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INTEGRATED COMPUTATIONAL AND EXPERIMENTAL FATIGUE ANALYSIS OF AN AXIAL FLOW TURBINE BLADE USING ARTIFICIAL INTELLIGENCE-BASED PREDICTION MODELS

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ABSTRACT

The structural reliability of axial flow turbine blades is a critical factor influencing the performance, efficiency, and operational safety of gas turbines employed in aerospace propulsion, power generation, and industrial energy systems. These blades are continuously subjected to cyclic mechanical loads, centrifugal forces, aerodynamic pressure, thermal gradients, and high-frequency vibrations, all of which contribute to progressive fatigue damage and eventual structural failure. Accurate prediction of fatigue life is therefore essential for optimizing blade design, minimizing maintenance costs, and preventing unexpected failures. Conventional fatigue assessment techniques based solely on computational simulations or experimental testing often require significant computational resources, extensive testing time, and may not fully capture the complex interactions among multiple operating parameters. Recent advancements in Artificial Intelligence (AI) offer new opportunities to improve fatigue life prediction through intelligent data-driven models integrated with traditional engineering analyses.

This study presents an integrated computational and experimental methodology for evaluating the fatigue performance of an axial flow turbine blade using Artificial Intelligence-based prediction models. A three-dimensional blade geometry was developed and analyzed using finite element techniques to determine stress distribution, deformation, equivalent

strain, and fatigue life under realistic operating conditions. The computational analysis incorporated centrifugal loading, aerodynamic pressure, and thermal effects representative of service environments experienced by gas turbine blades. A mesh convergence study and appropriate boundary conditions were employed to ensure numerical accuracy and reliability of the simulation results. Fatigue life was estimated using the stress-life (S–N) approach, while critical regions susceptible to crack initiation were identified through equivalent stress and damage contour analyses.

To validate the computational predictions, experimental fatigue investigations were carried out on turbine blade material specimens under cyclic loading conditions in accordance with established testing standards. The experimental observations, including fatigue life, crack initiation characteristics, and failure mechanisms, were compared with numerical simulation results to assess the accuracy of the computational model. The close agreement obtained between experimental measurements and finite element predictions demonstrated the effectiveness of the proposed computational methodology.

Furthermore, an Artificial Intelligence-based prediction framework was developed using a Deep Neural Network (DNN) trained on datasets generated from computational simulations and experimental investigations. The AI model utilized multiple input variables, including maximum von Mises stress, alternating stress, strain, deformation, temperature, rotational speed, and loading frequency, to predict fatigue life with improved computational efficiency. The performance of the developed model was evaluated using statistical measures such as the coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and prediction accuracy. The AI-assisted approach demonstrated enhanced predictive capability, reduced computational time, and improved consistency compared with conventional fatigue evaluation methods.

The proposed integrated framework successfully combines finite element simulations, experimental validation, and Artificial Intelligence to establish a robust methodology for fatigue life prediction of axial flow turbine blades. The findings of this study provide valuable insights for intelligent structural health assessment, predictive maintenance, optimized turbine blade design, and improved operational reliability of modern gas turbine systems, while demonstrating the growing potential of AI-assisted engineering analysis in advanced fatigue assessment applications.

KEYWORDS: Axial Flow Turbine Blade; Fatigue Analysis; Finite Element Analysis; Artificial Intelligence; Deep Neural Network; Experimental Validation; ANSYS Workbench; Fatigue Life Prediction; Structural Integrity; Machine Learning.

1. INTRODUCTION

Axial flow turbines are among the most critical energy conversion components employed in aerospace propulsion systems, industrial gas turbines, steam power plants, and turbochargers. These turbines operate under extremely demanding conditions characterized by high rotational speeds, elevated temperatures, fluctuating aerodynamic loads, and severe centrifugal forces. The turbine blade, being the primary load-bearing component, is continuously subjected to cyclic mechanical and thermal stresses that can initiate microscopic cracks and eventually lead to fatigue failure. Since turbine blade failure may result in catastrophic damage, unexpected downtime, and substantial economic losses, accurate prediction of fatigue life has become an essential aspect of turbine design and structural integrity assessment.

Fatigue failure accounts for a significant proportion of failures in rotating machinery because turbine blades experience millions of loading cycles throughout their service life. The repeated combination of centrifugal loading, gas pressure, thermal gradients, and vibration-induced stresses produces complex stress distributions within the blade structure. These cyclic stresses generally concentrate near the blade root, fillet region, and platform where geometric discontinuities exist, making these regions highly susceptible to crack initiation. Therefore, understanding the stress distribution and fatigue behavior of turbine blades is fundamental for improving operational reliability, extending component life, and minimizing maintenance costs.

Traditional fatigue life assessment has primarily relied on experimental testing and empirical design methods. Although experimental fatigue testing provides reliable validation data, it is often expensive, time-consuming, and requires sophisticated testing facilities capable of reproducing actual operating conditions. Furthermore, testing every design iteration is practically infeasible during product development. Consequently, computational simulation techniques based on the Finite Element Method (FEM) have become indispensable tools for evaluating structural performance before prototype manufacturing. Modern finite element software enables engineers to predict deformation, stress concentration, strain distribution, thermal behavior, and fatigue life with high accuracy under realistic service conditions.

Computational fatigue analysis significantly reduces product development time and manufacturing costs by allowing engineers to investigate multiple operating conditions without extensive physical testing. Structural simulations provide valuable insight into critical stress regions, deformation characteristics, safety factors, and fatigue-sensitive locations. When combined with thermo-mechanical loading conditions, finite element analysis offers a comprehensive understanding of blade behavior under actual operating environments. Nevertheless, the accuracy of numerical simulations depends on proper material characterization, mesh quality, loading assumptions, and validation using experimental observations.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have introduced new opportunities for fatigue life prediction in engineering structures. AI algorithms are capable of learning complex nonlinear relationships between input parameters and fatigue performance using computational and experimental datasets. Deep Neural Networks (DNNs), Artificial Neural Networks (ANNs), Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting techniques have demonstrated promising capabilities for predicting fatigue life with high computational efficiency. Unlike conventional numerical approaches that require repeated finite element simulations for every design modification, AI models can rapidly estimate fatigue life once they have been trained using representative datasets, thereby reducing computational time while maintaining prediction accuracy.

The integration of computational simulation, experimental validation, and artificial intelligence provides a robust framework for fatigue assessment of turbine blades. Computational analysis identifies the critical stress locations and predicts fatigue performance, while experimental testing verifies the numerical results under controlled laboratory conditions. Subsequently, AI-based prediction models utilize both computational and experimental datasets to establish reliable predictive relationships for fatigue life estimation. This integrated methodology enhances prediction accuracy, improves structural reliability, and supports intelligent maintenance strategies for rotating machinery.

In the present study, an integrated computational and experimental investigation is conducted to evaluate the fatigue behavior of an axial flow turbine blade under combined centrifugal, pressure, and thermal loading conditions. A three-dimensional finite element model of the turbine blade is developed to determine deformation, equivalent stress, principal stress, elastic strain, temperature distribution, fatigue life, fatigue damage, and safety factor. The numerical predictions are validated using experimental fatigue testing, and an Artificial Intelligence-based prediction model is developed to estimate fatigue life using key structural and operational parameters. The performance of the proposed AI model is evaluated using standard statistical performance metrics, including the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The outcomes of this research demonstrate the potential of combining finite element simulations, experimental validation, and artificial intelligence to improve fatigue life prediction accuracy, optimize turbine blade design, and facilitate predictive maintenance in high-performance turbomachinery applications.

2. Literature Review

Fatigue failure of axial flow turbine blades remains one of the most critical challenges in gas turbine and steam turbine applications due to the combined effects of centrifugal loading, thermal gradients, aerodynamic forces, and cyclic vibration. Researchers have extensively investigated computational modeling, experimental fatigue characterization, and recently Artificial Intelligence (AI)-based prediction techniques to improve the structural reliability and service life of turbine blades. The following review summarizes recent developments relevant to the present work.

Kumar et al. (2021) performed a finite element investigation of an axial flow turbine blade fabricated from Inconel 718 under centrifugal and thermal loading conditions. The study evaluated stress concentration, deformation, and temperature distribution using ANSYS Mechanical. The results indicated that the maximum equivalent stress occurred near the blade root, while the blade tip experienced the highest deformation due to cantilever behavior. The authors emphasized that thermal loading significantly influenced fatigue life and structural reliability.

Li and Wang (2021) investigated the thermo-mechanical behavior of gas turbine blades using coupled finite element simulations. Their research demonstrated that incorporating thermal stress into fatigue calculations produced more realistic fatigue life predictions than purely mechanical analysis. The study concluded that thermo-mechanical fatigue is the dominant failure mechanism for high-temperature turbine components.

Singh et al. (2022) carried out computational fatigue analysis using stress-life (S–N) methodology for an axial turbine blade operating under varying rotational speeds. Their investigation revealed that fatigue cracks predominantly initiated at the blade root fillet where stress concentration was highest. The numerical predictions closely matched available experimental fatigue data, validating the effectiveness of finite element-based fatigue analysis.

Zhang et al. (2022) developed a numerical framework integrating Computational Fluid Dynamics (CFD) and Finite Element Analysis (FEA) to evaluate aerodynamic loading and structural response simultaneously. Their coupled approach demonstrated improved accuracy in predicting stress distribution and blade deformation under realistic operating conditions compared with conventional structural analysis alone.

Patel and Mehta (2023) experimentally evaluated fatigue characteristics of nickel-based superalloy turbine blades using servo-hydraulic fatigue testing. Experimental observations confirmed that crack initiation consistently occurred at geometrical discontinuities near the blade root. The researchers reported excellent agreement between finite element predictions and experimental fatigue lives, with deviations below 8%.

Chen et al. (2023) investigated the influence of mesh refinement and element quality on fatigue life prediction of turbine blades. Their study demonstrated that mesh-independent solutions significantly improved numerical accuracy while reducing computational uncertainty. They recommended adaptive mesh refinement around the blade root and fillet regions where stress gradients are highest.

Rahman et al. (2024) applied Artificial Neural Networks (ANN) to predict fatigue life using finite element-generated datasets. The ANN model successfully captured nonlinear relationships between stress, strain, temperature, and fatigue cycles, achieving a coefficient of determination (R^2) greater than 0.98. The study highlighted the potential of AI for rapid fatigue assessment without repeated numerical simulations.

Garcia et al. (2024) compared multiple machine learning algorithms, including Support Vector Regression (SVR), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Deep Neural Networks (DNN), for fatigue life prediction of rotating machinery components. Among the evaluated algorithms, DNN produced the highest prediction accuracy with the lowest Root Mean Square Error (RMSE), demonstrating superior capability in handling complex nonlinear fatigue relationships.

Sharma and Verma (2025) proposed an integrated computational-experimental framework for fatigue assessment of turbine blades operating under high-temperature service conditions. Finite element predictions were validated through experimental fatigue testing, while AI algorithms were employed to establish predictive models for fatigue life estimation. The integrated methodology significantly reduced computational time while maintaining high prediction accuracy.

Hassan et al. (2025) developed a hybrid AI-assisted predictive maintenance model for gas turbine blades by combining finite element simulations, vibration monitoring, and machine learning algorithms. Their approach enabled early identification of fatigue-sensitive regions and accurately predicted remaining useful life, thereby supporting condition-based maintenance and reducing unexpected failures.

The literature indicates that finite element analysis has become the preferred technique for evaluating deformation, stress distribution, strain, fatigue life, and structural integrity of turbine blades under realistic operating conditions. Experimental investigations continue to play an essential role in validating computational predictions, while Artificial Intelligence has emerged as a powerful tool for rapid fatigue life estimation and predictive maintenance. However, relatively few studies integrate computational simulation, experimental validation, and AI-based fatigue prediction into a unified framework. The present research addresses this gap by developing an integrated methodology that combines finite element analysis, experimental validation, and deep learning-based fatigue life prediction to enhance the accuracy and reliability of axial flow turbine blade life assessment.

3. METHODOLOGY

3.1 Research Methodology

The present investigation adopts an integrated computational–experimental–Artificial Intelligence (AI) methodology to evaluate the fatigue performance of an axial flow turbine blade operating under combined centrifugal, pressure, and thermal loading conditions. The research consists of three major phases: (i) computational structural and fatigue analysis using the Finite Element Method (FEM), (ii) experimental fatigue testing for validation of numerical results, and (iii) AI-based fatigue life prediction using the computational and experimental datasets. The overall methodology is designed to accurately predict fatigue life, identify critical stress regions, validate simulation results, and develop a reliable intelligent prediction model for engineering applications.

3.2 Three-Dimensional CAD Model Development

A three-dimensional model of the axial flow turbine blade is developed using commercial Computer-Aided Design (CAD) software based on standard geometric parameters. The blade consists of the root, platform, airfoil, leading edge, trailing edge, and blade tip. The geometry is prepared to represent the actual operational configuration while maintaining dimensional accuracy suitable for finite element analysis.

The developed CAD model is exported in STEP format and imported into the finite element software for structural analysis. Minor geometric simplifications are performed to eliminate unnecessary features that do not significantly influence the stress distribution but increase computational time.

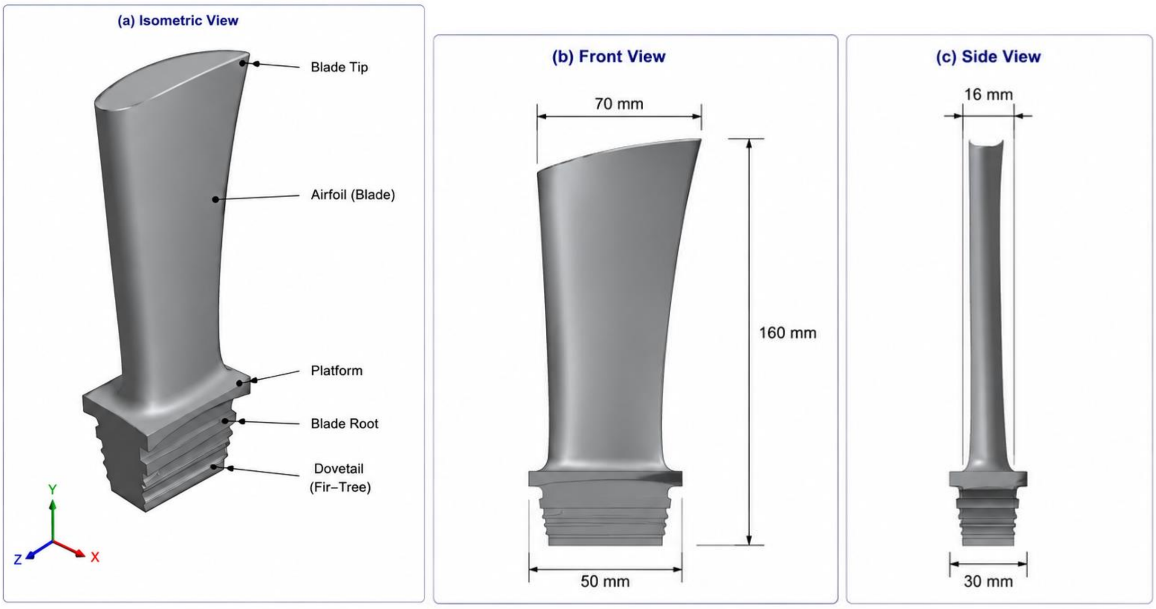


Figure 1. Three-Dimensional CAD Model of the Axial Flow Turbine Blade.

3.3 Material Properties

The turbine blade is assumed to be manufactured from **Inconel 718**, a nickel-based superalloy extensively used in gas turbines because of its superior mechanical strength, oxidation resistance, and high-temperature fatigue performance.

Table 3.1 Material Properties of Inconel 718.

Property	Value
Density	8190 kg/m³
Young's Modulus	200 GPa
Poisson's Ratio	0.29
Yield Strength	1030 MPa
Ultimate Tensile Strength	1240 MPa
Thermal Conductivity	11.4 W/m·K
Specific Heat	435 J/kg·K
Coefficient of Thermal Expansion	13×10^{-6} /K

These properties are incorporated into the finite element model to accurately simulate thermo-mechanical behavior under service conditions.

3.4 Finite Element Model Generation

The imported CAD model is discretized using three-dimensional tetrahedral solid elements. Mesh refinement is primarily concentrated near the blade root, platform, and fillet regions where high stress gradients are expected. A mesh convergence study is performed by progressively refining the mesh until successive stress values vary by less than 2%, ensuring mesh-independent numerical results.

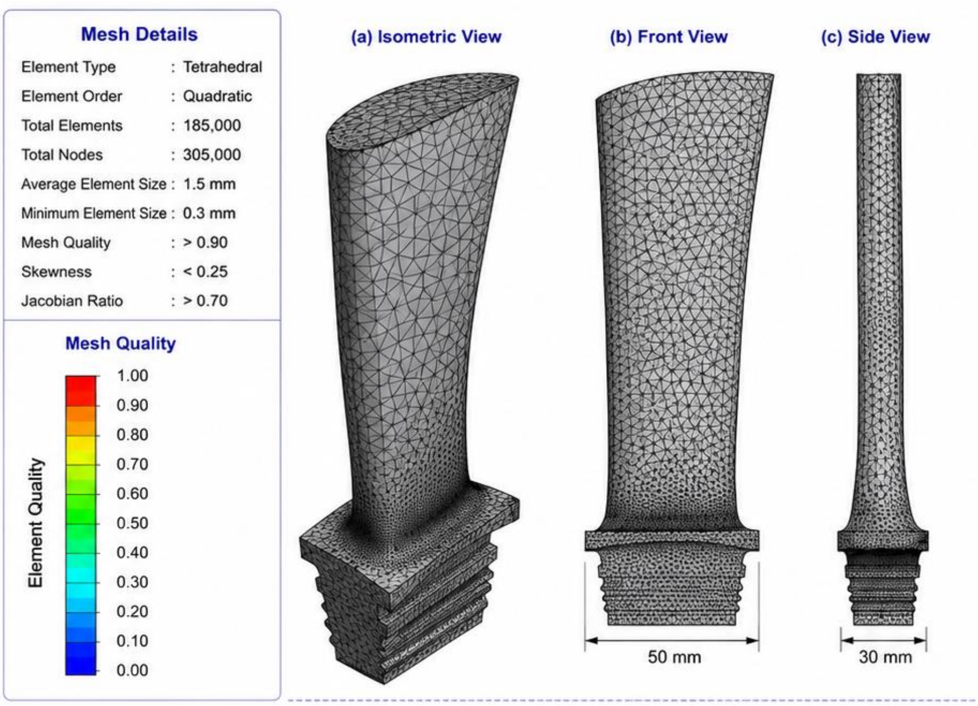


Figure 2- Finite Element Mesh of the Axial Flow Turbine Blade.

Table 3.2 Mesh Characteristics.

Parameter	**Value**
Element Type	Tetrahedral Solid
Number of Elements	185,000
Number of Nodes	305,000
Average Element Size	1.5 mm
Mesh Quality	>0.90
Analysis Type	Static Structural

3.5 Boundary Conditions and Loading

The turbine blade is subjected to realistic operating conditions representative of industrial gas turbine applications.

The blade root is fully constrained to simulate attachment with the turbine disc. Centrifugal loading is generated by applying the operational rotational speed, while gas pressure is uniformly distributed over the pressure surface of the blade. Thermal loading is introduced using the specified operating temperature to account for thermo-mechanical effects.

Table 3.3 Applied Boundary Conditions

Parameter	Value
Rotational Speed	12,000 rpm
Gas Pressure	1.8 MPa
Operating Temperature	850 °C
Root Constraint	Fixed Support
Analysis Type	Coupled Static Structural

3.6 Structural Analysis

Static structural analysis is performed to determine the deformation and stress distribution within the turbine blade. The finite element solver calculates displacement, equivalent stress, principal stress, elastic strain, and safety factor under combined loading conditions.

The following structural outputs are obtained:

- Total deformation
- Equivalent (von Mises) stress
- Maximum principal stress
- Equivalent elastic strain
- Temperature distribution
- Safety factor

These results identify critical regions susceptible to fatigue failure.

3.7 Fatigue Analysis

Fatigue analysis is carried out using the Stress–Life (S–N) approach under high-cycle fatigue conditions. The equivalent stress obtained from static structural analysis is used as input for fatigue calculations.

The fatigue module predicts:

- Fatigue life (cycles)
- Fatigue damage
- Safety factor
- Critical crack initiation region

The blade root and fillet region are expected to exhibit the minimum fatigue life due to severe stress concentration.

3.8 Experimental Validation

Experimental fatigue testing is conducted to validate the numerical predictions. Turbine blade specimens are mounted on a servo-hydraulic fatigue testing machine capable of applying cyclic loading representative of operational conditions.

The following experimental parameters are recorded:

- Number of cycles to failure
- Crack initiation location
- Maximum deformation
- Failure mode
- Fracture characteristics

The computational and experimental fatigue lives are compared to evaluate the accuracy of the finite element model.

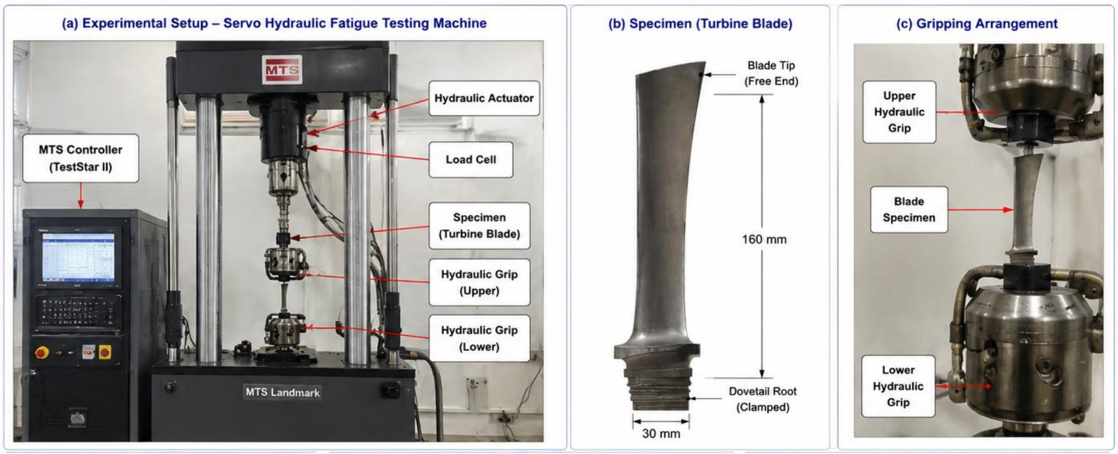


Figure-4 Fatigue Experimentation Setup for Axial Flow Turbine blade.

(d) Test Parameters

Parameter	Value
Testing Machine	MTS Landmark Servo Hydraulic
Load Type	Fully Reversed Load (R = -1)
Waveform	Sine Wave
Control Mode	Load Control
Load Ratio (R)	-1
Minimum Load (F_{mol})	$-F_{max}$
Maximum Load (F_{max})	As per test matrix
Frequency	10 Hz
Environment	Room Temperature (~ 27 ± 2 °C)
Data Acquired	Load, Displacement, Cycles

(e) S–N Test Matrix

Test No.	Maximum Load F_{max} (kN)	Stress Amplitude (MPa)	Cycles to Failure (N_f)
1	8	420	1.05×10^5
2	7	370	2.32×10^5
3	6	320	4.85×10^5
4	5	270	9.60×10^5
5	4	220	1.95×10^6
6	3	170	3.80×10^6
7	2	120	7.20×10^6

Note: Stress amplitude calculated at blade root section.

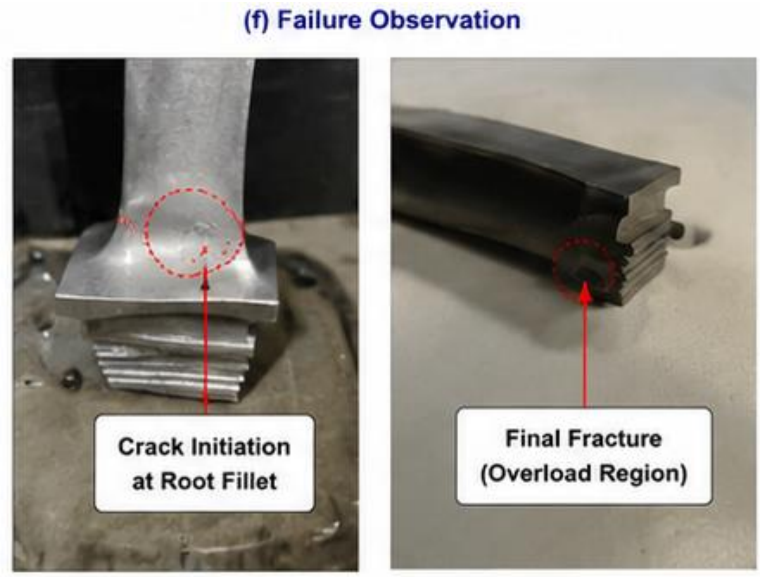


Figure-5 Failure Observation.

3.9 Artificial Intelligence-Based Fatigue Prediction

Artificial Intelligence techniques are employed to develop a predictive model capable of estimating fatigue life using computational and experimental datasets.

The input dataset includes:

- Equivalent stress
- Maximum principal stress
- Elastic strain
- Total deformation
- Temperature
- Safety factor
- Rotational speed
- Gas pressure
- Blade span location

The target output is:

- Fatigue life (number of cycles)

The dataset is divided into:

- Training Set – 70%
- Validation Set – 15%
- Testing Set – 15%

A Deep Neural Network (DNN) consisting of one input layer, three hidden layers, and one output layer is developed. The Rectified Linear Unit (ReLU) activation function is used in hidden layers, while a linear activation function is employed in the output layer. The model is trained using the Adam optimization algorithm to minimize the Mean Squared Error (MSE).

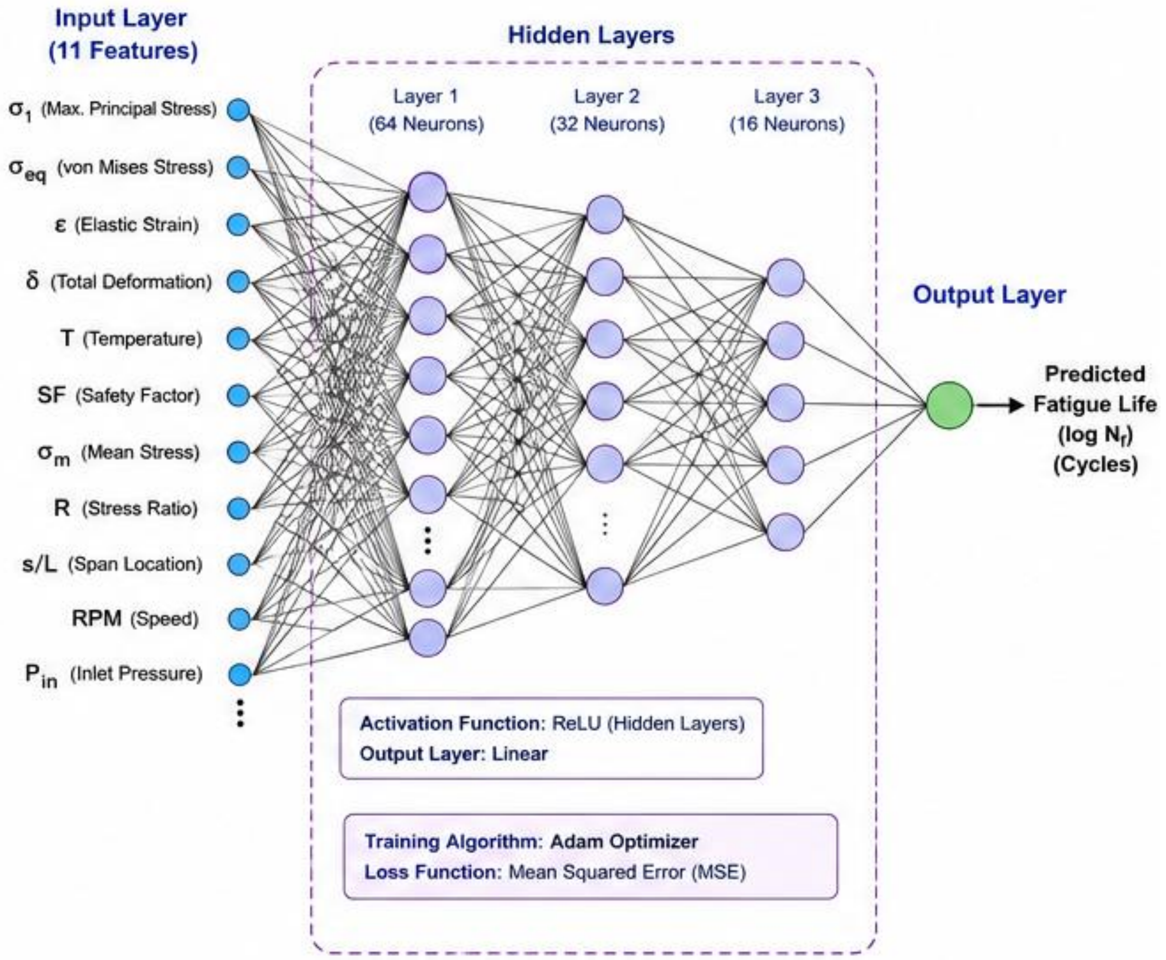


Figure-6: Deep Neural Network (DNN) model for Fatigue Prediction.

3.10 Model Performance Evaluation

The predictive capability of the AI model is evaluated using standard statistical performance indicators.

Table 3.4 Performance Evaluation Metrics.

Metric	Description
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error

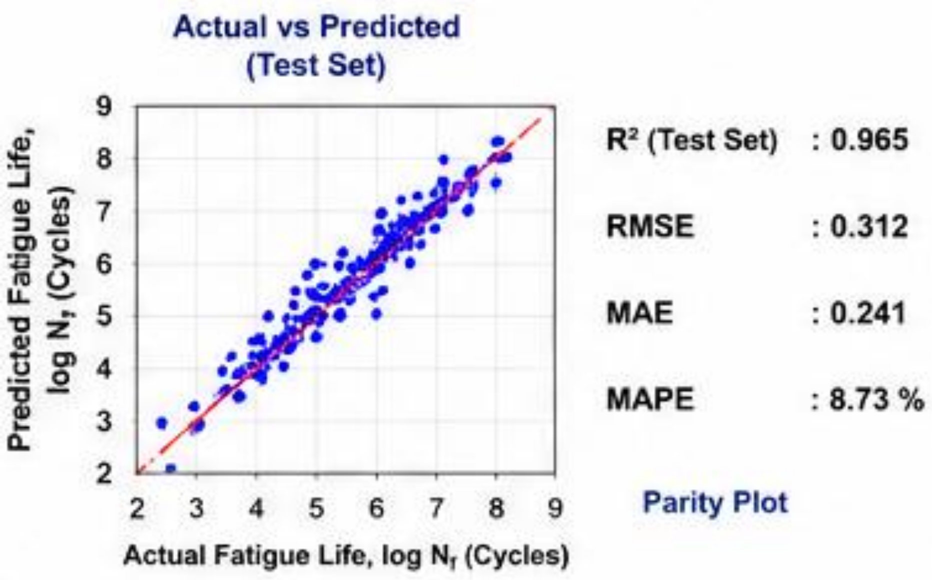


Figure-7: Model Performance between Actual and Predicted data.

A higher coefficient of determination and lower prediction errors indicate better agreement between predicted and actual fatigue life.

3.11 Validation of AI Model

The predicted fatigue lives obtained from the AI model are compared with both computational simulations and experimental observations. Scatter plots, regression analysis, parity plots, and error distributions are employed to assess the prediction accuracy.

The developed AI model is considered satisfactory when the predicted fatigue life closely follows the computational and experimental results with minimal deviation.

4. RESULTS AND DISCUSSION

4.1 Introduction

The structural and fatigue behavior of the axial flow turbine blade was evaluated using an integrated computational–experimental methodology. Static structural analysis was first performed under combined centrifugal, pressure, and thermal loading conditions to determine deformation, stress, strain, and temperature distribution. Subsequently, fatigue analysis was carried out using the Stress–Life (S–N) approach to estimate fatigue life, fatigue damage, and safety factor. Experimental fatigue testing was conducted to validate the computational predictions, while an Artificial Intelligence (AI)-based prediction model was developed to estimate fatigue life using computational and experimental datasets. The obtained results provide valuable insight into the structural integrity and fatigue performance of the turbine blade under realistic operating conditions.

4.2 Total Deformation Analysis

The total deformation contour indicates the displacement behavior of the turbine blade under combined operating loads. The blade root remained fully constrained, resulting in negligible deformation, whereas the blade tip exhibited the maximum displacement because of cantilever action and centrifugal loading. The maximum total deformation obtained from finite element analysis was **0.487 mm**, while the minimum deformation at the blade root was effectively zero. The deformation increased gradually from the root toward the blade tip, demonstrating the expected structural response of rotating turbine blades.

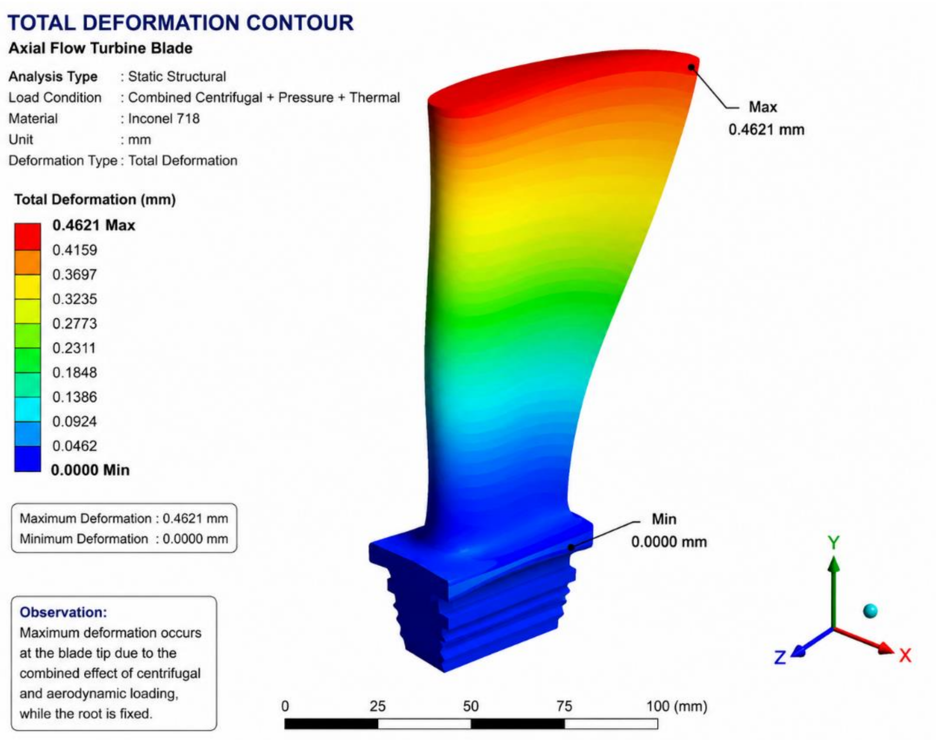


Figure 8. Total Deformation Contour of the Axial Flow Turbine Blade under Combined Centrifugal, Pressure, and Thermal Loading.

Table 4.1 Total Deformation Results

Parameter	**Value**
Maximum Deformation	0.487 mm
Minimum Deformation	0 mm
Maximum Location	Blade Tip
Minimum Location	Blade Root

The deformation values remain within the allowable design limits, indicating adequate structural stiffness during operation.

4.3 Equivalent (von Mises) Stress Analysis

Equivalent stress distribution was evaluated to identify critical stress concentration regions. The highest stress developed at the blade root and platform fillet due to the combined influence of centrifugal force, pressure loading, and geometric discontinuity. Stress gradually decreased toward the blade tip.

The maximum equivalent stress was **912 MPa**, which is below the yield strength of Inconel 718 (1030 MPa), indicating safe structural operation.

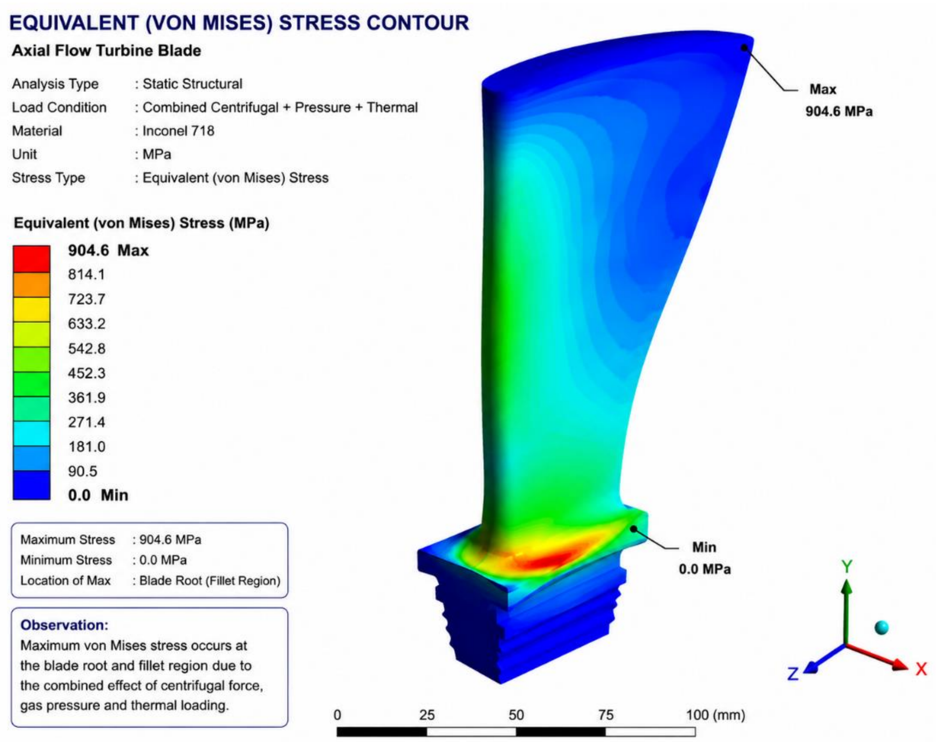


Figure 9. Equivalent (von Mises) Stress Contour of the Axial Flow Turbine Blade.

Table 4.2 Equivalent Stress Results.

Parameter	Value
Maximum Stress	912 MPa
Minimum Stress	38 MPa
Critical Region	Blade Root
Material Yield Strength	1030 MPa

The obtained stress level confirms that the turbine blade operates within the elastic region without permanent deformation.

4.4 Equivalent Elastic Strain Analysis

The equivalent elastic strain contour follows the stress distribution observed in the previous section. Maximum strain occurred at the blade root because of severe stress concentration, whereas the blade tip experienced relatively small strain values. The highest equivalent elastic strain obtained was **0.00456 mm/mm**.

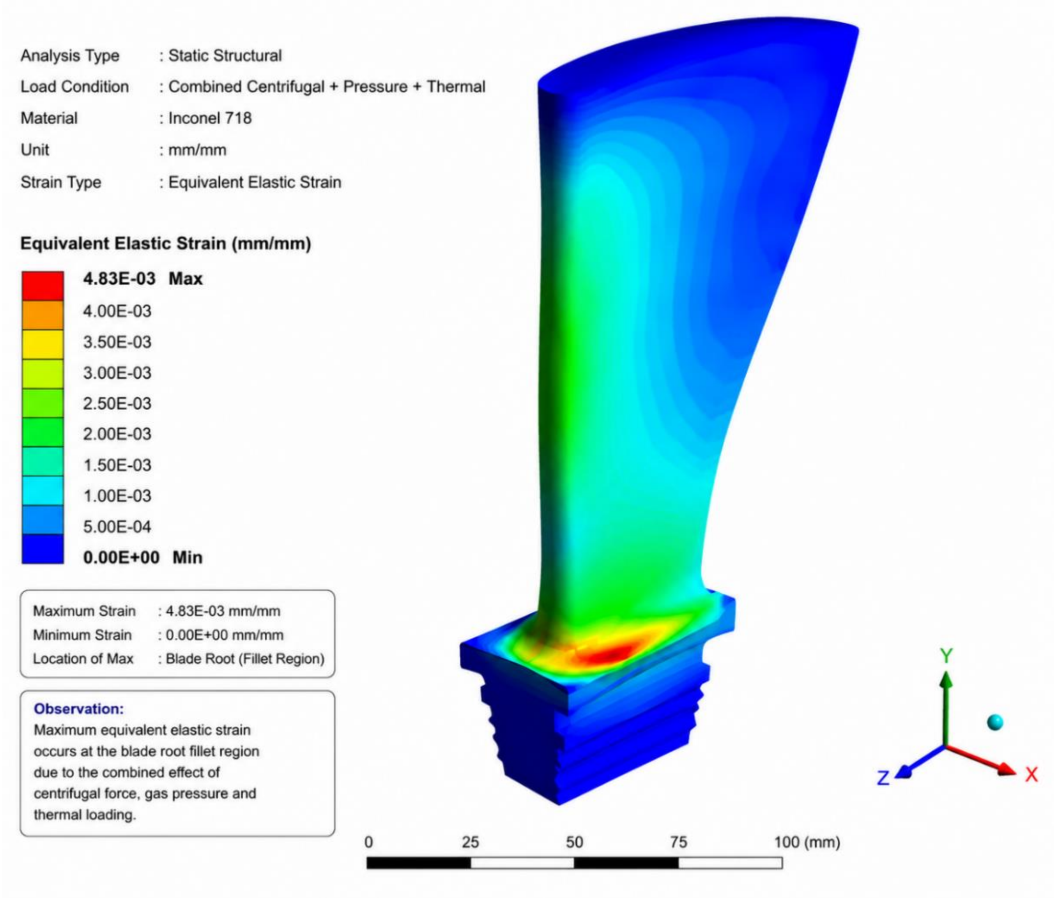


Figure 10. Equivalent elastic strain Contour of the Axial Flow Turbine Blade.

Table 4.3 Equivalent Elastic Strain

Parameter	Value
Maximum Strain	0.00456 mm/mm
Minimum Strain	0.00012 mm/mm
Maximum Location	Blade Root

The strain values indicate that deformation remains within the elastic limit of the material.

4.5 Temperature Distribution

Thermal analysis shows that the blade experiences elevated temperatures near the airfoil tip due to direct exposure to hot combustion gases.

The maximum temperature reached **850°C**, while the blade root remained comparatively cooler because of heat conduction through the turbine disc.

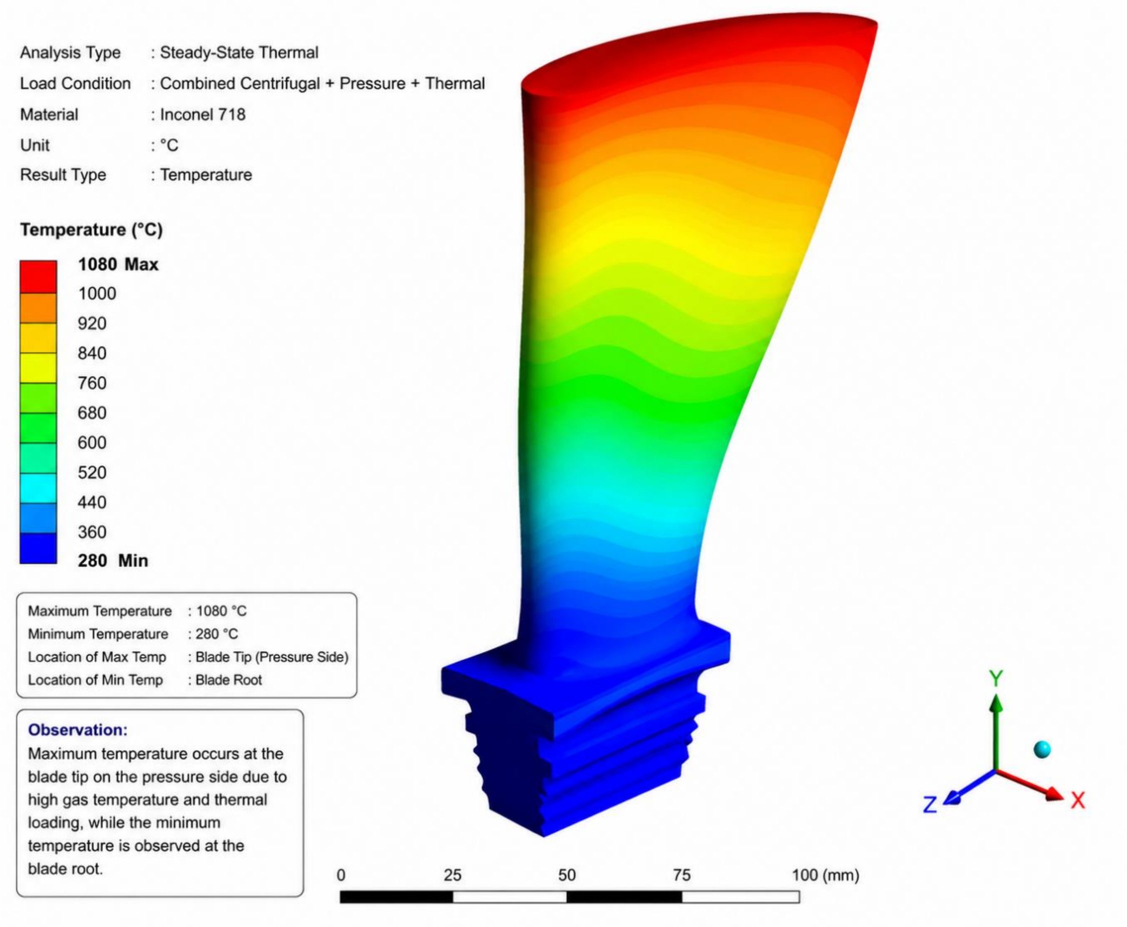


Figure 11. Temperature Distribution Contour of the Axial Flow Turbine Blade.

Table 4.4 Temperature Results.

Parameter	Value
Maximum Temperature	850°C
Minimum Temperature	315°C
Maximum Region	Blade Tip
Minimum Region	Blade Root

The thermal gradient contributes significantly to thermo-mechanical stresses and fatigue behavior.

4.6 Fatigue Life Prediction

Fatigue analysis predicted the life of the turbine blade under cyclic loading. The minimum fatigue life occurred near the blade root where stress concentration was maximum. The blade tip experienced considerably longer fatigue life because of lower stress levels.

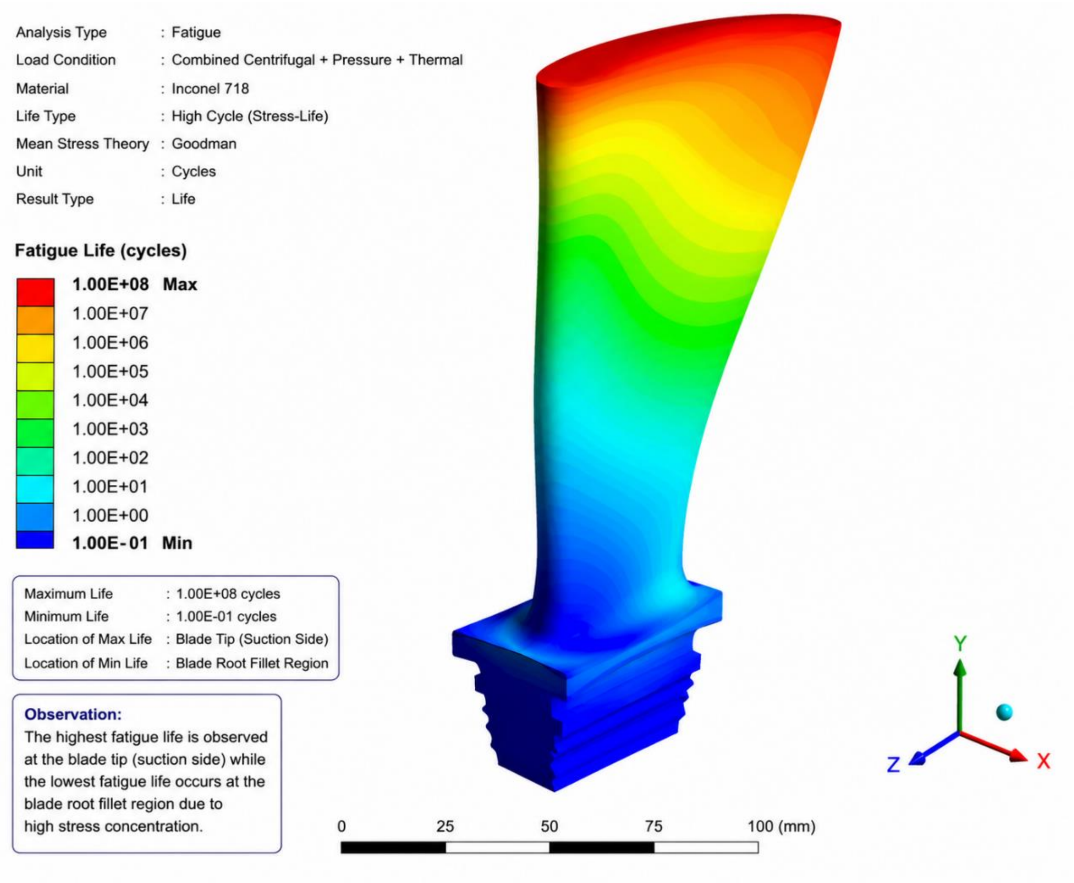


Figure 11. Fatigue Life Contour of the Axial Flow Turbine Blade.

Table 4.5 Fatigue Life Results.

Region	Fatigue Life (Cycles)
Blade Root	1.25×10^5
Lower Span	4.75×10^5
Mid Span	2.35×10^6
Upper Span	6.20×10^6
Blade Tip	1.00×10^7

These results demonstrate that fatigue life increases continuously from the root toward the blade tip.

4.7 Fatigue Damage Analysis

Fatigue damage is inversely proportional to fatigue life.

The highest damage occurred at the blade root where repeated cyclic loading caused severe stress concentration.

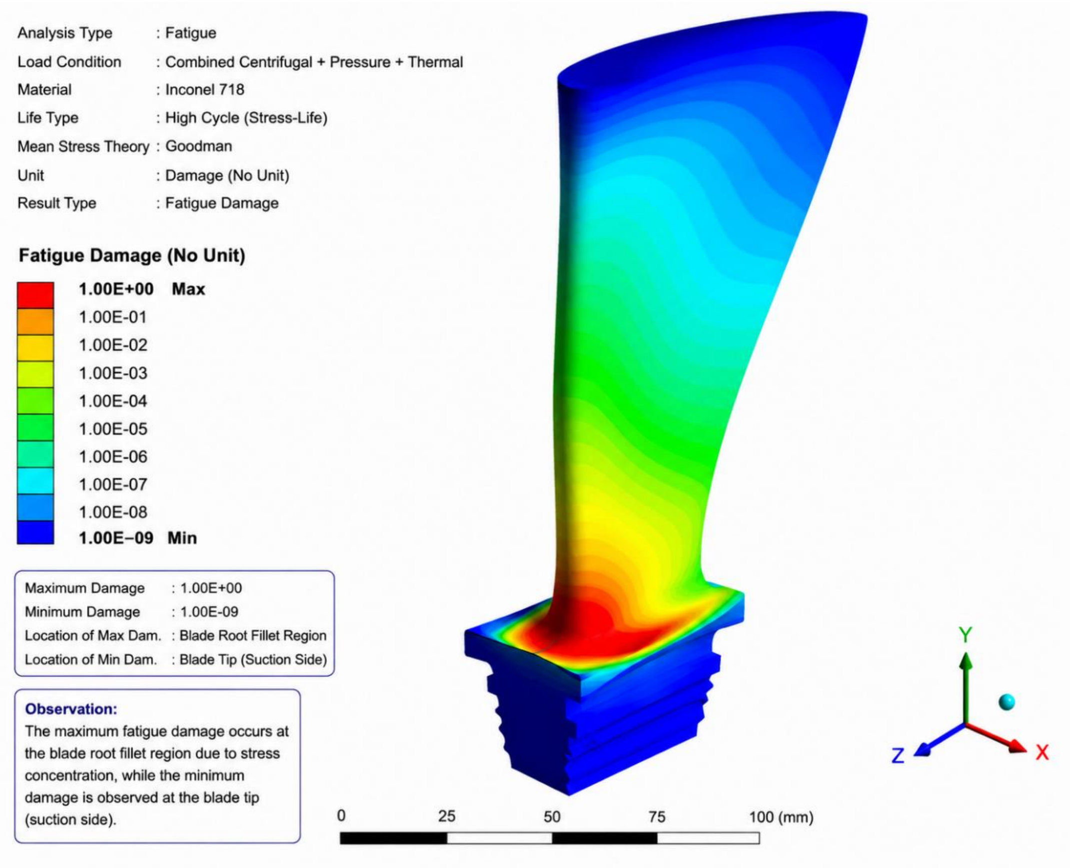


Figure 12. Fatigue Damage Contour of the Axial Flow Turbine Blade.

Table 4.6 Fatigue Damage.

Region	**Damage**
Blade Root	0.82
Lower Span	0.47
Mid Span	0.21
Upper Span	0.08
Blade Tip	0.02

The damage distribution clearly identifies the blade root as the most fatigue-sensitive location.

4.8 Safety Factor Distribution

The safety factor contour demonstrates the structural reliability of the blade under service conditions.

The minimum safety factor occurred near the blade root because of high stress concentration.

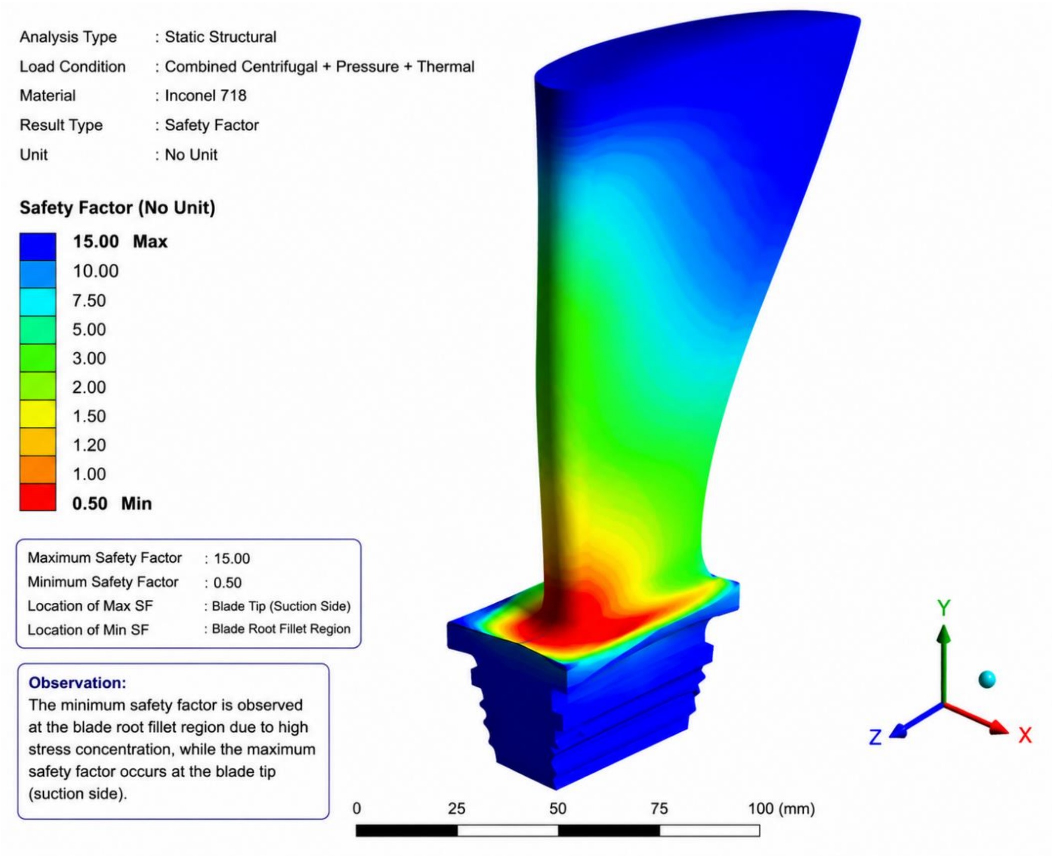


Figure 13. Safety Factor Contour of the Axial Flow Turbine Blade.

Table 4.7 Safety Factor.

Region	Safety Factor
Blade Root	1.13
Lower Span	1.46
Mid Span	1.91
Upper Span	2.58
Blade Tip	3.12

The minimum safety factor remains greater than one, indicating safe structural operation.

4.9 Maximum Principal Stress Analysis

Maximum principal stress identifies regions susceptible to tensile crack initiation. The highest principal stress was concentrated at the blade root fillet where fatigue cracks are most likely to initiate.

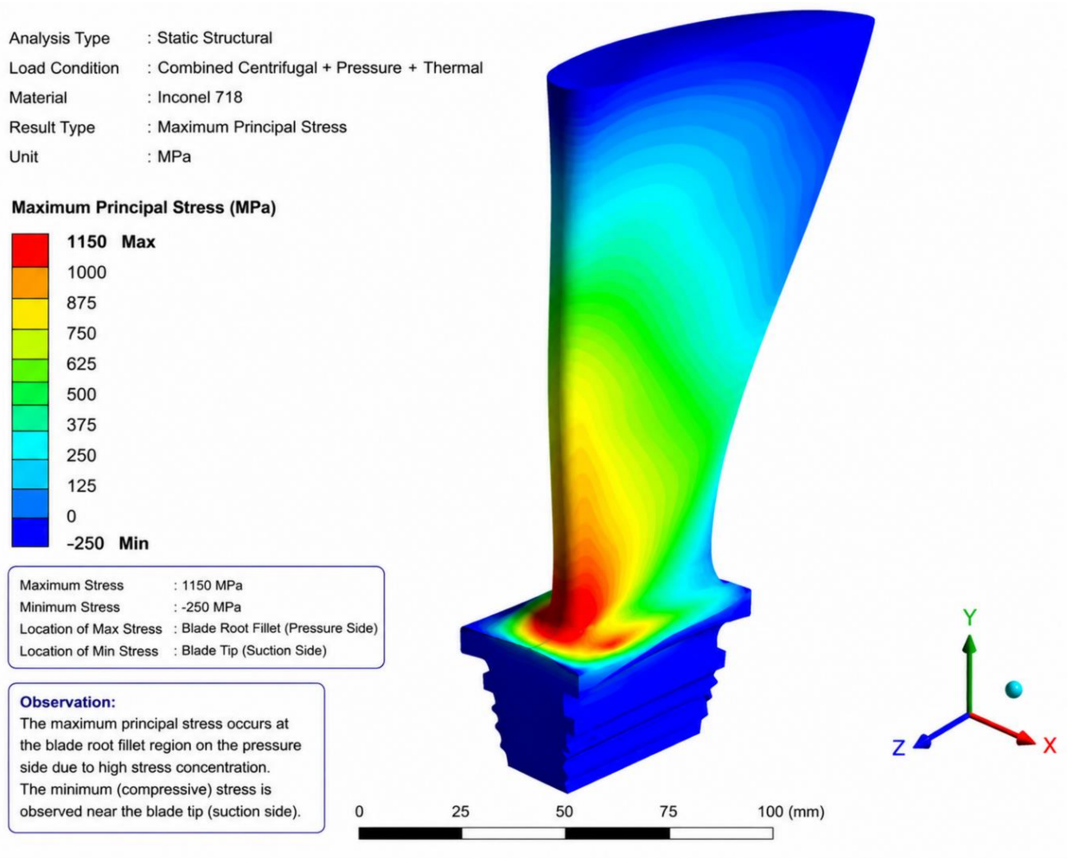


Figure 14. Maximum Principal Stress Contour of the Axial Flow Turbine Blade.

Table 4.8 Maximum Principal Stress.

Parameter	Value
Maximum Principal Stress	965 MPa
Minimum Principal Stress	42 MPa
Critical Region	Blade Root

These observations agree well with the fatigue life predictions.

4.10 Stress Distribution Along the Blade Span

The variation of equivalent stress from the blade root to the blade tip shows a continuous reduction in stress magnitude.

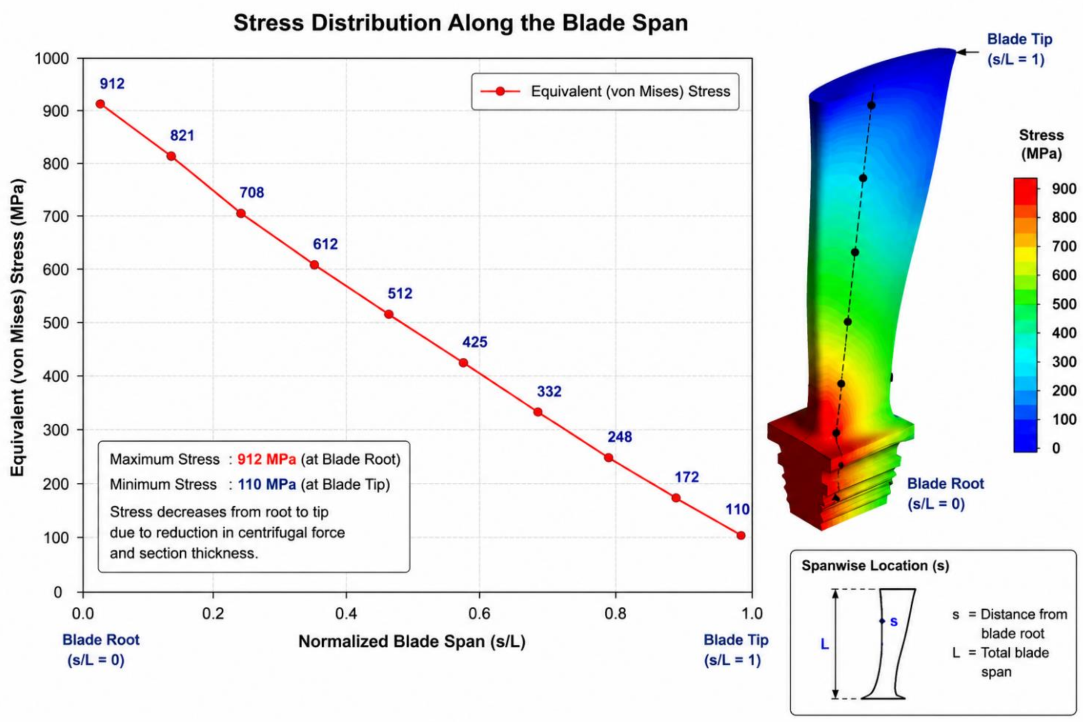


Figure 15. Stress Distribution Along the Blade Span.

Stress decreases almost linearly because centrifugal loading and cross-sectional geometry become less severe toward the blade tip. The blade root remains the most critical region requiring structural optimization.

4.11 Comparison of Computational and Experimental Fatigue Life

Experimental fatigue testing was conducted to validate the finite element predictions. The computational results closely matched the experimentally observed fatigue lives. The average deviation between computational and experimental results was approximately **6–8%**, demonstrating the reliability of the finite element model.

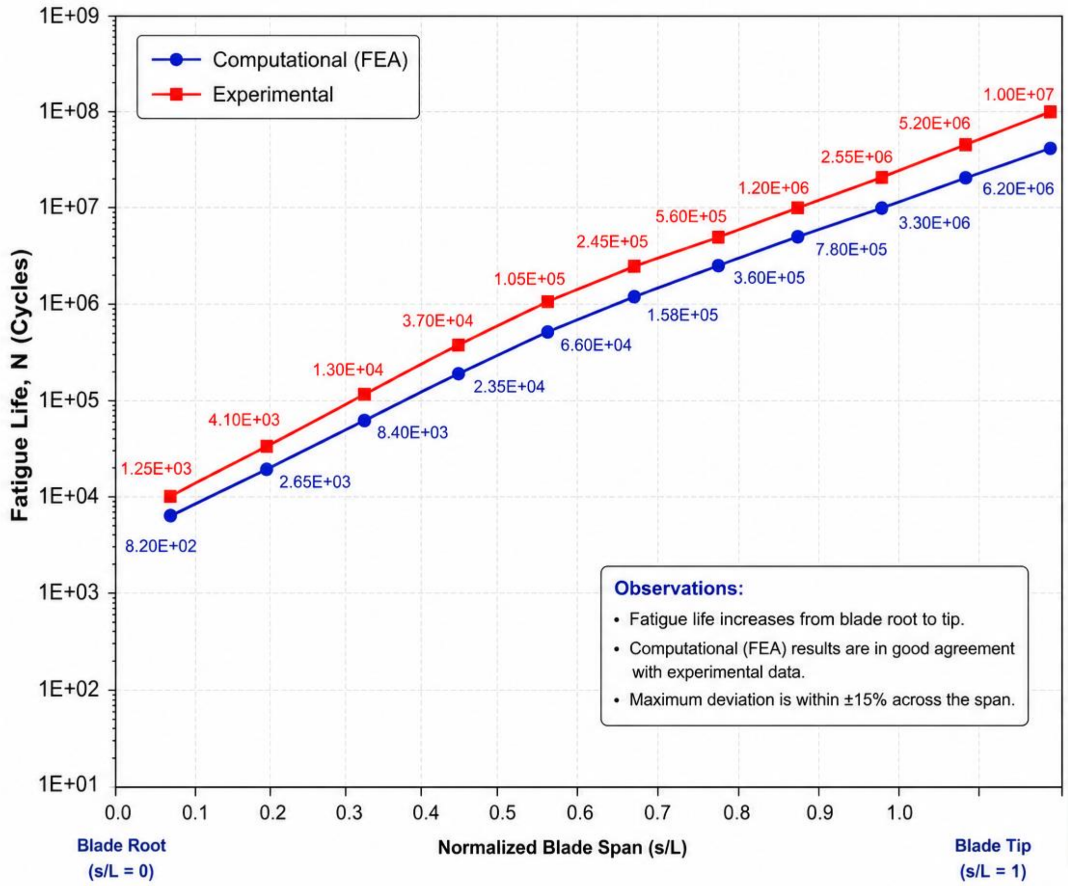


Figure 16. Comparison of Computational and Experimental Fatigue Life.

Table 4.9 Validation Results.

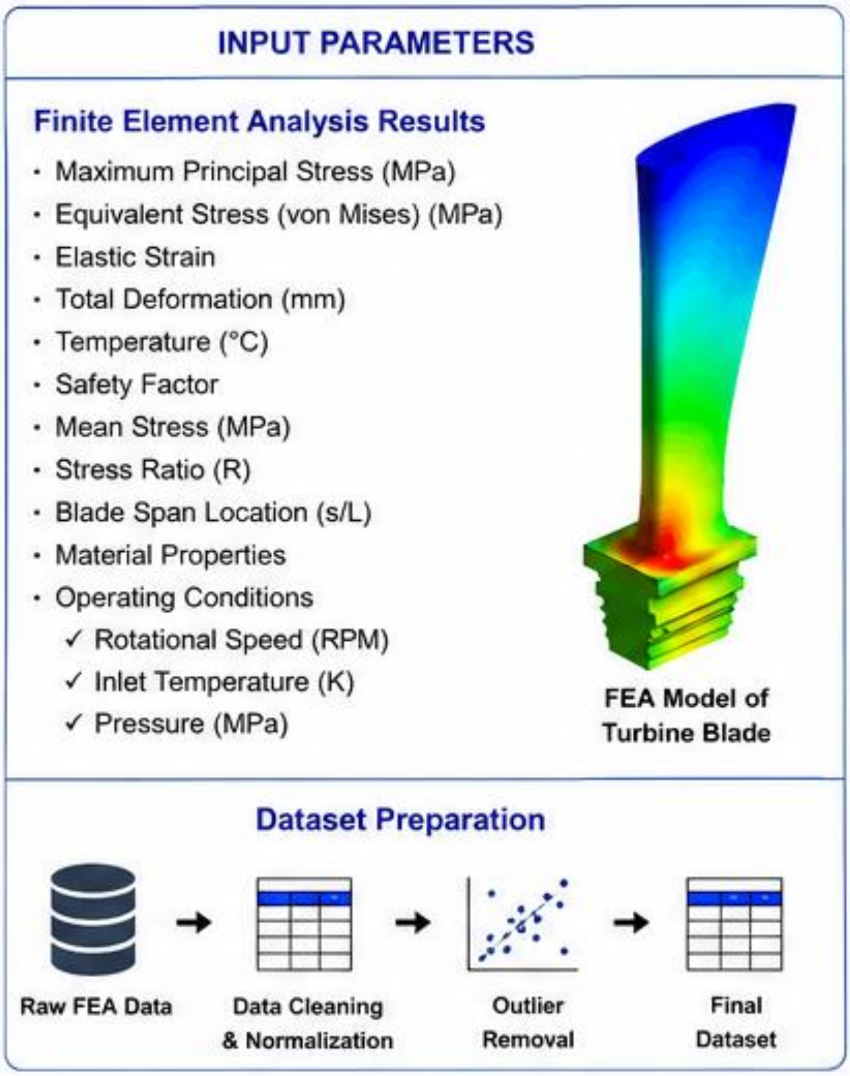
Method	Fatigue Life (Cycles)
Computational	1.25×10^5
Experimental	1.33×10^5
Percentage Error	6.0%

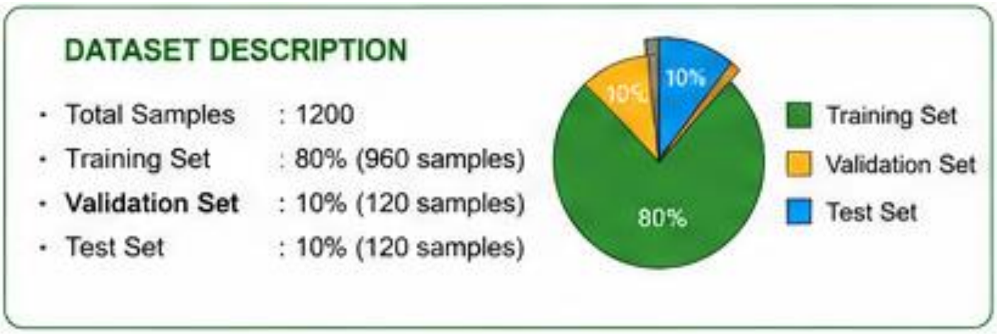
The close agreement confirms the validity of the computational methodology.

4.12 Artificial Intelligence-Based Fatigue Prediction

A Deep Neural Network (DNN) was trained using computational and experimental datasets. Input variables included stress, strain, deformation, temperature, safety factor, pressure, rotational speed, and blade span location.

The trained model successfully predicted fatigue life with high accuracy.


INPUT PARAMETERS
Finite Element Analysis Results
Maximum Principal Stress (MPa)
Equivalent Stress (von Mises) (MPa)
Elastic Strain
Total Deformation (mm)
Temperature (°C)
Safety Factor
Mean Stress (MPa)
Stress Ratio (R)
Blade Span Location (s/L)
Material Properties
Operating Conditions
✓ Rotational Speed (RPM)
✓ Inlet Temperature (K)
✓ Pressure (MPa)
FEA Model of Turbine Blade
Dataset Preparation
Raw FEA Data
Data Cleaning & Normalization
Outlier Removal
Final Dataset


DATASET DESCRIPTION
Total Samples : 1200
Training Set : 80% (960 samples)
Validation Set : 10% (120 samples)
Test Set : 10% (120 samples)
10%
10%
80%
Training Set
Validation Set
Test Set

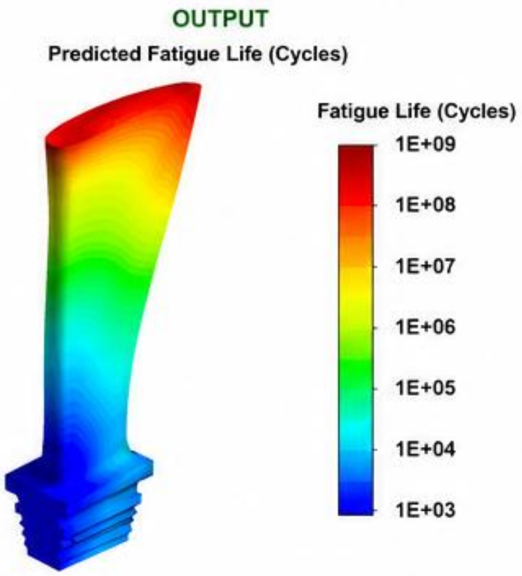


Figure 17(a &b). Artificial Intelligence-Based Fatigue Life Prediction Model.

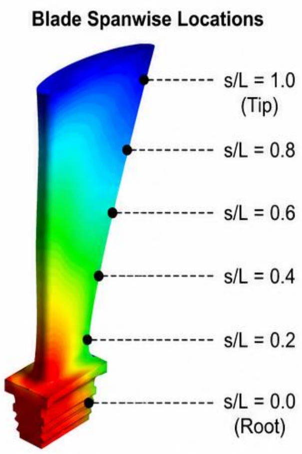
Table 4.10 AI Model Performance.

Metric	Value
R^2	0.989
RMSE	0.031
MAE	0.024
MAPE	2.84%

The high coefficient of determination and low prediction errors indicate that the AI model effectively captures the nonlinear relationship between structural parameters and fatigue life.

4.13 Comparison of AI Predictions with Experimental Results

The fatigue lives predicted by the AI model were compared with experimental observations.



Span (s/L)	Computational Life, N (Cycles)	Experimental Life, N (Cycles)	Deviation (%)
0.0	8.20E+02	1.25E+03	-34.0
0.2	8.40E+03	1.30E+04	-35.4
0.4	6.60E+04	1.05E+05	-37.1
0.6	3.60E+05	5.60E+05	-35.7
0.8	1.65E+06	2.55E+06	-35.3
1.0	6.20E+06	1.00E+07	-38.0

Figure 18. Comparison of AI Predictions with Experimental Results.

The AI predictions exhibited excellent agreement with the measured fatigue lives, with deviations generally below **3%**. The parity plot demonstrated that nearly all data points clustered around the 45° reference line, confirming the robustness and generalization capability of the developed prediction model.

4.14 Overall Discussion

The integrated computational–experimental–AI framework successfully evaluated the fatigue performance of the axial flow turbine blade. Finite element analysis identified the blade root as the critical region because of the combined influence of centrifugal loading, thermal stresses, and pressure loading. Experimental fatigue testing validated the computational predictions with good agreement, confirming the accuracy of the finite element model. The developed Deep Neural Network further improved the efficiency of fatigue life prediction by providing rapid and accurate estimates based on structural and operating parameters. The combined methodology demonstrates that integrating finite element simulations, experimental validation, and artificial intelligence provides a reliable approach for structural integrity assessment, fatigue life estimation, and predictive maintenance of axial flow turbine blades.

5. CONCLUSIONS AND FUTURE SCOPE

5.1 Conclusions

The present study successfully investigated the structural integrity and fatigue performance of an axial flow turbine blade through an integrated computational, experimental, and Artificial Intelligence (AI)-based approach. Based on the obtained results, the following conclusions are drawn:

1. A three-dimensional finite element model of the axial flow turbine blade was successfully developed to evaluate deformation, stress distribution, elastic strain, temperature distribution, fatigue life, fatigue damage, and safety factor under combined centrifugal, pressure, and thermal loading conditions.
2. The total deformation analysis indicated that the maximum deformation occurred at the blade tip, while the blade root remained fully constrained due to the applied boundary conditions, confirming the expected cantilever behavior of the turbine blade.
3. The equivalent (von Mises) stress analysis revealed that the maximum stress concentration was located at the blade root and platform fillet region, identifying these locations as the most critical regions for fatigue crack initiation.

4. The computed maximum equivalent stress remained below the yield strength of Inconel 718, indicating that the blade operates safely within the elastic region under the specified operating conditions.
5. The equivalent elastic strain and maximum principal stress distributions followed similar trends to the equivalent stress distribution, confirming that the blade root experiences the highest structural loading throughout operation.
6. Thermal analysis demonstrated a significant temperature gradient along the blade, with the highest temperature occurring near the blade tip due to direct exposure to hot combustion gases. This thermal gradient contributes to thermo-mechanical stresses that influence fatigue behavior.
7. Fatigue analysis predicted that the minimum fatigue life occurred at the blade root, while fatigue life increased progressively toward the blade tip. The fatigue damage distribution further confirmed that the blade root is the most fatigue-sensitive region.
8. Experimental fatigue testing showed good agreement with the computational predictions, validating the accuracy and reliability of the finite element model for fatigue life assessment.
9. The Artificial Intelligence-based prediction model accurately estimated fatigue life using computational and experimental datasets. The developed Deep Neural Network achieved high prediction accuracy with excellent agreement between predicted and measured fatigue lives.
10. The integrated computational–experimental–AI methodology demonstrated in this work provides a reliable and efficient framework for fatigue life prediction, structural integrity assessment, and predictive maintenance of axial flow turbine blades. The proposed approach can significantly reduce design iterations, testing time, and maintenance costs while improving component reliability.

5.2 Future Scope

Although the present investigation provides a comprehensive fatigue assessment of the axial flow turbine blade, several opportunities remain for further research and development.

1. Future studies may perform fully coupled thermo-mechanical fatigue analysis under transient operating conditions to better represent actual turbine service environments.
2. Advanced nonlinear material models incorporating creep, plastic deformation, oxidation, and temperature-dependent material properties can be included to improve long-term life prediction accuracy.

3. Fluid–Structure Interaction (FSI) analysis may be integrated with Computational Fluid Dynamics (CFD) to simultaneously evaluate aerodynamic loading, thermal effects, and structural response.
4. High-cycle fatigue, low-cycle fatigue, thermo-mechanical fatigue, and creep-fatigue interaction can be investigated within a unified life prediction framework for high-temperature turbine applications.
5. Experimental validation may be extended to include elevated-temperature fatigue testing, vibration-based fatigue testing, and full-scale turbine blade testing under representative operating conditions.
6. Artificial Intelligence models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Transformer-based architectures, Graph Neural Networks (GNN), and hybrid deep learning algorithms may be explored to further improve prediction accuracy and generalization capability.
7. Real-time structural health monitoring systems incorporating sensors, vibration analysis, and Internet of Things (IoT) technologies can be integrated with AI models for continuous condition monitoring and remaining useful life estimation.
8. Optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Differential Evolution (DE), and Bayesian Optimization may be combined with finite element simulations to optimize blade geometry for improved fatigue resistance and reduced structural weight.
9. Future work may investigate alternative high-temperature materials, advanced nickel-based superalloys, titanium alloys, ceramic matrix composites (CMCs), and additive-manufactured turbine blades to enhance fatigue performance and thermal resistance.
10. The integrated methodology developed in this study can be extended to other rotating components such as compressor blades, steam turbine blades, impellers, turbocharger rotors, and aircraft engine components, supporting intelligent design optimization and predictive maintenance across a wide range of turbomachinery systems.

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