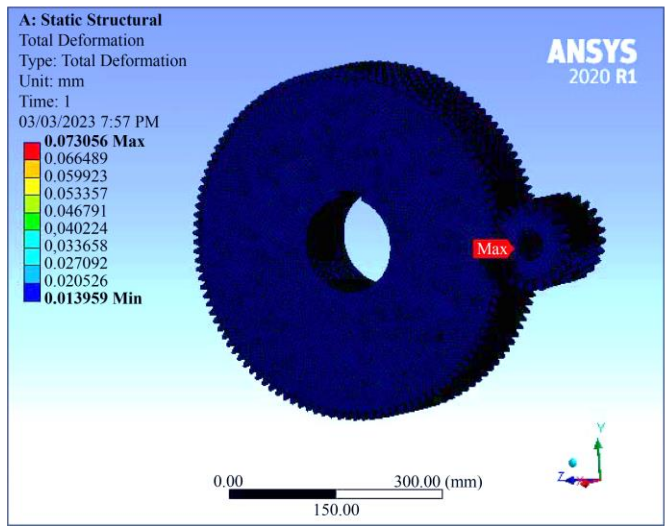

Fig. 10 Von-Mises stress in optimized gear pair

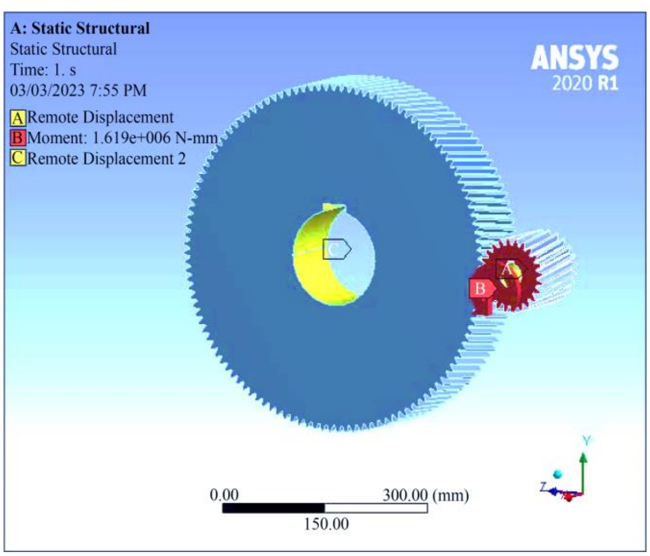

Fig. 8 Boundary condition

8. Conclusion

The gear is the most important component in a power transmission system and has a wide range of applications. The helical gear pair optimization problem is formulated in this paper with volume minimization as the objective function. The safety factor for pitting and bending gear teeth is considered a constraint in the problem. The design variables include the normal module, face width, number of teeth, and helix angle of the helical gear pair. To convert constrained optimization problems into unconstrained ones, the static penalty approach is employed as a constraint-handling method. The optimization problem is solved using the cohort intelligence algorithm, the genetic algorithm (GA), and the particle swarm optimization algorithm (PSO). The cohort intelligence algorithm (CIA) provided the optimal values for the helical gear pair, resulting in the minimization of volume. A helical gear pair with optimal parameters is designed in PTC Creo, followed by an FEA analysis in Ansys software for specific boundary conditions. The von Mises stress obtained from the FEA analysis is within the permissible limit for the material. The cohort intelligence algorithm (CIA) gives the optimal volume of a helical gear pair as $2.325 \times 10^{7,}$ which is lower than the actual design value, as well as the results obtained from the GA and PSO algorithms. The results indicate that the cohort intelligence algorithm can be effectively apply to real-world engineering design problems.

List of abbreviations

σ_H	Contact stress number
σ_b	Bending stress number
σ_{HP}	Allowable contact stress number
σ_{FP}	Allowable bending stress number
$[\sigma_H]_{eff}$	Effective allowable contact stress number
$[\sigma_F]_{eff}$	Effective allowable bending stress number
ε_α	Transverse contact ratio
g_β	Overlap ratio
m_n	Normal Module
b	Face width
$\boldsymbol{\phi}$	Pressure angle
β	Helix angle
Z_1	Number of teeth on the pinion
Z_2	Number of teeth on gear
Y_Z	Reliability factor
K_B	Rim thickness factor
$\varepsilon_{\alpha 1}$	Transverse contact ratio for pinion
$\varepsilon_{\alpha 2}$	Transverse contact ratio for gear
K_H	Load distribution factor
Z_R	Surface condition factor for pitting resistance
Z_I	Geometry factor for pitting resistance
Y_I	Geometry factor for bending resistance
Z_W	Hardness ratio factor
S_H	Safety factor for pitting
S_F	Safety factor for bending
Z_N	Stress cycle factor for pitting resistance
Y_N	Stress cycle factor for bending resistance
K_V	Dynamic factor
kg	Kilogram
mm	millimeter
Mpa	Megapascal
Gpa	Gigapascal
N	Newton
KW	Kilowatt

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Appendix A.

The expressions for safety factor, permissible bending and contact stresses are given below [2].

Effective allowable contact stress number

$$[\sigma_H]_{eff} \le \frac{\sigma_{HP}}{[S_H]_{min}} * \frac{Z_N}{Y_\theta} * \frac{Z_w}{Y_z}$$

Contact stress number

$$\sigma_H = Z_E * \sqrt{F_t\, K_O K_v\, K_B\, \frac{K_H}{d_1 b}\, \frac{Z_R}{Z_I}}$$

Safety factor for pitting

$$S_H = \frac{[\sigma_H]_{eff}}{\sigma_H} \ge [S_H]_{min}$$

Effective allowable bending stress number

$$[\sigma_F]_{eff} \le \frac{\sigma_{FP}}{[S_F]_{min}} * \frac{Y_N}{Y_\theta\, Y_z}$$

Bending Stress number

$$\sigma_{F=}\, F_t\, K_O K_v\, K_s\, \frac{1}{b\, m_t}\, \frac{K_H\, K_B}{Y_j}$$

Safety factor for bending

$$S_F = \frac{[\sigma_F]_{eff}}{\sigma_F} \ge [S_F]_{min}$$

Table 5. Designed Parameters for Pinion and Gear

m_n	Normal module (mm)	4
P	Input Power (KW)	1270
ϕ_t	Transverse pressure angle	20.138
α	Helix angle (degree)	7
f_r	Radial force (N)	11144.23
f_a	Axial force (N)	3731.46
ϕ_w	Working pressure angle (degree)	21.847
x_e	Sum of profile shift coefficient	0.8192
P_n	Normal base pitch	11.808
e_n	Normal space width	4.754
ε_α	Transverse contact ratio	1.55
Z_E	Elastic coefficient	189.65
$K_{H\alpha}$	Transverse load distribution factor	1
K_O	Overload factor	1
Y_N	Stress life cycle factor for pitting	0.657
C_h	Helical factor	1.18
K_B	Rim thickness factor	1
Z_R	Surface condition factor for pitting resistance	1
m_t	Transverse Module (mm)	4.030
$\boldsymbol{\phi}$	Pressure angle (degree)	20
r	Gear ratio	5.038
f_t	Tangential force (N)	30390.31
β_b	Base helix angle (degree)	5.5759
a′	Working centre distance (mm)	320
h	Whole depth (mm)	9.450
x	Sum of addendum modification coefficient	0.9489
P_t	Transverse base pitch	11.886
e_t	space width	4.796
g_β	Overlap ratio	1.26
K_v	Dynamic factor	1.11
$K_{H\beta}$	Face load distribution factor	1.202
K_z	Reliability factor	1
Z_N	Stress life cycle factor for pitting	0.785
K_Ψ	Helical overlap factor	1
Y_θ	Temperature factor	1
Z_N	Stress cycle factor for pitting resistance	0.657
σ_{HP}	Allowable contact stress number (Mpa)	1500
Y_N	Stress cycle factor for bending resistance	0.785
σ_{FP}	Allowable bending stress number (Mpa)	500

Table 6. Geometrical Parameter for Pinion and Gear

		Pinion	Gear
Z	Number of teeth	26	131
Z_v	Virtual no of teeth	26.5901	133.973
d	Reference diameter (mm)	104.781	527.93
S_n	Normal tooth thickness	7.521	7.805
h_a	Addendum (mm	5.55	5.55
h_f	Dedendum (mm)	3.8992	3.8992
d_b	Base diameter (mm)	98.375	495.65
d_f	Root diameter (mm)	96.982	520.91
d_a	Tip diameter (mm)	115.881	539.81
d_b	Base diameter (mm)	98.375	495.65

Table 7. Other Factors for Pinion and Gear

		Pinion	Gear
$\mathbf{K_f}$	Stress correction factor	1.504	1.577
Y	Tooth form factor	0.553	0.588
$\mathbf{m_N}$	Load sharing ratio	0.69	
$\mathbf{K_\Psi}$	Helix angle factor	0.98	