Engineering and Technology Journal
Journal homepage: https://etj.uotechnology.edu.iq

Finite element analysis and artificial neural network for stress distribution of an aircraft model in a wind tunnel

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HIGHLIGHTS

- FEA and ANSYS Fluent were used for wind tunnel simulations.
- ANN was utilized to predict stress distributions.
- ANN predictions were compared with real distributions using RMSE.
- High agreement between ANN predictions and real stress levels, with RMSE of 12%.
- ANN methods enhanced computational efficiency over traditional FEA methods

ARTICLE INFO

Handling editor: Mohammed A. Fayad

Keywords:
Finite element analysis; Artificial neural network; Wind tunnel; Stress distribution; Deformation.

ABSTRACT

Wind tunnels are instrumental in the aerodynamic analysis of aircraft model structures, enabling the replication of real circumstances for better design and performance evaluation. This paper presents a novel enhancement to stress distribution predictions in wind tunnel simulations by combining Finite Element Analysis (FEA) and Artificial Neural Networks (ANN). First, the research focuses on analyzing ANSYS Fluent data, which provides insights into the complex fluid dynamics inside the wind tunnel. The proposed approach combines the best available FEA and ANN techniques regarding prediction accuracy and computational efficiency. Such findings are those that evidence that predictions of real stress levels using ANN are quite near, with RMSE 12%, and, hence, quite accurate. The results indicated agreement between the functions generated by ANN and real stress levels and, therefore, were considered to manifest a very low error percentage. The methodology shows that it is significant for being computationally efficient since the ANN works much quicker compared to the conventional FEA approach. In addition, the methodology is significant in computations since the ANN works quicker than conventional FEA. These results thus indicate that the integrated FEA-ANN approach is beneficial and holds much promise in accurately and efficiently predicting stress distributions. Herewith, the provided method advances engineering simulations by making exact predictions of stress distributions necessary to improve design and structural analysis.

1. Introduction

Innovation and development in aerospace are constant efforts to gain larger magnitudes of safety, efficiency, and performance for an airplane [1]. The tension distribution in a model during wind tunnel testing is vital to aircraft design and operation [2]. Aerospace engineering, in its crux, is still dependent on the technology of wind tunnel testing, which allowed for exhaustive research in aerodynamics and structural behavior under controlled conditions [3,4]. To achieve optimal aircraft design, it becomes highly important that the analysis of stress distribution is carried out with high accuracy to ensure that the form and function of the structure are optimized [5].

The present paper explores an integrated approach that joins the Finite Element Method (FEM) with Artificial Neural Networks (ANN) to enhance the prediction of stress distribution with a higher order in aircraft models through wind tunnel simulations. Finite Element Analysis (FEA) has served as a common tool for engineering sciences for decades, allowing engineers to approximate complex structural behavior by subdividing problems into manageable elements [6–9]. From that moment on, developing complementing methodologies was necessary to assure predictions and, more importantly, shorten simulation time. The last decade has been characterized by the emergence of ANNs, which revolutionized the approach to many

http://doi.org/10.30684/etj.2024.149979.1755
Received 24 May 2024; Received in revised form 23 July 2024; Accepted 26 July 2024; Available online 24 August 2024
2412-0758/University of Technology-Iraq, Baghdad, Iraq

complex problems dramatically [10,11]. Since ANNs can find complex relationships in data, they make them suitable for tasks associated with pattern recognition and prediction [12–14].

Despite the advancements in FEA and ANN individually, there are several drawbacks and research gaps:

1) FEA alone can be computationally expensive and time-consuming, especially for complex models.
2) ANNs, while powerful, require large amounts of training data and may not inherently understand the physical constraints of engineering problems.
3) There is a lack of comprehensive studies that effectively integrate FEA and ANN to leverage the strengths of both methods for improved prediction accuracy and computational efficiency.

This paper aims to fill these gaps by demonstrating how integrating FEA and ANNs can lead to better stress distribution predictions in wind tunnel simulations. The main contributions of this paper are:

1) Developing a novel methodology that combines FEA and ANN for stress distribution predictions in wind tunnel simulations.
2) A detailed sensitivity analysis will be provided to show how combining FEA with ANN enhances the accuracy of the developed model.
3) Demonstrating the significant computational efficiency gained by using ANN alongside traditional FEA methods.
4) Presenting a comprehensive comparison between ANN-based predictions and real stress distributions, showcasing a low RMSE of 12%.
5) Highlighting the potential of the integrated FEA-ANN approach to revolutionize stress distribution analysis for aircraft models

In this paper, sensitivity analysis has been performed to show how the best accuracy of the developed model can happen when combining FEA with ANNs in the stress distribution for the aircraft models exposed to wind tunnel testing. Methodology: This integration means how FEA results can be used as training data for ANNs. We aim to illustrate the potential benefits of using artificial intelligence to enhance conventional engineering evaluations. The methodology uses FEA results as training data for ANNs, illustrating the potential benefits of using artificial intelligence to enhance conventional engineering evaluations.

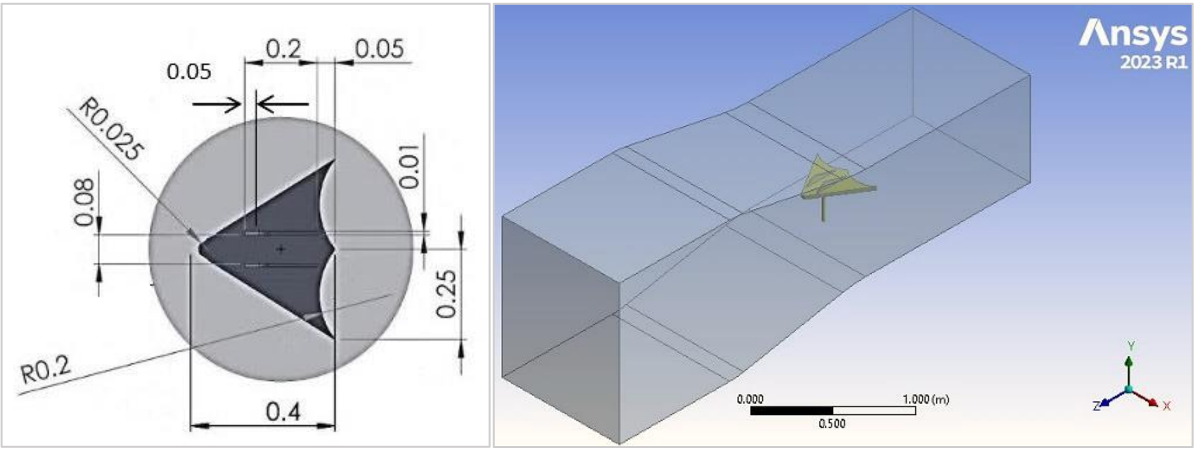
To describe the paper's remaining sections, details of the FEA procedure are discussed in Section 2, where the findings of this assessment describe how the complex structural characteristics of aircraft models could be broken down into manageable pieces for modeling. Section 3 discusses using ANNs, specifically how these networks could be trained using FEA-derived data to enhance stress distribution prediction. Section 4 presents the results of our combined FEA-ANN technique and conducts a thorough discussion with a comparison to standard FEA-based predictions. Finally, Section 5 concludes and synthesizes our findings and discussions to provide insightful conclusions that underline the potential of the FEA-ANN synergy to revolutionize stress distribution analysis for aircraft models in wind tunnel simulations.

2. Finite element analysis

Engineers use FEA as one of the backbone methods in structural engineering and simulation to analyze and predict the detailed behaviors of complex structures under diverse loading circumstances [15,16]. The importance of FEA lies in the fact that the analytical and computational cost-effective tool is used to understand stress distribution, deformation, and related essential mechanical characteristics. The complex system breaks down into discrete pieces, leading to a thorough knowledge of localized behavior, and design optimization and improvement in structural integrity result from that. In this section, basic concepts behind FEA are discussed, through which application in the context of aircraft models during wind tunnel simulations can be affected. A step-by-step process is mentioned in developing the finite element models, assigning materials, and considering boundary conditions to represent real-life situations. Benefits and limits are also discussed to understand the function of being a cornerstone in the integrated approach.

2.1 Computer-aided design

Computer-aided design (CAD) has transformed engineering by allowing the development, modification, and analysis of complex designs in a virtual environment [17]. CAD is critical in wind tunnel simulations because it generates precise geometric representations of the wind tunnel and the aircraft prototype model. The simulation will use a 3-meter-long wind tunnel with a cross-section of 0.8 meters by 0.8 meters, as indicated in Figure 1, with Figure 1a as the dimensions and Figure 1b as the tunnel. The work is an advancement and aenhancement to a previously published work [18]. The simulation will be done using software developed by ANSYS. A wind tunnel is important in ensuring that the flow characteristics' observations and reactions over the structural models are accurate. It also allows the dimensions of the aircraft and wind tunnel models to be accurately portrayed. The figure also indicates the dimensions in mm of the prototype model for the aircraft, which will be the subject of analysis during modeling in the wind tunnel using ANSYS. These will form the bedrock for further finite element analysis and distribution of stress prediction, which is crucial to ensure the safety and performance of the model within the wind tunnel. However, the inlet boundary condition is 5 m/s2, with a pressure outlet chosen.



(a) **(b)**

Figure 1: Geometrical approach: (a) Aircraft model geometry dimensions; (b) Geometry of the wind tunnel in the simulation analysis [6]

2.2 Computer-Aided Engineering

CAE has revolutionized the practice of engineering analysis with powerful tools to simulate and evaluate complex systems realistically. A foundation of CAE in this study is ANSYS software, which, in turn, can integrate fluid dynamics with structural analysis to examine the interaction regarding aerodynamics and structural integrity fully. As seen in Figure 2, the computation process is carried out in a coupled collaboration between ANSYS Fluent and ANSYS Mechanical: the coupling of an expert in fluid flow and an expert in static structure analysis. Such coupling allows for a detailed study of the interaction of aerodynamic forces with the associated stress distribution on the model of the aircraft prototype. Prediction of improvement in stress accuracy with fluid flow accords with the coupled simulation approach, allowing a better understanding of the interactions between fluid flow and the structural model behavior. This is one of the possible ways to improve the prediction of stresses. For further clarification, the mesh properties are added in Table 1 below.

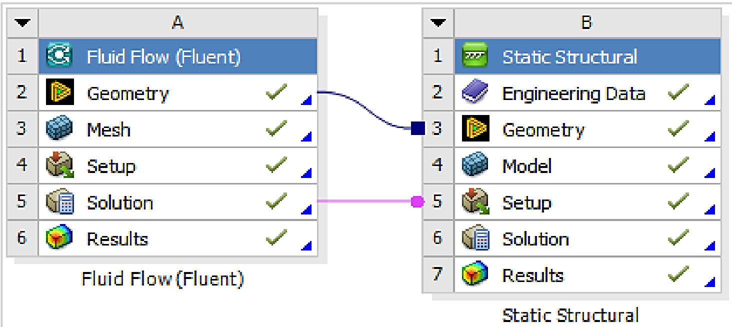


Figure 2: ANSYS program widgets [6]

Table 1: Mesh properties

Parameter	Value
Nodes	1106
Elements	506
Preference	Mechanical
Element size	Program controlled

3. Artificial neural network

Owing to their capability to scan large datasets for complex relationships, ANNs have come to find more and more applications in the field of predictive modeling and machine learning [19-22]. Section 3 deals with using ANNs to enhance further the stress distribution prediction in a wind tunnel simulation. The elementary mechanism of an ANN is depicted in Figure 3 and is composed of a series of operations to simulate the working of cells in the brain. Input features have weights given to them and are then passed through an activation function, described below in Equation 1, after an offset transformation in the form of bias. This function introduces nonlinearity in the network, which makes it able to make readings of overtly fine patterns in the input data. The changed input is finally passed through the information represented in the data. The network develops and learns to extract information through multiple levels, where it is finally passed. Table 2 elaborates on the parameters of the utilized shallow neural network, chosen using a try-error approach.

$$\tanh(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \quad (1)$$

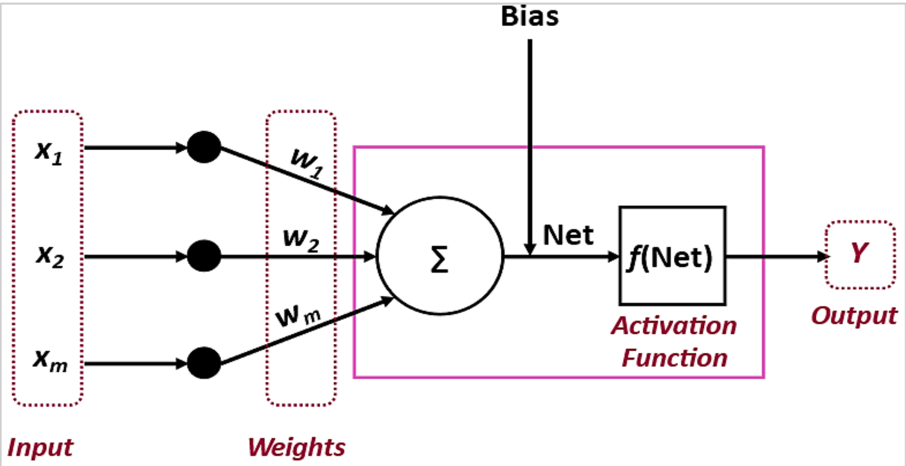


Figure 3: Neural Network Parameters [17]

Table 2: ANN parameters

Parameter	Value
No. of hidden layers	One
No. of neurons of hidden layer	6
Solver	Adam
Activation Function	Tanh

In determining the real-world applicability of any predictive model, two of the most significant variables are accuracy and dependability. A notable quantitative assessment of the forecast's correctness is necessary for stress distribution prediction to determine the technique's robustness. Such analysis benefits from the Root Mean Square Error (RMSE) as in Equation 2, a well-known assessment statistic providing an insightful understanding of the model's predictive ability. The RMSE measures the average size of deviations in results, giving a single result explaining the model's overall accuracy. The calculation involves squaring the mean error, taking the square root, and thus provides information on both the magnitude and distribution of errors. RMSE will be useful in the present study because it does not exclusively tell us how well the model captures the studied phenomena. More vitally, it indicates instances when the difference between the predicted value and the actual result is disproportionately large. We will use this knowledge in the next part of the study, where we perform an RMSE-based accuracy validation of the integrated method regarding stress distribution predictions in wind tunnel simulations.

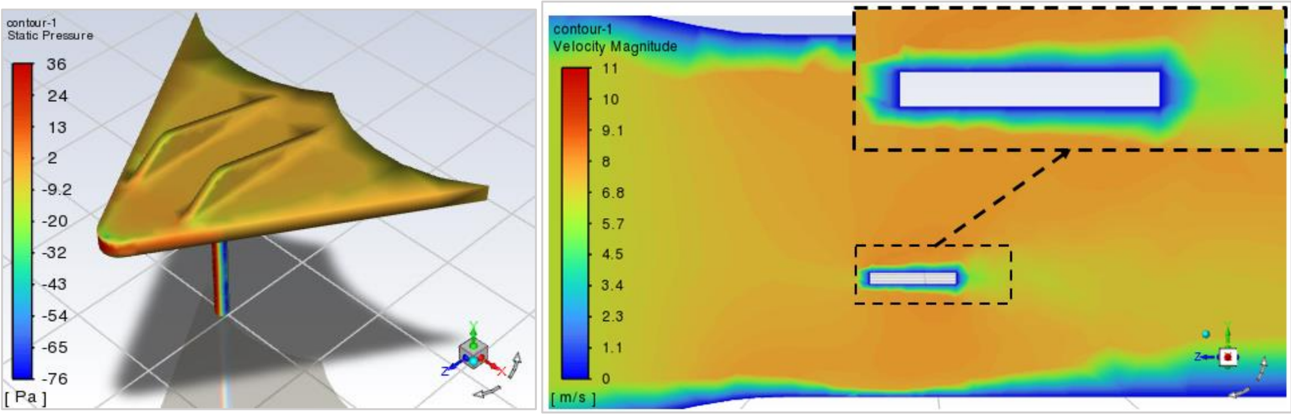
$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x_i - y_i)^2} \times 100 \quad (2)$$

4. Results and discussion

In particular, pressure and velocity distribution over the aircraft prototype model inside the wind tunnel were carefully probed to appreciate the fluid mechanics within the ANSYS Fluent simulations. This test, the results of which are shown in Figure 4, helped to understand the complexities of the airflow interactions. Figure 4a is the 3D view and Figure 4b is the 2d view. As it is obvious from the results, the velocity magnitudes show a complex pattern that blankets the surface of the prototype model within the limits of the wind tunnel, even though the input velocity was low. The variations in the velocity are oscillating within a dynamic range from 1 m/s to 12 m/s2, which is significantly prone to the complex turbulence dynamics that unravel over a 3-meter length of the wind tunnel. Such a vastly varying output indicates the complexities of the aerodynamic environment and the ability to generate dynamic flow characteristics with even a small beginning velocity.

Furthermore, the pressure distribution across the wind tunnel simulation depicts a pressure range from 0.2 Pa to 5 Pa. The measured pressure differentials are evidence of the dynamic aerodynamic forces in the simulation system. These pressure fluctuations justify the impact of fluid flow dynamics on the aircraft prototype model and the exacting nature of accounting for these complex interactions within stress distribution assessments. The distinct pressure and velocity profiles observed suggest significant implications for the aerodynamic performance of aircraft models, aligning with findings by [6], who reported similar complex interactions in wind tunnel tests under varied flow conditions. Such comparisons validate our simulation settings and enhance the credibility of our computational approach.

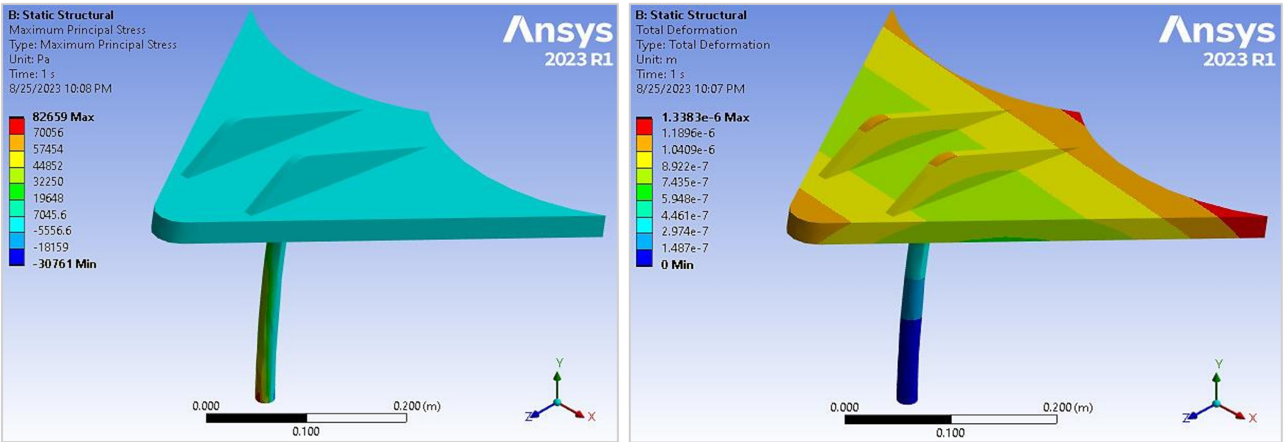
In the case of the ANSYS Fluent simulation, the results show a very delicate interaction of velocity and pressure distributions, with an exacting environment in the aero-dynamic regime experienced inside the wind tunnel. In this case, the results ensure an intensive fluid flow study to understand the mechanical behavior of the aircraft prototype model while testing. The elaboration provided in this discussion builds further on tying this fluid flow data into the overall FEA and ANN model to enhance stress distribution forecasts. This integration of FEA and ANN to predict stress distribution is a pioneering approach, potentially reducing computational times drastically, as demonstrated by recent studies such as those by [23-25].



(a) **(b)**

Figure 4: Pressure and velocity distribution across the aircraft prototype: (a) Static pressure; (b) velocity magnitude

Moreover, the stress in Pa and deformation in mm of the structure of the prototype when utilizing static structural analysis, is depicted in Figure 5, where Figure 5a is the stress and Figure 5b is the deformation. The deformation ranges from a value of 0.006 mm in the midsections to a value of 0.012 mm in the front and back sections. The stress, however, ranges from 1000 Pa in the front and back sections to 5000 Pa in the midsection.



(a) **(b)**

Figure 5: Deformation and stress across the aircraft model: (a) Stress distribution; (b) Deformation

The tabulated results in Table 3 offer an interesting comparison between real stress levels and the corresponding expected stress values created through the integration between FEA and ANN. Each entry in the table represents a given aircraft span value and indicates the stress related to the span and the predicted stress, where an RMSE value of 12% is carried through the analysis. When the real stress levels are matched with their expected counterparts, it is obvious that the integrated method offers a significant amount of accuracy. The low percentages of mistakes seen in each entry support the present thesis. The mistake percentages offer the proportional difference between predicted and real levels of stress; in this way, they offer a clear insight into prediction performance. It should be highlighted that those percentages range from 0.00% to 2.06%, which underlines the model's level of accuracy in predicting stress distribution patterns. Finally, the calculation efficiency of the two methods is provided; it is another dimension to compare. While the FEA method needs nearly 2 hours to conduct the stress simulation within the ANSYS environment, the ANN method needs just 10 seconds. The regression line and error histograms are depicted in Figures 6 and 7, respectively. Figure 7a is the error frequency and Figure 7b is the box plot of it.

Furthermore, the computational efficiency of the ANN approach not only underscores its utility in real-time applications but also aligns with the push toward more agile and adaptive simulation methods within the aerospace industry, as discussed by (Al-Haddad and Mahdi [11]. The huge difference in these data highlights the agility and reactivity of the ANN method as a real option. It opens possibilities concerning tasks that must be solved in real-time or with quick responses. In summary, the values reported in the above table result in a full stress distribution prediction analysis, reflecting the integrated approach's advantage. The computational efficiency of the ANN approach transforms stress analysis into an operation that is time-efficient and instantly suitable for current engineered simulations, as demonstrated by the low, incredibly low values of error percentages.

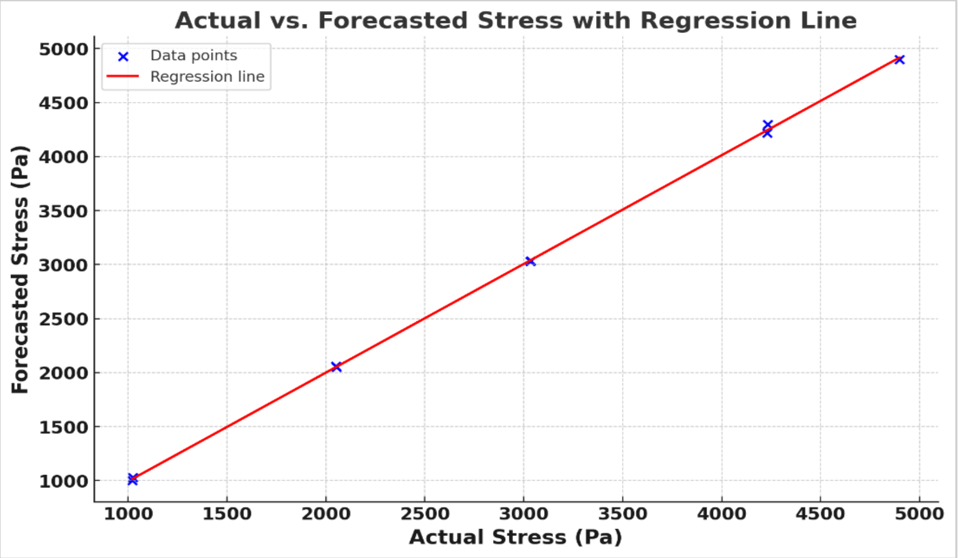
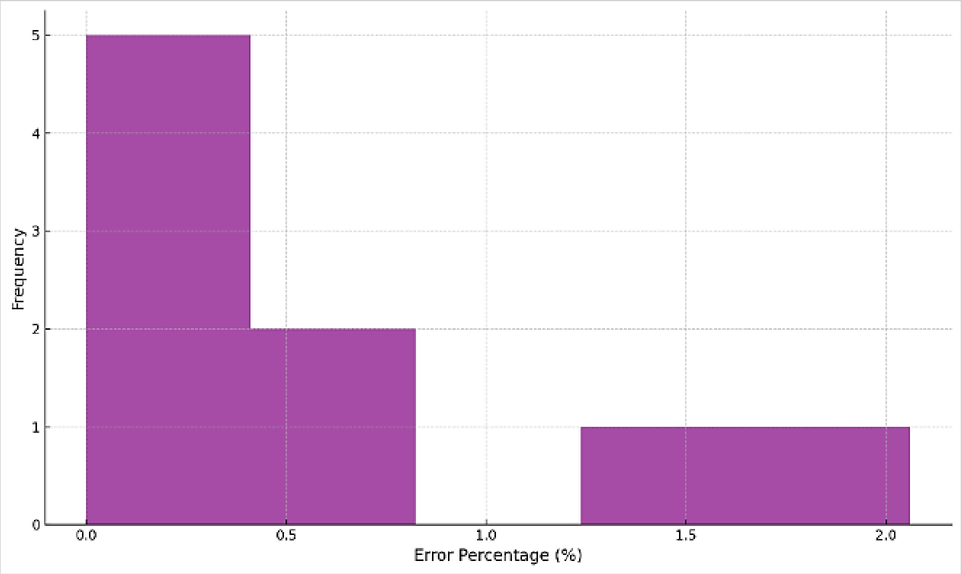
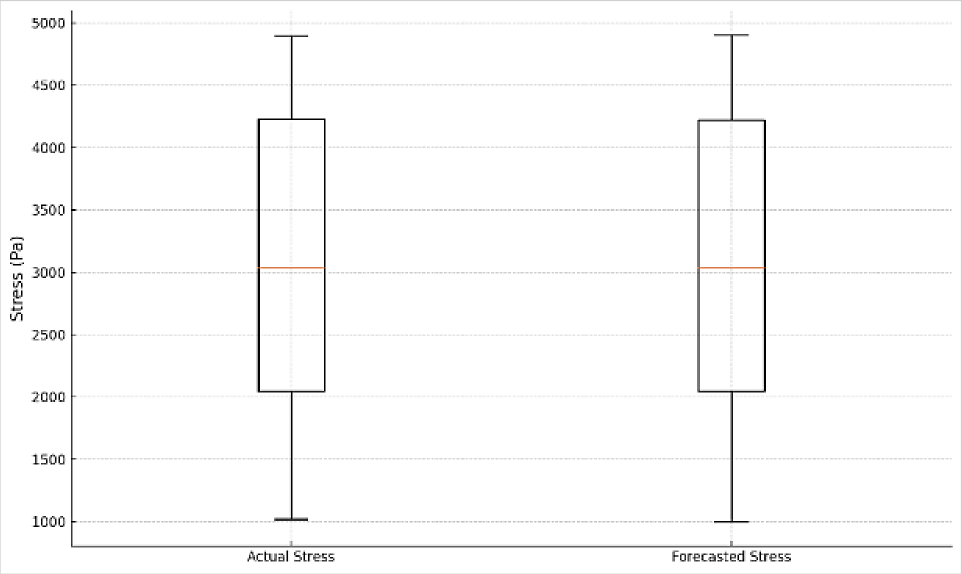


Figure 6: Regression line for the forecasts



(a)



(b)

Figure 7: Error histogram for the predictions (a): Error frequency; (b) stress box plot

Table 3: Forecasts and error percentages

Aircraft span value (m)	Stress (Pa)	Forecasted stress (Pa)	Error percentage (%)
0	1022	1001	2.06
0.05	2050	2060	0.49
0.1	3035	3035	0.00
0.2	4233	4299	1.56
0.25	4899	4901	0.04
0.3	4230	4219	0.26
0.4	3032	3032	0.00
0.45	2052	2050	0.10
0.5	1025	1032	0.68

5. Conclusion

This work presented a robust method that can improve the predictive ability of stress distribution in wind tunnel experiments using scale models of aircraft. A robust predictive model was derived from a stringent evaluation of ANSYS Fluent results and, further, employment of the ANN. Indeed, the tabulated comparison analysis, alongside the error percentages calculated, confirms the evaluation of the RMSE, indicating the integrated approach's feasibility. The remarkable predictions from ANN have shown great comparison with the real stress levels, and the measured RMSE of 12% has clearly shown that the model has good predictive reliability. Moreover, the ANN approach proved to be very effective in quick processing ability, and it gives new revolutionary insights into stress analysis, being very suitable for real-time and iterative applications. This last point is developed strategically because it opens the way for a bright trend in engineering simulation, aligning itself with the increasing demand for an optimum combination of accuracy and efficiency in predicting stress distribution toward designing a robust aircraft structure.

Author contributions

Conceptualization, **A. Al-Mulla Khalaf**., **S. Al-Hddadb**., **B. AL-Oubaidic**., **N. Ibrahimd**., **F. Abdulwahedd**., and **A. Hilal**.; formal analysis, **S. Al-Hddad**.; investigation, **S. Al-Hddad**.; methodology, **S. Al-Hddad**.; resources, **S. Al-Hddad**.; software, **S. Al-Hddad**.; validation, **S. Al-Hddad**.; visualization, **S. Al-Hddad**.; writing—original draft preparation, **S. Al-Hddad**.; writing—review and editing, **A. Al-Mulla Khalaf**., **B. AL-Oubaidi**., **N. Sabah**., **F. Abdulwahed**., and **A. Hilal**. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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