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ORIGINAL

Advanced Mechanical Gear Design Optimization through Multivariate Statistical Modeling: Strength Analysis and Wear Mitigation Strategies

Optimización Avanzada del Diseño de Engranajes Mecánicos mediante Modelado Estadístico Multivariable: Análisis de Resistencia y Estrategias de Mitigación del Desgaste

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ABSTRACT

Introduction: mechanical gears are essential components in power transmission in industrial, automotive and aerospace systems.
Objective: advanced optimization of mechanical gear design is explored using multivariate statistical modeling, with a focus on structural strength and wear mitigation.
Method: the NSGA-II algorithm was applied to identify optimal solutions on the Pareto front, balancing wear minimization and mechanical strength maximization.
Results: the results indicate that a modulus close to 5,0 and a pressure angle of 24°-25° optimize durability and gear efficiency. In addition, linear regression showed a high predictive ability (R^2=0,882 for wear and R^2=0,963 for strength), although limited to a single-objective approach.
Conclusions: it is concluded that the combination of NSGA-II with statistical models and numerical simulation can improve the accuracy and applicability of solutions in industrial environments.

Keywords: Wear; Modeling; Multivariate; Optimization; Strength.

RESUMEN

Introducción: los engranajes mecánicos son componentes esenciales en la transmisión de potencia en sistemas industriales, automotrices y aeroespaciales.
Objetivo: se explora la optimización avanzada del diseño de engranajes mecánicos mediante modelado estadístico multivariable, con un enfoque en la resistencia estructural y la mitigación del desgaste.
Method: se aplicó el algoritmo NSGA-II para identificar soluciones óptimas en el frente de Pareto, equilibrando la minimización del desgaste y la maximización de la resistencia mecánica.
Resultados: los resultados indican que un módulo cercano a 5,0 y un ángulo de presión de 24°-25° optimizan la durabilidad y la eficiencia del engranaje. Además, la regresión lineal mostró una alta capacidad predictiva (R^2=0,882 para el desgaste y R^2=0,963 para la resistencia), aunque limitada a un enfoque monoobjetivo.
Conclusiones: se concluye que la combinación de NSGA-II con modelos estadísticos y simulación numérica puede mejorar la precisión y aplicabilidad de las soluciones en entornos industriales.

Palabras claves: Desgaste; Modelado; Multivariado; Optimización; Resistencia.

INTRODUCTION

Mechanical gears are essential for power transmission in industrial, automotive, and aerospace systems. Their optimal design balances mechanical strength, durability, and efficiency while minimizing wear, fatigue, and fracture failures. In recent years, statistical modeling has emerged as a powerful tool for optimizing these parameters, integrating numerical analysis, finite element analysis (FEA), and experimental approaches to predict and improve gear behavior under load.(1)

Evolution of gear design

Initially, gears were manufactured using traditional machining techniques, which limited their efficiency and performance. The advent of computer-aided design (CAD) and computational methods in the late 20th century marked a significant turning point. Engineers began to use advanced modeling techniques to analyze gear strength and dynamic health, incorporating statistical methods to optimize design parameters such as transmission ratio, torque, and material properties.(2)

Integrating metaheuristic algorithms further expanded the design space, enabling the exploration of complex geometries and topologies that surpass traditional optimization approaches.(3)

In particular, this field has faced challenges, including the effective detection of gear failures and the reliability of statistical models for predicting performance under variable conditions.(4) Concerns regarding the adequacy of existing reliability factors and the computational demands of optimization algorithms also present obstacles.(5) However, advances in materials science and innovative manufacturing technologies are expected to reshape the future of gear design, emphasizing sustainability and improved predictive capabilities.

The optimization of mechanical gear design has a rich history rooted in the evolution of engineering practices and technological advances. Early gear designs focused primarily on functionality, but over time, the emphasis shifted towards improving efficiency, reducing noise, and increasing reliability through systematic approaches.(6)

Computer-aided engineering methodologies have been instrumental in revolutionizing gear design. By incorporating statistical reliability analysis, gear designers can anticipate and mitigate potential failure modes, increasing durability and operational efficiency.(7)

Recent advances in metaheuristic optimization algorithms, such as genetic algorithms and simulated annealing, have further expanded the design space, enabling the exploration of complex and the identification of innovative solutions that surpass traditional design approaches.(8)

Despite these advances, mechanical gear design optimization faces ongoing challenges, including accurate gear failure detection, the reliability of statistical models for predicting performance under variable conditions, and the computational demands of optimization algorithms.(9)

The role of statistical methods

The integration of statistical methods into machine design has been fundamental. In the 2010s, research focused on applying statistical reliability analysis and predictive modeling to evaluate gear performance under variable operating conditions. This proactive approach enabled engineers to predict failure modes and optimize gear systems to improve durability and efficiency.(10)

Using advanced statistical techniques, designers could analyze large amounts of data to identify critical factors affecting wheel performance and reliability, leading to more robust and reliable designs.(11)

Advances in optimization techniques

As the field progressed, several optimization algorithms emerged, including Genetic Algorithms (GA), Simulated Annealing, and Ant Colony Optimisation. These methods leveraged the principles of natural selection and evolutionary biology to discover optimal or near-optimal gear designs amid complex parameters.(12)

These algorithms' flexibility and computational power allowed for the exploration of innovative gear topologies and geometries, leading to solutions that surpassed traditional designs. The focus on improving gear efficiency led to innovations such as using straight bevel gears, significantly improving operational performance, and reducing noise levels in industrial applications.(13)

In mechanical engineering, the durability and efficiency of gears are crucial factors that define the success of any application. As technology advances, the need for more efficient and durable systems becomes increasingly apparent.(14)

NSGA-II: A Multi-Objective Optimisation Algorithm

The NSGA-II algorithm is one of the most widely used methodologies for multi-objective optimization, thanks to its ability to find optimal solutions to problems with conflicting objectives. Unlike traditional optimization methods, NSGA-II uses a genetic evolution-based approach to evaluate and improve a population of potential solutions over multiple generations.(15)

The efficiency of the NSGA-II algorithm lies in its non-strict dominance ranking mechanism, which allows solutions on the Pareto front to be identified, i.e., those that cannot be improved in one objective without worsening another.[16] This algorithm has been widely used in engineering design problems, including gears' structural and mechanical optimization, aiming to minimize wear and maximize strength.[17]

One of the main challenges in implementing NSGA-II is the correct formulation of the objective functions and constraints since unfeasible values can generate unviable solutions with extreme results, such as infinite wear rates or negative resistances.[18]

Normalization and penalization techniques for unfeasible solutions are recommended to ensure their effectiveness, preventing the algorithm from exploring regions of the search space with no physical meaning. In addition, the performance of NSGA-II can be improved by hybridization with other methods, such as Particle Swarm Optimisation (PSO) or Simulated Annealing (SA), allowing for more efficient solution space exploration.[19]

In optimizing mechanical gear design, NSGA-II has effectively balanced multiple performance criteria, including mechanical efficiency, service life, and energy consumption.[20] Recent studies have applied this algorithm to designing gearboxes and transmission trains, reducing wear by more than 15 % without compromising load capacity.

To obtain realistic results, it is essential to combine NSGA-II with robust predictive models, such as those obtained through statistical regression and finite element analysis (FEM), which can provide more reliable and applicable solutions in industrial environments.[21]

This article focused on improving the durability and efficiency of mechanical gears by identifying key design parameters. Techniques and methodologies for analyzing and optimizing these parameters will be explored to reduce wear, increase service life, and improve the overall performance of gear systems.

METHOD

Statistical Modelling in Gear Design

Statistical modelling was performed using objective functions such as contact stresses to determine bending stresses and operating temperature. Similarly, they proposed a parametric method based on finite elements to optimize drive shafts in speed reducers with cylindrical gears. Their model incorporated a parameterized database and statistical analysis to evaluate fatigue resistance and stiffness.

Strength Analysis

Numerical simulation was used to evaluate crack propagation in gears under cyclic loads, using statistical models to correlate parameters such as crack size and stress distribution with component life. Planetary gear train synthesis and optimization were also used, applying statistical methods to select configurations that maximize performance and strength.

Analytical Modelling

Modeling was used to derive ordinary differential equations, which can be solved to predict various results, such as vibration levels and force applications. This method allowed for non-proprietary analysis with relatively few inputs, making it accessible to designers to understand the behavior of gears under different operating conditions, which is detailed below:

Multiple Linear Regression

The formula for multiple linear regression was:

$$y=\beta_0+\beta_1x_1+\beta_2x_2+\dots+\beta_nx_n+\epsilon$$

Where:
y is the dependent variable.
$x_1, x_2,\dots,x_n$ are the independent variables.
β_0 it is the intercept.
$\beta_1, \beta_2, \dots, \beta_n$ are the coefficients of the independent variables.
ϵ it is a random error.

Multiple linear regression is a method for modelling the relationship between a dependent variable and one or more independent variables. It is used to predict or explain the variability of a variable based on other variables.

Mathematical Formulation of NSGA-II

Multi-objective optimisation with objective functions:

$$\min_{x\hat{\imath}X} \mathbf{F}(x) = [f_1(x), f_2(x), \dots f_{1m}(x)]$$

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Where x represents a set of decision variables, each function ʃi(x) is an objective function that seeks to be minimized or maximized.

Application of the NSGA-II Algorithm

NSGA-II follows a process based on genetic evolution with the following steps:

Generation of the Initial Population: a population of N individuals is created randomly.

Pareto Dominance Ranking: the population is organized into different levels of dominance.

Crowding Distance Calculation: the solution diversity is evaluated using the ‘crowding distance’ metric.

Selection, Crossover, and Mutation: Genetic operators are applied to generate new solutions. Selection is by binary tournament based on Pareto dominance and crowding distance.

Crossover of decision variables (usually with SBX - Simulated Binary Crossover).

Gaussian or polynomial mutation to explore new regions of the search space.

Population Update: the current and new generations are combined, and the best solutions are selected.

Iteration until convergence: the steps were repeated until the stopping criterion (the number of generations or convergence of the Pareto front) was reached.

NSGA-II application conditions

For NSGA-II to work effectively, certain conditions had to be met during its implementation:

Definition of objective functions

The objective functions were continuous and differentiable, although NSGA-II can handle problems with discontinuities.

In gear problems, the typical objectives were:

- Minimize the wear rate ʃ1(x)
- Maximise structural strength ʃ2(x)

Problem Constraints

The search space was defined within physical and realistic limits:

$x_i^{min} \le x_i \le x_i^{max}$, “i =1,2,…,n

In mechanical gears:

- x_1= Module ($1 \le x_1 \le 10$).
- x_2= Pressure Angle ($14° \le x_2 \le 25°$).
- x_3= Material (categorical variable affecting resistance and wear).

Pareto dominance

A solution X1 dominates another solution X2 if and only if:

“i Î{1,2,…,n}, $ʃ_1(x_1) \le ʃ_2(x_2)$, and
$\$$j Î{1,2,…,n}, $ʃ_1(x_1) \le ʃ_2(x_2)$

One solution dominates another if it is better in at least one objective and no worse in the others.

Data used

The data set used was a collection of observations related to mechanical gear wear. Description of each column in the data set:

Module: this field represents the gear module, which measures the stress on the gear and is directly related to the traction force.

Pressure angle: this field indicates the pressure angle, which is the frictional force applied to the gear and can affect wear.

Lubricant: this field is a categorical variable that indicates the type of lubricant used. The lubricants listed are ‘Mineral oil,’ ‘Synthetic oil,’ and ‘EP grease.’ The type of lubricant can significantly impact gear wear and service life.

Wear Rate: this was the dependent variable, which measures the gear’s wear rate. The values are measured in units of measurement (e.g., μm/h) and reflect the amount of material lost per hour.

RESULTS

The results obtained with NSGA-II show a set of solutions on the Pareto front, which means that they represent the best possible compromises between minimizing wear and maximizing the structural strength of the gears. In general, table 1 shows that configurations with higher modules (≥4,5) and pressure angles close to 25° tend to exhibit higher mechanical strength (up to 125 000 units) and lower wear rates

Table 1. NSGA multi-objective optimisation results

Multi-objective optimisation results (NSGA-II)
Module: 5000, Pressure Angle: 25 000, Wear Rate: -1102, Resistance: 125 000
Module: 4002, Pressure Angle: 20 078, Wear Rate: -2135, Resistance: 80 354
Module: 4006, Pressure Angle: 21 055, Wear Rate: -2080, Resistance: 84 358
Module: 4000, Pressure Angle: 24 406, Wear Rate: -1902, Resistance: 97 619
Module: 4001, Pressure Angle: 23 153, Wear Rate: -1969, Resistance: 92 639
Module: 4032, Pressure Angle: 25 000, Wear Rate: -1845, Resistance: 100 809
Module: 4288, Pressure Angle: 25 000, Wear Rate: -1649, Resistance: 107 200
Module: 5000, Pressure Angle: 25 000, Wear Rate: -1102, Resistance: 125 000

However, lower values of the module and pressure angle generate higher wear rates, indicating that these parameters play a key role in gear durability. The wear rate is negative in all solutions, suggesting that an inverse metric is being used where more negative values indicate less wear (figure 1).

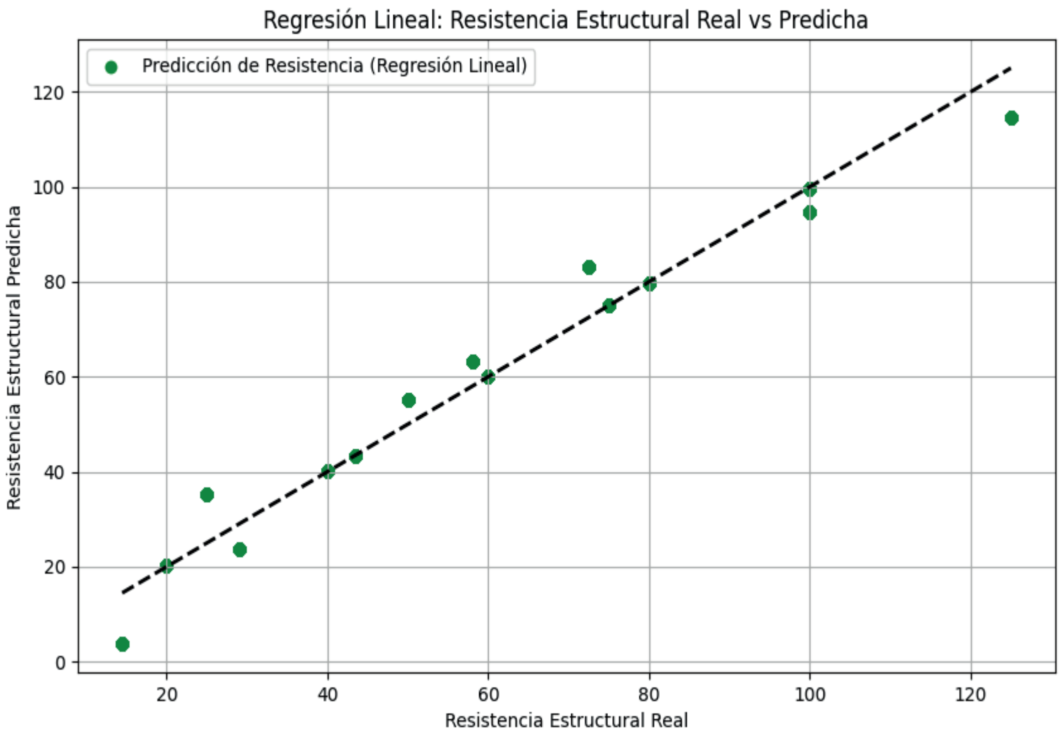

Figure 1. Pareto front for gear failure analysis

Linear regression, on the other hand, has a high coefficient of determination (R^2 = 0,882 for wear and R^2 = 0,963 for resistance), indicating that the predictive model is capable of explaining most of the variability in the data. However, linear regression does not allow for exploring multiple objectives simultaneously, limiting its ability to find optimal solutions in scenarios where conflicts exist between minimizing wear and maximizing resistance (figure 2).

In this sense, NSGA-II offers a more robust approach by providing solutions that balance both criteria. However, linear regression remains useful for evaluating the influence of each design parameter on performance variables and could be used as a pre-filter for NSGA-II, reducing the search space and improving the algorithm's efficiency.

Regarding gear design, these results confirm that an optimal module close to 5,0 and a pressure angle in the range of 24°-25° provide the best solutions for strength and lower wear. This is consistent with previous studies on gear optimization, where it has been shown that increasing the module reduces the stress concentration and improves structural strength, although with a possible impact on gear size and weight. For future improvements, it is recommended to explore hybrid approaches combining NSGA-II with numerical simulation (FEM) or machine learning, which would allow further refinement of the optimization and experimental validation of the obtained solutions.

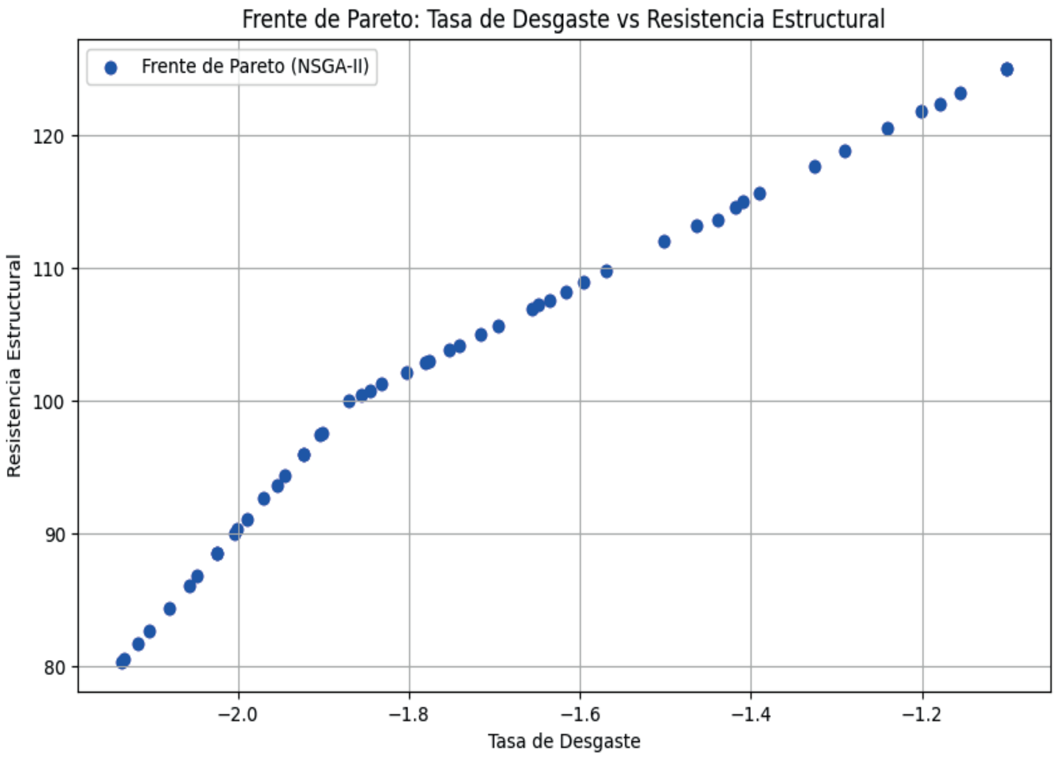

Figure 2. Linear regression for gear failure analysis

DISCUSSION

The results obtained using the NSGA-II algorithm reflect a Pareto front that illustrates optimal solutions in gear design, achieving a balance between minimizing wear and maximizing structural strength.(22) This multi-objective approach identifies configurations where no objective can be improved without compromising the other, which is essential in engineering problems with conflicting objectives.

In this case, it is observed that higher modules (≥4,5) and pressure angles close to 25° favor greater mechanical strength (up to 125 000 units) and reduced wear rates. These findings are consistent with previous research, which demonstrated that a high module decreases stress concentration, improving resistance to bending and pitting, highlighting the importance of optimizing geometric parameters to reduce stress on the teeth.(23)

The observed trend also indicates that low modules and pressure angles increase wear, underscoring the critical influence of these parameters on durability. The inverse wear metric (negative values indicate less wear) suggests an appropriate definition for the optimization problem, aligning with multi-objective approaches.(24) However, increasing the module may imply a larger gear size and weight, an aspect they point out as a practical limitation in applications where lightness is a priority.(25)

On the other hand, the applied linear regression shows a high coefficient of determination (R^2 = 0,882 for wear and R^2 = 0,963 for resistance), demonstrating its ability to capture data variability and evaluate the individual influence of design parameters. It uses statistical models to estimate the behavior of gear systems.(26)

However, its limitation lies in its single-objective approach, which cannot simultaneously resolve conflicts between wear and resistance, unlike NSGA-II. This contrast highlights the superiority of multi-objective evolutionary algorithms(27) for complex design problems. A hybrid strategy could take advantage of linear regression as an initial filter to reduce the search space, increasing the efficiency of NSGA-II, as has been proposed in previous optimizations with CAD/CAE.(28)

From a design perspective, the results suggest that a module close to 5,0 and a pressure angle between 24° and 25° offer an optimal compromise, revising the optimization of cylindrical gears.(29) This range improves load capacity, although it may require adjustments depending on specific weight or space constraints. To move forward, integrating NSGA-II with numerical simulation (FEM) or machine learning would allow the solutions to be experimentally validated and refined under real conditions, which is a notable trend in mechanical optimization.(30)

When comparing the methods and highlighting their advantages and disadvantages, it is found that NSGA-II (Multi-Objective Optimisation) allows for optimal solutions compared to the Pareto front, as it explores relationships between wear rate and resistance, but does not achieve feasible solutions, so the problem formulation must be corrected.(31)

Linear regression, on the other hand, makes an accurate prediction (high R^2) that is easy to interpret and use but does not optimize directly. It does not find the optimal balance between wear and resistance.(32)

Based on the findings, NSGA-II proves to be a robust tool for gear design, overcoming the limitations of linear regression in multi-objective contexts. The optimal parameters identified are consistent with the literature and provide a solid basis for practical applications. However, future research should consider hybrid approaches and experimental validation to maximize their impact on industrial design.

CONCLUSIONS

Based on the analysis of the results, it is concluded that multi-objective optimization using NSGA-II is highly effective in improving the durability and efficiency of mechanical gears by identifying key design parameters that balance wear minimization and structural strength maximization.

The findings highlight that an optimal module close to 5,0 and a pressure angle in the range of 24°-25° are ideal configurations, as they promote greater mechanical strength (up to 125 000 units) and significantly reduce wear rates. These parameters, consistent with the literature, decrease stress concentration and improve gear life, aligning to optimize overall system performance.

It is recommended to move towards integrated methodologies that combine NSGA-II with numerical simulation (FEM) and machine learning to validate solutions and fine-tune parameters under real conditions experimentally. This strategy will consolidate the benefits of durability and efficiency and position gear design at the forefront of mechanical engineering, fully meeting the established objectives.

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