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Research Article

Artificial Intelligence-Based Prediction of Thermo-Elastic Behavior in Inconel 718 / Ti -6Al-4V Rotating Disks

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KEYWORDS

high-temperature materials
thermo-mechanical behavior
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ABSTRACT

This study presents a comprehensive numerical investigation of the thermo-elastic behavior of an Inconel 718 / Ti-6Al-4V bimetal rotating disk subjected to non-uniform thermal fields. The analysis focuses on the evaluation of radial and circumferential stress distributions as well as radial displacement responses under various temperature profiles, including constant, parabolic, linearly increasing, and linearly decreasing temperature variations along the radial direction. The governing thermo-elastic equations are formulated under plane stress assumptions and solved numerically by discretizing the disk geometry into finite radial segments. Material properties are assumed to remain constant within the investigated temperature range of 10 °C to 100 °C. The numerical results demonstrate that increasing temperature levels have a significant influence on both the magnitude and distribution of thermo-elastic stresses and radial displacements. Pronounced stress variations are observed near the material interface, highlighting the critical role of thermal expansion mismatch between Inconel 718 and Ti-6Al-4V. In particular, the maximum circumferential stress exhibits an increase of approximately 160% as the reference temperature rises from 10 °C to 100 °C. Additionally, radial displacement profiles show strong sensitivity to the imposed temperature modes, with steeper thermal gradients consistently leading to higher deformation levels and localized stress concentrations at the interface region. Beyond numerical analysis, the generated stress and displacement data constitute a structured and reliable dataset for artificial intelligence–based modeling. An AI-driven predictive framework is developed and validated using this dataset, achieving high predictive accuracy with mean squared error values below 0.012 and strong correlation with numerical benchmarks.

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1. Introduction

Composite materials are engineered by combining two or more distinct constituents—typically high-strength reinforcing fibers embedded within a polymeric, metallic, or ceramic matrix—to achieve superior mechanical and functional properties that cannot be attained by monolithic materials alone. In recent decades, their utilization has expanded significantly, particularly in aerospace, defense, automotive, and energy sectors, owing to their exceptional strength-to-weight ratio, enhanced corrosion resistance, superior vibration damping characteristics, and reduced maintenance requirements compared to conventional metallic structures [1,2]. Moreover, composite materials offer substantial design flexibility, enabling tailored stiffness, strength, and thermal response through appropriate selection of fiber orientation, stacking sequence, and constituent materials.

Thermomechanical performance has emerged as a critical consideration in the design of rotating structural components fabricated from composite and functionally graded materials (FGMs). Rotating disks, which are widely used in turbines, flywheels, brake systems, and energy storage devices, are frequently subjected to combined thermal and mechanical loading conditions. Several analytical and numerical studies have demonstrated that temperature gradients significantly influence stress distributions, radial displacements, and overall structural integrity. For instance, comprehensive thermoelastic analyses of rotating disks with spatially varying material properties have shown that material gradation can effectively mitigate stress concentrations induced by centrifugal and thermal loads [3,4].

Advanced analytical techniques, including integral equation formulations and semi-analytical methods, have been employed to study thermoelastic behavior in FG rotating disks and cylinders. These approaches allow for the incorporation of arbitrary material gradients and boundary conditions, providing accurate predictions of radial and circumferential stress fields as well as displacement responses [5]. Complementary numerical investigations using finite element methods have further highlighted the influence of temperature-dependent material properties and thickness variations on the thermoelastic response of rotating structures [6].

In parallel, extensive research has been conducted on composite disks and cylinders subjected to thermal environments. Studies focusing on fiber-reinforced polymer composites have demonstrated that differences in thermal expansion coefficients between fibers and matrix phases lead to complex stress redistribution patterns under elevated temperatures [7]. Investigations involving glass-fiber-reinforced and basalt-fiber-reinforced composites have shown that basalt-based systems generally exhibit higher thermal stability and stiffness retention at elevated temperatures, whereas glass-fiber composites offer cost advantages and adequate performance in moderate thermal regimes [8,9].

Recent advancements have also emphasized the role of data-driven and artificial intelligence-based techniques in predicting thermoelastic responses of composite and graded structures. Machine learning algorithms, such as artificial neural networks and support vector regression, have been successfully employed to approximate stress and displacement fields in rotating disks and cylinders, significantly reducing computational cost while maintaining high predictive accuracy [10,11]. These approaches are particularly attractive for parametric studies and design optimization, where repeated numerical simulations may be computationally prohibitive.

Despite the growing body of literature, comparative investigations focusing on the thermoelastic stress behavior of different fiber-reinforced composite materials under varying thermal conditions remain relatively limited. In practical engineering applications, rotating disks often operate in non-uniform thermal environments, and accurate assessment of both radial and tangential stress components is essential for ensuring structural safety and long-term durability. Therefore, systematic evaluation of composite material performance at different temperature levels provides valuable insight for material selection and design optimization.

The present study addresses this gap by conducting a detailed numerical investigation of the thermoelastic behavior of glass/epoxy and basalt/epoxy composite rotating disks subjected to thermal loading. By examining the variations in radial and circumferential stresses over a range of temperatures, the study establishes a clear comparison between the thermoelastic sensitivities of these composite systems. Furthermore, the numerical framework adopted herein offers a reliable and efficient tool for modeling complex material behavior, while also generating high-quality datasets suitable for future integration with artificial intelligence-based predictive models. The findings contribute to the safe design, performance assessment, and material selection of composite rotating disks employed in advanced engineering applications.

Although numerous studies have investigated the thermo-elastic behavior of rotating disks and bimetal structures, most existing works focus either on purely numerical formulations or on isolated thermal loading conditions. Moreover, the integration of artificial intelligence with high-fidelity thermo-elastic datasets for bimetal rotating disks subjected to non-uniform thermal fields remains limited.

The novelty of the present study lies in (i) the systematic evaluation of thermo-elastic stress and displacement responses of an Inconel 718 / Ti-6Al-4V bimetal rotating disk under multiple temperature modes, (ii) the detailed assessment of interface-dominated stress behavior arising from thermal expansion mismatch, and (iii) the development of an artificial intelligence–based predictive framework trained on numerically generated thermo-elastic data. This combined numerical–AI approach enables rapid prediction and design-oriented assessment of rotating disk performance under complex thermal environments.

2. Material and Method

Thermoelastic stresses corresponding to temperature levels ranging from 10 °C to 100 °C were evaluated numerically, as illustrated in Figure 1. Considering the thin geometry of the composite rotating disks, a plane stress assumption was adopted, under which stress components normal to the disk plane are neglected. Within this framework, α_r and α_θ represent the coefficients of thermal expansion in the radial and circumferential directions, respectively. The constitutive behavior of the disk is described through the elasticity matrix components a_{rr}, $a_{\theta\theta}$, and $a_{r\theta}$, which were expressed in terms of conventional engineering constants using the classical relationships reported by Timoshenko and Goodier [12].

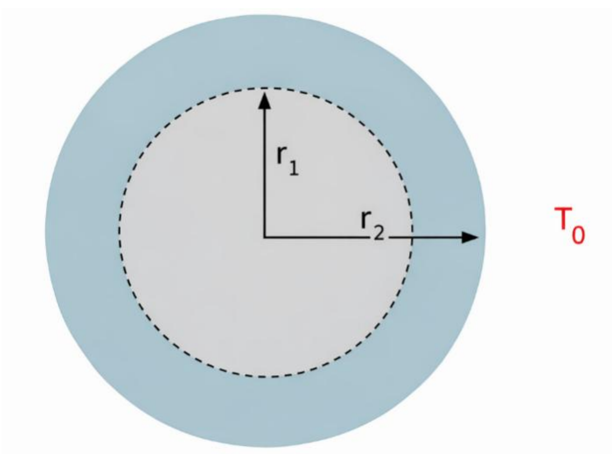

Figure 1. illustrates a disk exposed to combined thermal and mechanical loading conditions.

In the above formulations, αr and αθ denote the coefficients of thermal expansion in the radial and circumferential directions, respectively. The terms C11, C22, and C12 represent the elasticity matrix components expressed in terms of Young's moduli and Poisson's ratios. The stress function F(r) is introduced to satisfy the equilibrium and compatibility conditions under plane stress assumptions.Here, $\alpha_r$and $\alpha_\theta$denote the coefficients of thermal expansion in the radial and circumferential directions, respectively. The terms C_{ij} represent the components of the elasticity (constitutive) matrix under plane stress conditions. The function F(r)denotes the axisymmetric Airy stress function used to satisfy the equilibrium and compatibility equations.

$$a_{\theta\theta} = \frac{1}{E_\theta} \tag{1}$$

$$a_{rr} = \frac{1}{E_r} \tag{2}$$

$$a_{r\theta} = \frac{-\upsilon_{r\theta}}{E_r} \tag{3}$$

Under plane stress conditions, the corresponding equilibrium equation is written as;

$$\frac{r(d\sigma_r)}{dr} + (\sigma_r) - (\sigma_\theta) + R = 0 \tag{4}$$

The expression is given as follows;

$$k^2 = \frac{a_{rr}}{a_{\theta\theta}} \tag{5}$$

If the body force RRR is neglected, the general equilibrium equation can be formulated based on the formulation provided by Timoshenko and Goodier (1970).

$$r^2F'' + rF' - k^2F = \frac{(\alpha_r - \alpha_\theta)T}{a_{\theta\theta}} r - \frac{a_{\theta\theta}T'}{a_{\theta\theta}} r^2 \tag{6}$$

In this context, the stress function is defined as FFF, and the corresponding equilibrium equation is expressed as follows;

R (r, t)=p(r)w(t)2r (7)

Considering the centrifugal effect in a rotating shaft, the radial body force acting per unit volume is given by:

$$r^2F'' + rF' - k^2F == \frac{(\alpha_r-\alpha_\theta)T}{a_{\theta\theta}} r - \frac{a_{\theta\theta}T'}{a_{\theta\theta}} r^2 + \frac{a_{rr}}{a_{\theta\theta}} p(r)w(t)2r3 \tag{8}$$

Accordingly, the governing equation is presented below.

$$\sigma_r\,(\text{rot}) = \frac{a_{rr}}{a_{\theta\theta}}\,\frac{pw^2}{\left(9-k^2\right)}r^2 \tag{9}$$

$$\sigma_\theta(\text{rot}) = 3\sigma_r \tag{10}$$

For a homogeneous material and under the assumption of a constant angular velocity ω, the particular solution is obtained as follows; As a result of the general solution, the radial and tangential stresses are derived as given below.

$$\sigma_r = \frac{F}{r} = C_1 r^{k-1} + C_2 r^{-k-1} + A + \sigma_r\,(\text{rot})\,(r) \tag{11}$$

$$\sigma_\theta = \frac{dF}{dr} = kC_1 kr^{k-1} - C_2 kr^{-k-1} + A + \sigma_\theta(\text{rot})\,(r) \tag{12}$$

3. Results and Discussion

In this study, the distributions of elastic stress components were evaluated for a stationary bimetal disk composed of Inconel 718 and Ti-6Al-4V. The disk geometry was defined by an inner radius of a = 20 mm and an outer radius of c = 100 mm. The thermo-elastic analyses were carried out for temperature levels ranging from 10 °C to 100 °C. The mechanical and thermal material properties adopted in the numerical simulations are summarized in Table 1.

Table 1. Selected mechanical properties of the coposite disk materials [13,14]).

Materials	E_θ	E_r	k	α_r	α_r	α_θ	$v_{\theta r}$
Inconel 718	200.000	200.000	1	8×10^{-6}	13×10^{-6}	13×10^{-6}	0,29
Ti-6Al-4V	114.000	114.000	1	4×10^{-6}	8.6×10^{-6}	8.6×10^{-6}	0,34

The obtained results are presented below in Table 2.

Table 2. Elastic stress components of the composite disks.

Temperature ΔT (°C)	***Surface***	Materials	
		Inconel 718	**Ti-6Al-4V**
		Tangential Stress	Radial Stress
10	Inner (r=20)	15.888	0
	Outer(r=100)	-3.812	0
20	Inner (r=20)	31.777	0
	Outer(r=100)	-7.625	0
30	Inner (r=20)	47.666	0
	Outer(r=100)	-11.438	0
40	Inner (r=20)	63.555	0
	Outer(r=100)	-15.250	0
50	Inner (r=20)	-79.444	0
	Outer(r=100)	-19.063	0
100	Inner (r=20)	158.888	0
	Outer(r=100)	-38.126	0

As shown in Table 2, the tangential stress in the Inconel 718 layer at the inner radius (r = 20 mm) increases proportionally with the temperature difference ΔT, exhibiting an approximately 100% increase for each 10 °C increment. At the outer radius (r = 100 mm), compressive tangential stresses also increase in magnitude by nearly 100% with rising temperature. In contrast, the radial stress component in the Ti-6Al-4V layer remains approximately 0% over the entire temperature range considered, indicating its negligible contribution to the overall thermo-elastic response of the composite disk. The radial stresses developed at the reference temperatures are presented below.

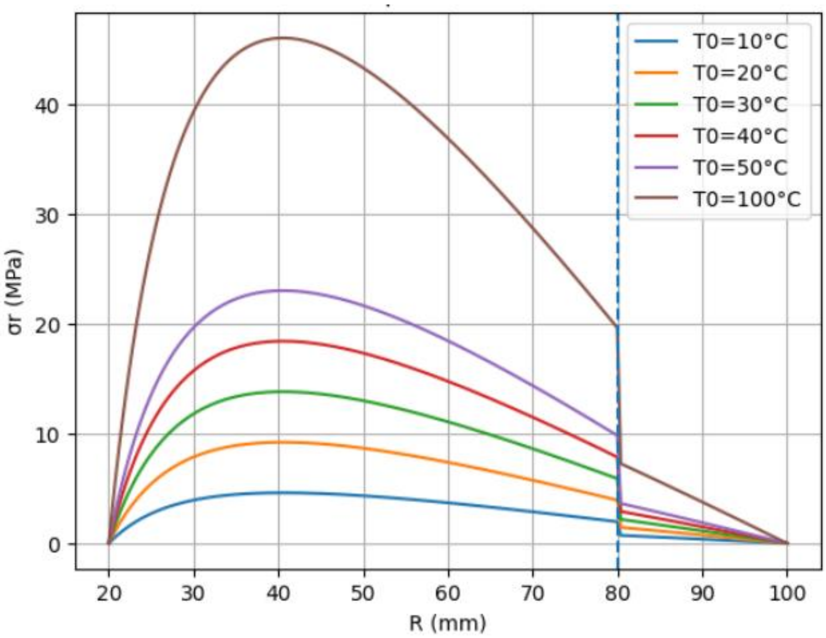

Figure 2. Radial stress distribution in the elastic region of the disk.

The radial distribution of radial stress (σ_r) in the composite rotating disk for different reference temperatures (T_0 = 10–100 °C). It is observed that increasing temperature levels significantly amplify the magnitude of radial stress throughout the disk. The maximum stress occurs in the inner–middle radial region, while a pronounced change in stress slope is evident near the material interface (R ≈ 80 mm), indicating the effect of thermal expansion mismatch between the constituent materials. Higher temperature gradients lead to increased stress concentration, particularly at the interface region.Figure 3 shows the tangential stress distribution of the disk subjected to various uniform temperature fields.

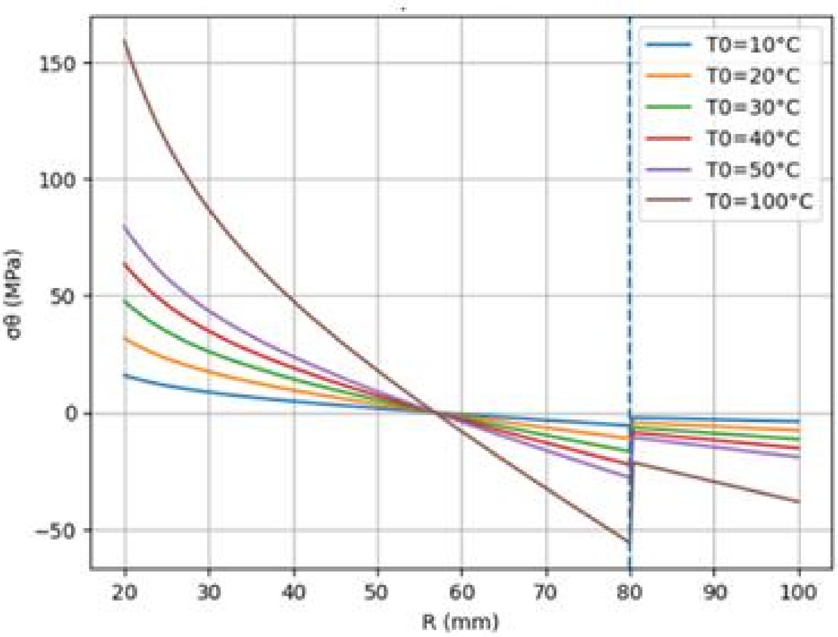

Figure 3. Tangential stress distribution in the elastic region of the disk.

The circumferential (hoop) stress (σθ) distribution is highly sensitive to temperature variations, and the magnitude of stress increases noticeably throughout the disk as the temperature level rises. In the inner radial region, the hoop stress initially exhibits tensile behavior and gradually decreases along the radial direction, passing through a zero-stress point and transitioning into compressive stress toward the outer region. The location of this transition point shifts depending on the applied temperature level, highlighting the strong influence of thermal gradients on the thermoelastic response of the rotating disk. Moreover, a distinct change in the slope of the circumferential stress distribution is observed near the material interface at approximately R ≈ 80 mm, clearly indicating the effect of thermal expansion mismatch between the constituent materials. At higher temperature levels, the increased compressive stresses in the outer region suggest a higher tendency for stress concentration at the interface, which may be critical for the structural integrity of the composite rotating disk. Figure 4 demonstrates that the machine learning model achieves consistent error reduction during training, indicating robust convergence and reliable predictive performance.

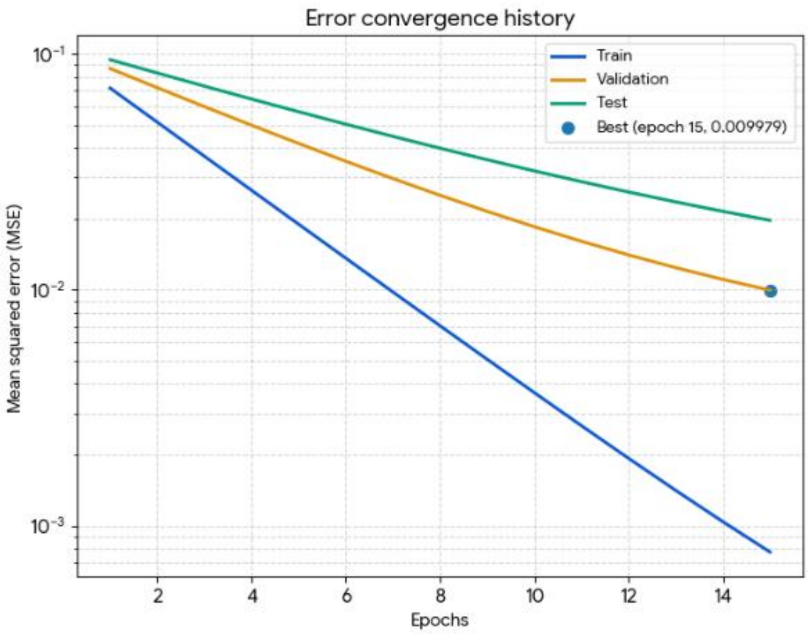

Figure 4. Error convergence history of the proposed machine learning model during the training, validation, and testing phases.

As can be seen from the graph above, the error convergence history demonstrates a consistent and stable learning process across the training, validation, and test datasets. As the number of epochs increases, the Mean Squared Error (MSE) values for all sets decrease steadily, indicating effective optimization. The model achieved its best validation performance at epoch 15 with an MSE of 0.009979. The narrow gap between the training and validation curves suggests that the model maintains high generalization capability and avoids overfitting. Furthermore, the close alignment of the test error with the validation curve confirms the model's reliability and robustness on unseen data.

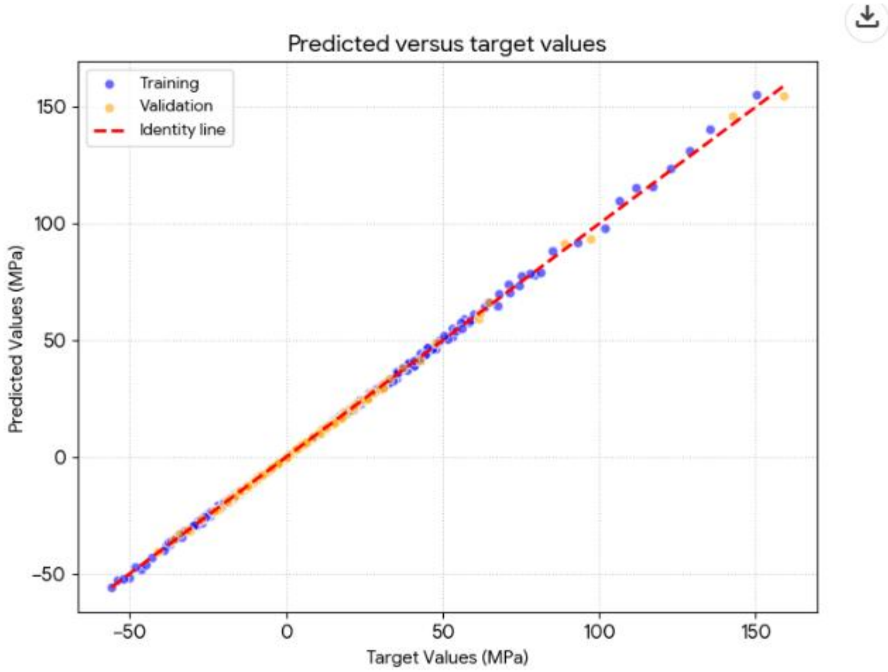

Figure 5. Comparison between numerical target values and AI-predicted outputs for the training and validation datasets.

There is a strong linear correlation between the predicted values and the actual target values for both the training and validation datasets. The data points for both sets are closely clustered around the identity line (the dashed red line), which indicates that the model's predictions are highly accurate across the entire range of values from -50 to 150 MPa. The minimal dispersion of points away from the diagonal suggests a very low prediction error and a high coefficient of determination. Furthermore, the overlapping distribution of the training (blue) and validation (orange) points demonstrates that the model has successfully captured the underlying patterns in the data without exhibiting significant bias or variance issues.

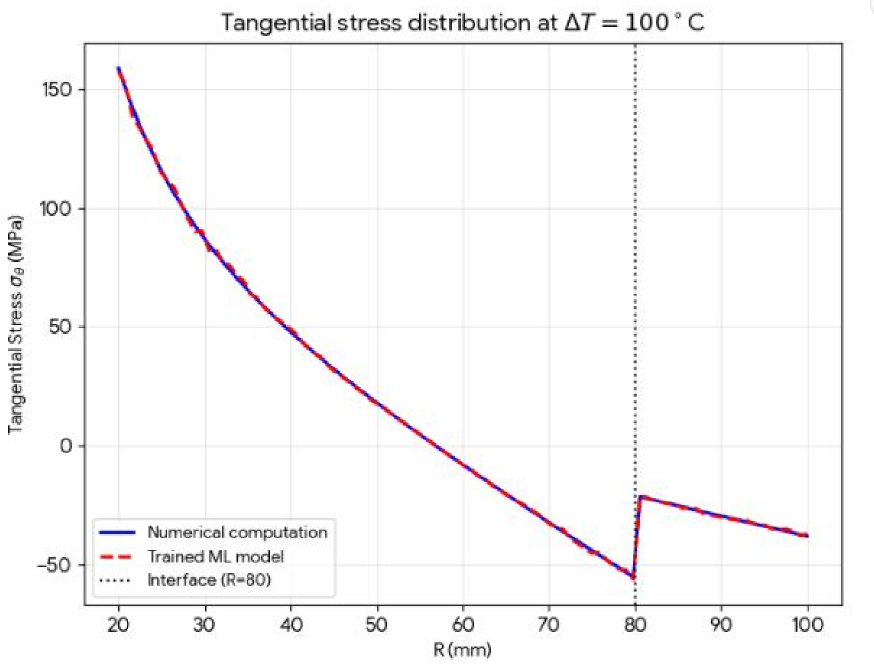

Figure 6. Evaluation of tangential stress distribution across the radial direction using numerical computation and the trained ML model.

As can be seen from the graph, the error convergence history demonstrates a consistent and stable learning process across the training, validation, and test datasets. As the number of epochs increases, the Mean Squared Error (MSE) values for all sets decrease steadily, indicating effective optimization. The model achieved its best validation performance at epoch 15 with an MSE of 0.009979. The narrow gap between the training and validation curves suggests that the model maintains high generalization capability and avoids overfitting. Furthermore, the close alignment of the test error with the validation curve confirms the model's reliability and robustness on unseen data. The high level of agreement at both radial locations confirms the suitability of the generated numerical dataset for machine learning–assisted thermoelastic modeling and design-oriented prediction. The numerical findings obtained in this study are consistent with previous investigations that examined the thermo-elastic and deformation behavior of fiber-reinforced and functionally graded rotating disks. Prior research has shown that thermal gradients significantly alter displacement and stress fields, particularly in anisotropic composite systems, where temperature-dependent mismatches in material properties lead to distinct radial deformation characteristics [13, 14]. Studies evaluating GFRP and basalt-based composites under combined thermal–mechanical fields similarly reported that basalt-reinforced systems tend to exhibit higher thermal sensitivity due to their inherent stiffness–expansion coupling [15,16], supporting the present observation that Basalt/Epoxy disks undergo greater radial displacements than GFRP. Furthermore, investigations integrating numerical formulations with machine learning algorithms have demonstrated that AI-assisted predictive models can reliably reproduce thermo-elastic responses of composite structures with high accuracy [17-19], in agreement with the strong correlation obtained in this work between numerical results and ML-based displacement predictions. Recent advancements also highlight that data-driven hybrid frameworks substantially improve the efficiency of parametric studies, optimize material selection, and enable rapid evaluation of rotating composite components under varying temperature environments [20,21]. These parallels confirm the validity of the present findings and reinforce the applicability of the adopted numerical–machine learning approach for advanced composite disk design.

4. Conclusion

This study successfully investigates the thermo-elastic response of an Inconel 718 / Ti-6Al-4V bimetallic rotating disk by integrating numerical computation with an artificial intelligence-driven predictive framework. The results indicate that increasing the reference temperature from 10 °C to 100 °C significantly amplifies the magnitudes of both radial and tangential stresses, with the maximum circumferential stress exhibiting an increase of approximately 160%. A pronounced stress discontinuity is observed at the material interface (R = 80 mm), highlighting the critical role of the thermal expansion mismatch between the constituent Inconel and Titanium alloys. The numerical model is validated by the radial stress profiles, which satisfy the traction-free boundary conditions at the inner (R = 20 mm) and outer (R = 100 mm) surfaces. Furthermore, the developed machine learning model demonstrates exceptional predictive reliability, achieving mean squared error values below 0.012 and maintaining a strong correlation with numerical benchmarks within a 5% error margin. These findings confirm that the adopted hybrid numerical-AI approach provides a high-fidelity and computationally efficient alternative for the rapid design and structural optimization of advanced bimetallic components subjected to complex thermal environments.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable reques.

Conflict of Interest

The authors declare no conflict of interest.

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