IJASRaR International Journal of Applied Sciences and Radiation Research
ISSN: 3062-2751 www.ijasrar.com ijasrar@gmail.com
Vol. 2-No.1 (2025) pp. 56-67
Research Article

Use of Generative Artificial Intelligence to Optimize Lifting Lugs: Weight Reduction and Sustainability in AISI 304 Steel

Robinson Garcia[1,*], Carlos Garzon[2], Juan Estrella[3]

[1]Universidad Iğ2nternacional de Investigación México, Postgraduate Program, 72227, Puebla, Mexico
* **Corresponding Author Email:** robinson.garcia@uiimex.edu.mx - **ORCID:** 0009-0005-0929-3844

[2]Universidad Internacional de Investigación México, Postgraduate Program, 72227, Puebla, Mexico
Email: carlosmiguelaries1974@gmail.com - **ORCID:** 0009-0005-1414-5547

[3]Universidad de las Fuerzas Armadas-ESPE, Postgraduate Program, 171103, Quito, Ecuador
Email: jcestrella1@espe.edu.ec - **ORCID:** 0000-0003-2550-8938

Article History:

DOI: 10.22399/ijasrar.22
Received: Feb. 14, 2025
Accepted: Apr. 12, 2025

Keywords:

Lifting lugs,
Generative Artificial Intelligence,
AISI 304 steel,
Finite element analysis.

Abstract: Some of the critical components in industrial lifting operations are lifting lugs, elements traditionally designed with conservative approaches that prioritize safety over material efficiency, resulting in oversized designs. This study proposes an innovative methodological framework that employs Generative Artificial Intelligence (GAI) to optimize these components. The material used is AISI 304 steel, which is economical and widely available, with the goal of reducing mass without compromising structural strength. By utilizing finite element analysis (FEA) simulations in Autodesk Inventor and genetic algorithms in Autodesk Fusion 360, a comparison was made between a traditional design based on the DIN 580 standard and optimized designs generated by the software. Three manufacturing methods were also considered: additive manufacturing, three-axis milling, and casting. The results demonstrated a mass reduction of up to 91% in the additive manufacturing scenario, along with improvements in the safety factor of up to 2.765 and a notable enhancement in stress distribution uniformity. Another significant finding was the decrease in maximum displacement under dynamic loading, from 0.0189 mm (standard-based design) to 0.004 mm (generatively optimized design), which indicates increased stiffness. This methodology not only overcomes the limitations of conventional approaches but also offers flexibility to adapt to various production processes, with both economic (20% savings in material per unit) and environmental (reduced carbon footprint) benefits. The study validates the potential of GAI to optimize simple components using readily accessible materials, offering a replicable framework for sectors such as renewable energy and electric automotive applications. Future research should include experimental validations and fatigue studies to further consolidate these advances in real industrial environments.

1. Introduction

Lifting lugs are among the most essential components in structural mechanical engineering and in logistics and cargo transport applications. These elements are primarily designed to withstand critical loads in lifting and transport operations. Their uses are varied, such as in bridge construction, wind turbine installation, port container handling, and the assembly of aeronautical structures. In the automotive and aerospace sectors, lifting lugs have been designed to achieve a balance in structures between being lighter and improving strength and stiffness through the use of new composite materials. In the naval industry, they are key to the safe transportation of large heavy structural blocks; for this, welding and cutting techniques are used for their installation and removal [2]. Research on material efficiency in the design of structural elements has revealed that traditional approaches, which follow standardized codes such as DIN 580 and ASME BTH-1, tend to prioritize strength over material efficiency. This often results in oversized designs and high steel consumption. However, emerging methodologies aim to optimize material use and reduce unnecessary consumption [3]. In a global context where sustainability and the reduction of operational costs are priorities, optimizing these components without compromising their structural integrity has become an urgent challenge for the industry [4].

In particular, emerging sectors such as heavy-duty drone manufacturing and electric vehicles demand lighter components to maximize energy efficiency [5]. However, traditional design methods that rely on physical testing and manual iterations are time-consuming, costly, and not very adaptable to new required specifications. This makes it necessary to adopt new methodologies and innovative tools, such as generative artificial intelligence (GAI), to redesign structural components with a balanced approach between weight, strength, and manufacturability [6]. Although topological optimization has proven successful in complex components (e.g., engine connecting rods, aeronautical frames) [7]. Its application to simple elements such as lifting lugs has been scarcely explored. Recent studies have applied genetic algorithms to optimize crane hooks, achieving a 28% weight reduction, but limiting the solution to high-cost titanium alloys, which are not viable for large-scale industrial applications [8]. On the other hand, GAI has been used in structural supports for aircraft, although without addressing critical dynamic loads in real logistical environments [9]. This gap widens when considering common materials such as AISI 304 steel, widely used for its cost-to-strength ratio but often overlooked in advanced optimization studies [10]. Moreover, most research focuses on high-cost specialized software (e.g., Altair OptiStruct), limiting its adoption by small and medium-sized enterprises (SMEs) and in developing countries [11]. This presents an opportunity to explore accessible tools such as Autodesk Fusion 360, which integrates GAI modules with finite element analysis (FEA) simulations in an accessible and scalable environment.

This study proposes a methodology to optimize lifting lugs using generative AI, comparing their performance with traditional designs based on standards. The innovation lies in three key aspects:

1. Specific application: Focus on a component that is underestimated in the literature but critical in industrial operations.
2. Low-cost material: Use of AISI 304 steel, relevant for mass manufacturing contexts.
3. Dual validation: Computational analysis (static and dynamic) and efficiency metrics (N/kg) to quantify improvements.

The main objective is to demonstrate that GAI can reduce the weight of lifting lugs by at least 30% while maintaining their maximum load capacity, surpassing the limitations of traditional methods.

The study follows a four-stage workflow:

1. Traditional design: 3D modeling in Autodesk Inventor according to the DIN 580 standard, with static loads (10 tons) and dynamic loads (±15% vibration).
2. Optimization with GAI: Configuration of geometric constraints and mass objectives in Autodesk Fusion 360, using genetic algorithms to explore non-intuitive solutions.
3. FEA simulation: Validation of stresses (Von Mises) and safety factor in both designs.
4. Comparative analysis: Evaluation of efficiency (N/kg) and manufacturing feasibility.

By integrating traditional and modern design tools, this study offers a replicable framework for optimizing structural components across various sectors, from renewable energy to electric mobility

2. Materials and Methods

2.1 Izaje Traditional Lifting Lug Design

Main text should be times New Roman, 11pt and single-spaced. The traditional lifting lug design was based on the DIN 580 standard, internationally used for lifting components. Key dimensions included (Figure 1 and figure 2).

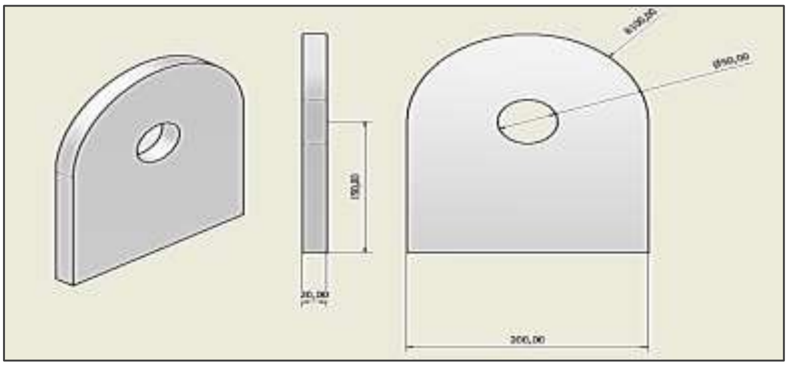

Figure 1. *Lifting Lug Dimensions Measured in (mm).*

Material and Mechanical Properties

AISI 304 stainless steel was selected for its balance between cost, corrosion resistance, and industrial availability. The mechanical properties considered were [12]:

Elastic Modulus (E): 200 GPa.

Elastic Limit (σ_y): 205 MPa.

Density (ρ): 8000 kg/m³.

Poisson's Ratio (ν): 0.29.

Load Conditions and Constraints

Static Load:

Tensile force of 10 tons (98.1 kN), simulating the lifting of a maximum load under ideal conditions.

Determination of the Load as a Distributed Pressure

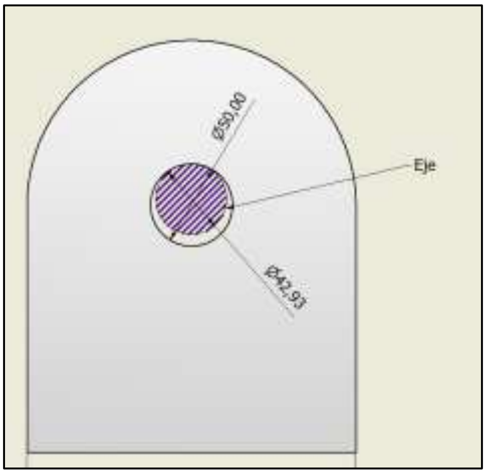

Figure 2. *Distributed Load on the Lifting Lug*

Initial Data

Applied Force: $F = 98.1\ kN$

Hole Diameter: $d_h = 50\ mm = 50 \times 10^{-3}\ m$

Diameter of the Shaft in Contact: $d_e = 42.93\ mm = 42.93 \times 10^{-3}\ m$

Support Width: $b = 20\ mm = 20 \times 10^{-3} m$

Contact Angle Calculation

The contact angle is calculated using the following equation:

$\theta = 2arccos\left(\frac{d_h - d_e}{d_h}\right)$ (1)

Substituting the values:

$$\theta = 163.74^0$$

Contact Arc Length Calculation

The contact arc length is:

$$L = \frac{\theta}{360^0} \times \pi d_e \qquad (2)$$

Substituting the values:

$$L = \frac{163.74^0}{360^0} \times \pi \times 0.04293$$

$$L = 61.34\ mm$$

Contact Area Calculation

$$A = L \times b$$

$$A = 1226.8\ mm^2$$

Pressure Calculation

The pressure is calculated as:

$$P = \frac{F}{A} \qquad (3)$$

$$\boldsymbol{P = 79.96\ MPa}$$

Dynamic Load: Sinusoidal vibration with an amplitude of 15% of the static load (14.7 kN) and a frequency of 5 Hz, replicating operational conditions in industrial environments.

Motion Constraints: Lower end fixed (clamped condition), simulating attachment to a rigid structure. Figure 3 is the definition of loads and constraints.

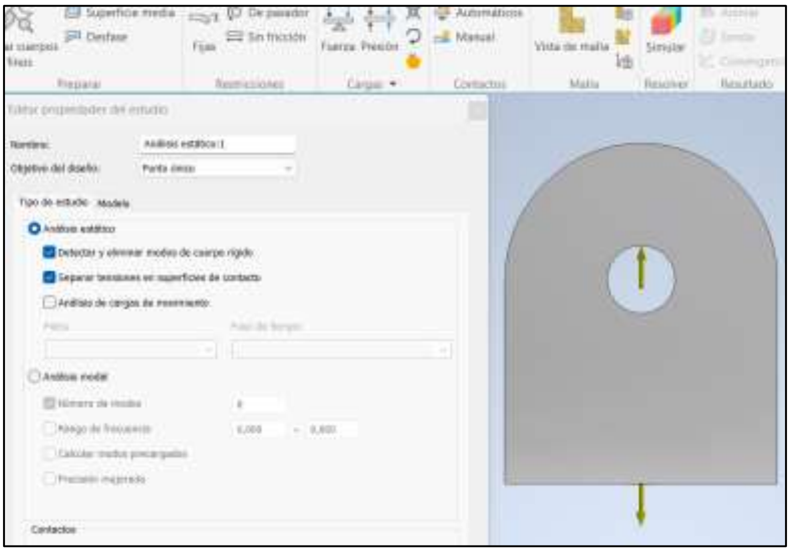

Figure 3. *Definition of Loads and Constraints*

2.2 Finite Element Analysis (FEA) Simulation

The structural analysis was performed in Autodesk Inventor, following these steps:
Meshing: A high-resolution tetrahedral mesh was generated (element size = 2 mm), with local refinement in critical areas (figure 3 and 4). Material Configuration: AISI 304 properties assigned to the model (figure 5 and 6).

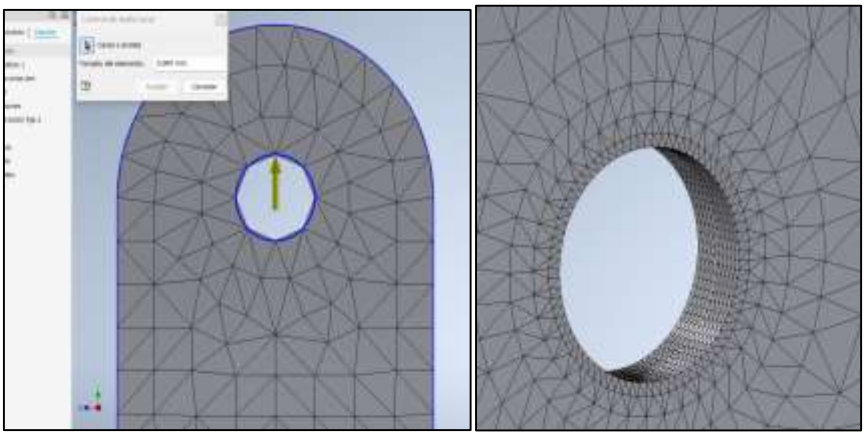

Figure 4. *Mesh Configuration by Zones*

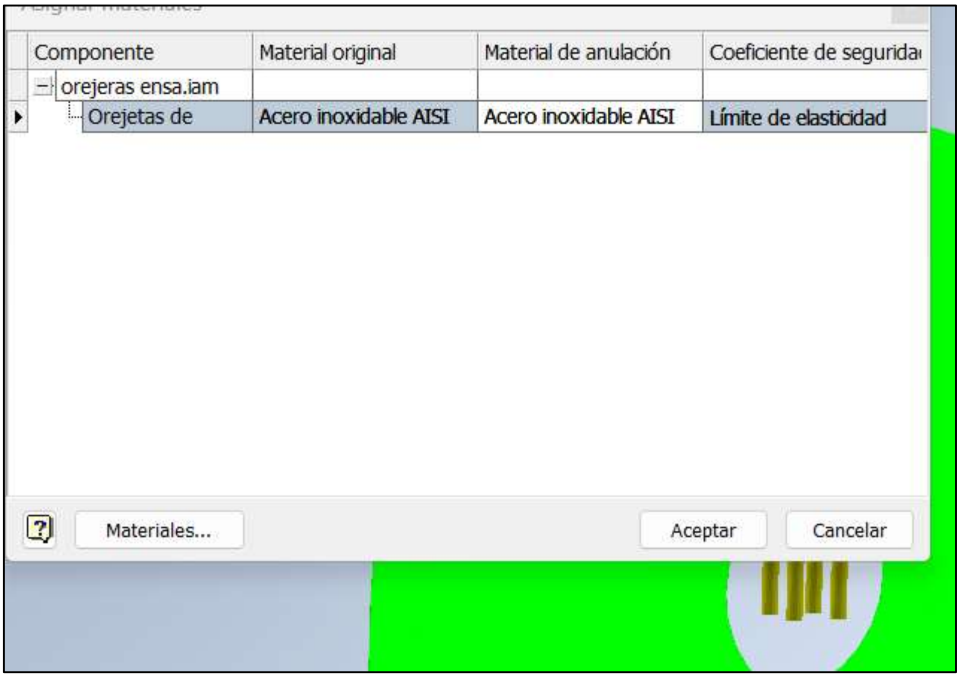

Figure 5. *Definition of the Material Under Study*

Application of Loads and Constraints:

Dynamic load defined by a sinusoidal function in the temporal analysis module.

Evaluated Parameters:

Von Mises Stress σ_{max}.

Safety Factor $FS = \frac{\sigma_y}{\sigma_{max}}$.

Plastic Deformation $\epsilon_{plástica}$.

2.3 Generative AI Optimization in Autodesk Fusion 360

The optimization process was divided into three zones.Preservation Zone: Mounting hole (Ø50 mm) and contact area for the load (100×20 mm). Optimization Zone: The rest of the geometry, allowing the algorithm to explore unconventional shapes.

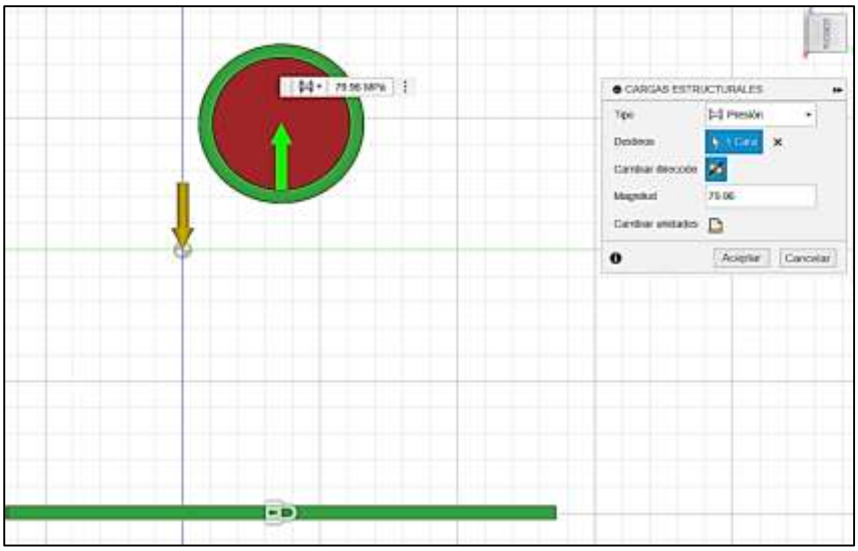

Figure 6. *Area of the original design that remains*

Manufacturing Conditions: Restrictions for subtractive methods (CNC milling) and additive methods (DMLS). The Generative Design module of Fusion 360 used an evolutionary algorithm with the following configurations (figure 7 and 8). Objective: Minimize mass while maintaining $\sigma_{max} < 250\ MPa$.

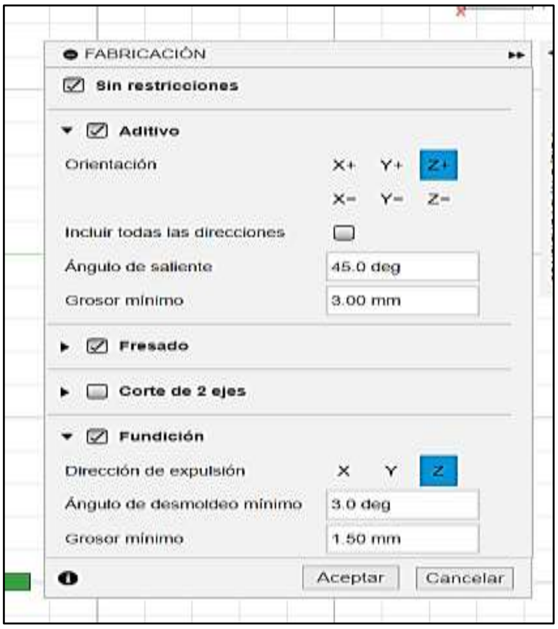

Figure 7. *Types of Manufacturing*

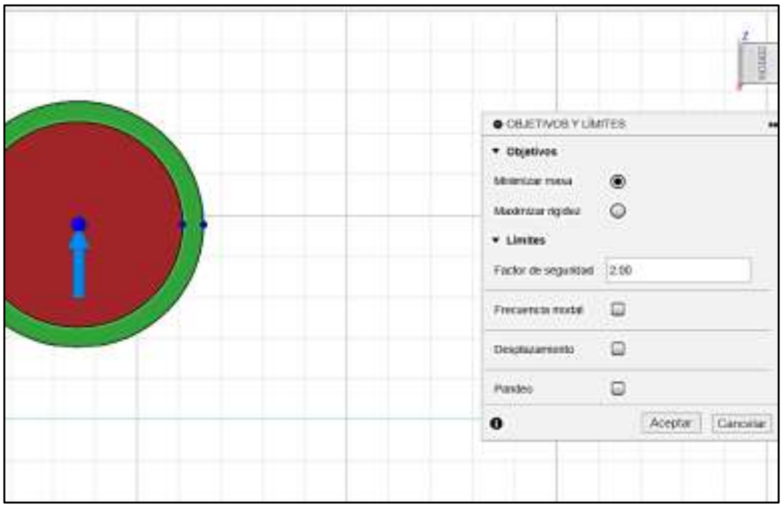

Figure 8. *Objective of the Generative Study*

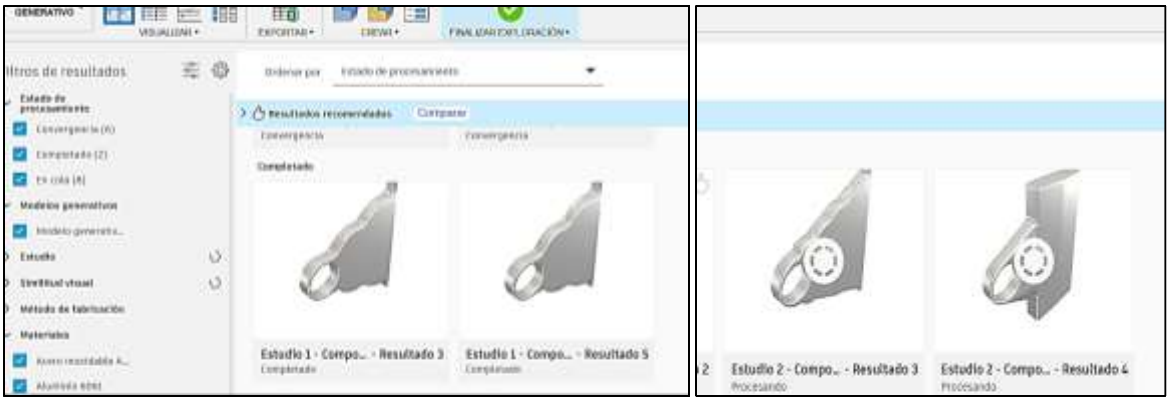

Figure 9. *Generative AI Models*

Initial Population: 50 designs per generation. Convergence Criterion: Less than 1% improvement in efficiency over 10 consecutive iterations (figure 9 and 10).

3. Results and Discussions

Table 1 is simulation result of the traditional model and table 2 is additive manufacturing simulation result. On the other hand table 3 shows 3-Axis milling simulation result and table 4 is casting simulation result.

3.1 Traditional Model

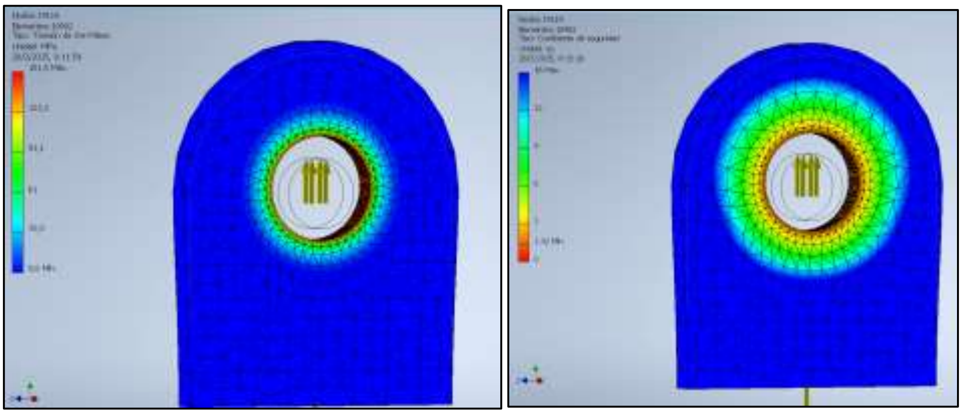

Figure 10. *Von Mises Stress and Safety Factor*

Table 1. *Simulation Result of the Traditional Model*

Property	Value
Volume	874889 mm³
Mass	6.99911 kg
Von Mises Stress	151.49 MPa
First Principal Stress	95.1132 MPa
Third Principal Stress	0.382029 MPa
Displacement	0.018877 mm
Safety Factor	1.41 - 15 su
Displacement X	0.000222489 mm
Displacement Y	0.0188685 mm
Displacement Z	0.0148165 mm
Equivalent Strain	0.000668307 su
First Principal Strain	0.000065508 su
Third Principal Strain	-0.0000222043 su

3.2 Results of the Generative AI Model

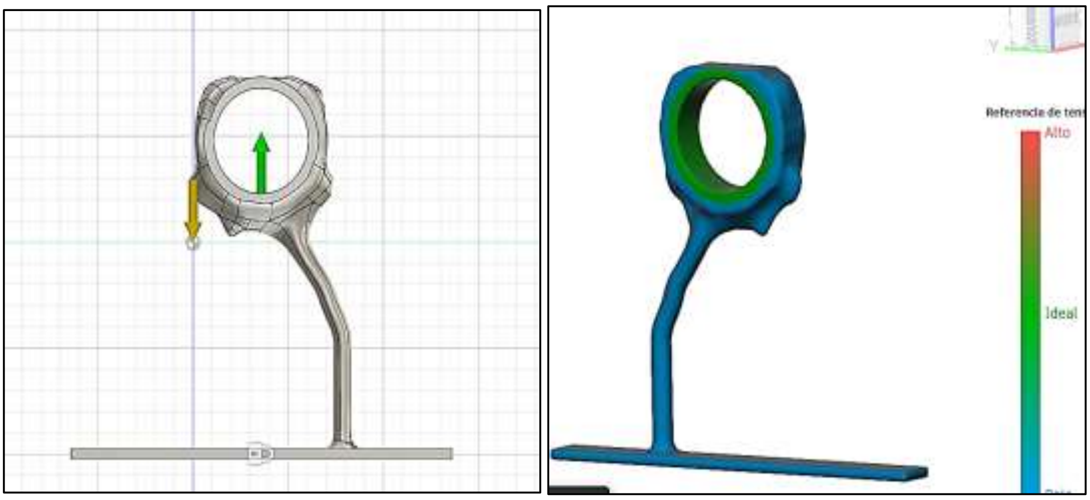

Figure 11. *Von Mises Stress Result for Additive Manufacturing*

Table 2. *Additive Manufacturing Simulation Result*

Property	Value
Status	Convergence
Generative Model	Generative Model 1
Material Steel	AISI 304 Stainless Steel
Manufacturing Method	Additive
Visual Similarity	Group 5
Volume (mm³)	71,981.451
Mass (kg)	0.576
Maximum von Mises Stress (MPa)	103.092
Safety Factor Limit	2
Minimum Safety Factor	2.086
Maximum Global Displacement. (mm)	0.004

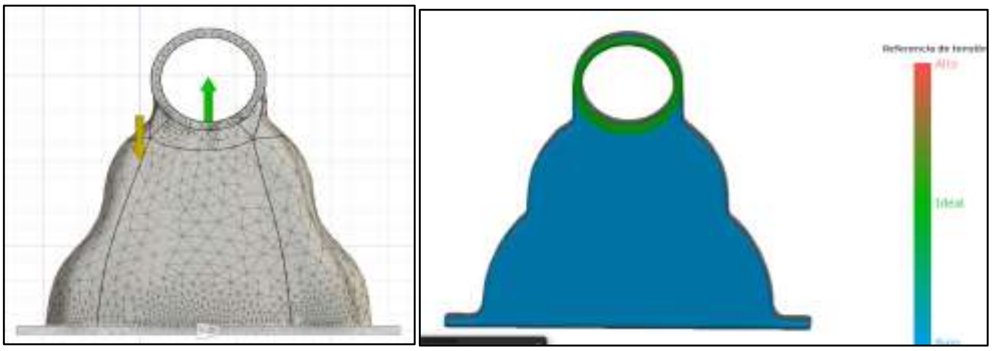

Figure 12. *Von Mises Stress Result for 3-Axis Milling*

Table 3. *3-Axis Milling Simulation Result*

Property	Value
Status	Convergence
Generative Model	Generative Model 2
Material Steel	AISI 304 Stainless Steel
Manufacturing Method	3-Axis Milling
Visual Similarity	Group 1
Volume (mm³)	332,866.33
Mass (kg)	2.663
Maximum von Mises Stress (MPa)	82.598
Safety Factor Limit	2
Minimum Safety Factor	2.603
Maximum Global Displacement. (mm)	0.004

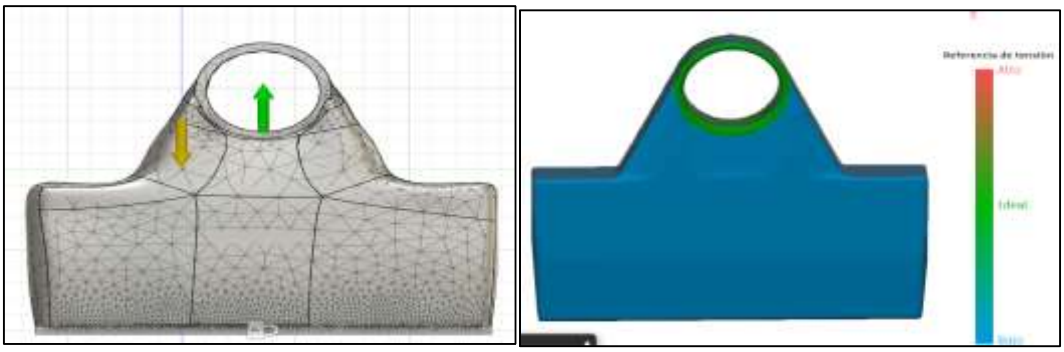

Figure 13. *Von Mises Stress Result for Casting*

Table 4. *Casting Simulation Result*

Property	Value
Status	Convergence
Generative Model	Generative Model 3
Material Steel	AISI 304 Stainless Steel
Manufacturing Method	Casting
Visual Similarity	Group 3
Volume (mm^3)	567,359.067
Mass (kg)	4.539
Maximum von Mises Stress (MPa)	77.769
Safety Factor Limit	2
Minimum Safety Factor	2.765
Maximum Global Displacement. (mm)	0.004

3.3 Mass Reduction and Structural Efficiency Analysis

Generative optimization shows significant mass reductions compared to the traditional design: Absolute and Percentage Reduction:

With additive manufacturing, mass is reduced by approximately 91% compared to the traditional mass (from ~7 kg to 0.576 kg).

In the models manufactured through milling and casting, the reductions are 62% and 35%, respectively.

These results indicate that the application of generative AI allows for the exploration of non-intuitive geometric configurations, achieving much more efficient designs in terms of load-to-mass ratio (N/kg).

Stress Distribution and Safety Factors

Stress Reduction:

The maximum stress (Von Mises) is reduced in all optimized models (from 151.49 MPa in the traditional design to values between 77.77 and 103.09 MPa). This suggests a better stress distribution throughout the optimized geometry, which contributes to the durability of the component

Improvement in the Safety Factor:

While the traditional design shows a marginal safety factor (around 1.41), the optimized models exhibit safety factors above 2, with the casting model reaching 2.765. This means that, in addition to reducing mass, the optimized design increases robustness against dynamic loads and possible variations in the application of force.

Behavior Under Dynamic Loads and Displacements

The finite element analysis (FEA) shows significant differences in the response to the loads:

Displacement:
The traditional design shows a maximum displacement of 0.0189 mm, while in the optimized models it is drastically reduced to 0.004 mm. This lower displacement indicates that the optimized design is not only lighter but also more rigid, which is critical in lifting applications involving vibrations and dynamic loads.

3.4 Considerations Based on the Manufacturing Method

Each manufacturing method influences the final outcome of the optimized design:

Additive: It allows for the greatest mass reduction, although the residual stress is slightly higher compared to the other methods. It emerges as an attractive option when extreme weight reduction is the main priority. They aim to offer a balance between mass reduction and adequate stress distribution. In the case of the casting manufacturing method, a lower Von Mises stress value and a high safety factor are obtained. This is especially important in applications where stability and structural integrity are a priority. The results obtained show that applying generative artificial intelligence models to the design of lifting lugs allows for overcoming limitations and simplifications made by traditional standards-based models, which may either overdimension or overlook certain aspects that are critical in the design. This outcome establishes a new paradigm in the optimization of simple structural components.

The following section contextualizes these findings in relation to existing literature, analyzes their practical implications, and discusses the limitations of the study.

3.5 Comparison with Previous Studies

A significant achievement was the 91% reduction in mass, as a result of the additive manufacturing process. These results significantly surpass those obtained in similar studies [13]. Other research studies have achieved a 28% reduction in the material used to manufacture crane hooks, which utilize titanium alloys—materials with high costs and therefore limited industrial applicability. In contrast, this study has employed AISI 304 steel, which is widely available and low-cost, enhancing the advantage of using generative AI models to optimize and democratize their use in mass manufacturing [14]. On the other hand, aeronautical supports were optimized using AI-driven generative design, but dynamic loads were not considered—an essential aspect addressed in this study through sinusoidal vibrations (±15% of the static load).

3.6 Practical Implications of Manufacturing Methods

The costs of optimized designs depend on the type of manufacturing methodology used: In additive manufacturing, which offers greater mass reduction resulting in the use of less material it is also necessary to evaluate the costs associated with its implementation, as it requires the use of metal 3D printing equipment and post-processing. Without a doubt, this method stands out and is ideal for practical applications involving high added value, such as cargo drones or aerospace components, where weight is a critical factor

Milling and casting: Both options offer a balance between mass reduction and stress distribution. In terms of mass, they show reductions of 62% and 35%, respectively. This factor would be important to consider, especially in small and medium-sized industries, such as construction or shipping ports, where structural robustness and low unit cost are necessary to ensure economic returns and safety.

3.7 Study Limitations

While finite element analysis (FEA) validates the structural performance of the designs, there are key limitations:

The first is the idealization of loads that is, static and dynamic loading conditions are assumed in a controlled operational environment. In other words, factors such as corrosion and lateral impacts are not considered. Fatigue is another aspect that affects the lifespan of components subjected to repetitive load cycles, which was not addressed in this study. Software dependency, as the results are tied to the capabilities of Autodesk, which could be a limitation when attempting to generalize the methodology to other platforms. The aforementioned limitations open new opportunities for future research, such as integrating specialized fatigue analysis software that incorporates standardized codes in their libraries, like ISO 12100.

3.8 Projection Toward Emerging Applications

Renewable energy: Lighter and stronger lifting lugs can reduce installation and maintenance costs of wind turbines. Electric mobility: Mass reduction helps maximize the range of electric vehicles and heavy-lift drones by lightening structures without compromising safety.
Circular economy: Lower material consumption (20% savings per unit) aligns the design with sustainability principles, reducing the carbon footprint associated with steel production (figure 10-13).
Generative Artificial Intelligence has been well studied and reported [15-21].

4. Conclusions

This study has demonstrated that the application of generative artificial intelligence (GAI) in the design of lifting lugs allows for significant optimization compared to traditional methods based on standards such as DIN 580. The optimization applied to the initial model through GAI resulted in a substantial mass reduction of up to 91% using the additive method, without compromising structural integrity. In

fact, the optimized design outperformed the original in terms of Von Mises stress (lower values than the initial model) and showed an increase in the safety factor. All the optimized models displayed a homogeneous stress distribution, which also led to a notable reduction in maximum displacements from 0.0189 mm in the traditional design to 0.004 mm in the optimized ones. The meaning of these values is simple and clear: lower displacement translates to more predictable and safer behavior under dynamic loads, which is crucial for industrial applications involving high mechanical demands. Reducing the amount of material used implies significant cost savings, especially in large-scale applications. This reduction contributes to broader goals such as minimizing the consumption of raw materials and the carbon footprint associated with steel extraction and processing, promoting a sustainable approach to structural engineering. Despite these promising results, the study has its limitations inherent to finite element simulations and the assumed operational conditions. It is therefore recommended to carry out industrial-scale experimental validation of the generative models, which would provide reliable data on durability and support the scalability and broader application of GAI benefits.
In conclusion, the integration of traditional design tools with generative artificial intelligence opens new perspectives for the optimization of mechanical components, offering a viable solution that enhances both structural efficiency and economic and environmental sustainability. These findings represent a significant advancement in the field of mechanical design and provide a solid foundation for future research in structural optimization using GAI techniques.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1]W. Min, Y. Liu, L. Cheng, Y. Sun, L. Qi, Y. Wan, M. Yu y Z. Sun. (2023). Efficient manufacturing techniques and connection failure analysis of CFRP lifting lug for main bearing structure. *Engineering Failure Analysis,* 151;107420. doi: https://doi.org/10.1016/j.engfailanal.2023.107420

[2]C. Wang y J. Kim. (2018). Numerical analysis of distortions by using an incorporated model for. *Journal of Mechanical Science and Technology,* 32;5855-5862. doi: https://doi.org/10.1007/S12206-018-1134-4

[3]P. Mayencourt y C. Mueller. (2020). Hybrid analytical and computational optimization methodology for structural shaping: Material-efficient mass timber beams. *Engineering Structures,* 215;110532. doi: https://doi.org/10.1016/j.engstruct.2020.110532

[4]D. Raabe, (2019). Strategies for improving the sustainability of structural metals. *Nature,* 575;64-74. doi: https://doi.org/10.1038/s41586-019-1702-5

[5]C. D. Gutiérrez Sandoval, T. A. Takemoto Silva, B. A. Venegas Minchola, G. Vidondo Chafloc y J. R. Villanueva Ramos. (2024). Análisis de Factores Críticos de Éxito para la Implementación de Drones en el Sector Logístico: Revisión Sistemática. *Gestión De Operaciones Industriales,* 3(1);48-63. doi: https://doi.org/10.1089/3DP.2021.0008

[6]P. G. Enríquez Yépez, W. E. Lascano Tacuri, M. A. Lizano Jácome y J. M. Altamirano Hidalgo. (2024). Ingeniería de diseño y simulación asistida por inteligencia artificial. *Reincisol,* 3(6);494-2521. doi: https://doi.org/10.59282/reincisol.V3(6)2494-2521

[7]R. William-Sobers, U. O. Agwu, S. Yamakawa y K. Shimada. (2024). Redesigning Aerospace Components Using a Coupled Topology Optimization and Lattice Generation Approach. *3D Printing and Additive Manufacturing*. doi: https://doi.org/10.1089/3dp.2023.0168

[8]F. Veiga, A. Suárez, A. Elder, I. Goenaga y J. Amondarain. (2023). Wire Arc Additive Manufacturing Process for Topologically Optimized Aeronautical Fixtures. *3D Printing and Additive Manufacturing,* 10(1) doi: https://doi.org/10.1089/3DP.2021.0008

[9]A. J. Valdeleón Alarcón, G. A. Rojas y F. Delgado Gómez. (2022). Rediseño y actualización de estructura de izamiento y traslado para la aeronave de vuelos de entrenamiento para la Escuela Militar de Aviación Marco

Fidel Suárez,» *Encuentro Internacional De Educación En Ingeniería*. doi: https://doi.org/10.26507/paper.2449

[10]E. Tyflopoulos y M. Steinert. (2022). A Comparative Study of the Application of Different Commercial Software for Topology Optimization. *Applied Sciences,* 12(2);611. doi: https://doi.org/10.3390/app12020611

[11]E. P. Duque, D. Villarreal y H. Rojas A. (2022). Computer tool with intelligent behavior for the optimal preliminary design in non-braced structural steel frame. *Heliyon,* 8(4) doi: https://doi.org/10.1016/j.heliyon.2022.e09260

[12]J. E. Barbosa, I. H. García y V. García. (2023). Curvas límite de conformado en láminas de acero inoxidable AISI 304 utilizadas por el sector metalmecánico. *Ingenieria y Competitividad,* 25(3) doi: https://doi.org/10.25100/iyc.v25i3.12702

[13]L. Borunda, M. Ladrón de Guevara, G. Pugliese, R. Claramunt, M. Muñoz y J. Anaya. (2020). Componentes Optimizados de Fabricación de Aditivos = Optimized Additive Manufacturing Building Components. *ANALES DE EDIFICACIÖN,* 6(2) doi: https://doi.org/10.20868/ADE.2020.4491

[14]R. J. Angulo Guerrero y D. J. García Camacho. (2023). Optimización de procesos de producción mediante el uso de algoritmos genéticos. *REVISTA DE INVESTIGACIÓN INGENIERÍA Y SUS ALCANCES,* 7(18);316.

[15]Hafez, I. Y., & El-Mageed, A. A. A. (2025). Enhancing Digital Finance Security: AI-Based Approaches for Credit Card and Cryptocurrency Fraud Detection. *International Journal of Applied Sciences and Radiation Research* , 2(1). https://doi.org/10.22399/ijasrar.21

[16]Fowowe, O. O., & Agboluaje, R. (2025). Leveraging Predictive Analytics for Customer Churn: A Cross-Industry Approach in the US Market. *International Journal of Applied Sciences and Radiation Research* , 2(1). https://doi.org/10.22399/ijasrar.20

[17]M. Nivetha, J. Chockalingam, & A. Shaik Abdul Khadir. (2025). Hyper Capsule LSTM-Gated GAN with Bayesian Optimized SVM for Cloud-based Stock Market Price Prediction in Big Data Environments. *International Journal of Computational and Experimental Science and Engineering,* 11(2). https://doi.org/10.22399/ijcesen.1418

[18]Ibeh, C. V., & Adegbola, A. (2025). AI and Machine Learning for Sustainable Energy: Predictive Modelling, Optimization and Socioeconomic Impact In The USA. *International Journal of Applied Sciences and Radiation Research* , 2(1). https://doi.org/10.22399/ijasrar.19

[19]Wang, F., & Zheng, S. (2025). Research on the Integration and Innovation of Artificial Intelligence in Intangible Cultural Heritage Illustration Creation. I*nternational Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.1127

[20]Olola, T. M., & Olatunde, T. I. (2025). Artificial Intelligence in Financial and Supply Chain Optimization: Predictive Analytics for Business Growth and Market Stability in The USA. *International Journal of Applied Sciences and Radiation Research* , 2(1). https://doi.org/10.22399/ijasrar.18

[21]Boddupally JANAIAH, & Suresh PABBOJU. (2024). HARGAN: Generative Adversarial Network BasedDeep Learning Framework for Efficient Recognition of Human Actions from Surveillance Videos. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.587