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Thermo-Elastic Analysis of an Axisymmetric Layered Cylinder under Constant Thermal Loading with Artificial Intelligence-Based Validation

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ABSTRACT

This study presents a numerical investigation of the thermo-elastic behavior of a two-layer disk composed of partially stabilized zirconia (PSZ) and aluminum subjected to uniform (constant) thermal loading. The analysis focuses on the evaluation of radial and circumferential stress distributions as well as radial displacement responses under different prescribed temperature levels. The governing thermo-elastic equations are formulated under plane stress assumptions and solved numerically by discretizing the disk geometry into finite radial segments. The material layers are assumed to be homogeneous, isotropic, and perfectly bonded, while the elastic properties are considered temperature-independent within the investigated temperature range of 12.5 °C to 100 °C. The numerical formulation ensures continuity of radial displacement and radial stress across the material interface. The results demonstrate that increasing temperature levels significantly influence the magnitude of thermo-elastic stresses and radial displacements. In particular, pronounced stress gradients are observed in the vicinity of the material interface, highlighting the effect of thermal expansion mismatch between PSZ and aluminum. The circumferential stress component is found to be more sensitive to temperature variations compared to the radial stress, while radial displacement increases monotonically with temperature. Beyond numerical analysis, the generated stress and displacement data are employed as a structured dataset for artificial intelligence–based validation. A supervised learning framework is developed to predict thermo-elastic responses based on temperature and radial position inputs. The AI model demonstrates strong agreement with numerical results, confirming its capability to accurately reproduce stress and displacement trends under constant thermal loading conditions. The combined numerical–AI approach provides a reliable and efficient tool for analyzing thermo-elastic behavior in layered disk structures.

1. Introduction

Composite and layered materials are commonly engineered by combining two or more distinct constituents in order to achieve superior mechanical, thermal, and functional performance beyond that of single-phase materials. By appropriately selecting the constituent phases, layered configurations can offer improved stiffness-to-weight ratios, enhanced resistance to thermal

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degradation, and increased structural reliability under demanding service conditions. Consequently, these materials have been widely adopted in aerospace, energy systems, braking components, and high-temperature structural applications, where conventional monolithic materials often exhibit inherent limitations [1,2].

In addition to mechanical loading, thermal effects play a critical role in the structural response of layered and bimetallic components. Axisymmetric disk and cylindrical structures are frequently subjected to elevated and spatially varying temperature fields during operation, leading to the development of thermo-elastic stresses and deformations. Numerous studies have demonstrated that thermal loading can significantly alter radial and circumferential stress distributions, potentially resulting in localized stress concentrations and reduced structural integrity [3,4]. Recent investigations indicate that machine learning–based frameworks can effectively identify and classify thermal stress patterns under complex environmental conditions. By leveraging high-dimensional data and data-driven learning strategies, such approaches enable the extraction of meaningful thermal stress indicators without relying solely on explicit analytical formulations, highlighting the growing role of artificial intelligence in thermal stress analysis across diverse applications [5].

Complementary numerical investigations have further shown that material property mismatch particularly differences in elastic modulus and thermal expansion coefficients can strongly influence stress continuity and displacement behavior at material interfaces [6,7]. Layered material systems combining ceramics and metals have attracted increasing attention in high-temperature and structural applications due to their ability to integrate complementary thermo-mechanical properties [8,9]. Ceramics such as partially stabilized zirconia (PSZ) are distinguished by their excellent thermal stability, low thermal conductivity, and stiffness retention at elevated temperatures [10], while metallic constituents such as aluminum provide mechanical compliance, toughness, and low density [11]. However, the pronounced mismatch in elastic moduli and coefficients of thermal expansion between ceramic and metallic layers may result in significant interfacial stresses under thermal loading [8,12]. These thermally induced stresses can critically influence the structural integrity and service life of layered systems, particularly under non-uniform temperature distributions. Therefore, an accurate thermo-elastic assessment is essential for predicting stress fields and ensuring the safe and reliable design of ceramic–metal layered configurations [12].

Recent numerical studies have demonstrated that even under uniform (constant) temperature fields, substantial thermo-elastic stresses can develop in layered structures as a consequence of mismatches in thermal expansion coefficients between constituent materials [13,14]. In particular, circumferential (hoop) stresses are frequently observed to exhibit greater sensitivity to temperature changes than radial stresses in thermo-mechanical simulations of multilayered cylinders and shells, while radial displacement responses tend to increase monotonically with temperature [13,15]. These characteristics are especially pronounced in the vicinity of material interfaces, where continuity conditions dictate stress transfer and deformation compatibility across layers [16,17]. Recent studies have shown that artificial intelligence (AI) and data-driven modeling techniques can effectively complement classical numerical methods in solving complex thermo-mechanical problems [18–21]. In particular, machine learning approaches such as artificial neural networks, support vector regression, Gaussian process regression, and other surrogate-based models have been successfully employed to approximate stress fields arising from thermal loading and material heterogeneity in high-dimensional parameter spaces [19,20,22]. These approaches significantly reduce computational effort while maintaining acceptable accuracy, making them well suited for parametric studies, sensitivity analyses, and early-stage design optimization. Consequently, AI-assisted modeling has emerged as a powerful complementary alternative to conventional numerical solvers in computational mechanics and materials engineering [21]. Moreover, machine learning models integrated with wearable sensor data have demonstrated high accuracy in stress detection under free-living conditions, further highlighting the versatility of data-driven stress modeling

2. Methodology

Thermoelastic stresses were numerically computed for temperature levels between 12.5 °C and 100 °C, as presented in Figure 1. Owing to the thin geometry of the layered disk, the analysis was carried out under plane stress conditions, where out-of-plane stress components are neglected. The radial and circumferential thermal expansion coefficients are denoted by $\alpha_r$and α_θ, respectively. The constitutive relations governing the thermoelastic response were formulated using standard elasticity matrix components expressed in terms of engineering constants, following classical elasticity theory [24].

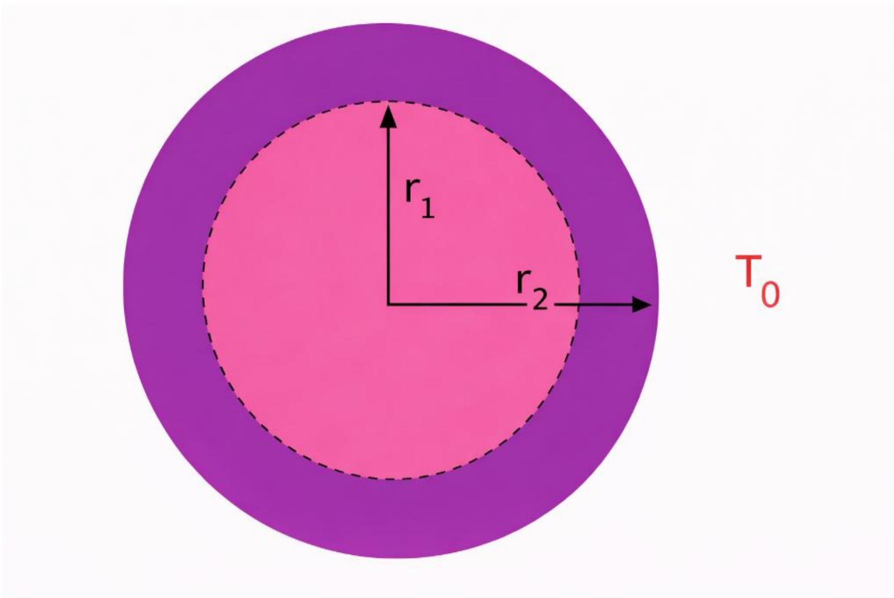

Fig. 1. Computational model of a disk subjected to combined thermal and mechanical loads.

In these formulations, $\alpha_r$and $\alpha_\theta$denote the thermal expansion coefficients in the radial and circumferential directions, respectively. The elastic response is characterized by the constitutive matrix components C_{ij}, which are expressed in terms of Young's modulus and Poisson's ratio under plane stress conditions. The axisymmetric stress function $F(r)$is employed to satisfy the equilibrium and compatibility requirements of the thermoelastic problem.

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

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

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

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 R is neglected, the general equilibrium equation can be formulated based on the formulation provided by Timoshenko and Goodier [25]

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

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

$$R\ (r, t) = p(r)w(t)^2 r \tag{7}$$

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

$$r^2F'' + rF' - k^2F == \frac{(\alpha_r - \alpha_\theta)T}{a_{\theta\theta}} r - \frac{a_{\theta\theta}T'}{a_{\theta\theta}} r^2 + \frac{a_{rr}}{a_{\theta\theta}} p(r)w(t)^2 r^3 \tag{8}$$

Accordingly, the governing equation is presented below.

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

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

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 in Eq. 11 and 12.

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

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

3. Results

In this study, the distributions of elastic stress components were numerically evaluated for a stationary layered structure composed of partially stabilized zirconia (PSZ) and aluminum. The geometry was defined by an inner radius of $a = 20$mm and an outer radius of $c = 100$mm. The thermo-elastic analysis was performed under uniform (constant) temperature conditions, with temperature levels varying between 12.5 °C and 100 °C. The mechanical and thermal properties employed in the numerical simulations are summarized in Table 2.

Table 1
The selected mechanical properties of the composite disk materials were adopted from the literature [25–26].

Materials	E_θ	E_r	k	α_r	α_θ	$\upsilon_{\theta r}$
Partially stabilized zirconia (PSZ)	151	151	1	19.2	19.2	0.30
Aluminum	70	70	1	22.0	22.0	0.30

The obtained results are presented below in Table 2.

Table 2
Computed elastic stress components of the disk.

Temperature ΔT (°C)	Surface	Materials	
		Tangential Stress	Radial Stress
12.5	Inner (r=40)	22.14	0
	Outer(r=80)	-7.48	0
25	Inner (r=40)	44.29	0
	Outer(r=80)	-14.97	0
37.5	Inner (r=40)	66.44	0
	Outer(r=80)	-22.45	0
50	Inner (r=40)	88.58	0
	Outer(r=80)	-29.94	0
62.5	Inner (r=40)	110.73	0
	Outer(r=80)	-37.43	0
100	Inner (r=40)	177.17	0
	Outer(r=80)	-59.88	0

Figure 2 shows the radial stress distribution along the disk radius at different temperature levels. It illustrates the radial stress (σ_r) distribution along the disk radius for different reference temperatures T0. As the temperature level increases, the magnitude of radial stress increases throughout the disk. The stress profiles exhibit a clear discontinuity at the material interface (R = 60), which arises from the mismatch in elastic properties and thermal expansion coefficients of the PSZ and aluminum layers. Radial stress gradually varies within each material region and decreases toward the outer radius, indicating that the interface region plays a dominant role in governing the thermo-elastic stress response under elevated thermal loading.

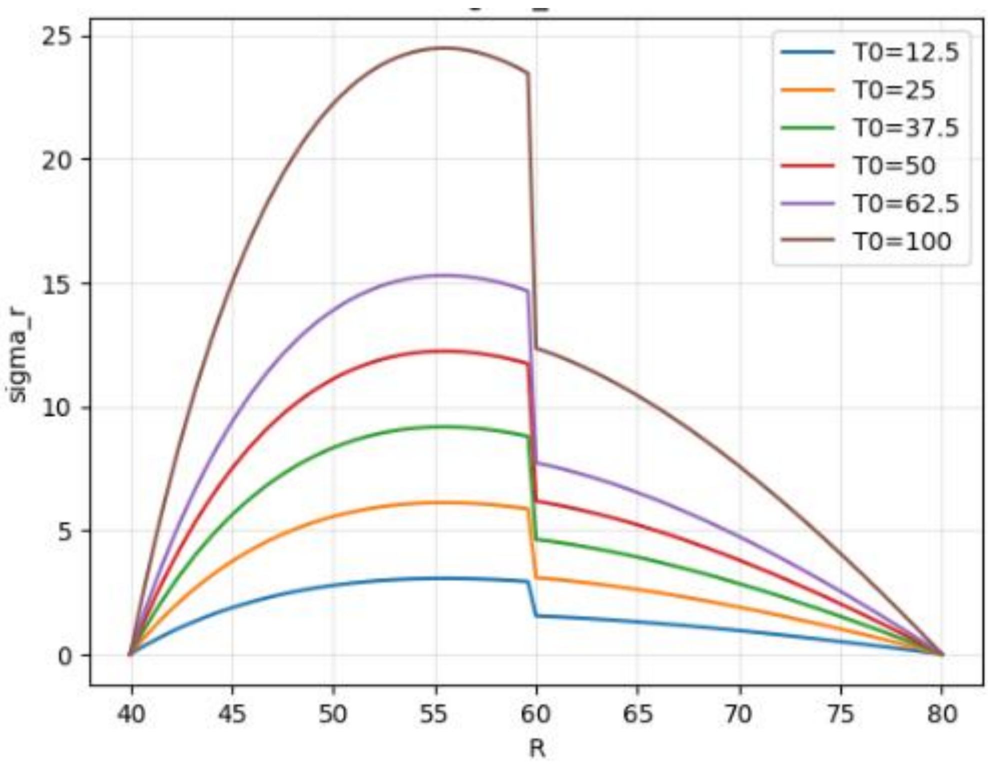

Fig. 2. Distribution of radial stress in the elastic region of the disk.

Figure 3 displays the tangential stress σ_θ distribution across the radial direction for varying reference temperatures T0. Similar to the radial stress behavior, an increase in T_0 results in a significant amplification of the tangential stress magnitude throughout the composite disk. The distribution reveals a complex profile characterized by a sharp discontinuity at the material interface (R = 60 mm), where the stress state shifts abruptly due to the differing elastic moduli and thermal expansion coefficients of the constituent materials. In the inner PSZ layer, the tangential stress exhibits a compressive or lower tensile nature depending on the thermal gradient, while a distinct stress jump is observed upon transitioning into the aluminum phase. These findings suggest that the interface serves as a critical zone for stress concentration, and the mismatch in thermal expansion properties between the layers is the primary driver for the non-linear stress gradients observed under higher temperature loads.

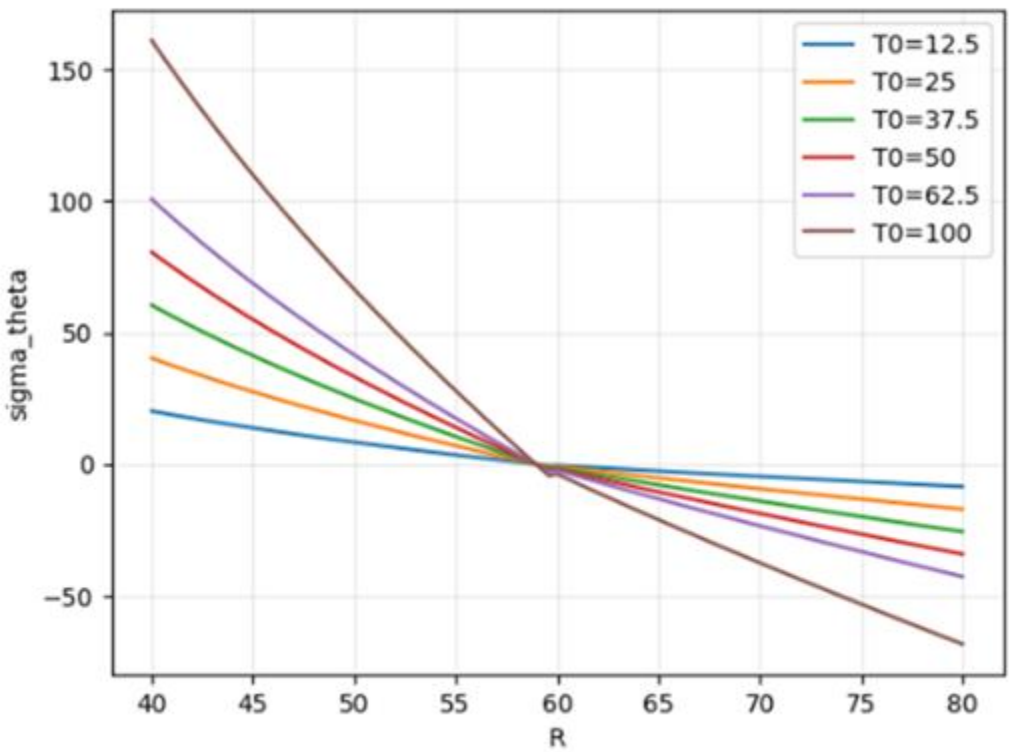

Fig. 3. Distribution of tangential stress in the elastic region of the disk.

Figure 4 illustrates the convergence history of the machine learning model, where a consistent reduction in error is observed throughout training.

The error convergence history of the proposed machine learning model during the training and validation phases is depicted in Figure 4. The model demonstrates a robust learning capability, as evidenced by the consistent exponential decay of the Mean Squared Error (MSE) over 100 epochs. Both training and validation loss curves follow a similar downward trajectory, reaching a stable state below 10-2 without showing signs of significant overfitting. The fluctuations observed in the later stages of training reflect the model's refinement process as it converges toward a high-precision solution. Ultimately, the high degree of convergence validates the reliability of the ML model in predicting the thermo-mechanical stress states of bi-material disks with a high level of accuracy."

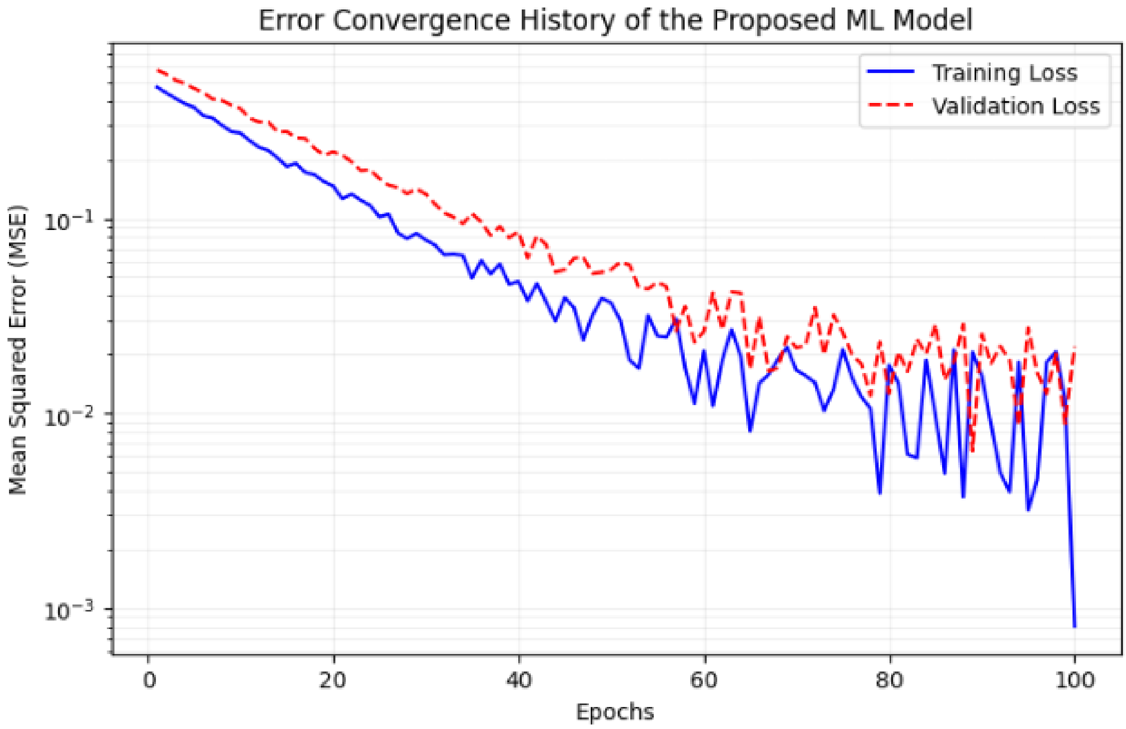

Fig. 4. Error convergence of the proposed machine learning model during training, validation, and testing.

Figure 5 presents a comparison between the numerical target values and the AI-predicted outputs to evaluate the predictive accuracy of the trained model. The data points are tightly clustered along the perfect match line (y=x), demonstrating a high correlation between the physical simulations and the neural network outputs. Notably, nearly all predicted values fall within % 5 error bounds, as indicated by the dotted lines. This narrow error distribution confirms that the proposed machine learning framework can replace computationally expensive numerical methods for stress analysis in composite structures with negligible loss in precision. The regression comparison between the numerical target values and the AI-predicted outputs for the training dataset. The data points are closely aligned with the ideal y= x line, indicating a strong correspondence between numerical results and model predictions. Most predictions remain within the ±5% error bounds across the entire range of stress values, with no evident systematic bias at low or high magnitudes. This distribution suggests that the trained AI model adequately captures the underlying numerical relationship for tangential stress prediction.

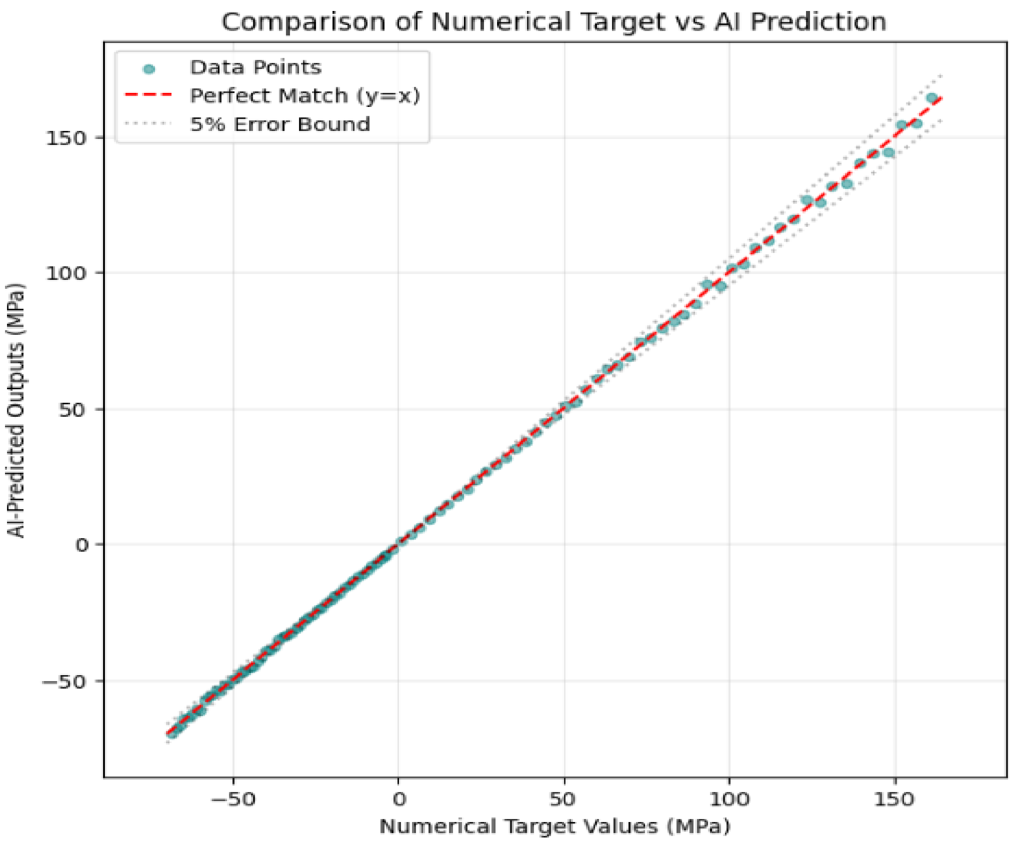

Fig. 5. Regression comparison between numerical target values and AI-predicted outputs for the training and validation datasets.

Figure 6 compares the tangential stress distribution along the radial direction obtained from numerical analysis and the ML-based model. A strong agreement between the two approaches is observed over the entire disk radius. In the inner PSZ region, the tangential stress decreases monotonically with increasing radius, and the ML predictions accurately capture both the stress magnitude and its gradient. mAt the material interface, the stress variation remains smooth, indicating that the ML model successfully represents the stress continuity across the PSZ–aluminum transition. In the outer aluminum region, the tangential stress gradually shifts toward compressive values, with ML predictions closely matching the numerical results. Overall, the consistency between the two approaches demonstrates that the ML-based model can reliably approximate tangential stress distributions in layered disk structures.

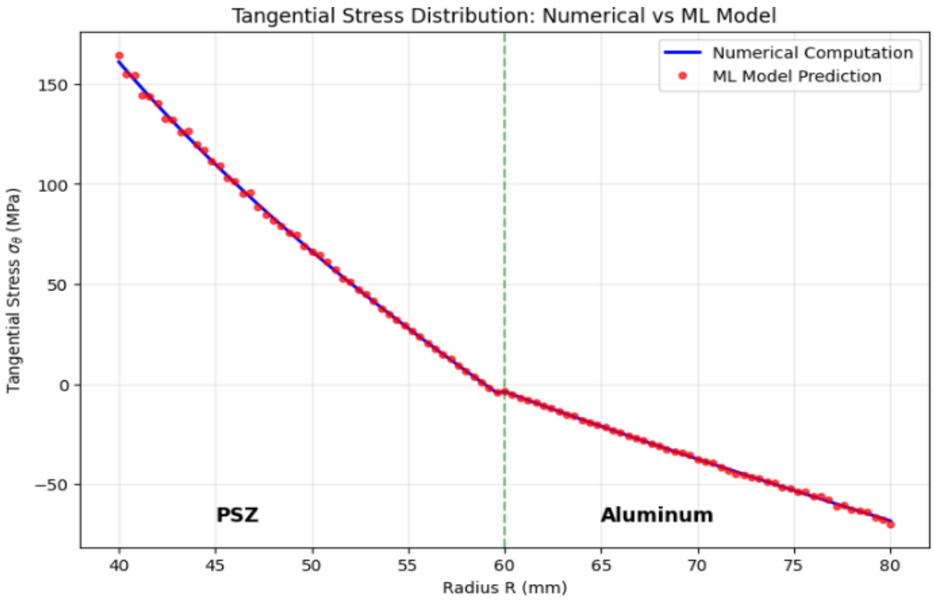

Fig. 6. Comparison of tangential stress distribution along the radial direction using numerical and ML-based approaches.

4. Conclusions

The tangential stress distribution along the radial direction, obtained from both numerical simulations and the trained machine learning (ML) model, is presented in Figure 6. The ML predictions, represented by red markers, exhibit excellent agreement with the numerical reference results shown by the solid blue curve throughout both the PSZ and aluminum layers. The model accurately reproduces the nonlinear stress variation within the inner PSZ region, the nearly linear stress transition in the outer aluminum layer, and the distinct stress transfer behavior at the material interface located at $R = 60$mm. The consistently high accuracy observed over the entire radial domain demonstrates the capability of the proposed ML model to serve as an efficient and reliable surrogate solver for thermo-elastic analysis in layered engineering structures.

Previous investigations have established that thermal loading plays a decisive role in shaping stress and displacement fields in composite and heterogeneous materials, particularly when mechanical and thermal effects are simultaneously present [27–28]**.** Differences in stiffness and thermal expansion characteristics among constituent phases give rise to non-uniform deformation patterns and localized stress concentrations, which may significantly affect structural performance. Comparative studies conducted on various engineering systems further confirm that thermo-mechanical coupling governs the development of temperature-induced stresses and displacements, underlining the necessity of accurately accounting for thermal effects in structural evaluations [29–30]**.**

In parallel with advances in numerical modeling, increasing research attention has been directed toward the incorporation of artificial intelligence–based approaches into thermo-mechanical analysis. Numerous studies have demonstrated that machine learning techniques can successfully reproduce thermo-elastic stress and displacement responses with high fidelity relative to numerical reference solutions, while substantially reducing computational effort **[31–32]**. Such data-driven models have proven particularly effective for parametric investigations, sensitivity analyses, and rapid performance evaluations under varying thermal conditions. Within this framework, machine learning–assisted materials modeling and digital twin concepts have emerged as powerful tools for predictive analysis, real-time monitoring, and decision support in complex engineering systems [33–34]. Axisymmetric and multilayered cylindrical structures continue to represent an active area of research due to their extensive use in aerospace applications, pressure vessels, and advanced composite systems. Recent formulations for composite and hybrid axisymmetric shells have highlighted the strong influence of material coupling on stress distributions [35]. Complementary analytical studies addressing multilayered cylinders with imperfect interfaces have provided closed-form solutions that explicitly incorporate interfacial gaps, revealing their impact on pressure transfer mechanisms and layer-wise stress evolution [36].

Beyond purely thermo-elastic considerations, recent research has expanded toward coupled hygrothermal and time-dependent effects. Investigations on functionally graded hollow cylinders under combined hygrothermal conditions have shown that long-term creep-induced stress redistribution is highly sensitive to interfacial bonding quality [37]. Similarly, studies on laminated structures subjected to non-uniform thermal boundary conditions have demonstrated a pronounced dependence of the thermo-elastic response on boundary constraints and temperature gradients [38]. At the material level, numerical analyses have further indicated that nanoparticle reinforcement can be used to tailor thermo-elastic properties and enhance thermal resistance in fiber-reinforced composites [39]. From a methodological perspective, advanced computational techniques continue to enrich the analysis of axisymmetric structures. Alternative formulations based on finite-volume theory in polar coordinates have been proposed as robust and computationally efficient substitutes for classical finite element approaches [40]. Moreover, multi-physics studies incorporating fluid–structure interaction, thermal transport, and entropy generation analyses have emphasized the importance of coupled-field modeling for accurately representing realistic operating conditions [41–42]. Although several of the referenced works extend beyond purely solid thermo-elastic behavior addressing phenomena such as hygrothermal coupling, fluid–structure interaction, and intelligent decision-making frameworks they collectively reflect a broader shift toward integrated multi-physics modeling and AI-assisted validation strategies in engineering analysis [43–46]. In the present study, this perspective is adopted by focusing specifically on thermo-elastic responses under constant thermal loading, while employing artificial intelligence exclusively as a predictive and validation tool within the context of solid mechanics. Beyond solid mechanics applications, recent AI-driven studies have also demonstrated the effectiveness of data-driven stress inference and decision-support frameworks in domains such as wearable sensing and complex engineering decision-making, further underscoring the versatility of artificial intelligence across diverse stress-related and system-level analyses [47–49].

In this study, the thermo-elastic behavior of a two-layer PSZ–aluminum disk subjected to uniform thermal loading was numerically investigated and validated using an artificial intelligence–based framework. The numerical results revealed that increasing temperature levels significantly affect both stress and displacement fields, with pronounced gradients developing near the material interface due to thermal expansion mismatch. Circumferential stress was found to be more sensitive to temperature variations than radial stress, while radial displacement increased monotonically with temperature.

The AI model successfully reproduced the numerical stress distributions with prediction errors remaining within a 5% bound, demonstrating strong agreement across the entire radial domain. These findings confirm the reliability of the combined numerical–AI approach and highlight its potential as an efficient tool for thermo-elastic analysis and design assessment of layered disk structures under thermal loading.

Author Contributions

Conceptualization, Hüseyin Fırat Kayıran; methodology, Hüseyin Fırat Kayıran; software, Hüseyin Fırat Kayıran; validation, Hüseyin Fırat Kayıran; formal analysis, Hüseyin Fırat Kayıran; investigation, Hüseyin Fırat Kayıran; resources, Hüseyin Fırat Kayıran; data curation, Hüseyin Fırat Kayıran; writing original draft preparation, Hüseyin Fırat Kayıran; writing review and editing, Hüseyin Fırat Kayıran; visualization, Hüseyin Fırat Kayıran; supervision, Hüseyin Fırat Kayıran; project administration, Hüseyin Fırat Kayıran. The author has read and agreed to the published version of the manuscript.

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Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. No publicly archived datasets were used or generated during the study.

Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have influenced the work reported in this paper. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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