

Review

Optimization of Structures and Composite Materials: A Brief Review

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Abstract: Neural networks (NNs) have revolutionized various fields, including aeronautics where it is applied in computational fluid dynamics, finite element analysis, load prediction, and structural optimization. Particularly in optimization, neural networks and deep neural networks are extensively employed to enhance the efficiency of genetic algorithms because, with this tool, it is possible to speed up the finite element analysis process, which will also speed up the optimization process. The main objective of this paper is to present how neural networks can help speed up the process of optimizing the geometries and composition of composite structures (dimension, topology, volume fractions, reinforcement architecture, matrix/reinforcement composition, etc.) compared to the traditional optimization methods. This article stands out by showcasing not only studies related to aeronautics but also those in the field of mechanics, emphasizing that the underlying principles are shared and applicable to both domains. The use of NNs as a surrogate model has been demonstrated to be a great tool for the optimization process; some studies have shown that the NNs are accurate in their predictions, with an MSE of 1×10^{-5} and MAE of 0.007%. It has also been observed that its use helps to reduce optimization time, such as up to a speed 47.5 times faster than a full aeroelastic model.

Keywords: review; machine learning; aircraft structures; composite materials; genetic algorithm; topology optimization



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1. Introduction

Over the years, the field of aeronautical engineering has experienced constant evolution in searching for solutions aimed at improving aircraft performance, efficiency, and safety. According to Bishop [1], in recent years, neural networks (NNs) have seen significant growth, leading to numerous practical applications across various fields and providing a robust set of tools for solving a wide range of problems. With this in mind, the use of NNs together with optimization methods can offer great potential for improving structural design and the speed of optimization processes.

In the aeronautical area, NNs have emerged as a powerful tool in several areas, one of which is the area of optimization. In this field, NNs can help improve the optimization process by integrating it with an optimization method, such as the genetic algorithm (GA). Thus, the following two areas have emerged with the potential for innovation, development, and advancement: structural and composite material optimization. This can be seen in Lagaros et al. [2], who used NNs to improve the performance of evolutionary strategies (ESs) in structural optimization, or Caixeta and Marques [3], who emphasized multi-objective optimization in the design of aircraft wings using NN metamodels, showing the integration of structural and material optimization in obtaining superior designs.

Structural optimization brings with it the potential to promote improvements in the performance of structures, that is, improving rigidity, strength, ductility, resilience, safety, and other points. Optimization can also help us find the best point at which the structure will deliver the best performance while reducing mass. Therefore, the search for better structural configurations is also aligned with the objective of increasing the performance, efficiency, and safety of aircrafts. In this context, the use of NNs integrated with an optimization method can open up frontiers such that it is possible to achieve new structural designs that were previously difficult to achieve through more conventional methods. Some articles have shown the use of NNs in the optimization of structures, such as those by Lagaros et al. [2] and Caixeta and Marques [3] (optimization using the evolutionary method), as well as Freitag et al. [4] and Jeong et al. [5] (topological optimization).

On the other hand, material selection is crucial for the development of a project; it is necessary to know the characteristics and properties of the material to choose the best one according to the objective. In aeronautical engineering, aluminum alloys are widely used but, currently, the use of composite materials (fiberglass and carbon fiber) is increasing. This is occurring due to the characteristics of composite materials that help them achieve specific performance requirements such as strength, stiffness, and weight reduction. Just as structural optimization aims to improve the performance of the structure, material optimization also seeks to obtain better performance by maximum strength, stiffness, and low weight. Similarly, NNs integrated with an optimization method can help in the optimization of composite materials, as can be seen in [6–8].

Therefore, it is noted that both material and structural optimization are necessary for improving structural properties. Structural and material optimization are processes that are connected, as one can influence the other. In structural optimization, it is possible to determine the best configurations and geometries that improve its performance, but material optimization can occur by optimizing the layer stacking or optimizing the fiber directions in each layer [9,10]. Furthermore, material optimization will bring benefits to structural design due to its influence on stiffness, strength, and weight. Therefore, optimizing both structure and material iteratively will help us to achieve the objective of improving the structural properties.

Over the years, technology has evolved and increasingly brings alternatives that contribute to enhancing processes, such as optimization. Computers are becoming more powerful, and this is helpful to increase the use of NNs, which is advantageous for engineering. This tool provides an alternative for structural optimization to accelerate processes. Because of this, research about the use of neural networks in optimization is increasing and there are many works about this topic. However, when searches for similar studies are carried out in aeronautics, there are fewer papers than in mechanics. The novelty of this article is to present not only aeronautical works but also mechanical works, as the ideas are similar and can be applied in both areas.

The sections of this article are as follows: A bibliometric analysis will be presented to provide an overview of the research landscape related to aircraft structural optimization and composite material optimization. This will be followed by a section on NNs, where the key concepts of NNs and deep neural networks (DNNs) will be explained. The third section will delve into training methods, covering both supervised and unsupervised learning techniques that are essential for the development and implementation of effective NN models. In the fourth section, a survey of the previous literature will be conducted, presenting a comprehensive review of the research on aircraft structural optimization and composite material optimization, emphasizing the integration of NNs in these areas. The fifth section will present a discussion on the findings, implications, and future directions for research and application. Finally, the last section will conclude the article, summarizing the key points and contributions of the study.

2. Bibliometric Survey

The significance of the union between NNs and optimization algorithms has been noted, so it is important to carry out a bibliometric survey to understand the use of NNs over the years and what the future projections are. The subsequent paragraphs present a survey on the optimization of aircraft structures using NNs, as well as more general research on the topic (also including articles without the use of NN), revealing interesting trends.

Although research into aircraft structure optimization using NN is more recent, as can be seen in Figure 1, it shows a notable growth trajectory. This growth is indicative of the growing interest and recognition of the potential benefits that NNs offer in optimizing aircraft structures. On the other hand, research into aircraft structural optimization in a general context has a longer history, dating back to 1918, as can be seen in Figure 2. This longer period reflects the traditional structural optimization approaches that have been employed over the years. Despite the recent emergence of NNs in this field, there continues to be a significant body of research conducted without the use of this tool. Furthermore, when analyzing the number of documents on optimization in both cases, two countries, China and the United States, emerge as the main contributors, as can be seen in Figures 3 and 4. This could highlight the global interest and involvement in the optimization of structures, regardless of the methodologies employed.

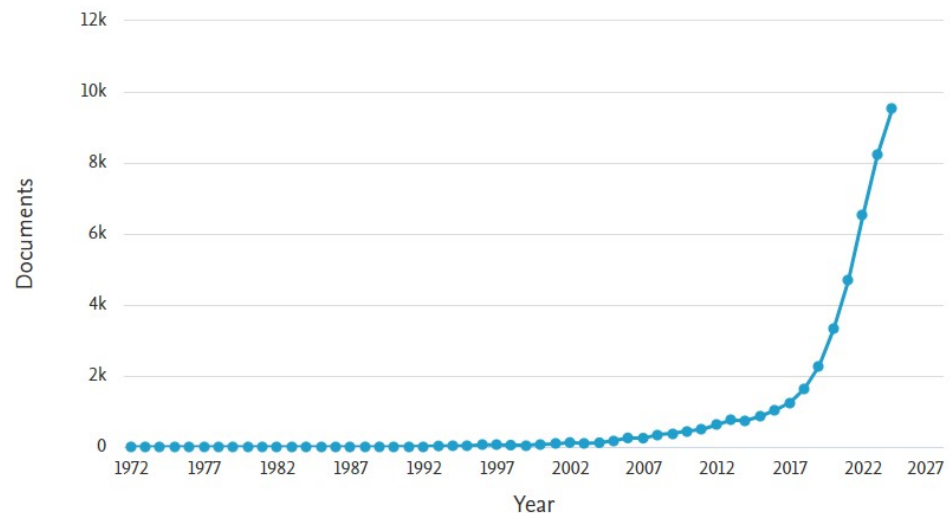


Figure 1. Structure Optimization Documents Using NNs by Year [11].

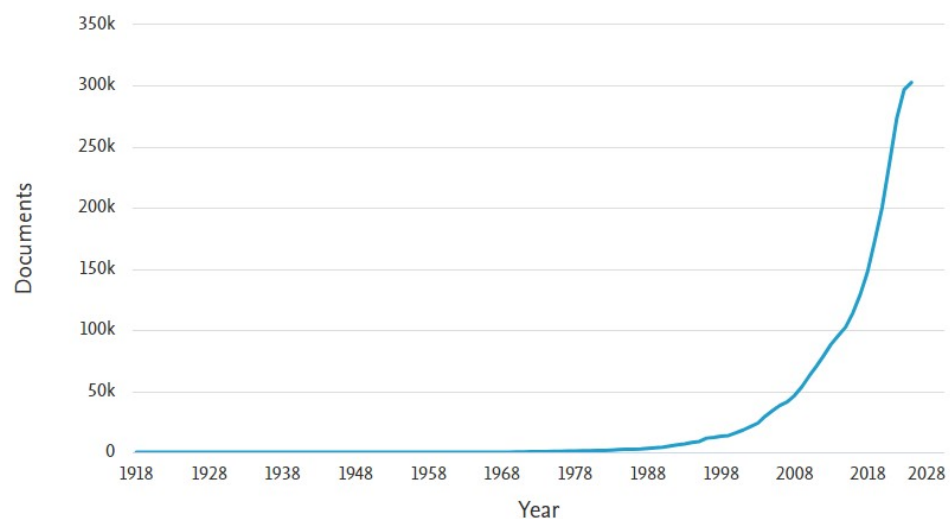


Figure 2. Structure Optimization Documents by Year [12].

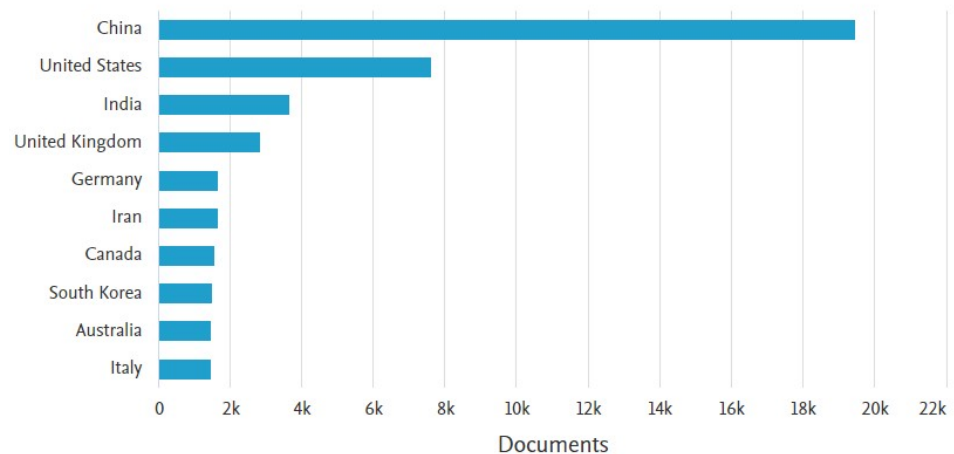


Figure 3. Structure Optimization Documents Using NNs by Country [11].

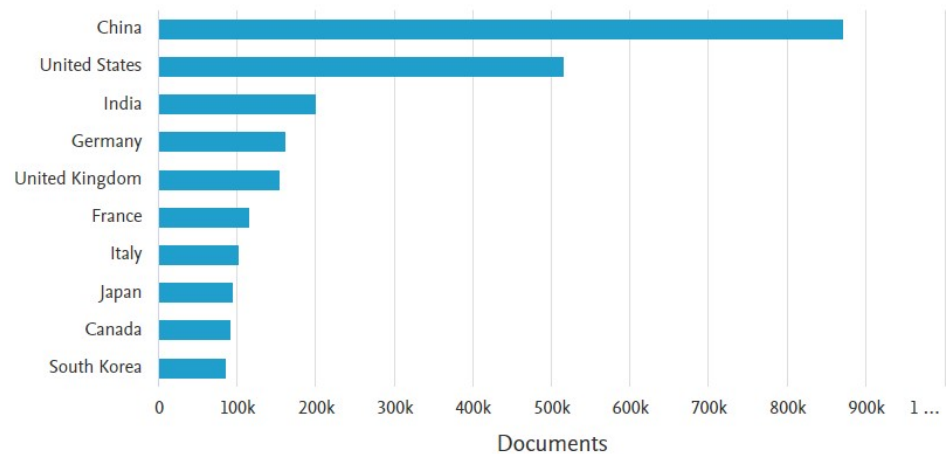


Figure 4. Structure Optimization Documents by Country [12].

On the other hand, it is also important to carry out a bibliometric analysis of the optimization of composite materials. The bibliometric analysis carried out includes research on the optimization of composite materials that used NNs in the process, as well as more comprehensive research on this topic that used or did not use NNs, in order to elucidate trends and patterns in the previous research activities within this domain.

Composite materials are one of the most used material on aircrafts. Due to that, a bibliometric analysis of the optimization of composite materials was carried out to provide insights into the evolution and trends of research in this field. Research focused on optimizing composite materials using NNs is more recent, beginning only in 1992, as can be seen in Figure 5. In contrast, optimizing composite materials without the use of NNs has a longer history, dating back to 1918, as can be seen in Figure 6. General bibliometric research on the optimization of composite materials reveals a growing trend in research activity over the years. When examining geographic distribution, research into the optimization of composite materials using NNs is prominent in China, India, and the United States, as can be seen in Figures 7 and 8.

Finally, delving deeper into NN applications and optimization methodologies is crucial to understanding the current research efforts. This paper offers invaluable insights into the methodologies, advancements, and applications in this field. Specifically, this article highlights the importance of understanding NNs along with optimization techniques such as GA and topology optimization. By exploring these technologies, we hope to present a more comprehensive understanding of their role in the design of aeronautical structures and in composite materials thus paving the way for future innovations and advances in this field.

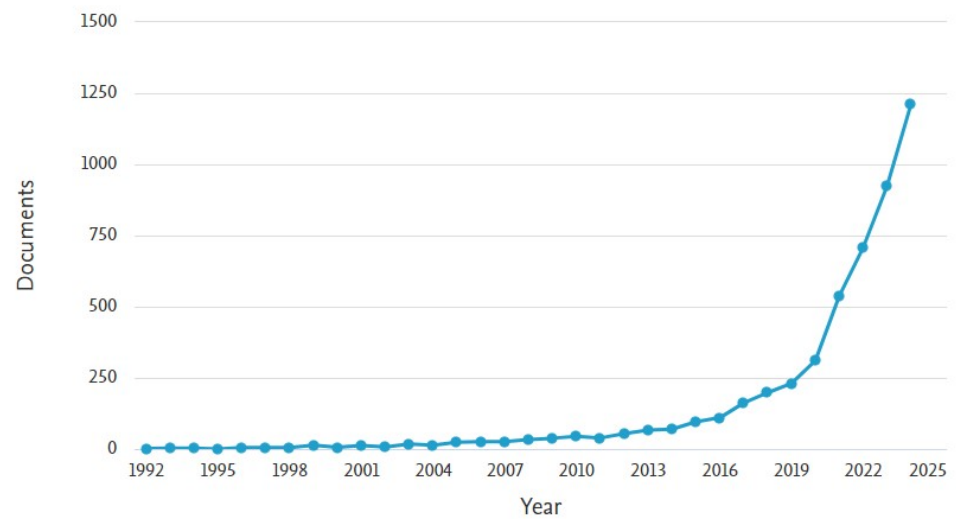


Figure 5. Composite Material Optimization Documents Using NNs by Year [11].

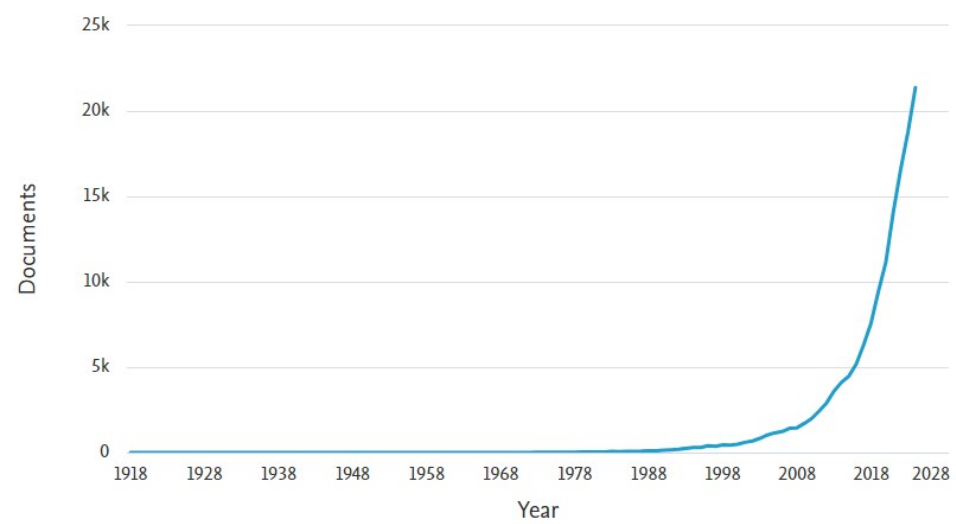


Figure 6. Composite Material Optimization Documents by Year [13].

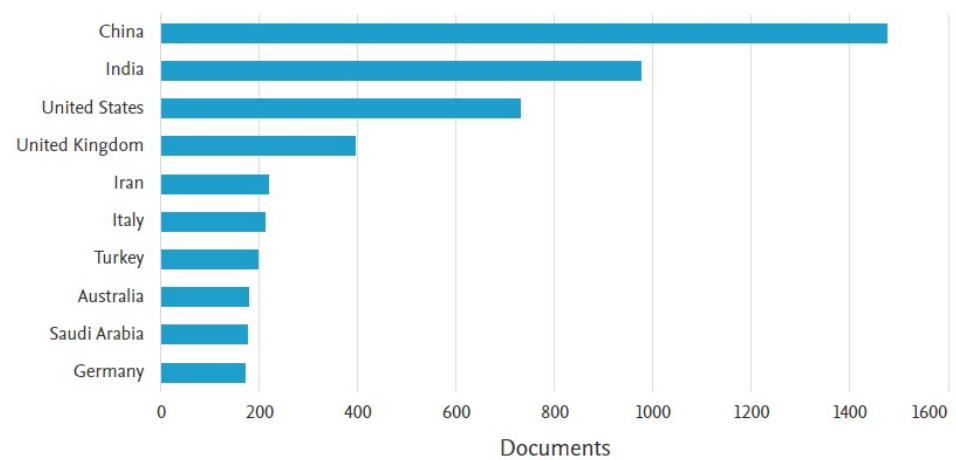


Figure 7. Composite Material Optimization Documents Using NNs by Country [11].

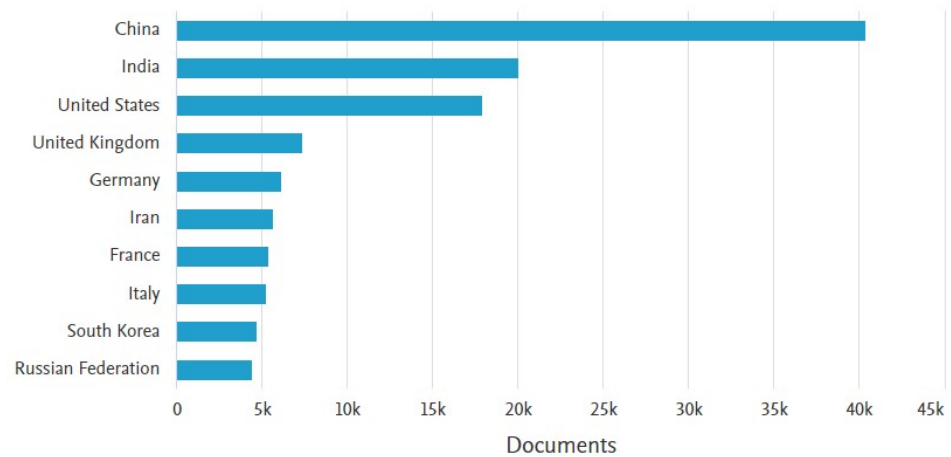


Figure 8. Composite Material Optimization Documents by Country [13].

3. Applications of Neural Networks in Aeronautical Engineering

This section aims to demonstrate the use of NNs in the aeronautical field. With this in mind, some of the articles that will be presented have used NNs in different fields of aeronautical engineering. Articles focused on structures or composite materials will be presented in Section 5.

NNs are a machine learning (ML) method inspired by the workings of the human brain, as can be seen in Figures 9 and 10. NNs are composed of interconnected nodes like neurons in the brain and are organized in layers, as can be seen in Figure 11. The training process is carried out with a set of data, which is composed of inputs and outputs; in this process, weights are assigned that are iteratively adjusted until the error is minimized. At the end of this process, NNs are capable of generalizing and predicting data or behavior with a certain accuracy. This can be seen in Reed [14], where a dataset was obtained and used to train the implemented NN. In aeronautical engineering, some of the applications of NNs include aerodynamic performance prediction, fault detection and system diagnosis, and structural optimization, among others. According to Brunton et al. [15], the impact of data science will be evident across multiple fields, including aerospace engineering, influencing areas such as inspection, design and performance, materials and composites, maintenance, and the development of future products.

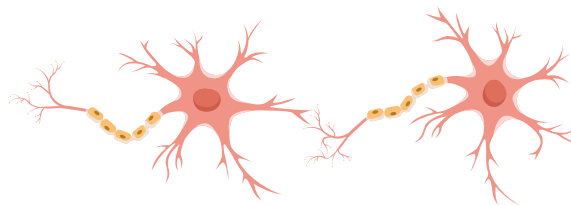


Figure 9. Representation of human neurons.

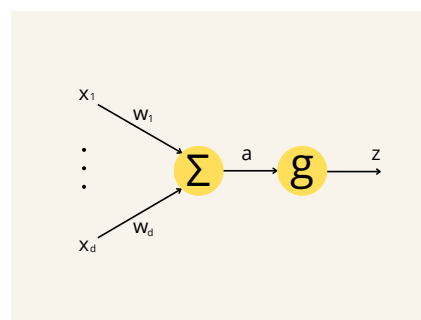


Figure 10. Representation of the model of a neuron in the NN.

The presented works showcase the innovative applications of NNs in diverse aerospace engineering domains. Wu et al. [16] presented a multi-fidelity neural network (MFNN) optimization framework for designing efficient propellers for an electric aircraft. Combining blade element momentum theory (BEMT) with high-fidelity computational fluid dynamics (CFD) simulations, the method improved propeller design accuracy while reducing computational costs. Results showed a notable increase in propeller cruise efficiency, from 82.3% to 87.1%, highlighting the effectiveness of the approach in achieving better optimization outcomes with enhanced efficiency.

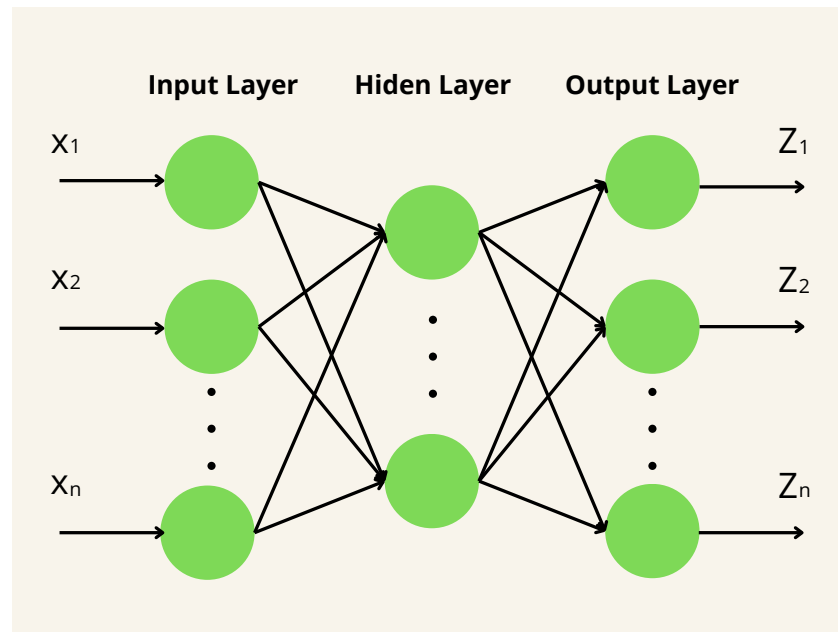


Figure 11. NN with 1 hidden layer.

Addressing challenges like limited communication and disturbance, Jia et al. [17] introduced a method for robust attitude synchronization in multi-spacecraft formations. It leveraged a dynamic event-triggered mechanism and a self-learning neural network control law (SLN2C), which utilized a radial basis function neural network (RBFNN) to compensate for disturbances. Numerical simulations validated the effectiveness of the method in achieving robust synchronization despite communication limitations and disturbances.

In spacecraft attitude stabilization, Zhang et al. [18] proposed a neural network-based fault-tolerant control scheme for spacecraft attitude stabilization in the presence of disturbances and actuator faults. A neuro-adaptive estimator approximated the disturbances, enabling an integrated event-based control scheme. This approach ensured system convergence and minimized actuator updates, conserving onboard resources. Numerical simulations validated the effectiveness of the proposed algorithms.

Lastly, Mazhar et al. [19] introduced a novel technique using an artificial neural network (ANN) to apply aerodynamic pressure loads on unmanned aerial vehicles (UAVs) for finite element (FE) analysis during structural design. By training the ANN models to approximate pressure functions based on aerodynamic pressure data, the method enabled the accurate application of pressure loads in FE analysis. Compared to conventional techniques, the ANN-based approach yielded a superior performance in matching the actual pressure profiles on the aircraft, offering a reliable and efficient solution for UAV structural design.

If more layers are added to the NN and the number of layers is greater than three, this NN could be named as a DNN. This happens because DNNs are a kind of NN; however, DNNs have more hidden layers compared to NNs, as can be seen in Figure 12. Due to their greater number of layers, DNNs are capable of learning more complex data structures than traditional NNs. According to Deng [20], deep learning (DL) is a subset of ML techniques

that utilizes multiple layers of information processing in hierarchical architectures, which are leveraged for pattern classification and feature or representation learning. However, the training of DNNs requires a greater amount of data and computational capacity, such that the adjustment of the hyperparameters is carried out in the best way where the error is as small as possible. In aeronautical engineering, DNNs have the same applications as NNs; however, their greater capacity is highly desired.

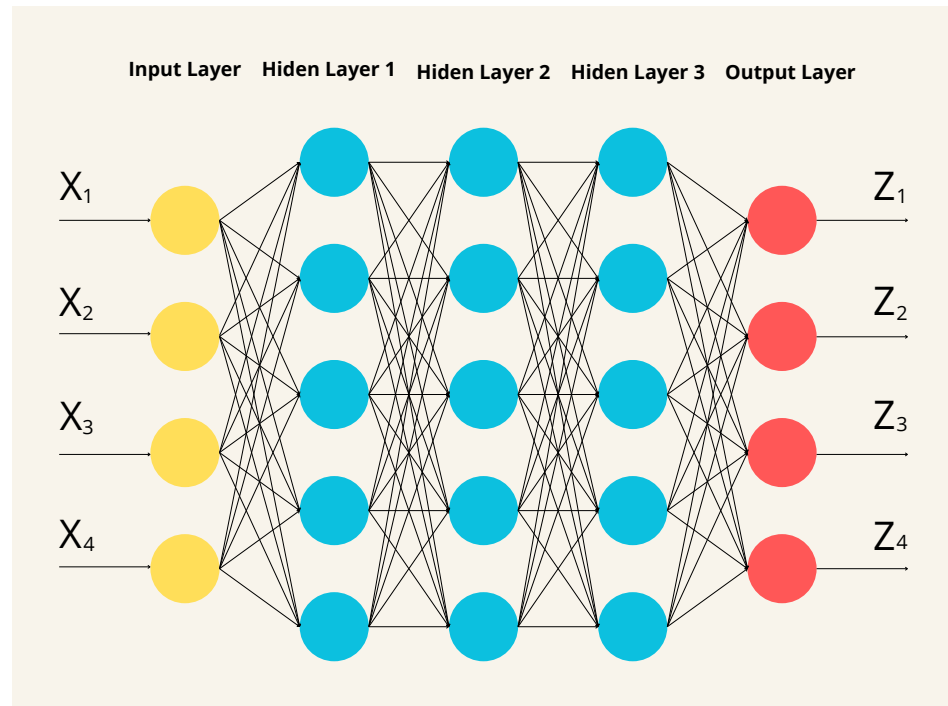


Figure 12. DNN with 3 hidden layers.

Recent advancements in aerospace engineering have showcased the transformative potential of integrating DNNs into various applications. Wang et al. [21] introduced DNN-MS, a method combining DNNs and multiagent synergism to evaluate high cycle fatigue (HCF) in aircraft engine compressor rotors. It improved accuracy and efficiency compared to other methods, offering a promising solution for reliability assessments.

In a similar vein, Zhou et al. [22] introduced a hybrid deep neural network (HDNN) for identifying hazards in aircraft auxiliary power units (APUs). By combining multiple CNN-BiLSTM models, the HDNN achieves high accuracy and stability in identifying potential risks. This method offers a promising approach to enhancing safety in civil aviation.

Investigating dynamic soaring, a technique inspired by albatross flight, Kim et al. [23] explored the extraction of energy from wind gradients. Their study introduced a DNN coupled with a feedback control law to execute dynamic soaring maneuvers based on mechanical energy extraction mechanisms. Results indicate that the trained network was proficient in maneuver execution across various wind profiles, highlighting the potential of NNs in replicating complex natural behaviors for aviation applications.

Meanwhile, Tao et al. [24] introduced the Abaqus-DNN mechanics system, coupling the Abaqus FE code with a DNNs. This system learned constitutive laws for fiber-reinforced composites without presuming specific functions, ensuring accuracy and adherence to physics laws. It accurately learned engineering constants and progressive damage laws for composites, offering a versatile approach for learning unknown physics within mechanical systems.

Furthermore, XIONG et al. [25] proposed a point cloud DL method to reduce costs in 3D aerodynamics simulations. Using PointNet architecture, it established an NN meta-model to map object surface positions to Computational Fluid Dynamics (CFD) quanti-

ties. The approach constructed point clouds from grid vertices, maintaining boundary smoothness and allowing for the detection of small geometric changes. Validation on the ONERA M6 wing demonstrated improved accuracy compared to the traditional methods, showcasing the effectiveness of the proposed approach for aerodynamic prediction and shape optimization.

4. Training Methods

As previously stated, both NNs and DNNs need to be trained so that they can perform the desired tasks. Shobha and Rangaswamy [26] highlighted the following:

“ML is broadly classified as supervised, unsupervised, semisupervised, and reinforcement learning. A supervised learning model has two major tasks to be performed, classification and regression. Classification is about predicting a nominal class label, whereas regression is about predicting the numeric value for the class label. However, in the unsupervised learning, the model is trained without the use of labels in order for the model to identify and learn hidden patterns.”

Also according to Shobha and Rangaswamy [26], in unsupervised learning, the objective is to identify regularities in the input data, recognizing patterns that occur more frequently than others, as well as to learn to distinguish common occurrences from anomalies. The choice of each method will depend on the nature of the data and the goal of the problem to be solved.

4.1. Supervised Learning

In supervised learning, model training is carried out in a guided way, as the relationships between the inputs and outputs are known. Therefore, training aims to reduce the error between the prediction and the real outcome. This type of learning may include linear regression and classification algorithms, such as a decision tree or logistic regression. Some of its applications include image and speech recognition, predictive analysis, etc.

A novel approach called aerodynamic strength prediction graph neural network (ASP-GNN), introduced by Li et al. [27], utilizes supervised graph learning to swiftly and accurately predict gas turbine characteristics. ASP-GNN efficiently forecasts the aerodynamic strength features and temperature fields of complex gas turbine blades, demonstrating superior performance and generalizability with limited training samples. It offers a fast analysis tool for turbomachinery design and analysis, potentially reducing the workload of complex engineering simulations.

For a shaker blower used in aeronautical systems, Cannarile et al. [28] developed a fault diagnostic system. It extracted features from condition monitoring signals using the ELastic NET (ELNET) algorithm and employed multinomial logistic regression (MLR) for classification. Experimental validation demonstrated a satisfactory diagnostic performance, highlighting the method's potential for developing robust classifiers with limited training data.

Using convolutional neural networks (CNNs), a form of supervised learning, [29] introduced a data-driven approach for predicting airfoil pressure distribution. Instead of relying on time-consuming CFD, this method trained the CNN to approximate the mapping between airfoil geometry and aerodynamic performance. By employing a flexible parametrization method called signed distance function, the CNN efficiently predicted pressure coefficients for unseen airfoils with less than 2% mean square error in seconds.

Incorporating a supervised ML model and fuzzy logic algorithm, the adaptive Kalman filter presented by Zhang and Hsu [30] demonstrated its ability to accurately classify global navigation satellite system (GNSS) accuracy levels and dynamically adjust noise covariance. This adaptive approach significantly improved the positioning accuracy of quadcopters operating in urban environments, ensuring reliable navigation despite challenging GNSS conditions.

4.2. Unsupervised Learning

Unlike supervised learning, unsupervised learning does not perform training with labeled data, as this approach aims to learn and identify patterns presented by the data. Some of the most used techniques are clustering and dimensionality reduction. According to Shobha and Rangaswamy [26], clustering is a mode of unsupervised learning used to infer patterns from datasets that lack class labels or target values, making it valuable for exploratory data analysis to uncover hidden structures. In dimensionality reduction, the focus is on reducing the number of features in the dataset without losing key information. Huang et al. [31] stated that although these dimensionality reduction techniques can eliminate redundant data and increase model accuracy, crucial features can lose their physical interpretation after reduction, making the model less explainable. Some of the uses of unsupervised learning are in anomaly detection, feature engineering tasks, and exploratory data analysis.

Introducing a method using unsupervised learning, particularly generative adversarial networks (GANs), to generate realistic inflow boundary conditions for turbulent channel flow simulations, Kim and Lee [32] presented an innovative approach. By learning from direct numerical simulation (DNS) data, the GAN can produce flow fields that match DNS statistics. The approach, called RNN-GAN, combines the GAN with a recurrent neural network (RNN) to generate time-varying fully developed flow, showcasing the effectiveness of unsupervised learning in synthesizing realistic turbulence fields.

Focusing on improving surrogate models for accurate aircraft fuel burn evaluation during missions, Liem et al. [33] utilized methods like adaptive sampling and a mixture of experts (MoE) approach. MoE proved superior, offering better approximation with fewer samples. Additionally, a cluster-based preprocessing step separated clustering in the y-space and the x-space using unsupervised and supervised learning algorithms like the Gaussian mixture model (GMM) and regularized Gaussian classifier, enhancing model efficiency and accuracy.

Introducing DeepESVDD-CNN, a system for the warning of a compressor rotating stall in aircraft power systems, Jin et al. [34] presented an innovative approach. By combining anomaly detection with DL, specifically unsupervised learning, it effectively identified stall precursors from dynamic pressure signals using a new method called Deep Ellipsoid Support Vector Data Description (DeepESVDD). This approach simplified model training and outperformed the traditional warning methods across various compressor operating modes, showing promise for real-time stall warning tasks.

For the super-resolution reconstruction of turbulent flows, Kim et al. [35] introduced an unsupervised learning model utilizing a cycle-consistent generative adversarial network (CycleGAN). Unlike supervised learning, which requires paired data, this model can be trained with unpaired turbulence data, making it more applicable in practical scenarios. Results demonstrate the model's effectiveness in reconstructing high-resolution flow fields from various turbulence datasets, showcasing its potential for wide application in the super-resolution reconstruction of turbulent fields.

5. Survey of Literature

An NN is a valuable tool that could predict the results of analysis via FEM or experimental loads. On the other hand, the optimization process inspired by Darwin's theory of evolution can be combined with an NN during the iterative optimization process. One of the proposals is to use the power of NNs to learn and predict FEM results. First, several simulations are carried out using FEM. Then, these results are used to train the NN. After training, the slow FEM calculations can be replaced by the NN predictions, with high accuracy and precision, and they are very fast compared to the FEM calculations. When the GA is executing the optimization, at each iteration, a set of parameters must be tested to evaluate its output in terms of optimization criteria. In this process, the mating pairs are selected using a selection technique such as elitism, in which the best individuals, those having the best outputs, are selected. In order to determine the best individuals,

tests must be carried out to assess which are the best. Hence, each individual with a set of parameters can be tested using FEM analysis. Another costly alternative is actual mechanical testing, in which each sample, representing a set of parameters, is experimentally tested, and then these experimental results can also be used to train the NN. Although FEM analysis can speed up the learning process compared to the experimental results, it can be time-consuming to run a simulation if one has a trained NN capable of predicting the same results as the FEM. Hence, as mentioned above, NNs can replace FEM simulations during the iterative process of optimization. Therefore, the NN's only task is to evaluate the best individuals, and it does not take part in other processes such as crossover, so it has no interaction with the genes (strings) and chromosomes.

5.1. Structural Optimization

Optimizing an aircraft is extremely important, as this is a fundamental practice for improving it. When optimizing an aeronautical structure, the objective is to improve the aircraft's performance. To this end, there is a focus on improving stiffness, reducing weight, as well as aerodynamic efficiency. Such objectives can be achieved using the traditional optimization methods, but the integration between NNs and optimization methods can bring great benefits to the area.

The evolution of ML, such as NNs, is important for several industries. Its integration with GA has proven to be a great tool for structural design. According to Lagaros et al. [2], over the past decade, artificial intelligence and soft computing techniques have emerged as valuable tools for replacing time-consuming computational tasks in various scientific and engineering applications. NNs can be trained to predict the results of analyses via FE to speed up this process. Some works have studied this for structural design [36–39]. Therefore, the use of NNs will accelerate the FE analysis process of each optimized model obtained via GA.

This union has proven to be fundamental in structural design and this occurs due to the GA optimization process that is inspired by natural selection. According to Rao [40], genetic algorithms (GAs) are grounded in the principles of natural genetics and selection, incorporating the key elements of reproduction, crossover, and mutation in their search process. In this method, optimization occurs through the evolution of a population, evolving according to the potential solutions and thus iteratively converging to an optimal point. Combining NNs with GA allows for a better evaluation of each generation and the development of projects adapted to each predefined criteria throughout each generation.

Another example of an application is the prediction of load distribution along the aircraft. In this case, the NNs are trained with data from flight histories and simulations to be able to accurately predict loads, stress distribution, and strain in different flight conditions. Cao et al. [41] introduced a method using ANNs to identify loads on aircraft wings. Hoffman [42] used NNS to predict strain in critical parts of an aircraft's structure, bypassing the limitations of traditional equations.

In the context of structural optimization, many authors have used NNs together with some evolutionary method, as can be seen in [2,3,43–47]. Evolutionary methods are characterized by being inspired by principles of biological evolution and natural selection. According to Lagaros et al. [2], evolutionary algorithms (EAs), including GAs and evolutionary strategies (ESs), are now widely recognized as a powerful family of methods for addressing structural optimization problems.

Aiming to improve the computational efficiency of evolutionary algorithms in structural optimization, Lagaros et al. [2] presented an endeavor towards enhancing performance. They introduced an NN strategy to predict design feasibility, reducing the need for costly FE analysis. The adaptive NN was updated during the optimization process, offering computational advantages for optimizing skeletal structures in both sequential and parallel computing environments.

Exploring multidisciplinary design optimization (MDO) for flexible aircraft wings, with a focus on structural and aeroelastic characteristics, Caixeta and Marques [3] presented

an in-depth investigation. They used ANNs to predict critical flutter speeds efficiently. Multi-objective optimization (MOO) with GA was aimed at maximizing flutter speed and minimizing structural mass. Results show the effectiveness of this approach in achieving optimal design trade-offs.

Discussing the optimization of aircraft components, such as composite panels of a vertical tail plane, using GAs and NNs, Ruijter et al. [45] presents an insightful examination. This approach adjusts the design variables to improve performance and reduce weight, with the NNs predicting constraint function values from FE analysis data. It offers flexibility for implementing new variables and is robust for high-dimensional design problems, with proposed modifications to enhance accuracy and reduce preparation time.

In addition to GAs, some works have also addressed topological optimization together with NNs [4,5,48–51]. In his optimization process, Hansen and Horst [51] also relied on an evolutionary algorithm to drive the advancements. Topology optimization is typically an iterative process that uses FE analysis to determine the optimal material distribution within a design domain by minimizing an objective function while satisfying one or more constraints [52].

Introducing topology optimization via the neural reparameterization framework (TONR), a method that combines DL with topology optimization, Zhang et al. [52] presented an innovative approach. TONR directly used NNs for optimization, transforming design variable updates into NN parameter updates. It addressed various optimization problems without needing a pre-constructed dataset and avoided structural disconnection issues. Numerical examples showed TONR's effectiveness compared to the conventional methods.

Introducing a methodology that considers uncertain load and material parameters, Freitag et al. [4] presented an innovative approach to topology optimization. It integrated compliance minimization and reliability-based design to handle uncertainties efficiently. To reduce computational costs, it used ANNs instead of FE simulations. Case studies demonstrated its effectiveness on different structural configurations.

Presenting a multilevel optimization method for implementing structural design changes in aircraft, Hansen and Horst [51] offered an alternative approach to the field. It optimized topology parameters and thicknesses/cross-sections using detailed FE models. Examples showcased its effectiveness in sizing and topology optimization of the framework structures and fuselage structures of a blended wing body aircraft.

As can be seen in the previous paragraphs, it is possible to understand the relevance of using NNs as a tool in structural optimization. The advanced computational capabilities of NNs can help us to obtain greater efficiency in the prediction and optimization of structural performance. Some of the above-mentioned articles are related to the mechanical field, while some are related to the aeronautical field. However, despite the few works in the aeronautical area, it is possible to see the importance of using NNs in the optimization of structures in this field. In addition to the works already presented, it is possible to see this application in other works such as [53,54]. These works are related to the structural optimization of unmanned aerial vehicles (UAVs), which is a type of aircraft that is growing in use. Below are some examples in which NNs have demonstrated an impact on the optimization of aeronautical or aerospace structures.

The paper by Park et al. [55] presented an approach for structural analysis using orthogonal decomposition and NNs to achieve the efficient and accurate optimization of wing structures using a reduced-order model. NN increased the ability to perceive and model the complex relationships between design variables and wing deformation due to fluid–structure interaction. This integration allowed for a more accurate prediction of aerodynamic and structural performance, ultimately leading to more efficient and effective wing designs. The impact of employing NNs in optimization lies in their ability to handle complex and nonlinear relationships and large datasets, resulting in more reliable and optimized design results compared to the conventional methods.

Furthermore, the combination of NNs with genetic algorithms can have an impact on the optimization of composite panels in aircraft structures, as seen in Ruijter et al. [45]. NNs provide a powerful tool for approximating complex functions and predicting performance metrics such as deformation and buckling multipliers. By training NNs with data from finite element analyses, researchers can create accurate models that predict the behavior of composite panels under various conditions. This capability enables the efficient exploration of the design space, enabling the identification of optimal configurations that balance performance and weight. Integration with genetic algorithms enhances the optimization process by enabling robust and efficient searches for optimal solutions in a high-dimensional design space. This combined approach reduces computational costs and setup time, making it feasible to optimize assemblies consisting of multiple components, thereby improving the overall design and performance of aircraft structures.

Finally, integrating NNs with modified backpropagation learning algorithms can significantly impact the optimization of aerospace components by increasing the efficiency and accuracy of the design processes, as can be seen in the study by Kodiyalam and Guru-moorthy [56]. By integrating a modified feedforward multilayer NN with an optimization algorithm, the approach provided a more sophisticated method for determining optimal design parameters. This is particularly crucial for aerospace components, which often require precise specifications to ensure performance, safety, and reliability. The modification to the standard backpropagation training allowed for faster convergence and required fewer hidden layer nodes, making the learning process more efficient and less resource-intensive. This led to faster prototyping and iteration cycles in the development of complex components such as aircraft engine guide vanes and satellite reflectors. Ultimately, this work could result in more robust and optimized aerospace designs, potentially reducing costs and time to market while improving the overall quality and performance of aerospace systems.

NNs are a very powerful tool that can assist in the design and optimization of structures due to its ability to work with complex data or problems, as can be seen in the previous paragraphs. Therefore, NNs can also be used to predict loads according to the mission of the optimized aircraft. This is important, as each type of aircraft will present different loading conditions, and the same aircraft can operate in different missions. Therefore, optimization should target a specific aircraft type and different missions so that the NN can predict the loads more accurately and thus the optimization will be more appropriate. Some of the articles presented here, such as those by Caixeta and Marques [3], Ruijter et al. [45], and Hansen and Horst [51], trained their NN models with different datasets so that the predictions obtained were appropriate.

The integration of NNs with GAs or other optimization methods represents a promising approach. However, it is essential to evaluate the effectiveness of such methodologies. Ruijter demonstrated in his work that the trained NN achieved a mean squared error (MSE) of less than or equal to 1×10^{-5} , indicating high accuracy. Conversely, Mazhar highlighted challenges in his study, where the NN struggled to capture the exact pressure profile due to the non-linearity and significant variability of the data. Despite this, the final NN achieved a mean absolute error (MAE) of 0.007%, reflecting good performance. Meanwhile, Caixeta emphasized the computational efficiency of NN compared to a full aeroelastic model, reporting that the NN was approximately 47.5 times faster.

Therefore, the importance of integrating both techniques becomes evident, as there is the possibility of developing and improving configurations that were previously complex and, at the same time, speeding up design processes. This section presented the use of NNs in structural optimization; similarly, the next section will present articles on NNs in composite material optimization.

5.2. Composite Materials Optimization

The use of composite materials, such as carbon fiber-reinforced polymers (CFRPs), has emerged as a good alternative to the aluminum alloys that are commonly used in the aeronautical sector. According to Chen and Xu [6], composite materials, known for

their exceptional design flexibility, have replaced traditional metallic materials in many applications. This phenomenon arises from the inherent characteristics of these materials, which are used in structural design, including high flexural modulus, high specific strength, low density, corrosion resistance, design flexibility, etc. [7].

However, there are other challenges to using these materials, such as more precise optimization to improve and maximize their structural performance. This is due to the fact that composite materials have anisotropic characteristics, which requires more sophisticated techniques for material design. Bisagni and Lanzi [57] introduced a post-buckling optimization method for designing composite stiffened panels under compression loads. Abouhamze and Shakeri [58] proposed a method to optimize the stacking sequence of laminated cylindrical panels for improved natural frequency and buckling load. It employed ANNs to simulate panel behavior and a GA for optimization. Marin et al. [59] introduced an optimization method for designing a composite material stiffened panel with a conventional stacking sequence, considering static analysis and hygrothermal effects. Pitton et al. [60] presented an optimization methodology for improving the buckling resistance of thin-walled cylindrical shells subjected to axial loads by using variable stiffness through curvilinear fibers. This approach aims to enhance the critical load associated with buckling.

In this context, NNs can be used as a tool capable of predicting the loads on a material under different working conditions, thereby determining a better design. To achieve this objective, it is necessary to train the model with an extensive amount of data that covers material properties and performance criteria. As a result, this predictive capability can facilitate better understanding and assist in selecting composite materials tailored to specific aircraft components.

In the field of optimizing composite materials, there is a predominant use of evolutionary methods, such as GA. Some works that have used this method are as follows: [6–8,57,61–65]. Some of these works also address the use of NNs [7,8,57,61–64,66,67] or DL [6,7] integrated with the use of GA.

Introducing an optimization framework for efficiently designing composite aircraft wings, Kilimtzidis et al. [64] offered a novel approach to the field. They employed a low-cost numerical approach and optimization techniques to minimize wing mass while meeting loading constraints. Results were validated against 3D finite element method (FEM) models, confirming accuracy. The framework provided the optimal lay-ups and dimensions for the wing components.

Introducing a new method that combines deep learning and GAs, Chen and Xu [6] offered an innovative approach to studying and optimizing the interfacial shear behavior in SiC fiber-reinforced SiC composites. By analyzing various microstructures and temperatures through molecular dynamics simulations, the approach accurately predicted shear properties and identified optimal microstructures, offering potential for advanced composite material development and intelligent manufacturing.

Combining ANNs with evolutionary algorithms (EAs), Tran-Ngoc et al. [7] introduced a new method for detecting damages in laminated composite structures. By integrating the global search capacity of EAs with the fast convergence of gradient descent, the approach efficiently found the optimal solutions and avoided local minima. Results showed improved accuracy and reduced computational time compared to traditional methods.

Introducing a novel optimization approach for composite sandwich structures, Mohammed Sahib and Kovács [65] utilized GAs and ANNs to advance the field. By minimizing weight and cost, the method targeted applications in aerospace and automotive industries. Through Monte Carlo simulation and ANN predictions, the study achieved multi-objective optimization, leading to Pareto optimal points. FEM validation confirmed the effectiveness of the approach, highlighting substantial weight reductions with CFRP or fiber metal laminate (FML) face sheets compared to all-aluminum structures.

For designing composite stiffened panels under compression loads, Bisagni and Lanzi [57] introduced a post-buckling optimization technique that has advanced the field. It

employed NNs trained with FE analyses and GAs to reduce computational costs. The method achieved an 18% weight reduction by allowing local skin buckling between stiffeners.

In the pursuit of optimizing the weight of composite laminates, Liu et al. [63] introduced a streamlined methodology, offering a fresh perspective to the field. They utilized ANNs to predict buckling loads, reducing evaluation time. By incorporating lamination parameters and dimensional inputs, computational costs were minimized. The approach integrated ANN models with a GA for efficient laminate optimization, validated against other methods for buckling load prediction.

Describing an optimization process utilizing the ϵ -constraint method, Ehsani and Dalir [66] aimed to maximize the critical buckling load and minimize the structural weight of an angle grid plate. They employed an artificial ANN trained with data from the Mindlin plate theory and Ritz method to approximate the buckling load. Integrated with GAs, this approach identified optimized design variables for the angle grid structure, providing designers with options for maximizing buckling load while minimizing structural weight.

Exploring hierarchical origami-corrugation meta-sandwich (HOCM) structures, Yue et al. [67] illuminated their multifunctional potential, providing valuable insights for the field. They derived a compressive modulus, conducted experimental testing and simulations, and analyzed critical geometric parameters. The ANN-based surrogate model approximated the specific peak strength (SPS) and specific energy absorption (SEA), enabling a multi-objective optimization approach for designing HOCM structures with superior properties.

In addition to NNs, another point to be explored is GAs which, due to their approach, are capable of generating several sets of possible solutions that can evolve over generations until an optimal solution is found. However, for this to be possible, it is necessary to consider several design variables, such as the orientation of the fibers and thickness of the layers. This allows engineers to evaluate a set of design solutions that evolve into an ideal configuration that meets their requirements [9,10].

Another point to be explored here is the reliability of composite materials. As with other materials, composite materials are subject to failure. One of the techniques currently used to predict damage in composite materials and consequently to measure their reliability is continuous damage mechanics (CDM). CDM can measure the progressive load-bearing capacity when these materials are under stress as strain accumulates [68]. To predict the damage in the material, it is necessary to develop an FE model and implement the CDM as a user material subroutine (UMAT) [9,69]. Another option that is being explored is to train an NN with data from the FE model and replace the FE with the NN [70].

5.3. Future Research Directions and Emerging Trends

The articles presented in Section 5 show the different ways of using NNs in the optimization of structures or composite materials. These different ways indicate the future directions in research and trends in this field. One of the trends is the use of NNs to improve the optimization process, that is, using NNs to learn FE and perform analyses to accelerate the optimization process. Another perspective is the use of NNs to recognize patterns in topological optimization and thus determine the best material distribution that offers the best weight-to-strength ratio. Finally, there is also the possibility of using NNs to predict the distribution of loads in structures or composite materials in order to assist with the optimization process. It is noted that this field, optimization with the use of NNs, presents a growth trend over the years, as despite the fluctuation in the number of publications on the topic over the years, 2023 presented more publications in relation to 2022, as can be seen in Figures 1 and 5.

6. Conclusions

As seen previously, some works have presented the combination of NNs and GA for structural optimization. The articles presented show the different approaches to the use of NN during the optimization process. One of the approaches is the use of an NN to

predict loads; in this case, training must be carried out with a large amount of data relating to different scenarios and in relation to the type of aircraft studied. This will help us to understand unobserved patterns and will also help to better predict the loads acting on the aircraft in that scenario in which the optimization will occur. Another approach is the use of NNs to predict FE analyses. In this case, the NNs must be trained with various data relating to the different configurations, types of structures, and load cases, so that the NNs understand the analysis process via FE and then carry out the process independently. Here, the objective is to speed up the FE process, because at the same time as the NNs provide the predictions, it will also optimize the process.

Still in the field of structure optimization, other authors have combined NNs or DL with topological optimization. Some works presented address the use of NNs or DL to assist in the optimization process, understanding patterns and determining the best material distribution in the structure. However, other authors have used NNs to analyze FE, as stated in the previous paragraph. It should be noted that, in both cases, the main objective is to minimize optimization time.

Just as previously seen, for structural optimization, the same techniques are observed in the optimization of composite materials. To optimize these materials, it is also necessary to predict the loads acting on the structures in which these materials are used in order to understand their capacity to withstand efforts and optimize them better. NNs are also used to carry out the FE analysis process, and the objective of accelerating the optimization process is also noted. Thus, the NNs are integrated with the GAs, such that the latter performs the optimization while the NNs analyze each optimized material at each stage of the optimization and thus help determine the best configuration.

Therefore, it is possible to notice that the use of NNs in the optimization of aeronautical structures and composite materials has shown remarkable potential and effectiveness. The main scientific contributions of this study include the following:

1. **Enhanced Optimization Process:** By employing NNs to learn finite element (FE) analysis and subsequently incorporating it into each stage of the GA optimization process, researchers have been able to effectively evaluate numerous structures and determine optimal configurations with greater speed. This integration allows for a more efficient and thorough exploration of the design space.
2. **Pattern Recognition in Topology Optimization:** NNs have been instrumental in identifying patterns during topology optimization, aiding in the selection of material distributions that offer ideal strength-to-weight ratios. This contributes to the development of lighter yet stronger aeronautical structures.
3. **Prediction of Load Distributions:** The use of NNs to predict load distributions on structures has facilitated the optimization of composite materials. This ensures that structures are tailored to different flight conditions and that materials used are optimally suited for their specific applications, improving both performance and safety.
4. **Reduced Optimization Time:** Leveraging NNs has significantly minimized optimization time, streamlining the iterative process and accelerating the design cycle. This reduction in time is crucial for meeting tight development schedules in the aerospace industry.

As previously stated, the use of NN shows good results. Even though, in certain circumstances, the NN may present difficulties, with cases where there is greater non-linearity, adjustments can be made to improve its performance. A well-trained NN can present good precision, such as an MSE of 1×10^{-5} and an MAE of 0.007%, as shown previously. In addition to presenting good precision, the NN shows a higher speed compared to other methods, being able to be 47.5 times faster, as mentioned, and thus showing that the NN can present good results.

Previously, the main scientific contributions and some practical results of this study were presented; however, some recommendations for designers and mechanical engineers are as follows:

1. Adoption of NN-GA Integration: Designers and engineers should consider integrating NNs with GAs in their optimization workflows to enhance the efficiency and effectiveness of their design processes. This approach allows for the rapid evaluation and optimization of complex structures.
2. Utilization in Topology and Material Selection: The pattern recognition capabilities of NNs can be leveraged to identify optimal material distributions, improving the strength-to-weight ratios of structures.
3. Predictive Load Analysis: Implementing NN-based predictive models for load distribution can lead to more precise and reliable designs, ensuring structural integrity under various flight conditions.
4. Streamlined Design Cycles: The time savings achieved through NN integration can be used to accelerate the design and development process, enabling faster iteration and refinement of designs.

Recapping the future research directions and emerging trends, the integration of neural networks (NNs) in optimizing structures and composite materials shows great promise. NNs can accelerate the optimization process by learning finite element (FE) analysis, enhance material distribution through pattern recognition in topological optimization, and predict load distributions to support the optimization process. The increase in publications from 2022 to 2023 highlights the growing interest and potential in this field, emphasizing its importance for future advancements in aeronautical engineering.

Overall, the use of NNs for optimization represents a powerful approach for the optimization of aircraft structures and composite materials. By leveraging the capabilities of NNs to learn and predict complex relationships within the optimization process, researchers can efficiently identify optimal solutions that meet performance requirements while minimizing weight and maximizing structural integrity. This approach holds significant promise for advancing the design and optimization of aircraft structures and composite materials in the future.

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