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Artificial Intelligence-Based Stress Prediction for Rotor Blisk in Gas Turbine Engines

Ufuk KORTAĞ[1]

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Abstract

Gas turbine engines are critical components in aerospace, power generation, and industrial applications, consisting of complex rotating and stationary parts subject to extreme mechanical, thermal, and aerodynamic loads. A key component in modern gas turbines is the rotor blisk, which combines the blades and disk into a single unit. Due to its complex geometry and harsh operating conditions, the rotor blisk experiences significant mechanical stresses that must be accurately calculated to ensure reliability, safety, and optimal performance. Traditional methods, such as finite element analysis (FEA), are widely used to calculate stress distributions under various loading conditions. However, FEA is computationally expensive, especially when analyzing multiple scenarios for different operating conditions. This computational cost can become a bottleneck in iterative design studies and real-time decision making. To address this challenge, this study proposes a novel approach that uses deep learning to predict stresses in rotor blisks under varying loads. A deep neural network (DNN) was trained on FEA-generated stress data to learn the relationships between input parameters and resulting stress distributions. The AI-based model was validated using unseen load scenarios for radial, axial, and tangential stress distributions and maximum-minimum stress results, with a maximum deviation of 6% to 15% from FEA results. In addition, the Artificial Intelligence (AI) approach reduced the computational cost by 13,000 times faster than FEA by predicting results instead of solving complex equations. The AI approach enables rapid stress predictions and facilitates real-time design iteration and optimization. These results highlight the transformative potential of AI in engineering simulation, enabling faster, more efficient structural assessments and advancing the optimization of gas turbine components in the aerospace and energy industries.

Key Words: Artificial Intelligence (AI), Finite Element Analysis (FEA), Gas Turbine Engine, Rotor Blisk, Deep Learning

JEL Classification: C45, C63.

Gaz Türbinli Motorlarda Rotor Blisk için Yapay Zeka Tabanlı Gerilme Tahmini

Öz

Gaz türbinli motorlar; havacılık, enerji üretimi ve endüstriyel uygulamalarda kritik bileşenler olup, aşırı mekanik, termal ve aerodinamik yüklere maruz kalan karmaşık döner ve sabit parçalardan oluşmaktadır. Modern gaz türbinlerinin temel bileşenlerinden biri, kanatları ve diski tek bir bütün halinde birleştiren rotor blisktir. Karmaşık geometrisi ve zorlu çalışma koşulları nedeniyle rotor blisk, güvenilirliğin, emniyetin ve optimal performansın sağlanabilmesi için doğru bir şekilde hesaplanması gereken önemli mekanik gerilmelere maruz kalmaktadır. Sonlu elemanlar analizi (SEA) gibi geleneksel yöntemler, farklı yükleme koşullarında gerilme dağılımlarını hesaplamak için yaygın şekilde kullanılmaktadır. Ancak, SEA özellikle farklı çalışma koşulları için çoklu senaryoların analizinde hesaplama açısından maliyetli olup, bu hesaplama yükü tekrarlamalı tasarım çalışmalarında ve gerçek zamanlı karar vermede bir darboğaz hâline gelebilmektedir. Bu zorluğun üstesinden gelmek amacıyla, bu çalışma rotor blisklerde farklı yükler altında gerilmeleri tahmin

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etmek için derin öğrenme kullanan yeni bir yaklaşım önermektedir. Bir derin sinir ağı (DSA), giriş parametreleri ile ortaya çıkan gerilme dağılımları arasındaki ilişkileri öğrenebilmek için SEA tarafından üretilmiş gerilme verileri üzerinde eğitilmiştir. Yapay zeka tabanlı model, radyal, eksenel ve teğetsel gerilme dağılımları ile maksimum-minimum gerilme sonuçları için görülmemiş yük senaryoları kullanılarak doğrulanmış ve SEA sonuçlarına kıyasla %6 ila %15 arasında maksimum sapma göstermiştir. Ayrıca, yapay zeka yaklaşımı karmaşık denklemleri çözmek yerine sonuçları tahmin ederek SEA'ya kıyasla hesaplama maliyetini 13.000 kat azaltmıştır. Yapay zeka yaklaşımı, hızlı gerilme tahminleri yapılmasını mümkün kılmakta ve gerçek zamanlı tasarım yinelemelerini ve optimizasyonu kolaylaştırmaktadır. Bu sonuçlar, mühendislik simülasyonunda yapay zekânın dönüştürücü potansiyelini vurgulamakta, daha hızlı ve daha verimli yapısal değerlendirmeleri mümkün kılmakta ve havacılık ile enerji endüstrilerinde gaz türbini bileşenlerinin optimizasyonunu ilerletmektedir.

Anahtar Kelimeler: Yapay Zeka (YZ), Sonlu Elemanlar Analizi (SEA), Gaz Türbinli Motor, Rotor Blisk, Derin Öğrenme

JEL Sınıflandırma: M10, M19.

INTRODUCTION

Gas turbine engines are integral components in a wide range of industries, including aerospace, power generation, and industrial sectors. They are designed to operate under extreme mechanical, thermal, and aerodynamic loads, where high efficiency, reliability, and performance are of paramount importance (Mane et. al, 2023). These engines consist of complex rotating and stationary components that work in tandem to convert energy into mechanical power. Among these components, the rotor blisk which combines the disk and blades into a single structure plays a critical role. Rotor blisks are typically used in compressors, as they offer significant advantages such as weight reduction, enhanced aerodynamic performance, and improved thermal management (Kumar, 2013). The integration of the disk and blades into a single unit eliminates the need for traditional fastening methods, resulting in a more streamlined and efficient design, as shown in Fig. 1.

Figure 1. Compressor rotor blisk

Source: Bandini et. al, 2024

Due to their complex geometry and harsh operating conditions, rotor blisks are subjected to substantial mechanical stresses. These stresses are a result of various factors, including rotational speed, aerodynamic forces, and thermal expansion effects, all of which vary depending on the engine's operating conditions. The accurate calculation of these stresses is essential for ensuring the component's reliability, preventing fatigue failures, and optimizing its lifespan (Elhefny & Megahed, 2018). Traditional methods such as finite element analysis (FEA) are widely used to perform stress analysis under different loading conditions. FEA is a powerful tool that provides high-fidelity results by breaking down complex geometries into smaller, manageable elements and solving the governing equations. However, while FEA is highly accurate, it is computationally expensive, particularly when multiple loading scenarios must be analyzed. As a result, this computational burden limits the feasibility of real-time analysis and optimization in many engineering applications, hindering timely design decisions and innovation (Zhang et. al, 2016).

In recent years, artificial intelligence (AI) has emerged as a promising solution to accelerate structural simulations and address the limitations of traditional methods like FEA. AI-driven models, particularly those based on machine learning (ML), have shown the potential to reduce the computational cost associated with structural analysis without compromising accuracy. These models, often referred to as surrogate models, are trained on large datasets generated through FEA or experimental testing. Once trained, they can predict stress distributions under various loading conditions much faster than traditional FEA, thus enabling real-time simulations (Shivaditya et. al, 2022). In particular, deep learning, a subset of AI, has demonstrated significant promise due to its ability to capture complex, non-linear relationships between input parameters and output results. Several studies have applied machine learning-based methods in fields such as structural health monitoring, material property prediction, and topology optimization, showcasing their ability to streamline design and analysis processes (Plevris & Papazafeiropoulos, 2024). However, despite the growing body of research on AI applications in engineering, the use of AI for stress prediction in structural components under varying operational conditions is still an emerging field.

The application of AI in gas turbine engineering has already shown considerable potential in improving performance and reducing maintenance costs. For instance, one study reviewed AI applications in condition assessment and fault detection, noting the success of machine learning models in enhancing the reliability of turbine systems (Zhao et. al, 2021). Similarly, another study introduced a hybrid temporal convolutional network–autoencoder model for real-time fault detection, improving diagnostic accuracy in gas turbine systems (Guo et. al, 2021). Other studies have proposed deep learning-based models for predicting low-cycle fatigue life in turbine blades (Zhu et. al, 2022), optimizing turbine blisk temperature distributions (Wang et. al, 2022), and enhancing fault detection under noisy conditions (Chen et. al, 2022). One study applied dynamic neural networks to diagnose engine failures at an early stage, while another leveraged AI-driven topology optimization to enhance the performance of compressor rotor blisks, improving their strength and efficiency [13,14]. A convolutional neural network (CNN) approach has been proposed for probabilistic low-cycle fatigue life prediction of turbine blisks, demonstrating significant accuracy improvements over conventional methods (Fei et. al, 2024). A comprehensive review of machine learning strategies in turbine cooling design optimization has also been conducted, emphasizing the role of surrogate models in reducing simulation time and design complexity (Li et. al, 2024).

Furthermore, a reduced-order modeling technique based on deep learning has been introduced to predict unsteady pressure fields on turbine blades, substantially decreasing computational effort while maintaining high fidelity (Joachim et. al, 2025). Another study investigated reinforced symbolic learning with logical constraints for predicting turbine blade fatigue life, integrating interpretability with predictive performance (Li et. al, 2024). In addition, recent reviews have focused on AI-driven frameworks for predictive maintenance and diagnostics in turbomachinery, addressing fault detection, anomaly prediction, and reliability enhancement (Bunyan et. al, 2025).

These studies underscore the growing recognition of AI's potential to optimize turbine systems and improve their performance across various stages of the life cycle, from design and operation to maintenance and failure prediction. Despite these advancements, the application of AI in predicting the stress distribution of complex components like rotor blisks under varying operational conditions remains an open challenge. Traditional FEA methods require detailed geometric models and significant computational resources, which makes it difficult to apply these methods in iterative design processes and real-time decision-making. Deep learning-based approaches, on the other hand, offer a potential solution by enabling faster and more efficient simulations.

This study introduces a novel deep neural network (DNN) approach for predicting stress in rotor blisks subjected to a variety of loading conditions, including rotational speed, gas pressure, and thermal loads. By training the DNN model using comprehensive FEA-generated stress data, the model effectively learns the complex, non-linear relationships between these input parameters and the resulting stress distributions. This research addresses the existing gap by demonstrating how AI can significantly accelerate stress prediction for critical aerospace components, thereby overcoming the computational limitations of traditional FEA for design optimization and real-time assessment. Once trained, the model can provide rapid predictions, with a maximum deviation of just 15% from traditional FEA results, while reducing computational costs by approximately 3300%. This dramatic reduction in computational load makes real-time design optimization feasible and opens up new possibilities for rapid prototyping and iterative design processes in gas turbine engineering. Moreover, the DNN-based approach provides an efficient way to perform sensitivity analysis, enabling engineers to explore the effects of different loading conditions on the component's performance without the need for extensive FEA simulations.

The main objectives of this study are:

- To develop a robust deep learning model for accurate stress prediction in rotor blisks under varying operational conditions.
- To demonstrate the significant computational efficiency gains of the AI-based approach compared to traditional FEA.
- To provide a framework for integrating AI into the design and analysis workflows of gas turbine components, facilitating faster design iterations and optimization.
- To analyze and compare the radial, tangential, and axial stress distributions predicted by the DNN with high-fidelity FEA results, identifying the model's strengths and

limitations in capturing complex stress patterns.

The subsequent sections of this paper are organized as follows: Section-2 details the material and methods, including the finite element analysis of the blisk model and the architecture of the deep learning model. Section-3 presents the results and a comprehensive discussion of the stress predictions. Finally, Section-4 provides the conclusions drawn from this study and outlines potential avenues for future research.

1. MATERIAL AND METHOD

1.1. Finite Element Analysis of the Blisk Model

The finite element method (FEM) is a numerical technique widely used for solving complex engineering problems involving structural, thermal, and dynamic analyses. It discretizes a continuum domain into smaller subdomains, known as finite elements, connected at nodes, thereby transforming partial differential equations into a system of algebraic equations that can be solved computationally. The general governing equation of motion in FEM for a dynamic system is expressed can be expressed as given in Equ. 1 (ANSYS, 2024).

$$[M]\{\ddot{u}\} + [C]\{\dot{u}\} + [K]\{u\} = \{F\} \tag{1}$$

Where M is the mass matrix, C is the damping matrix, K is the stiffness matrix, u is the displacement vector, and F represents the external force vector. Depending on the problem type, static or dynamic equilibrium conditions are enforced to obtain the solution. Since external forces does not vary with time in this study, inertial and damping effects are neglected and the general governing equation of motion becomes as given in Equ. 2.

$$[K]\{u\} = \{F\} \tag{2}$$

In this study, FEA was employed to simulate the behavior of a blisk model under operational conditions typically encountered in high-pressure compressor rotors. The geometry of the blisk was generated using SpaceClaim, and the numerical simulations were carried out using ANSYS Mechanical. To reduce computational costs while still capturing the key structural behaviors, a one-blade sector representation of a 70-bladed blisk was chosen for the finite element (FE) model. To replicate the behavior of the full blisk assembly without simulating all 70 blades, cyclic symmetry boundary conditions were applied to the boundary faces of the sector model as shown in Fig. 2. The model was meshed using 22,400 SOLID185 linear hexahedron elements, which were selected for their suitability in accurately capturing the complex geometries and stresses of the blisk while maintaining computational efficiency and constrained in both the axial and tangential directions from the forward side face of the disc bore and constrained only in tangential direction from aft side of the disc bore to simulate the physical boundary conditions of the actual component as shown in Fig. 3.

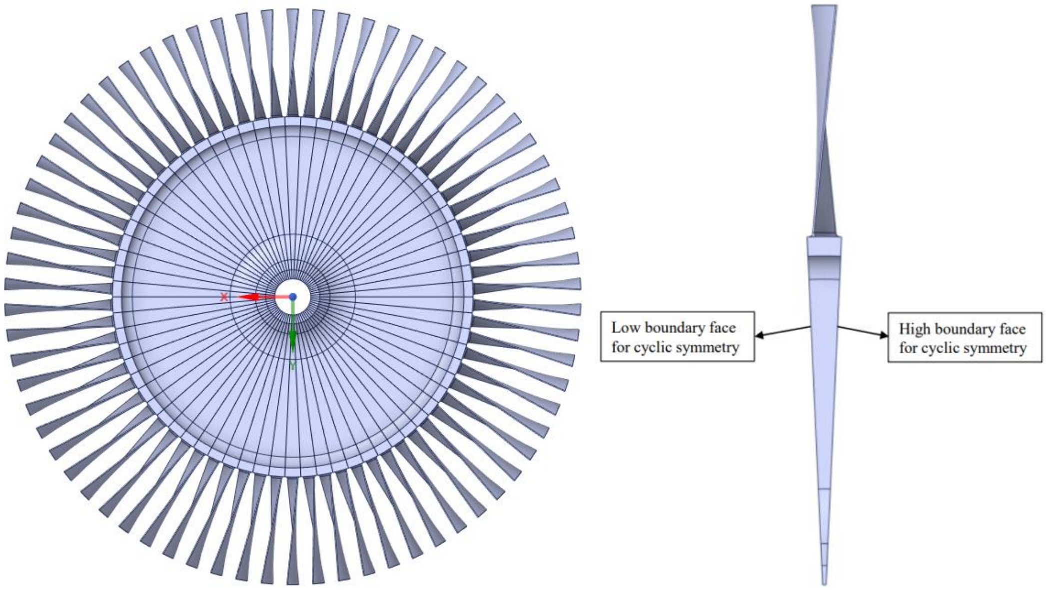

Figure 2. Compressor rotor blisk: 360° model (left), Cyclic sector model (right)

The material used in the simulations was assumed to be isotropic and temperature-dependent, reflecting the characteristics of high-performance titanium alloys commonly used in compressor rotor blisks. This choice allows for the incorporation of the temperature-induced variations in material properties, such as Young's modulus, Poisson's ratio, and thermal expansion, which are critical when assessing the blisk's performance under the extreme conditions encountered in turbine operation.

The loading conditions applied to the model were designed to simulate the real operational environment of high-pressure compressor rotors in gas turbine engines. These included centrifugal forces, represented by varying the rotational speed between 0 to 12,000 RPM, and aerodynamic loads, modeled by gas pressures ranging from 0 MPa to 0.5 MPa. To capture the effects of temperature that occur during engine operation, thermal loads were applied, with temperatures ranging from 0°C to 1,500°C, simulating both the thermal expansion of the material and the resulting stress redistribution within the structure as shown in Fig. 4. Geometric nonlinearity was taken into account in numerical simulations.

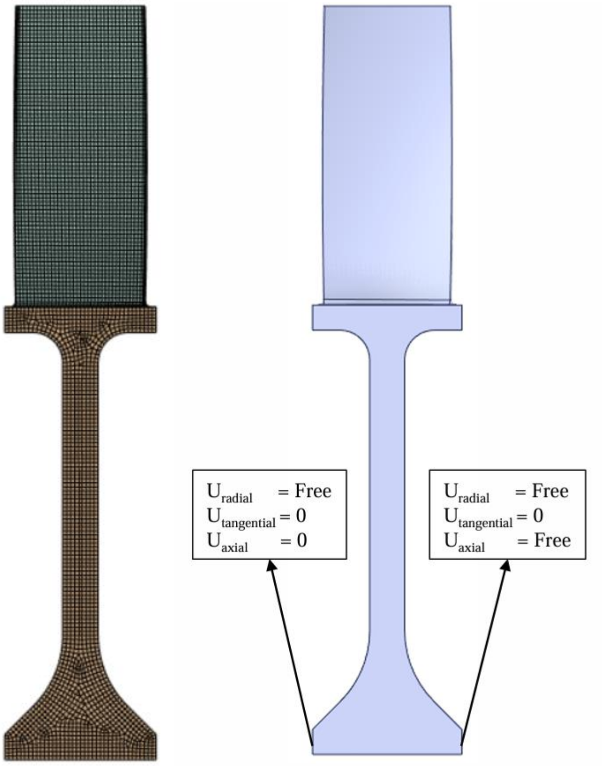

Figure 3. Compressor rotor blisk: FE model (left), Boundary conditions (right)

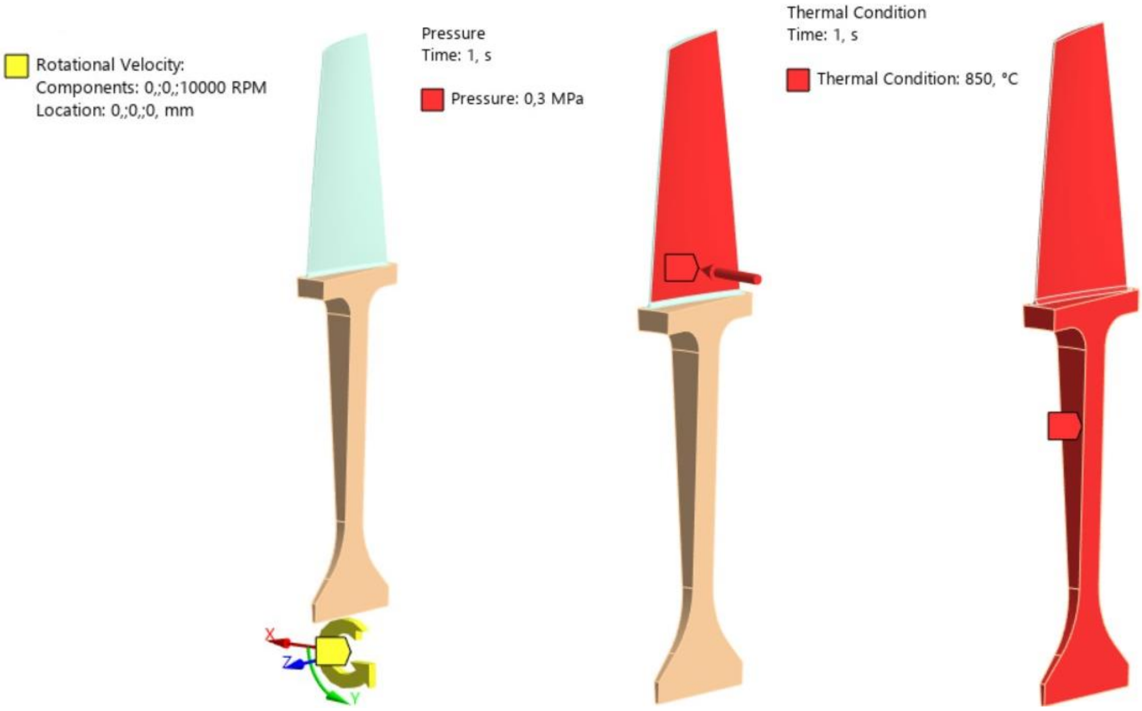

Figure 4. Applied loads for rotor blisk model: Rotational velocity (left), Gas pressure (middle), Temperature (right)

The solution phase involved performing static analyses to evaluate stress distributions at different load cases. A total of 10 distinct load cases were examined to obtain a comprehensive dataset, which could later be used for further validation and potential deep learning applications as shown in Table 1. The key performance indicators extracted from the results included radial, tangential, and axial stresses for the blisk sector under various loading conditions. These findings provide valuable insights into the structural integrity and operational safety of the compressor rotor, contributing to the optimization of its design and performance.

Table 1. Applied loading conditions for the blisk model

Rotational Velocity (RPM)	Gas Pressure (MPa)	Temperature (°C)
0	0.25	0
0	0	1000
500	0.01	50
1000	0	0
2500	0.03	150
4000	0.2	250
5000	0.08	450
7000	0.12	600
10000	0.3	850
12000	0.5	1500

1.2. Deep Learning Model

Artificial neural networks (ANNs) are computational models inspired by the human brain, consisting of interconnected units called perceptron. A perceptron is the fundamental building block of an ANN, mimicking biological neurons by receiving weighted inputs, applying an activation function, and producing an output using Equ. 3 as shown in Fig. 5. When multiple perceptron is organized into layers, they form an ANN, which can learn patterns from data and make predictions. Deep learning refers to a subset of machine learning where ANNs contain multiple hidden layers, enabling them to model complex and highly nonlinear relationships in data. These deep networks are particularly effective in tasks such as image recognition, natural language processing, and engineering simulations (Al-Mahasneh et. Al, 2018).

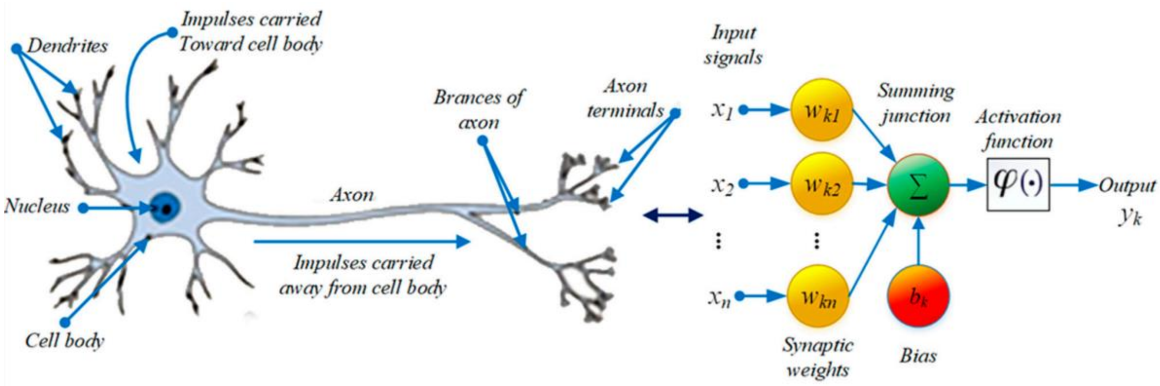

Figure 5. A biological neuron (left), a perceptron (right)

Source: Melina et. al, 2023

In this study, a deep neural network (DNN) was developed to predict the stress distribution in the rotor blisk, leveraging FEA-generated data under various operating conditions. The methodology and model architecture are comprehensively detailed as follows:

• Data Preprocessing:

The input features (RPM, aerodynamic pressure, temperature) and output stress components (radial, tangential, axial) were normalized to the range [–1, 1] to enhance convergence and training stability. The dataset was divided into nine subsets for training and one subset for validation. Additionally, an unseen load case was reserved to rigorously assess the model's generalization capability.

• Neural Network Architecture:

The model comprises an input layer accepting normalized parameters, followed by four fully connected hidden layers, each containing 256 neurons. The activation function used in all hidden layers is the Rectified Linear Unit (ReLU), which transforms negative input values to zero while keeping positive values unchanged. This function is computationally efficient and helps mitigate the vanishing gradient problem, making it a preferred choice for deep networks. The output layer employs a linear activation function that preserves the continuous output values. These activation functions are defined in Equations 4 and 5.

• Training and Optimization:

Training minimizes the Mean Squared Error (MSE) loss function (Equation 6), which calculates the mean of the squared differences between predicted and actual values. MSE is widely used in regression problems involving continuous variables, as it penalizes larger errors more heavily. The optimization uses the RMSProp algorithm (Equation 7), which dynamically adjusts the learning rate for each parameter, improving stability and convergence on the validation dataset. The learning rate is set to 0.001, balancing gradual convergence and avoiding excessive fluctuations. The model is trained for 500 epochs to ensure sufficient learning of complex data patterns while monitoring validation loss. These hyperparameters, summarized in Table 2, were carefully selected to optimize the model’s performance and enhance its generalization ability.

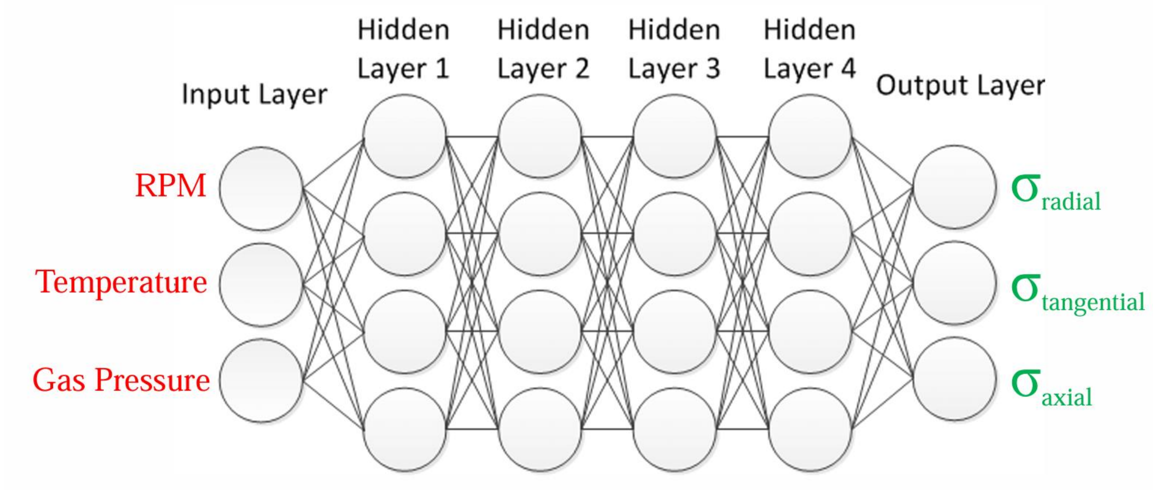

Figure 6. The deep neural network structure

$$y_i = \sum_j f\,(W_{ij} y_j + b_i) \tag{3}$$

$$f = f(x) = \begin{cases} x, & x > 0 \\ 0, & otherwise \end{cases} \tag{4}$$

$$f\ (x) = x \tag{5}$$

$$\mathcal{L}(\theta) = \frac{1}{n}\sum_{i=1}^{n}\left(y^{(i)} - \hat{y}^{(i)}\right)^2 \tag{6}$$

$$\begin{aligned} u_t &= \beta * u_t + (1-\beta)(\nabla w_t)^2 \\ w_{t+1} &= w_t - \frac{\eta}{\sqrt{(u_t) + \epsilon}}\nabla w_t \end{aligned} \tag{7}$$

Table 2. Hyperparameters for the deep learning model

Hyperparameter	**Value**
Number of Layers	4
Neurons per Layer	256
Activation Function	ReLU, Linear
Loss Function	MSE
Optimizer	RMSProp
Learning Rate	0.001
Epochs	500

For the validation, a single validation load set was utilized to assess the convergence of the model. The evaluation metric used to measure model accuracy is the Mean Squared Error (MSE). A lower MSE indicates improved model accuracy and better alignment with the actual data. Figure 8 presents the evaluation of loss and MSE on both the training and validation sets. The trends depicted in the graphs provide key insights into the network's learning behavior. At the beginning, with a limited number of epochs, MSE values are relatively high, showing that the network struggles to accurately capture the complex relationships between the input and target variables. As the number of epochs increases, a steady decrease in MSE is observed, which is in line with the expected behavior as the network continuously adjusts its weights and biases. This ongoing adaptation improves the network's ability to more accurately predict the free response of the test bench. To validate the DNN model, the predictions made by the trained model using the validation dataset were also checked as shown in Fig. 7.

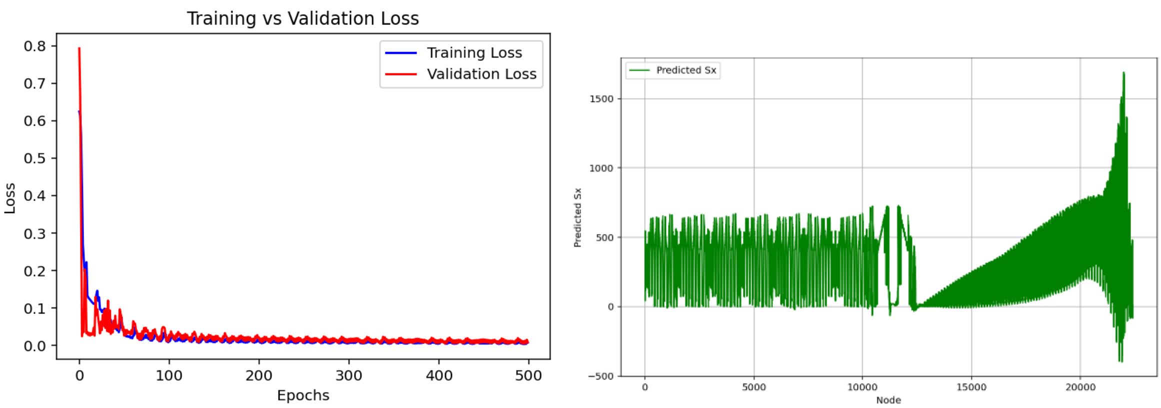

Figure 7. Training and validation loss through epochs (left), predicton of nodal radial stresses for validation load set (right)

The proposed framework follows a structured pipeline comprising several key steps as shown in Table 3: data generation via FEA simulations, data preprocessing and normalization, deep neural network training, and final stress prediction.

Table 3. Workflow Stages for AI-Based Stress Prediction

Step No	Stage	Description
1	Data Generation	Stress data were generated by finite element simulations
2	Preprocessing	Data were normalized and split for training and validation
3	Model Architecture	A deep neural network with four hidden layers was established
4	Training	The network was trained over 500 epochs
5	Prediction	The model predicts stresses quickly for given inputs
6	Evaluation	Accuracy was validated on unseen data

2. RESULTS AND DISCUSSION

This study investigates the stress distribution in a compressor rotor blisk subjected to centrifugal, gas pressure, and thermal loads using both finite element analysis (FEA) and deep neural networks (DNNs). Radial, tangential, and axial stress components were analyzed under ten different load cases, and the results were supplied to the DNN for training. The model was subsequently tested on an unseen load case, with its predictions compared to FEA results.

Radial stress distribution exhibited a characteristic gradient along the blisk, with maximum stress concentrations occurring near the root of the blade due to the transition in cross-sectional geometry as shown in Fig. 8. FEA results indicated a maximum radial stress of 1770.3 MPa, whereas the DNN-predicted value for the same location was 1789.5 MPa, demonstrating a relative error within an acceptable range. The minimum radial stress was observed at the root of the blade, where tensile and compressive stresses balanced out due to centrifugal loading effects, with FEA predicting -257.69 MPa and the DNN predicting -228.96 MPa. The overall radial stress distribution predicted by the DNN closely followed the FEA solution, with minor deviations attributed to the interpolation behavior of the neural network in regions with high stress gradients.

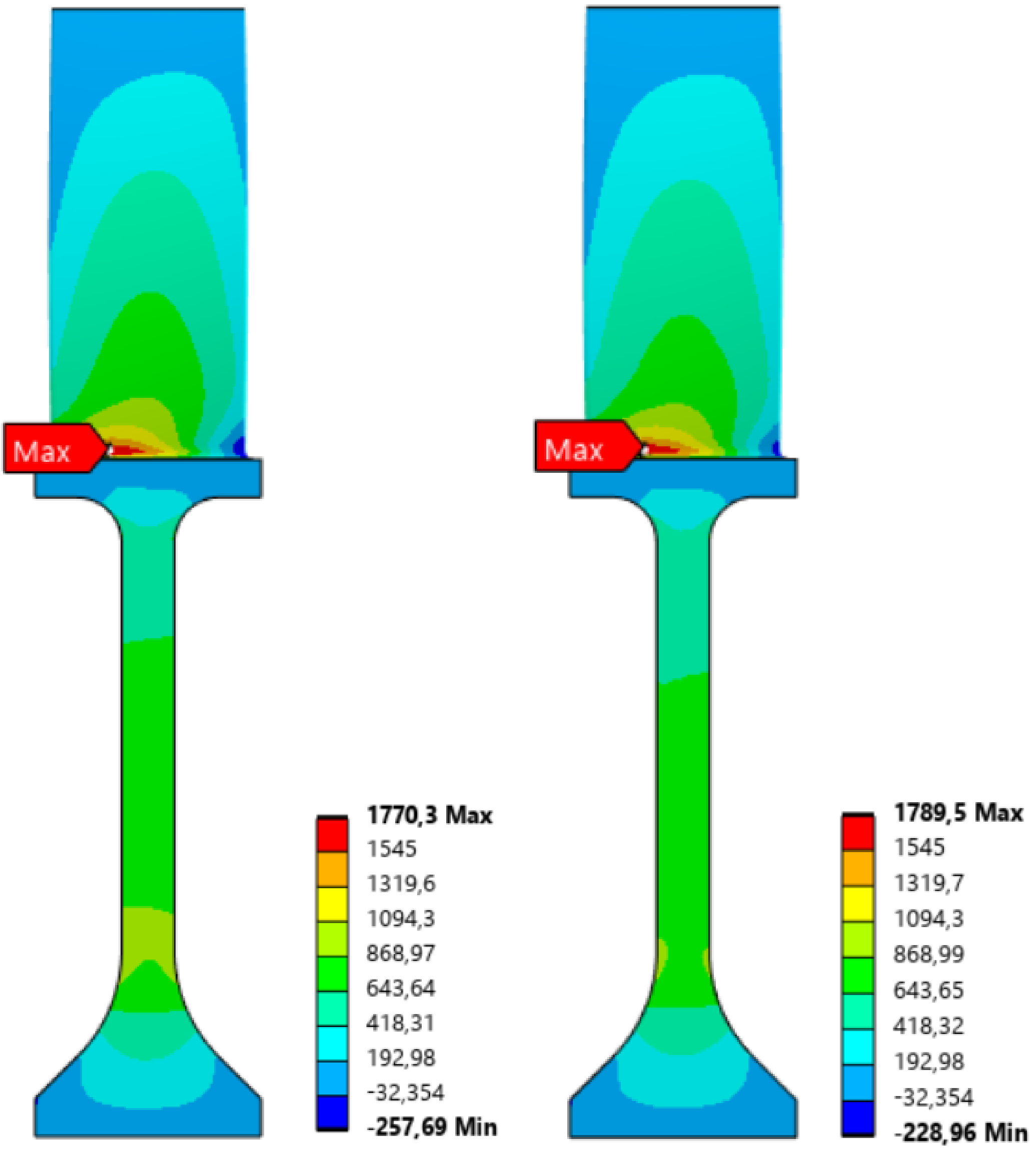

Figure 8. Compressor rotor blisk radial stress results: FEA (left), AI prediction (right)

Tangential (hoop) stresses, which primarily result from centrifugal forces acting on the rotating structure, showed peak values in the vicinity of disk upper bore region due to the accumulation of rotational inertia as shown in Fig. 9. FEA simulations revealed a maximum tangential stress of 790.13 MPa, while the DNN prediction yielded 661.68 MPa, showing a slight underestimation. The minimum tangential stress was located near the inner hub region, where compressive forces counterbalanced the tensile effects, with FEA predicting -257.32 MPa and DNN predicting -294.99 MPa. Despite the minor discrepancies, the overall stress distribution trends were accurately captured by the DNN, reinforcing its capability to generalize stress patterns under unseen conditions.

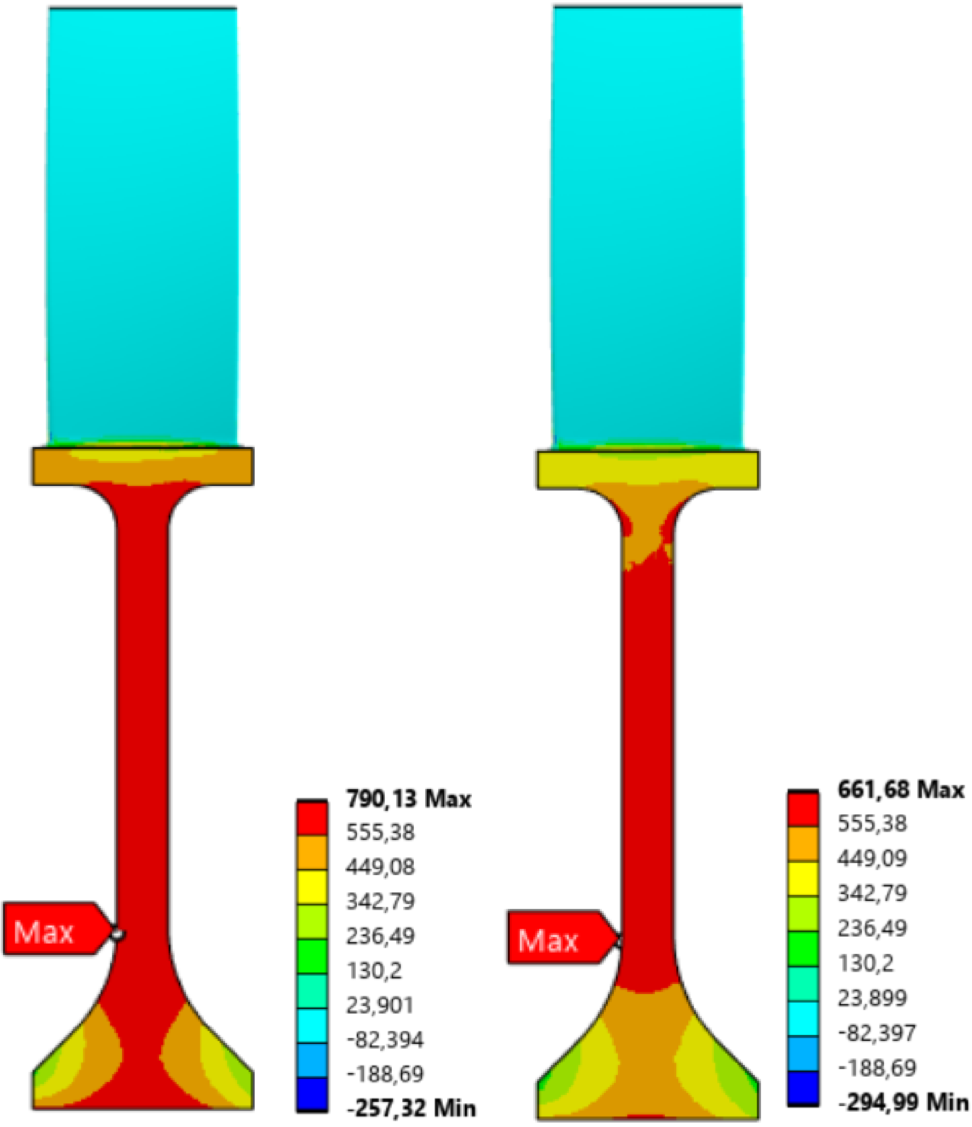

Figure 9. Compressor rotor blisk tangential stress results: FEA (left), AI prediction (right)

Axial stress, influenced by both thermal expansion and mechanical loads, exhibited its highest values near the disk-blade interface, where constraints on radial expansion induce tensile stress as shown in Fig. 10. FEA results showed a peak axial stress of 327.94 MPa, whereas the DNN-predicted value was 288.83 MPa, indicating a slight underestimation. The minimum axial stress was recorded at the lower disk section, with FEA predicting -418.86 MPa and the DNN predicting -422.89 MPa, demonstrating strong agreement in compressive stress regions. The stress distribution across the component followed a consistent trend, with the DNN capturing the overall pattern effectively, though minor deviations were observed in localized stress concentrations.

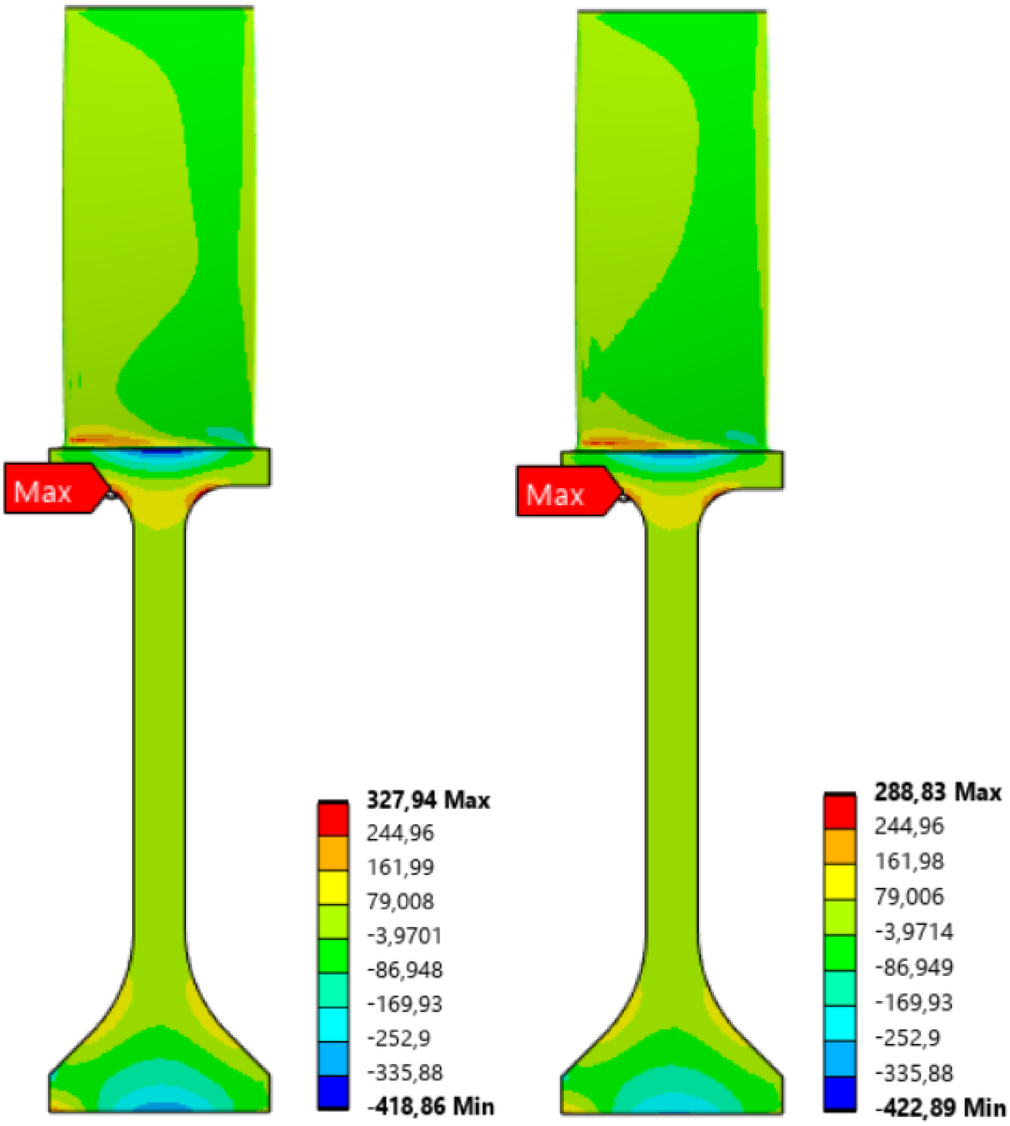

Figure 10. Compressor rotor blisk axial stress results: FEA (left), AI prediction (right)

A key advantage of the DNN approach was its significant reduction in computational time. The trained neural network predicted stress distributions in 0.005 second, compared to 50 seconds required for a single FEA run. This computational speed-up makes the DNN method highly suitable for real-time applications such as optimization, digital twins, and structural health monitoring. Future work will focus on improving prediction accuracy through refined training strategies, expanding the dataset with additional load cases, and incorporating physics-informed machine learning techniques to enhance generalization. Additionally, integrating uncertainty quantification methods will provide confidence intervals for the DNN predictions, further increasing its reliability in engineering applications.

The findings from this study confirm the promising potential of deep learning as a powerful tool for accelerating stress analysis in complex engineering components. While minor discrepancies exist between DNN predictions and FEA results, particularly in highly localized stress concentration regions, the overall accuracy and the substantial reduction in computational time underscore the practical applicability of this approach.

Additionally, the main findings and their comparison with existing literature are summarized as follows and presented in Table 4:

- The deep neural network (DNN) model accurately predicted radial, tangential, and axial stresses within a maximum deviation of 15% compared to finite element analysis (FEA), confirming its capability to generalize under unseen loading conditions.
- The DNN approach achieved a computational speed-up exceeding 13,000 times compared to conventional FEA, highlighting its potential for real-time structural analysis and optimization.
- The significant reduction in computational storage requirements (from approximately 34 MB for FEA results to 0.36 MB for the DNN model) supports the feasibility of deploying this model in resource-constrained environments.
- Minor discrepancies in stress concentration regions indicate opportunities for further refinement, possibly through enhanced training datasets or physics-informed machine learning techniques.
- Compared to previous studies focused on fatigue life prediction [10], temperature distribution [11], and topology optimization [14], this study uniquely presents full-field stress prediction with a considerably higher speed-up, thereby extending the application of AI in gas turbine blisk analysis.
- The proposed framework lays the foundation for integration with digital twin technologies and structural health monitoring systems, which require rapid and reliable stress predictions.

Table 4. Summary of key findings and comparison with literature

Finding	Description	Comparison with Literature
Stress prediction accuracy	Maximum deviation of 15% for radial, tangential, and axial stresses	Comparable accuracy to [10], [11], [14]
Computational speed	Prediction time of 5 ms compared to 66 s for FEA (~13,200× speed-up)	Significantly higher speed-up than prior studies
Storage efficiency	Model size 0.36 MB vs. 34.25 MB for FEA results	Enables lightweight deployment
Applicability to unseen load cases	Successful generalization to previously unseen load conditions	Demonstrates robustness beyond training data
Potential for real-time application	Suitable for design iteration, optimization, digital twins, and structural health monitoring	Extends AI utility in gas turbine component analysis

3. CONCLUSION

This study demonstrates the potential of combining finite element analysis with deep learning for efficient stress prediction in the complex geometry of rotor blisks used in gas turbine engines. By leveraging FEA to model the blisk's structural behavior under realistic loading conditions, a high-fidelity dataset was created that includes various combinations of centrifugal forces, aerodynamic loads, and thermal effects. The application of cyclic symmetry allowed for computational efficiency, reducing the need to simulate the full blisk geometry while maintaining accuracy. The obtained FEA results served as the foundation for training a deep learning model capable of predicting stress distributions in rotor blisks under different operational conditions. The deep learning model, trained on the FEA dataset, exhibited strong predictive capabilities, providing a rapid alternative to traditional FEA simulations. In comparison, to survey stress results for each node with the traditional FEA approach requires 66 seconds for only one loading condition, whereas DNN predicts stress results for each node within only 5 milliseconds. Moreover, traditional FEA requires 34250 kilobytes disk storage whereas DNN only requires 363 kilobytes. By reducing the time required to perform complex simulations, this approach holds great promise for improving design optimization and life prediction of gas turbine components, which are critical in aerospace and energy industries. The deep learning model's ability to predict stress with high accuracy offers a powerful tool for structural engineers, reducing reliance on computationally expensive and time-consuming FEA simulations. Through this research, we have also shown the potential of AI-enhanced numerical simulations, where the integration of deep learning can significantly reduce analysis time without sacrificing accuracy.

Future studies can focus on enhancing the deep learning model by exploring more advanced neural network architectures, such as convolutional or recurrent networks, to better capture spatial and temporal dependencies. Expanding the dataset to include a wider range of operational conditions and failure modes will also improve model accuracy. Further validation through experimental testing and the use of transfer learning for different geometries and conditions could make the model more adaptable.

This study successfully addresses the computational bottleneck associated with traditional FEA methods by proposing an accurate and efficient AI-based stress prediction framework for rotor blisks. The demonstrated speed-up and reduced storage requirements underscore the practical utility of this approach for real-time engineering applications and iterative design processes. The insights gained pave the way for more efficient and robust design of critical gas turbine components, contributing to advancements in aerospace and energy sectors.

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