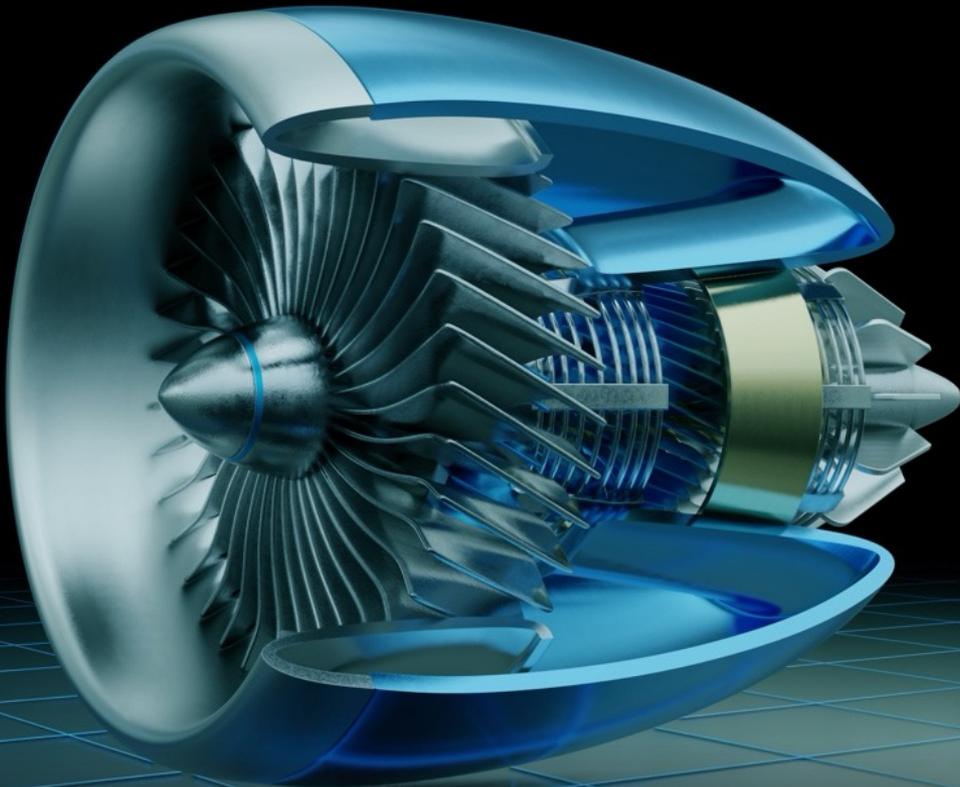


## SYNERGIZING DOE AND GEOMETRIC DEEP LEARNING FOR RAPID INTEGRATED BLADED ROTOR (IBR) DESIGN

Accelerating predictions, reducing computational overhead, and enabling efficient engineering workflows. Integrating DOE with predictive models for smarter decisions, in IBR development.



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## ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly influencing advanced engineering workflows by enabling faster insights while preserving analytical rigor. In complex design environments, their impact value lies not in replacing physics-based methods, but in augmenting them to improve efficiency and enhance decision reliability.

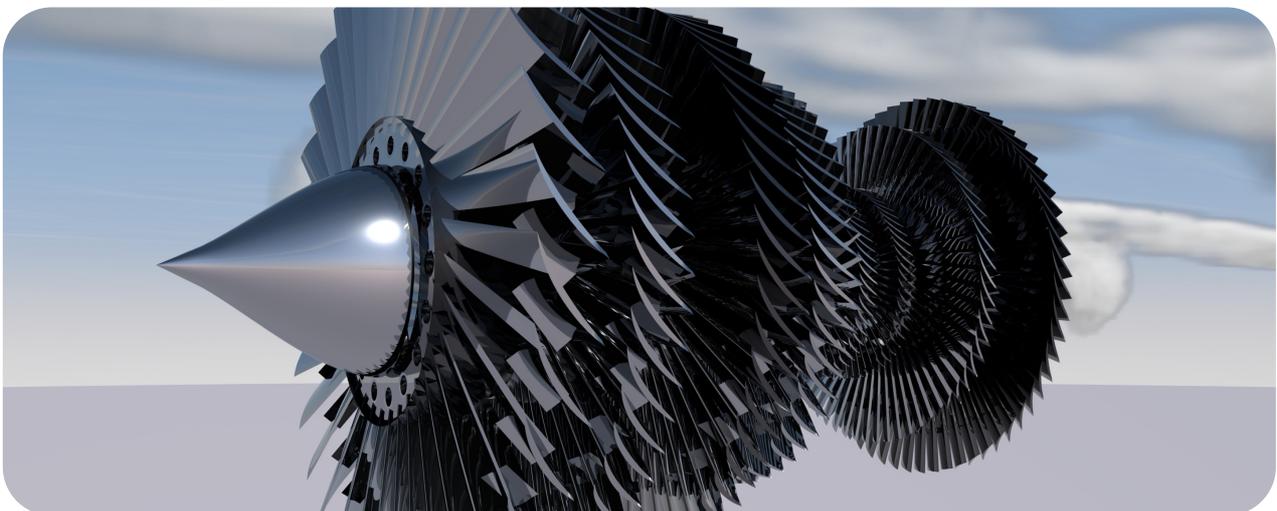
This paper presents a hybrid workflow that combines Design of Experiments (DOE) with Geometric Deep Learning (GDL), implemented via Altair Physics AI, to accelerate predictions. DOE provides a structured mechanism to explore design variability and identify key influencing parameters. However, its scalability across large parameter spaces and intricate geometries is enhanced when combined with GDL-based predictive modeling.

Integrated Bladed Rotors (IBRs or blisks) pose significant design challenges due to wide geometric design spaces and complex operational load environments. Using a sector-based IBR finite element model, multiple DOE techniques - Latin Hypercube, Central Composite, Box-Behnken, Sparse Grid, are employed to generate structured datasets. These datasets are then used to train mesh-aware GDL models that deliver rapid predictions within the sampled design envelope.

Results show that prediction accuracy varies significantly across DOE methods, with distinct error patterns emerging, particularly near extreme parameter ranges. These observations highlight the importance of dataset quality, domain coverage, and effective outlier management. The combined DOE-GDL workflow reduces simulation burden and shortens iteration cycles while maintaining engineering reliability, reinforcing the role of human insight alongside AI-driven acceleration.

## INTRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) are reshaping simulation driven engineering by enabling fast, data informed predictions and reducing reliance on repeated high fidelity analyses. AI refers to computational systems capable of learning and reasoning from data, while ML focuses on models that improve performance through training rather than explicit programming. Within Computer-Aided Engineering (CAE) workflows, these capabilities shorten analysis cycles and support rapid virtual prototyping without compromising engineering discipline.



Geometric Deep Learning (GDL) extends deep learning to non Euclidean data structures (graphs, meshes, and point clouds), allowing models to learn directly from geometry and topology. By consuming mesh based inputs that preserve connectivity, GDL supports predictive and surrogate modeling for structural mechanics, fluid dynamics, and materials problems. This approach significantly reduces computational cost compared to traditional solvers, especially when exploring large and nonlinear design spaces.

Integrated Bladed Rotors (IBRs, or blisks) present a compelling use case for such hybrid methods. Their design spans wide geometric parameter spaces and must withstand severe operational loads such as centrifugal forces, aerodynamic pressures, and thermal gradients. While Finite Element Analysis (FEA) remains the benchmark for detailed evaluation, exhaustive parametric studies are computationally expensive. This motivates hybrid workflows that retain fidelity while accelerating iteration.

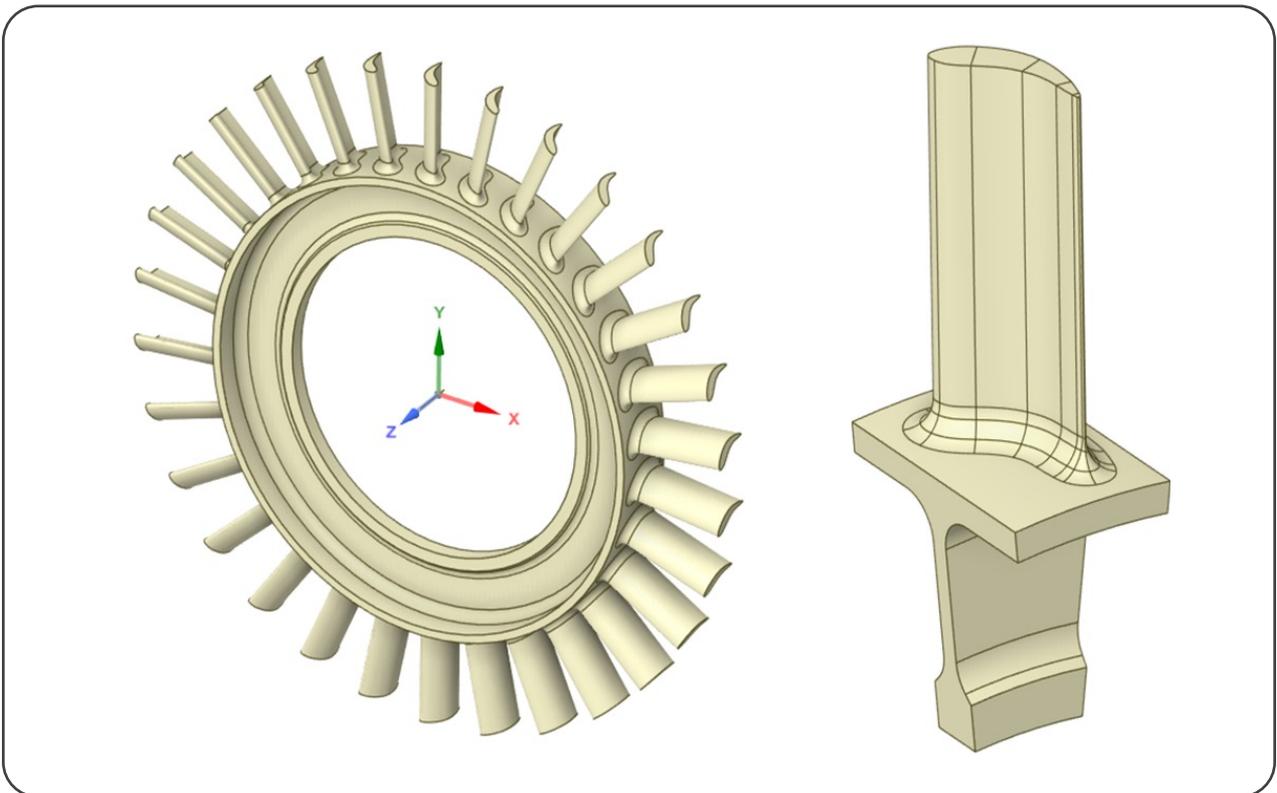


Figure 1: Integrated Bladed Rotors (IBRs, or Blisks) Model

This paper introduces a DOE–GDL workflow that combines structured sampling with geometry-aware predictive modeling using Altair Physics AI. DOE generates labeled datasets from sector-based FEA, while Physics AI trains mesh-aware surrogates capable of rapid inference within the trained domain. Predictions outside the sampled envelope or involving topology changes are intentionally excluded, underscoring the importance of disciplined data preparation and domain control.

### Workflow Overview

1. DOE generates structured design samples and corresponding FEA labels (stress and deformations).
2. Physics AI (GDL) trains on mesh based inputs and simulation labels to learn geometry informed mappings.
3. Trained surrogates provide rapid predictions for new configurations within the sampled envelope.
4. Predictions are validated against FEA, with iterative data refinement and retraining as required.

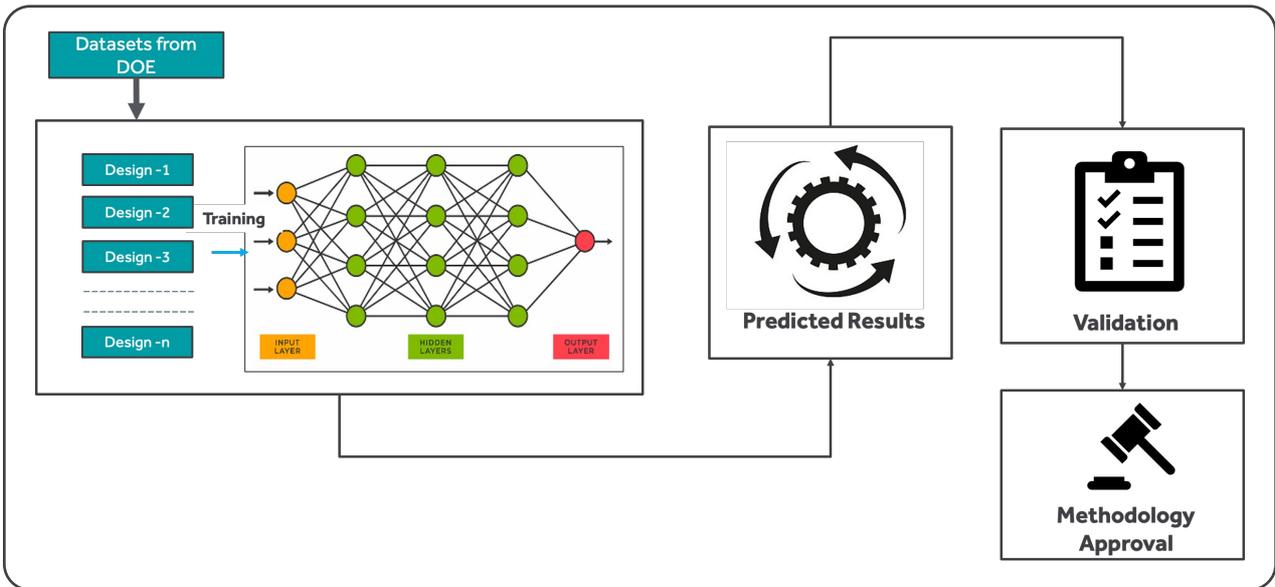


Figure 2: Physics AI Workflow

## OBJECTIVES AND SCOPE OF THE WORK

The objective of this study is to evaluate the effectiveness of combining Design of Experiments (DOE) with Geometric Deep Learning (GDL) to improve efficiency in the design and analysis of Integrated Bladed Rotors (IBRs). Specifically, the work assesses how GDL models trained on DOE-generated datasets can reduce simulation workload and accelerate design iterations for complex turbomachinery components.

### The scope of this research includes:

- Evaluating multiple DOE methods used for structured dataset generation
- Training and validating GDL models using simulation-based datasets
- Assessing prediction accuracy within the sampled design envelope

This study does not aim to replace high-fidelity FEA for final validation. Instead, it presents a complementary workflow that supports early-stage design exploration and optimization.

## PARAMETRIC IBR MODEL DEVELOPMENT

In the aerospace industry, the structural performance of Integrated Bladed Rotors (IBRs) is critical for ensuring engine reliability and efficiency. To support rapid design iterations, a parametric IBR model was developed that enables systematic variation of key geometric features while maintaining aerodynamic and structural integrity.

The model parameterizes key geometric features such as bore radius, neck radius, fillet radius, rim width, and web fillet radius, allowing efficient exploration of the design space and sensitivity analysis. This approach enables engineers to assess stress distribution and deformation behavior across multiple configurations without manual redesign. Through this parametric framework (Fig. 3), the synergy between DOE and AI/ML techniques is enhanced, enabling improvements in predictive accuracy, computational efficiency, and design robustness.

## FINITE ELEMENT MODELING, LOADS, AND BOUNDARY CONDITIONS

A complete finite element (FE) model of the bladed disk was developed in ANSYS to simulate realistic operating conditions, including centrifugal forces, aerodynamic pressure, and thermal gradients (Fig 4).. The geometry was meshed to accurately capture stress and deformation at critical regions such as blade roots and fillets. Material properties reflected high-temperature alloy behavior representative of actual rotor conditions.

To balance computational efficiency with structural fidelity, a cyclic-symmetry sector model was employed.. Boundary conditions replicated constrained motion and thermal environments encountered during operation.

### Key loads included:

- Centrifugal forces correspond to the design rotational speed.
- Aerodynamic pressure distribution across blade surfaces.
- Thermal gradients representing engine operating conditions.

This FE model served as the reference for validating predictive accuracy across all design scenarios.

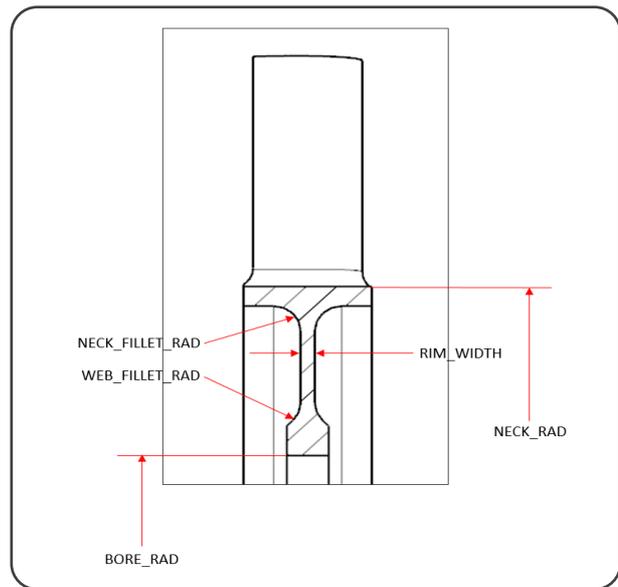


Figure 3: Disk Parametric Model

Sl. No	Parameter	Description	Baseline Values (in)
1.	BORE_RAD	Bore radius	7.73
2.	NECK_FILLET_RAD	Fillet radius at the neck	0.50
3.	NECK_RAD	Radius of the neck section	10.80
4.	RIM_WIDTH	Width of the rim section	0.26
5.	WEB_FILLET_RAD	Fillet radius at the web	0.50

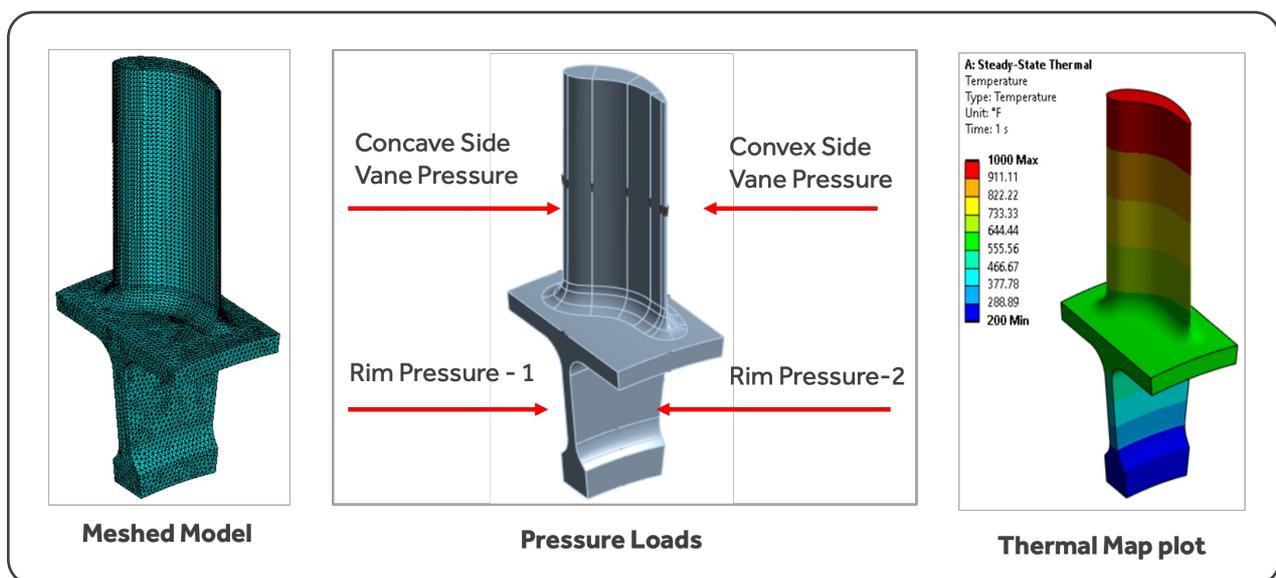


Figure 4: FE Meshed Model and boundary condition

## DOE METHODOLOGY

The Design of Experiments (DOE) approach was employed to systematically quantify the influence of multiple geometric parameters on Integrated Bladed Rotor (IBR) performance. A total of 150 design points were generated using complementary sampling strategies to efficiently capture nonlinear behavior across the design space. Table 1 presents an excerpt of 20 representative design points from the full DOE matrix.

### The DOE techniques used included:

- **Latin Hypercube Sampling (LHS):** Space filling design that reduces clustering and provides uniform coverage across parameter ranges.
- **Central Composite Design (CCD):** Augments factorial designs with center and axial points to capture curvature for second order response surfaces.
- **Box–Behnken Design (BBD):** Efficient quadratic modelling that avoids extreme corner combinations and reduces run count.
- **Sparse Grid Initialization:** Hierarchical sampling that scales more favorably in higher dimensions and improves coverage of multi parameter interactions.

Each design point was analyzed using sector-based finite element simulations to obtain stress and deformation responses.

Sl. No	Bore_Radius	Neck_Radius	Rim_Width	Neck_Fillet_Radius	Web_Fillet_Radius	Maximum Principal Stress	Equivalent Stress Maximum
1	7.9104	10.8900	0.1781	0.6725	0.6815	98,283	83,394
2	7.9120	10.8900	0.1781	0.6725	0.6815	91,633	82,366
3	8.1087	10.8900	0.1781	0.6725	0.6815	98,150	88,590
4	7.9104	10.8900	0.1781	0.6725	0.6815	82,894	7,473
5	7.9104	10.8900	0.1781	0.6725	0.6815	113,400	100,300
6	7.9104	10.8900	0.1781	0.6725	0.6815	90,735	81,552
7	7.9104	10.8900	0.2261	0.6725	0.6815	98,805	87,802
8	7.9104	10.8900	0.1781	0.4805	0.6815	98,283	83,394
9	7.9104	10.8900	0.1781	0.6725	0.6815	91,633	82,366
10	7.9104	10.8900	0.1781	0.6725	0.6815	98,150	88,590
11	7.9104	10.8900	0.1781	0.6725	0.6815	82,894	7,473
12	7.9104	10.8900	0.1781	0.6725	0.6815	113,400	100,300
13	7.6561	10.8630	0.1644	0.6208	0.6529	99,027	83,257
14	7.6566	10.8630	0.1644	0.6208	0.6529	100,000	81,895
15	7.6566	10.8630	0.1644	0.6208	0.7376	98,997	89,909
16	7.6566	10.8630	0.1967	0.6208	0.7376	98,997	89,909
17	7.6566	10.8630	0.1967	0.6208	0.7376	98,997	89,909
18	7.6566	10.9180	0.1967	0.6208	0.7376	98,997	89,909
19	7.6566	10.9180	0.1967	0.6208	0.7376	98,997	89,909
20	7.6566	10.9180	0.1967	0.6208	0.7376	98,997	89,909
21	7.6566	10.9180	0.1967	0.6208	0.7376	98,997	89,909

Table 1: DOE Matrix

## DOE Results (Response Surfaces & Validation)

Response surface models (surrogates) were developed from DOE data to predict performance metrics without requiring full scale simulations. These surrogates significantly reduce computational effort and enable rapid optimization in subsequent design iterations. The DOE dataset also served as high quality training data for mesh aware GDL models.

The DOE results were validated by comparing response surface predictions with FEA results at the root fillet location. Table 2 summarizes predicted values against actual simulation results.

- **Method performance:** Prediction accuracy varied across DOE methods. LHS provided strong coverage and robust accuracy for moderate parameter ranges
- **High range discrepancies:** Errors increased for configurations with higher geometric parameter values, reflecting the challenge of modelling highly nonlinear behaviour in complex spaces.
- **Dataset observations:**
  - Equivalent stress and principal stress correlate strongly with each other, but show weak linear correlation with individual geometric parameters.
  - Outliers materially impact surrogate accuracy, highlighting the need for data cleaning and adaptive sampling.

Overall, the DOE framework enabled efficient exploration, informative sensitivity analysis, and credible surrogate construction. The observed error patterns reinforce the importance of careful sampling, data curation, and the combination of DOE with machine learning and physics informed AI to sustain predictive performance in highly nonlinear regions.

Case	DOE Method	Geometrical Parameters	Sampling size	Response Surface Prediction (ksi)	Actual (ksi)	Error Prediction
Case_1	Central Composite Design	2	9	76.8	81.8	6.51%
Case_2	Central Composite Design	5	27	81.7	81.8	0.18%
Case_3	Central Composite Design	7	71	Not Generated	81.8	NA
Case_4	Latin Hypercube Sampling	5	150	83.2	81.8	-1.62%
Case_5	Latin Hypercube Sampling	5	98	83.0	81.8	-1.34%
Case_6	Latin Hypercube Sampling	5	55	83.0	81.8	-1.34%
Case_7	Box-Behnken Design	2	5	76.8	81.8	6.59%
Case_8	Box-Behnken Design	5	27	82.2	81.8	0.40%
Case_9	Box-Behnken Design	7	57	Not Generated	81.8	NA
Case_10	Sparse Grid Initialization	2	5	77.1	81.8	6.11%
Case_11	Sparse Grid Initialization	5	11	87.8	81.8	-6.81%
Case_12	Sparse Grid Initialization	7	15	Not Generated	81.8	NA

Table 2: Response Surface Prediction

## GEOMETRIC DEEP LEARNING (GDL)

Altair's Physics AI uses Geometric Deep Learning (GDL) with mesh-based inputs derived from rotor geometry. that preserve topology and connectivity. Graph Neural Networks (GNN) treat meshes as graphs, enabling learning of geometry-driven and physics-informed patterns. This representation is particularly effective for predicting stress and deformation in complex rotor geometries.

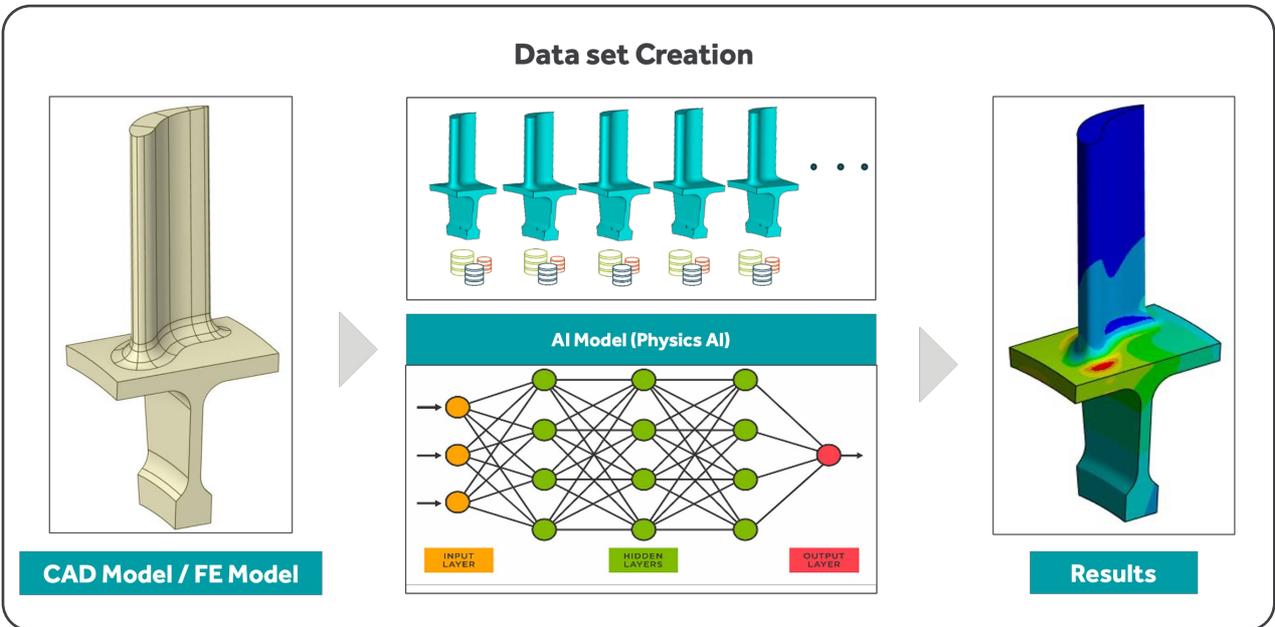


Figure 5: Physics AI Workflow

### Hyperparameters

**Width:** Number of neurons per hidden layer; wider networks capture complex patterns but require more data.

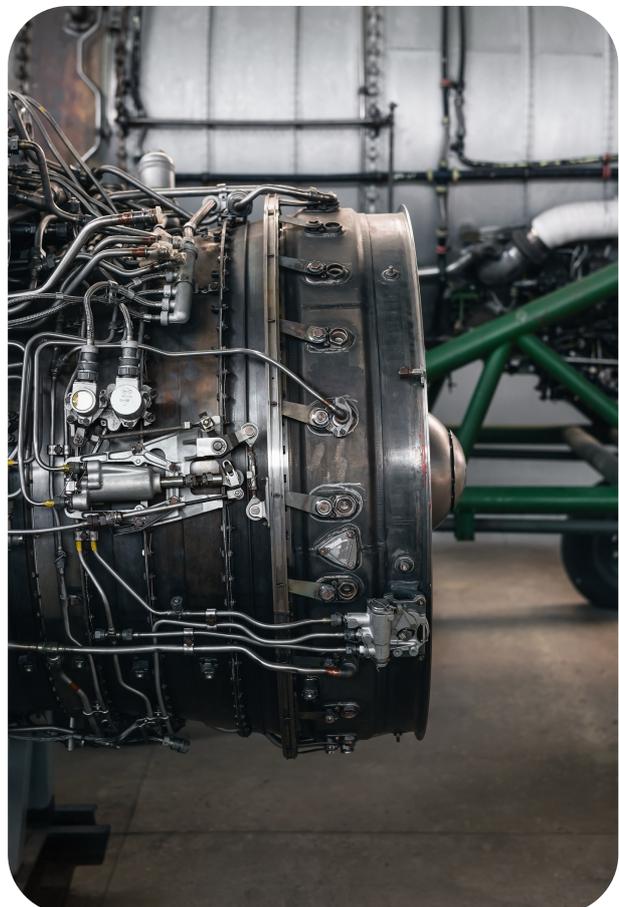
- **Range:** 30–50
- **Impact:** Higher width improves pattern learning but increases complexity.

**Depth:** Number of hidden layers; deeper networks learn abstract features but increase training time.

- **Range:** 3–5
- **Impact:** Greater depth enhances feature extraction but risks overfitting.

**Epochs:** Number of full passes through the training dataset; more epochs improve learning but risk overfitting

- **Range:** 1000
- **Impact:** Higher epochs allow better convergence but risk in overfitting.



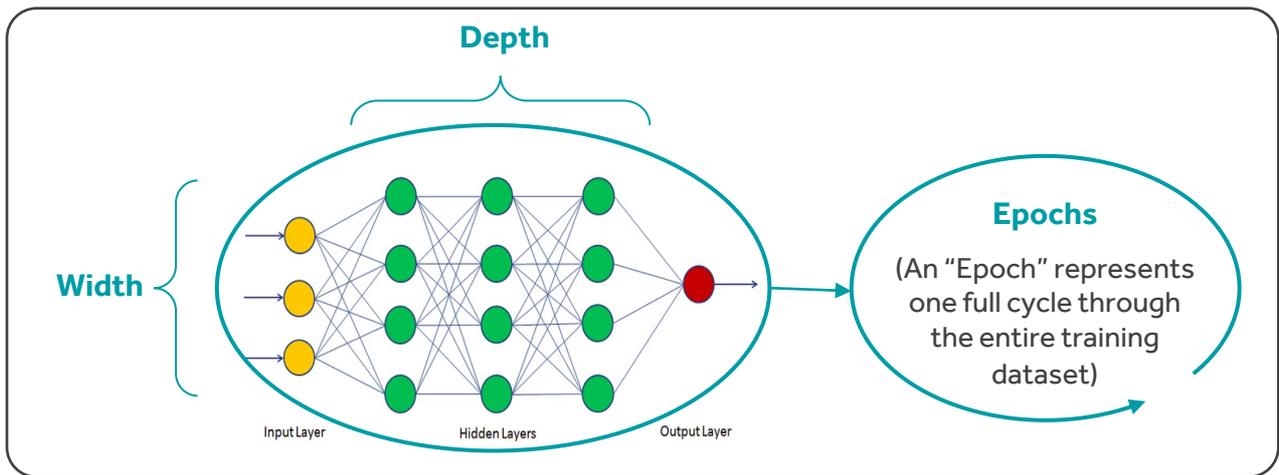


Figure 6: GDL Hyper Parameters

### Loss Functions

**Mean Absolute Error (MAE):** Measures average prediction error magnitude without direction; simple and robust to outliers.

- **Range:** 0 to  $\infty$
- **Accuracy:** Lower is better; 0 = perfect prediction.

**Coefficient of Determination (R<sup>2</sup>):** Indicates how well the model explains variance in the target variable.

- Range:  $(-\infty, 1]$
- Accuracy:
  - 1 = perfect fit
  - 0 = no improvement over baseline
  - Negative = worse than baseline

### Geometric Deep Learning (GDL) – Model Training and Results

Three machine learning models (ML\_1, ML\_2, ML\_3) were trained and tested on 150 DOE design points. Models used mesh based inputs

and FEA labels from a cyclic symmetry sector model. Hyperparameters were varied for width (30–50 neurons per layer) and depth (3–5 hidden layers), with epochs fixed at 1000. Performance was evaluated using Mean Absolute Error (MAE) and Coefficient of Determination (R<sup>2</sup>), and training stability was monitored via loss curves. Table 3 shows GDL model details and their results.

- **MAE/Peak:** All models achieved very low error values ( $\approx 2.03E-03$  to  $2.13E-03$ ), indicating high precision in stress prediction.
- **R<sup>2</sup> (R2mesh):** Values close to 1.0 (0.9996 - 0.9997) confirm excellent correlation between predicted and actual results, demonstrating strong explanatory power.
- **Loss Curve:** All models show converging loss curves, signifying stable training and effective learning without divergence.

Model	Width	Depth	Epochs	MAE/Peak	R <sup>2</sup> (R2mesh)	Loss Curve
ML_1	30	3	1000	2.13E-03	0.9996	Converging
ML_2	40	4	1000	2.03E-03	0.9996	Converging
ML_3	50	5	1000	2.03E-03	0.9997	Converging

Table 3: GDL Model Configuration

Three design points (A, B, and C) were used to validate the predicted stresses from GDL models against FEA results as shown in Figure 7. The performance of each model was assessed using error percentage and confidence score. All models demonstrate efficiency, but their accuracy strongly depends on high-quality training data that adequately covers the design space.

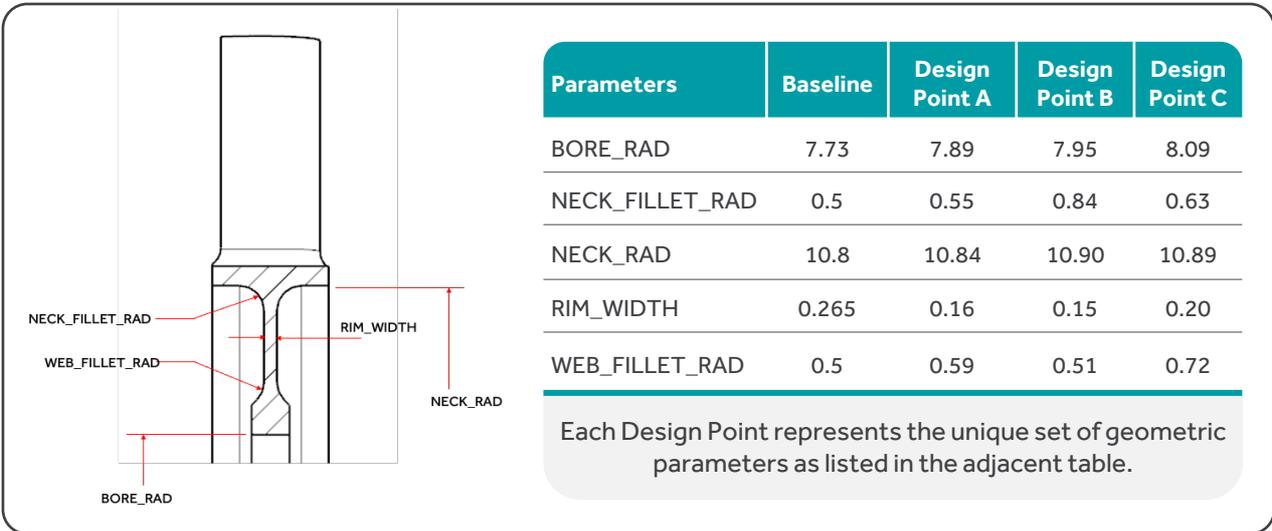


Figure 7: Design points considered for Validation of GDL Models

Figure 8 presents the predicted and actual maximum principal stress distributions for three representative design points (A, B, and C) using the ML\_1 model. The visual comparison highlights the stress contours and prediction differences. The predicted contours generally follow the actual stress distribution, with deviations ranging from 2.75% to 5.12%. Specifically, the error percentages for these points are 2.75% (A), 4.14% (B), and 5.12% (C).

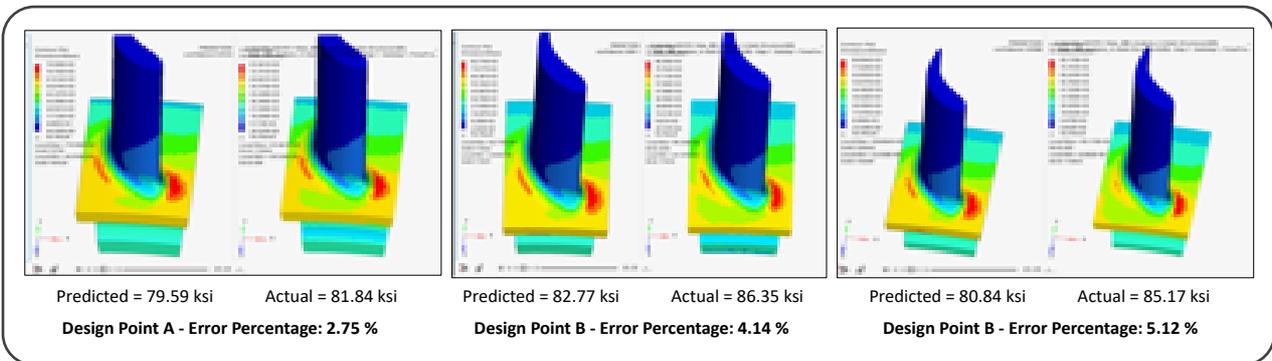


Figure 8: Maximum Principal Stress plots for design points A, B, and C in the ML\_1 model

Figure 9 compares predicted and actual stress values for three models (ML\_1, ML\_2, ML\_3), where ML\_2 consistently aligns closer to actual values, suggesting better generalization. Figure 10 further highlights the percentage error trend, with ML\_2 achieving the lowest error (1.74%–3.99%) and overall error range across all models and points remaining between 1.74% and 5.12%. This consistent performance across multiple design points confirms that AIML-based approaches are reliable for structural stress prediction, while emphasizing the need for comprehensive training data to minimize variability in complex regions.

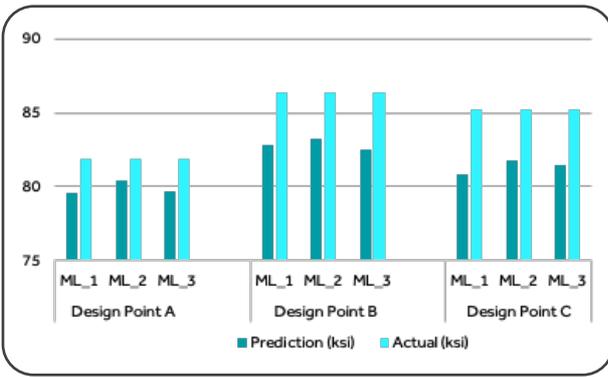


Figure 9: Predicted vs Actual stresses

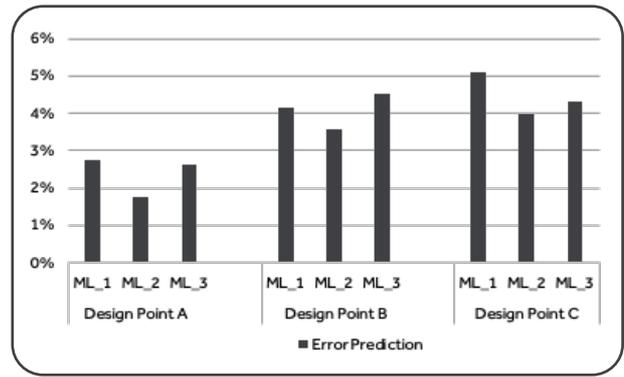


Figure 10: %error prediction of stresses

### SYNERGIZING DOE AND GDL for Data Optimization

In the combined DOE and GDL methodology, the design space is systematically explored using Design of Experiments (DOE) techniques to capture physics-based relationships. Simulation results from DOE are organized into three datasets to evaluate the impact of data reduction on GDL model accuracy:

100% Dataset	70% Dataset	55% Dataset
140 points (after outlier removal from the original 150)	98 points	75 points

The data undergoes rigorous segregation, cleaning, and outlier removal, followed by allocation into training and testing subsets to ensure robust learning. Unlike standalone DOE, which primarily supports sensitivity analysis and response surface generation, or purely data-driven approaches that demand large datasets, this integrated strategy leverages high-quality DOE data to train efficient predictive models. This fusion combines the robustness of physics-based exploration with the speed and generalization capability of GDL, enabling rapid and reliable response prediction even under limited data conditions. The approach significantly reduces simulation time while maintaining accuracy, making it suitable for complex design scenarios such as bladed rotor optimization.

Dataset quality and organization remain critical to dependable AI-driven predictions. Disciplined data preparation including segregation, cleaning, and optimization using tools such as HyperStudy, ensures improved accuracy and consistent performance across a wide range of design conditions.

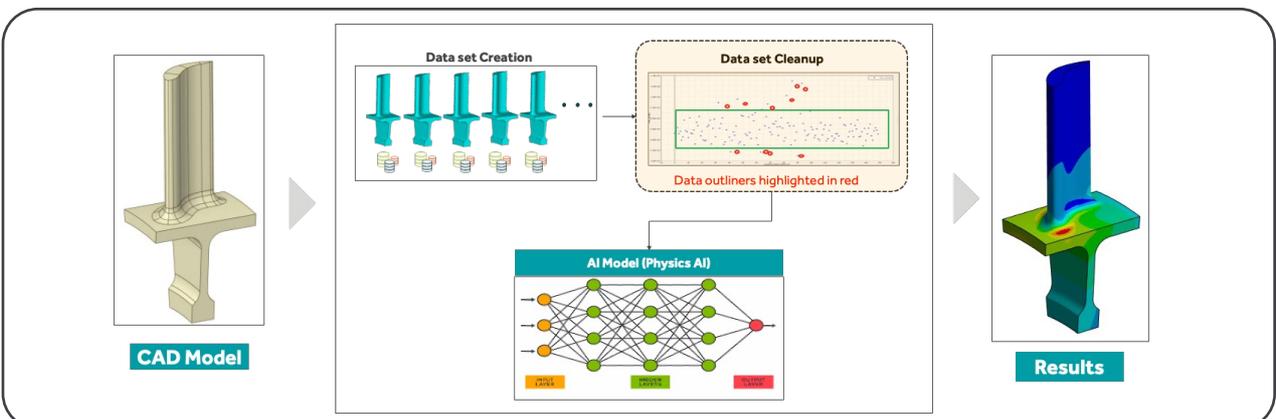


Figure 11: Combined Approach Workflow

## Synergizing DOE and GDL: Integrated Results

This approach leverages Design of Experiments (DOE) to generate high-quality datasets, which are then carefully segregated into training and testing sets, with outlier elimination performed using HyperStudy. These optimized datasets are used to train Physics AI models efficiently, enabling accurate predictions even with reduced data volumes.

The combined methodology demonstrates the efficiency and robustness of GDL-based models, delivering reliable predictions while minimizing the amount of training data

required. Validation across three design points (A, B, and C) shows that even with reduced datasets (70% and 55%), prediction errors remain within a controlled range:

The combined methodology demonstrates the efficiency and robustness of GDL-based models, delivering accurate predictions while minimizing the amount of training data required. Validation across three design points (A, B, and C) shows that even with reduced datasets (70% and 55%), prediction accuracy remains high:

Design Point A	Design Point B	Design Point C
Error ranges from <b>2.22%</b> to <b>2.62%</b> , with the lowest error at <b>2.22%</b> using <b>70%</b> of the dataset.	Error ranges from 3.29% to 4.46%, with the lowest error at 3.29% using 100% of the dataset.	Error ranges from <b>4.10%</b> to <b>4.60%</b> , with the lowest error at <b>4.10%</b> using <b>70%</b> of the dataset.

These results confirm that data optimization enables reliable predictions even with reduced datasets, significantly reducing computational effort without compromising prediction quality. The method also demonstrates strong performance at critical locations, where prediction errors remain between **2.22% and 4.60%**, validating the robustness of the combined DOE–GDL approach. Overall, this integrated framework ensures dependable AI/ML-based stress predictions while minimizing training data requirements.

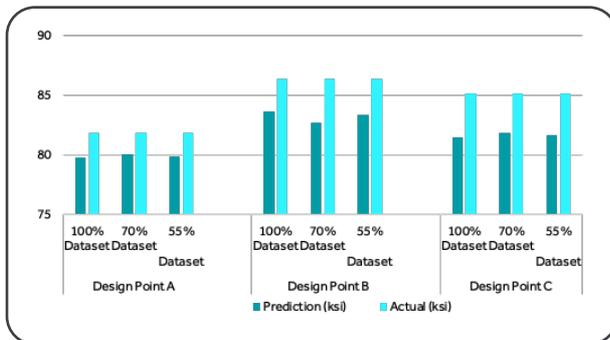


Figure 12: Predicted vs Actual stresses

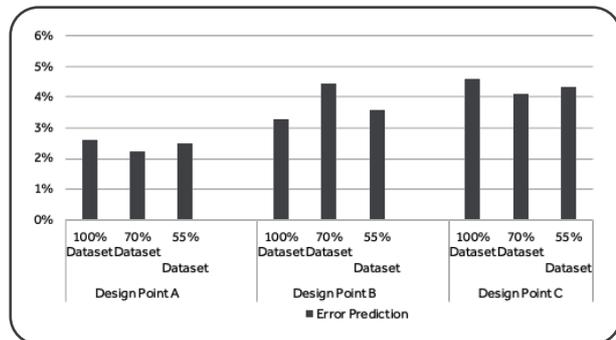


Figure 13: %error prediction of stresses

## Comparison of GDL and GDL–DOE Approaches

The standalone GDL approach uses the full dataset of 150 design points without outlier elimination, achieving prediction errors between 1.74% and 5.12% across design points. In contrast, the integrated GDL–DOE methodology applies outlier elimination, reducing the dataset to 140 points for 100%, and further to 98 points (70%) and 75 points (55%) for optimized training. Eliminating outliers minimizes the influence of anomalous data, leading to more consistent and accurate predictions. Despite the reduction in dataset size, the combined approach maintains errors within 2.22% to 4.60%, demonstrating that DOE-driven optimization and outlier filtering enhance model robustness and efficiency. This synergy significantly reduces computational effort and data requirements while preserving prediction reliability, validating its suitability for practical applications.



## DISCUSSION

### Effectiveness of the DOE–GDL Approach

- GDL surrogates enable rapid trade studies and early design optimization with high accuracy at critical stress locations.
- Integrating DOE with Physics-Based AI supports efficient exploration of nonlinear design spaces without exhaustive simulations.
- In complex IBR applications, Physics-Based AI embedded in CAE workflows accelerates design iteration while maintaining engineering relevance.

### DOE and GDL: Complementary Strengths

- DOE is effective for structured parameter exploration, sensitivity analysis, and response modeling within bounded design spaces.
- DOE scalability is limited in high-dimensional problems due to sampling cost.
- GDL provides fast and accurate predictions within the trained design envelope, subject to data coverage.

### Data Quality and Model Validity

- Reliable predictions depend on consistent data generation, including meshing strategy, material definitions, boundary conditions, and stress extraction.
- Proper data segregation and outlier control are essential for stable training and validation.
- Optimized datasets can retain accuracy while reducing overall simulation effort.

### Limitations

- Model predictions are valid only within the sampled parameter space and should not be used for extrapolation.
- Significant geometry or topology changes require surrogate retraining or full FEA.
- Changes in mesh, material models, or load definitions may degrade accuracy and require reassessment.

## CONCLUSION

The integrated DOE–GDL framework significantly reduces simulation burden and accelerates design iterations for Integrated Bladed Rotors (IBRs) while maintaining accuracy within the sampled design envelope. GDL models deliver high predictive fidelity, achieving low MAE and strong correlation metrics, and data optimization ensures reliable performance even when training datasets are reduced to 70% or 55%. Outlier elimination plays a critical role in minimizing prediction errors and improving model stability. This synergy lowers computational effort without compromising prediction quality, making the approach suitable for complex turbomachinery applications.

Future work will focus on extending the parametric design envelope to evaluate surrogate generalization under broader geometric variations. Controlled sensitivity studies on loading and material properties will further assess reliability beyond baseline conditions. Additional enhancements will include uncertainty quantification using ensemble GDL models and dropout-based approaches to identify regions of high prediction variance and guide adaptive DOE sampling, supporting active-learning strategies for turbomachinery design.

Finally, the trained DOE–GDL surrogate can be integrated as a lightweight module within existing CAE optimization workflows, enabling rapid screening and trade-off studies prior to high-fidelity FEA runs. This integration aligns with best practices in surrogate modeling for accelerating design space exploration in aerospace components. Overall, the workflow combines disciplined engineering judgment in data preparation with geometry-aware learning to accelerate early-stage design exploration.

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## ABOUT THE AUTHORS



**Ayyappa Gadhi** is a Mechanical Engineering graduate with strong expertise in Finite Element Analysis (FEA), covering both static and dynamic simulations. He has experience in aeroengine stress analysis and specializes in applying AI and machine learning to Computer-Aided Engineering (CAE) workflows. Ayyappa leverages advanced tools like PhysicsAI to enhance early-stage design simulations and has contributed to developing ML models for physics-based frameworks. His core interest lies in integrating AI/ML with traditional engineering processes to improve simulation accuracy and efficiency.



**Raviraj Shrivastava** is a Mechanical Engineer with a master's degree from BITS Pilani and has hands-on experience in the FEA domain, specializing in structural and modal analysis. He worked as a CAE Engineer at Cyient. His expertise includes parametric modeling, DOE setup, fatigue analysis, and design automation using tools like ANSYS, HyperMesh. Raviraj is passionate about applying simulation-driven design approaches to enhance structural reliability in the automotive and aerospace sectors.



**Leela Kishore Haresamudra** holds an M.Tech degree from Bangalore University and has over 19 years of experience in the Aerospace and Defense sector. He has extensive expertise in the design, analysis, and simulation of complex engineering systems. His core areas of specialization include Stress Analysis and Engineering Vibrations, with advanced proficiency in Low-Cycle Fatigue (LCF), High-Cycle Fatigue (HCF), and multidisciplinary optimization techniques.



**Srinivasa Rao Rongala** has over 19 years of experience in aero engine stress analysis. He is an expert in the structural analysis of critical components such as rotors and blades, ensuring durability and performance under demanding conditions. His specialization includes advanced assessments like bird strike analysis and fan blade impact evaluations, contributing to enhanced safety and reliability in aero engine design. With deep technical expertise and a strong focus on structural integrity, Srinivasa Rao plays a key role in solving complex engineering challenges in the aerospace domain.



**Lakshman Kasina**, an M.Tech graduate from IIT Madras, has over 24 years of extensive experience in design, analysis, and simulation across various engineering domains. His expertise spans Stress Analysis, Impact Dynamics, Engineering Vibrations, and Composite Modeling. He is proficient in Low-Cycle Fatigue (LCF) and High-Cycle Fatigue (HCF), as well as advanced simulation techniques like multidisciplinary optimization. Lakshman has published over 10 papers in national and international conferences, demonstrating his significant contributions to the field.

## About Cyient

Cyient (Estd: 1991, NSE: CYIENT) delivers intelligent engineering solutions across products, plants, and networks for over 300 global customers, including 30% of the top 100 global innovators. As a company, Cyient is committed to designing a culturally inclusive, socially responsible, and environmentally sustainable tomorrow together with our stakeholders.

For more information, please visit [www.cyient.com](http://www.cyient.com)



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