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Data-Driven Optimization and Performance Analysis of Aircraft Structural Design Using Material Properties and Computational Efficiency Metrics

[1*]Dr. Vivek Arora, [2]Dr. Hannah Collins

[1*]Department of Aerospace Engineering, Indian Institute of Science, Bengaluru, India

[2] Department of Mechanical and Aerospace Engineering, University of California, San Diego, La Jolla, CA, USA

Dr. Vivek Arora, Email:vivek.arora.research@iisc.ac.in

ABSTRACT

Purpose: This study aims to develop a data-driven framework for optimizing aircraft structural design by balancing weight reduction, structural strength, and computational efficiency, addressing the limitations of traditional physics-based approaches in large-scale optimization. **Methodology:** A structured dataset of 300 samples with 22 variables was used, incorporating material properties (Young's modulus, density, tensile strength), structural parameters, and computational efficiency metrics. Machine learning models, namely Logistic Regression and Random Forest, were applied to predict weight efficiency. Correlation analysis and feature importance techniques were employed to identify key influencing variables, along with evaluation of computational performance through optimization time and iteration count. **Findings:** Random Forest model had a higher ability to model nonlinear relationship with an accuracy of 61.67% as compared to 58.33% than the Logistic Regression one. The most important factors were identified to be the material properties, especially the density and tensile strength, which affected the structural performance, and structural parameters increased the design flexibility. Computational study showed that there was variability in optimization time, and thus efficient algorithms are important. **Conclusion:** The proposed framework supports efficient and scalable aircraft structural optimization by enabling identification of critical design parameters and improving decision-making in aerospace engineering. This paper offers a new combination of machine-learning and aircraft structural design with a data-driven solution that will increase optimization efficiency and lead to scalable solutions in aerospace design.

Keywords: aircraft structural design; machine learning; structural performance analysis; computational efficiency; Random Forest

Article Type: **Research**

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1. Introduction

The aircraft structural design is a significant aspect of aerospace engineering that directly affects the safety, performance and efficiency of the system. Minimization of structural weight and adequate strength and durability represent one of the main issues in this area. Lightweight structures are associated with better fuel economy and less emissions, but the reduction of weight should not be at the expense of the capability of the structure to resist the aerodynamic forces, and environmental pressure. The progress in structural materials and design methodologies has further increased the need to incorporate material behavior and the overall structural performance in order to obtain optimal design results (Qi et al., 2025) In the conventional method of designing aircraft structures, physics-based modeling methods, like finite element analysis and multidisciplinary design optimization are used. Although these are correct and reliable, they are computationally costly and time-consuming especially in complicated systems. To overcome these issues, the optimization frameworks that are knowledge-based have been created to increase efficiency and minimize the cost of computation (Setayandeh & Babaei, 2020).

The use of data analysis techniques and machine learning has proven to be a useful means of solving complicated engineering problems. The reason for this is that such techniques make it possible to identify hidden patterns and relationships between different variables. Machine learning has been extensively used in aerospace engineering to predict its performance, optimize, and analyze the system (Sun et al., 2019). In particular, its application in aerodynamic and structural optimization has shown promising results in improving design efficiency and accuracy (Li et al., 2022). Moreover, the use of artificial intelligence methods is becoming more frequent in aerospace systems to guide and control systems and decision-making processes (Izzo et al., 2019).

Widening applications of artificial intelligence in aerospace engineering have also resulted in additional applications, such as system level optimization and exploration of space. Rapid performance of system and facilitation of more effective data analysis in complex aerospace settings have been improved using AI-driven approaches (Biswal, 2023). Also, the use of AI technologies in aerospace systems has brought up critical issues regarding ethics and implementation, emphasizing the necessity of responsible and reliable implementation (Mirindi et al., 2025). The most recent developments also indicate the prospective in enhancing the efficiency of the operations through AI, such as airspace and traffic management systems (Sundaresan, 2025).

In spite of these developments, one of the constraints in the existing studies is the absence of a unified model which can concurrently address material characteristics, structural parameters, and computational performance indicators. Numerous investigations are conducted on optimization methods alone, without the inclusion of predictive modelling methods. As an example, the application of metaheuristic optimization methods has been extensively studied to address aerospace problems, but data-driven models have rarely been combined with them (da Silva Junior et al., 2024). In the same way, hybrid artificial intelligence models have been created to use in complex computational tasks, and their use in structural optimization is in its infancy (Khanchandani et al., 2025).

New challenges can now be tackled using new opportunities in machine learning-based optimization, developed in recent years. Combinatorial optimization using machine learning makes it possible to explore large design spaces and enhances decision-making (Bengio et al., 2021). Moreover, data-driven methods have been effectively used in aircraft system analysis, such as engine performance analysis and design analysis (Tong, 2024). The reliability of machine learning models has also become a significant concern in aerospace applications, which has prompted the creation of formal verification methods to enhance model robustness (Razzaghi et al., 2025). Moreover, optimization techniques based on AI have been considered to improve fuel consumption and the overall performance of the aerospace, and they have proven to be practical in aerospace systems (Jain, 2025).

This research intends to create a data-driven model of aircraft structural design optimization by combining material properties, structural parameters, and computational efficiency measures, and the study is expected to analyze the correlation between these variables, assess the ability of machine learning models to forecast structural performance and determine the most significant factors that impact weight efficiency and durability under the condition of computational performance constraints.

2. Methodology

2.1 Data Collection and Description

In the current study, a structured dataset that is acquired with the use of Kaggle is used, comprising 300 samples and 22 variables that reflect the material properties, structural parameters, environmental conditions, and computational performance indicators (Ziya, n.d.). The data covers the major material properties, which are, Young modulus, density and tensile strength, as well as, structural parameters, wing span, fuselage length and structural thickness. Also, the computational parameters, including optimization time and the number of iterations, are included in order to analyze the efficiency of the algorithms. The categorical output variables, representing the efficiency of weight and durability are also included in the dataset and can be used as a target variable in performance analysis.

2.2 Feature Selection and Correlation Analysis

The correlation analysis was done to determine the most appropriate variables that affect structural performance. A correlation matrix was calculated to investigate correlation between material properties, structural parameters and computational metrics. On the basis of this analysis, it was possible to select a subset of the most important features and enhance interpretability and decrease redundancy. After that, a correlation heatmap was created to show the interactions between these features and can provide information about the dependence of variables and the choice of input features to be used in the development of the model.

2.3 Model Development

Prediction of structural performance was done using supervised machine learning methods. Logistic Regression and Random Forest were chosen to be compared, which are the linear and nonlinear modeling techniques, respectively. To divide the data into training and testing sets, an 80:20 ratio was used. The two models were trained using the training data and tested using the testing data to predict the weight efficiency based on the material, structural and computational properties.

2.4 Performance Evaluation

The accuracy of classification was used as the main measure of the performance of the developed models. The ratio of the number of correctly classified instances to the number of observations is called accuracy. The two models were compared to establish the most effective model to predict structural performance. The analysis findings were given in a tabular and graphical format in order to make them easier to understand and interpret.

2.5 Feature Importance Analysis

The feature importance analysis was performed with the help of the Random Forest model to identify the most influential parameters influencing structural performance. The scores of importance were obtained using the contribution of each feature to the predictive power of the model. The most significant features were selected and prioritized, which gave information on the relative significance of material properties, structural parameters, and computational metrics. This analysis aids in identifying important variables in optimization of design.

2.6 Computational Performance Analysis

Besides structural performance, computational efficiency was also measured in terms of optimization time and number of iteration. These indicators give a clue of the efficiency of the optimization process as well as its convergence pattern. A statistical analysis was performed as the variability of these metrics in various situations was examined. The correlation between the time and number of iterations was also examined in order to comprehend the cost of computation due to the optimization procedure.

2.7 Data-Driven Optimization Approach

The data-driven method was used to determine the best design setups through the analysis of the relationships between input variables and performance results. The study is a multi-objective view of structural design of aircraft by incorporating material properties, structural parameters, and computational metrics. This method provides the ability to identify the trends related to greater weight efficiency and durability with built in consideration of the computational limitations.

3. Results

3.1 Descriptive Analysis of Variables

Table 1 shows the descriptive statistics of the most important variables that were taken into account in the given study. The analysis shows a great variation in material, structural and computational parameters, which are a reflection of the diversity of the aircraft design configurations represented in the data. The material properties that are within wide ranges include the Young modulus and density with a range of 50.10 to 199.83 Gpa and 1520.93 to 4495.76 kg/m to 3 respectively. This difference suggests that there are various material types, lightweight composite materials and heavier metallic alloys. Likewise tensile strength is highly dispersive, indicating that there are variations in the material performance properties of interest in structural life.

Table 1. Statistical summary of key material, structural, and computational variables

Variable	**Mean**	**Minimum**	**Maximum**
Young’s Modulus (GPa)	124.21	50.10	199.83
Density (kg/m³)	3018.02	1520.93	4495.76
Tensile Strength (MPa)	503.72	200.54	799.88
Wing Span (m)	34.91	20.12	59.87

Structural Thickness (mm)	25.37	10.05	49.92
Optimization Time (sec)	102.26	51.45	149.83
Number of Iterations	1238.01	523.00	1983.00

There is also variation in structural parameters such as the wing span and the structural thickness. Wing span measures between 20.12 m and 59.87 m, and structural thickness is between 10.05 mm and 49.92 mm. These are the variations that are based on the various aircraft configurations and design requirements. There is also evidence from computational calculations showing that the optimization time can range between 51.45 seconds and 149.83 seconds in optimizing the model with a number of iterations ranging between 523 and 1983. There is variability that indicates different rates of convergence for the various algorithms and their complexities.

3.2 Correlation Analysis

To determine the relationship between these important variables, correlation analysis was performed, and the results are illustrated in Figure 1 below. The correlation heat map presents a general overview of the relationship between material properties, structure variables, and computational variables. The heat map is simpler to comprehend and reveal the most significant relationships which are valuable in the aircraft structure design. The results show that there is a strong relationship between tensile strength and Young's modulus. This implies that the harder the material, the greater its tensile strength. Further, density and structural thickness have significant associations with performance-related factors, which imply their effects on weight efficiency and durability. There are moderate correlations between the computational parameters, including optimization time and number of iterations, which shows the reliance of computational cost on the convergence behavior of the algorithm. Overall, the correlation analysis provides valuable insights into the interdependencies among key variables and supports the identification of critical parameters for optimization

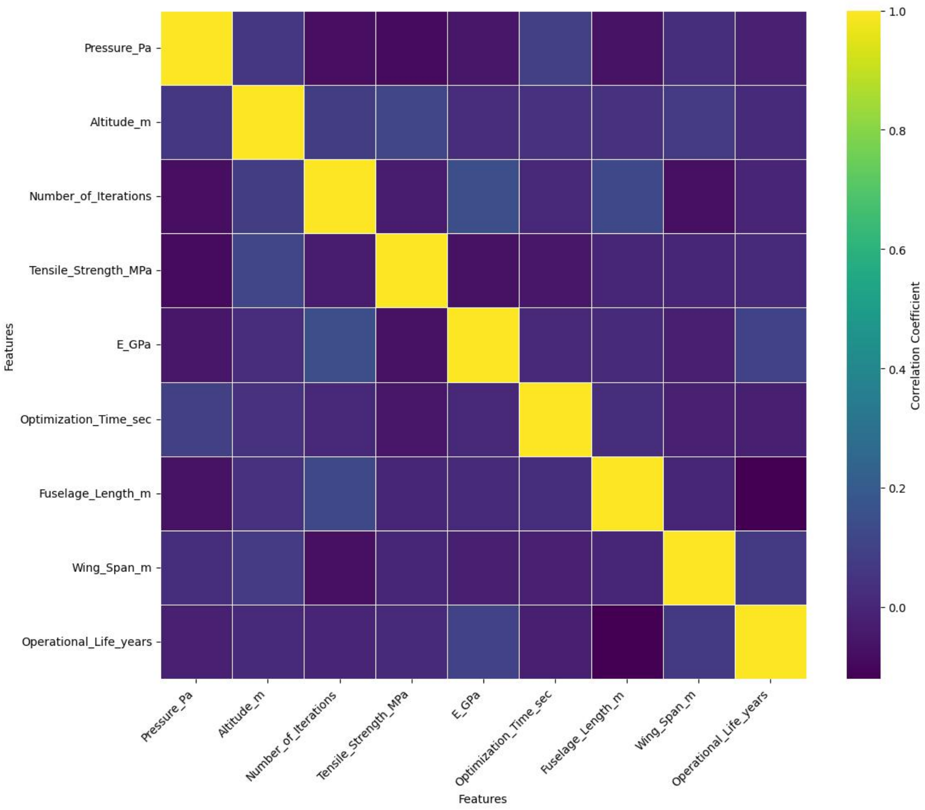

Figure 1. Correlation heatmap showing relationships among selected material, structural, and computational features

3.3 Model Performance Evaluation

To determine the predictive ability of the machine learning models employed in this study, the predictive performance of these models was tested to determine how well they can predict weight efficiency. Table 2 is a summary of the results of this evaluation. Two models, i.e. Logistic Regression and random forest, were run and tested with a standard training and testing split.

Table 2. Classification performance of Logistic Regression and Random Forest models for weight efficiency prediction

Model	**Accuracy (%)**
Logistic Regression	58.33
Random Forest	61.67

Random Forest model had an accuracy of 61.67 and was better than the Logistic Regression model which had an accuracy of 58.33. This better performance by the Random Forest model can be explained by the fact that it is an ensemble model and thus it is able to capture nonlinear associations among the input variables. Conversely, the relatively poorer performance of Logistic Regression implies that it may not be able to model nonlinear interactions in data. Although the accuracy values are low, the results prove that it is possible to apply machine learning techniques to aircraft structural performance prediction. After the tabulated comparison, a graphical representation of the model performance is given to enable easier interpretation of the results is drawn in Figure 2. The graphical comparison shows the relative gain that the Random Forest model makes over the Logistic Regression model and supports the appropriateness of nonlinear modeling methods in the prediction of the structural performance.

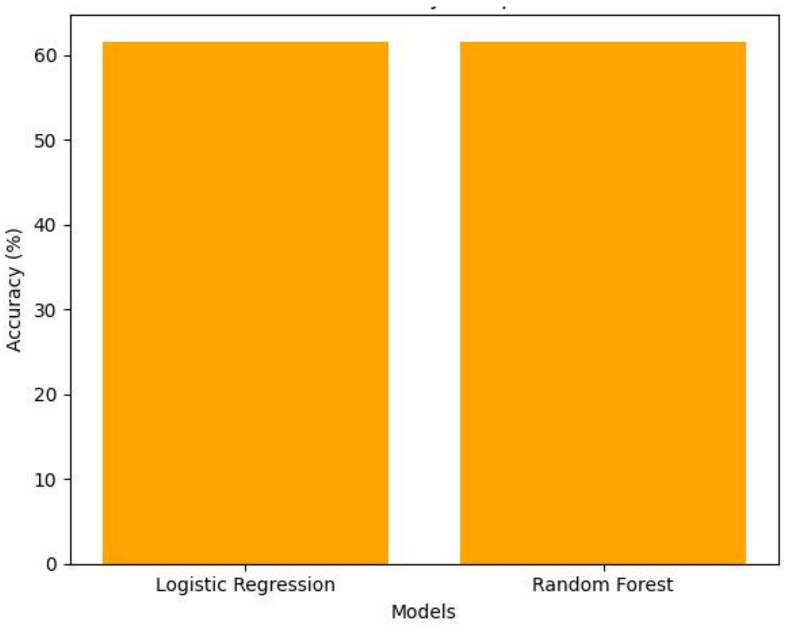

Figure 2. Comparison of prediction accuracy between Logistic Regression and Random Forest models for weight efficiency classification.

3.4 Feature Importance Analysis

The analysis of the importance of the features with the help of the Random Forest model was performed in order to identify the strongest parameters influencing the structural performance. Figure 3 shows the results, ranking the most important features by their scores. The results demonstrate that the properties of the material become predominant in comparison with other factors in terms of their influence on weight efficiency. This conclusion is consistent with the concept of engineering in which lightweight yet strong materials are employed to optimize the structure.

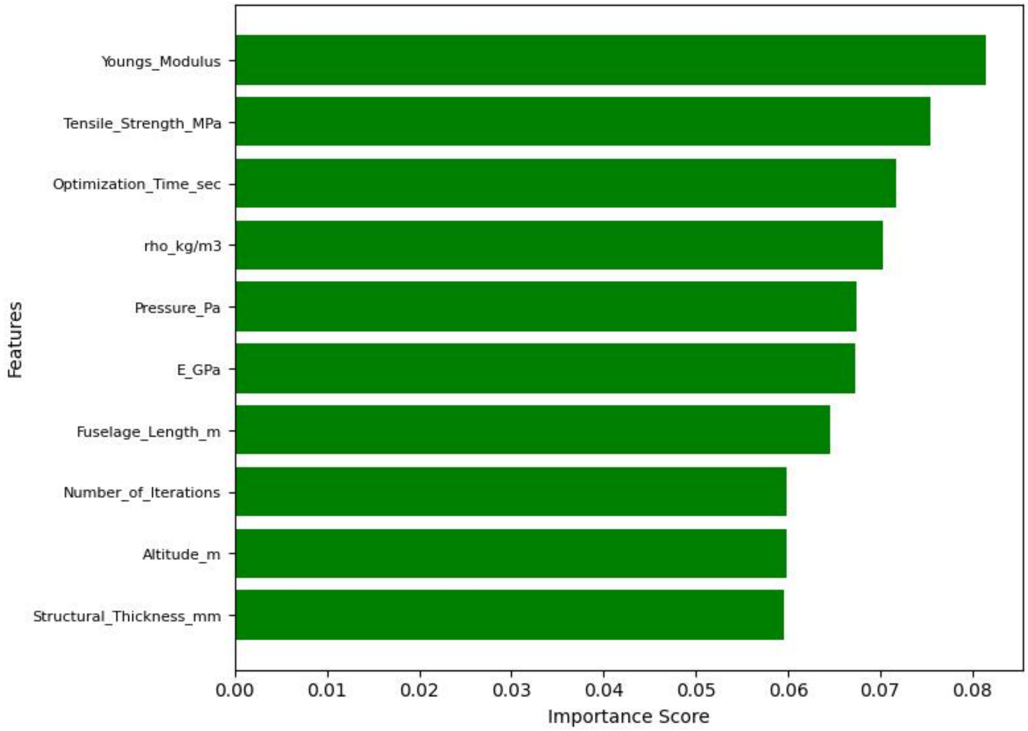

Figure 3. Feature importance ranking from the Random Forest model highlighting key factors influencing structural performance

The important structural variables of the thickness and span also play significant roles because they can affect the design of optimization. On the other hand, the computational parameters do not affect structural performance; they only determine optimization performance indirectly. These results underscore the need to combine material and structural aspects in optimization of aircraft design.

3.5 Computational Performance Analysis

The optimization performance of the optimization process is summarized in Table 3, which provides important metrics of optimization time and the number of iterations. The findings show that the duration of optimization can range between 51.45 seconds and 149.83 seconds with the mean time of 102.26

seconds. Equally, the iterations vary within 523 and 1983 which implies that the convergence rates in various optimization problems are not consistent.

Table 3. Computational performance based on optimization time and iteration count

Metric	**Mean**	**Minimum**	**Maximum**
Optimization Time (sec)	102.26	51.45	149.83
Number of Iterations	1238.01	523.00	1983.00

The relationship between the computation time and the number of iterations indicates that the computational cost is highly dependent on the number of iterations they need to converge. This underscores the need to choose effective optimization algorithms to reduce computational costs. The difference in the measure of computation also indicates that the various design configurations demand varying degrees of computation effort, which further implies the necessity of effective optimization strategies.

The findings of this research illustrate that material properties are the most influencing factors on aircraft structural performance, but structural parameters allow more flexibility in design optimization. Random Forest model performs better than logistic Regression thus showing that there are nonlinear relationships in the data. The correlation and feature importance analyses also indicate that density, tensile strength, and structural thickness are important factors to consider when making performance outcomes. Also, computational performance analysis indicates inconsistency in the efficiency of optimization, so it is necessary to balance the performance goals with computer cost. Comprehensively, the results confirm the usefulness of a data-driven method of aircraft structural design optimization and offers useful information on how to make the design more efficient.

4. Discussion

The results of this research indicate the usefulness of a data-driven method to conduct the analysis and optimization of aircraft structural design based on the material property and computational performance measures. The findings are significant to the understanding of the impact of key variables on the performance of the structure, especially weight efficiency and durability. There has been a growing interest in the use of data-driven methods in aerospace engineering because it can mirror the behavior of complex systems, with recent research indicating a growing interest in this field (Le Clainche et al., 2023; Brunton et al., 2021).

The variability in material, structural and computational parameters as observed is realistic in nature in terms of engineering design. The broad spectrum of material properties such as the Youngs modulus, density and tensile strength show the existence of various material types, which is necessary in assessing structural performance under various conditions. It is consistent with the more general data-driven science and engineering, in which complex systems are represented by integrated datasets (Brunton and Kutz, 2022). Moreover, structural variability is a crucial factor in design flexibility, which is essential in multidisciplinary optimization models like OpenMDAO (Gray et al., 2019).

The variable interactions indicate that there are very strong interdependencies between structural performance and material properties. The stiffer a material, the stronger it is, which is in line with the structural dynamics theory in aerospace systems (Friedmann et al., 2023). On the other hand, the impact of density reflects a trade-off relationship between structural weight and structural integrity, which plays a critical role in optimizing aerospace structures. In this regard, topology optimization involves the same kinds of trade-offs, and aims at finding the optimal distribution of the materials used for designing structures (Bendsoe & Sigmund, 2013; Guo et al., 2014).

Based on the analysis of machine learning models applied, ensemble methods are more effective for handling nonlinear dependencies compared to linear models. This conclusion corresponds with the rapid development of machine learning applications to aerospace systems involving complex nonlinearities in variables. It means that the results of the research confirm the recent findings about nonlinear relations between features in physics-based machine learning problems (Le Clainche et al., 2023; Scarselli and Nicassio, 2025). The moderate predictive performance suggests the presence of complex relationships within the dataset that might be addressed through the use of more advanced modeling techniques. For example, physics-informed machine learning approaches can be used to improve the predictive performance of models.

The analysis of feature importance suggests that the material characteristics, density and tensile strength in particular, are the most important features affecting the structural performance. This observation is in line with optimization strategies that emphasise material selection as a major determinant in the realisation of better efficiency and longevity. Moreover, surrogate modeling methods have been extensively applied to approximate the complex relationships between aerodynamics and structures at reduced cost without compromising accuracy (Keane and Voutchkov, 2020). Likewise, multifidelity techniques offer a beneficial solution to integrating low- and high-fidelity information to enhance optimization efficiency (Peherstorfer et al., 2018).

The performance analysis of computation highlights the significance of efficiency of the algorithm in optimization. The correlation between optimization time and iteration count shows that convergence behavior is very sensitive to the computational cost. The use of advanced metaheuristic optimization methods has been extensive to overcome these challenges and provide better performance in complex optimization problems (Abd Elaziz et al., 2021). Also, the recent advances in multi-fidelity and physics-informed neural networks have proven to be highly promising in improving the efficiency of computations when it comes to aircraft design optimization (Sarker, 2024).

The integration of data-driven methods with structural health monitoring systems increases the likelihood of successful implementation of such systems within the field of aerospace manufacturing. Machine learning models have demonstrated their potential as effective tools for assessing structural integrity and predicting the moment of failure of aerospace components, paving the path to the development of more reliable and effective designing procedures (Scarselli and Nicassio, 2025).

The analysis reveals the relevance of implementing a model based on data in order to integrate material and structural properties, as well as computations, into the process of structural optimization in aerospace vehicles. The study shows the collaboration between machine learning, optimization techniques, and calculations to provide useful inferences on structural behavior. But there are also several limitations that relate to the method employed in the study. Specifically, the lack of physical models restricts the opportunities to conduct a thorough evaluation of the real structural performance, and the rather low predictive power of the model demands the use of advanced techniques. Future studies may be aimed at incorporating the physics-based models into the data-driven methods to enhance the validity and strength of the predictions. Topology optimization and multi-fidelity modeling methods could be incorporated together with surrogate models in the design process to make it even more efficient. Moreover, the potential of enhancing the efficiency and effectiveness of aircraft structural design through machine learning methods like physics-informed neural networks is immense.

5. Conclusion

This work has offered a data-driven paradigm of airplane structure design optimization and performance study integrating the material properties, structural parameters, and computing efficiency measures. It was analyzed that material properties particularly the density and tensile strength outcomes play a predominant profile in structural performance and structural parameters are free to superimpose structural performance to come up with optimized designs. The efficiency in weight was successfully predicted with the help of machine learning models that showed that the Random Forest model was more successful than the Logistic Regression that suggested the necessity to consider nonlinear relations in complex engineering systems. The findings also revealed the significance of computational performance metrics e.g. optimization time and number of iterations in comparison of efficiency of design processes. The difference in these measures as experienced underscores the need to have powerful optimization algorithms that give the appropriate tradeoff between the cost of computation, and the accuracy of the performance. Using correlation analysis in combination with feature importance techniques provided valuable insights into the correlation of the variables, which can be applied to make effective choices in aircrafts design. In general, the results support the notion that the data-driven approach may become a helpful instrument in the process of aircraft structural optimization as it helps to identify the most essential factors and increase predictive power. The model provides an efficient and scalable substitute of traditional approaches. The directions of future can be in the form of physics-based modelling, more complex machine learning techniques and real-time optimization techniques to enhance the accuracy and applicability of the proposed method further.

REFERENCES

1. Abd Elaziz, M., Dahou, A., Abualigah, L., Yu, L., Alshinwan, M., Khasawneh, A. M., & Lu, S. (2021). Advanced metaheuristic optimization techniques in applications of deep neural networks: a review. *Neural Computing and Applications*, *33*(21), 14079-14099.
2. Bendsoe, M. P., & Sigmund, O. (2013). *Topology optimization: theory, methods, and applications*. Springer Science & Business Media.
3. Bengio, Y., Lodi, A., & Prouvost, A. (2021). Machine learning for combinatorial optimization: a methodological tour d'horizon. *European Journal of Operational Research*, *290*(2), 405-421.
4. Biswal, M. (2023). A Short Review on Machine Learning in Space Science and Exploration. *Acceleron Aerospace Journal*, *1*(4), 84-87.
5. Brunton, S. L., & Kutz, J. N. (2022). *Data-driven science and engineering: Machine learning, dynamical systems, and control*. Cambridge University Press.

6. Brunton, S. L., Nathan Kutz, J., Manohar, K., Aravkin, A. Y., Morgansen, K., Klemisch, J., ... & McDonald, D. (2021). Data-driven aerospace engineering: reframing the industry with machine learning. *Aiaa Journal*, *59*(8), 2820-2847.
7. da Silva Junior, C. A., Pereira, M. A., & Passaro, A. (2024). A Systematic Study on Solving Aerospace Problems Using Metaheuristics. *arXiv preprint arXiv:2411.02574*.
8. Friedmann, P. P., Lesieutre, G. A., & Huang, D. (2023). *Structural Dynamics: Volume 50: Theory and Applications to Aerospace and Mechanical Engineering* (Vol. 50). Cambridge University Press.
9. Gray, J. S., Hwang, J. T., Martins, J. R., Moore, K. T., & Naylor, B. A. (2019). OpenMDAO: An open-source framework for multidisciplinary design, analysis, and optimization. *Structural and Multidisciplinary Optimization*, *59*(4), 1075-1104.
10. Guo, X., Zhang, W., & Zhong, W. (2014). Doing topology optimization explicitly and geometrically—a new moving morphable components based framework. *Journal of Applied Mechanics*, *81*(8), 081009.
11. Izzo, D., Märtens, M., & Pan, B. (2019). A survey on artificial intelligence trends in spacecraft guidance dynamics and control. *Astrodynamics*, *3*(4), 287-299.
12. Jain, K. M. (2025). AI-driven fuel optimization in VTOL aircraft: A comprehensive review. *Acceleron Aerospace Journal*, *4*(6), 1176-1185.
13. Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, *3*(6), 422-440.
14. Keane, A. J., & Voutchkov, I. I. (2020). Surrogate approaches for aerodynamic section performance modeling. *AIAA Journal*, *58*(1), 16-24.
15. Khanchandani, M. P., Buch, S., & Patel, B. (2025, December). A Hybrid AI-Based Model for Secure Image Encryption in Cloud Storage Systems. In *International Conference on Soft Computing and its Engineering Applications* (pp. 295-310). Cham: Springer Nature Switzerland.
16. Le Clainche, S., Ferrer, E., Gibson, S., Cross, E., Parente, A., & Vinuesa, R. (2023). Improving aircraft performance using machine learning: A review. *Aerospace Science and Technology*, *138*, 108354.
17. Li, J., Du, X., & Martins, J. R. (2022). Machine learning in aerodynamic shape optimization. *Progress in Aerospace Sciences*, *134*, 100849.
18. Mirindi, D., Sinkhonde, D., Mirindi, F., & Bezabih, T. (2025). A review on aerospace-AI, with ethics and implications. *JOURNAL OF CIVIL, CONSTRUCTION AND ENVIRONMENTAL ENGINEERING Учредители: Science Publishing Group*, *10*(2), 60-74.
19. Peherstorfer, B., Willcox, K., & Gunzburger, M. (2018). Survey of multifidelity methods in uncertainty propagation, inference, and optimization. *Siam Review*, *60*(3), 550-591.

20. Qi, Q., Li, T., Yang, H., Lv, A., Liu, Y., & Meng, F. (2025). Recent advances in structural engineering of ceramic microwave absorption materials: From nano/micro architectures to macroscale design. *Journal of Advanced Ceramics*.
21. Razzaghi, P., Memarzadeh, M., & Kalyanam, K. (2025). Formal verification of a machine learning tool for runway configuration assistance. *Frontiers in Aerospace Engineering*, *4*, 1463425.
22. Sarker, A. (2024). Efficient aircraft design optimization using multi-fidelity models and multi-fidelity physics informed neural networks. *arXiv preprint arXiv:2412.18564*.
23. Scarselli, G., & Nicassio, F. (2025). Machine Learning for Structural Health Monitoring of Aerospace Structures: A Review. *Sensors*, *25*(19), 6136.
24. Setayandeh, M. R., & Babaei, A. R. (2020). Multidisciplinary design optimization of an aircraft by using knowledge-based systems: MR Setayandeh, A. Babaei. *Soft Computing*, *24*(16), 12429-12448.
25. Sun, S., Cao, Z., Zhu, H., & Zhao, J. (2019). A survey of optimization methods from a machine learning perspective. *IEEE transactions on cybernetics*, *50*(8), 3668-3681.
26. Sundaresan, S. (2025). Integrating Artificial Intelligence with Space-Based ADS-B for Next-Generation Space Traffic Management. *Acceleron Aerospace Journal*, *5*(2), 1368-1376.
27. Tong, M. T. (2024). *The Development and Deployment of Machine Learning Models for Aircraft Engine Concept Assessment* (No. E-20285). National Aeronautics and Space Administration.
28. Ziya.(n.d). *Aerospace structural design dataset*. Kaggle. https://www.kaggle.com/datasets/ziya07/aerospace-structural-design-dataset