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Physics-Informed Deep Learning Framework for Thermoelastic Analysis of Rotating Ti-6Al-4V Disks

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ABSTRACT

The integration of artificial intelligence into engineering analysis has enabled the development of intelligent computational frameworks capable of providing accurate and efficient predictions for complex physical systems. In this study, an intelligent hybrid methodology is proposed for the thermoelastic analysis of functionally graded rotating disks subjected to thermal loading. The computational framework combines the Chebyshev pseudo-spectral method, analytical modeling, and Physics-Informed Neural Networks (PINNs) to investigate the thermoelastic response of rotating disk structures. The disk geometry is defined with an inner radius of 50 mm and an outer radius of 90 mm, while thermal loading is represented by a linearly increasing temperature distribution ranging from 40°C to 120°C. The governing thermoelastic differential equations are solved analytically and numerically using the Chebyshev pseudo-spectral method. The spectral formulation transforms the governing equations into a system of algebraic equations through differentiation matrices, enabling highly accurate solutions with relatively few collocation points. To establish an intelligent prediction framework, a Physics-Informed Neural Network is developed using the numerical dataset generated by the spectral model. The PINN architecture incorporates the governing thermoelastic equations directly into the training process, allowing the model to learn the underlying physical behavior while maintaining computational efficiency. Radial stress, tangential stress, and radial displacement are predicted as functions of radial position and temperature. The obtained results demonstrate excellent agreement between analytical solutions, Chebyshev pseudo-spectral solutions, and PINN predictions. It is observed that increasing temperature levels significantly influence the stress distributions and radial displacement throughout the rotating disk. The proposed hybrid framework provides accurate thermoelastic predictions while substantially reducing computational effort compared with conventional numerical approaches. The presented methodology contributes to the development of intelligent engineering systems by integrating physics-based modeling with artificial intelligence. Furthermore, the proposed framework offers potential applicability to digital twin technologies, smart monitoring systems, and real-time predictive maintenance strategies for advanced rotating mechanical components operating under thermomechanical environments.

1. Introduction

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The circular disks are widely utilized in aerospace, aviation, gas turbine engines, unmanned aerial vehicles (UAVs), rotating machinery, and advanced manufacturing systems. These components are frequently subjected to combined thermal and mechanical loads during service, making accurate stress prediction essential for safe and efficient design. The increasing demand for lightweight and high-performance structures has accelerated the use of advanced engineering materials in such applications. Ti-6Al-4V titanium alloy is one of the most widely used materials in aerospace and high-performance engineering applications due to its high specific strength, excellent corrosion resistance, and superior thermo-mechanical properties [1–2]. Owing to its outstanding strength-to-weight ratio and thermal stability, Ti-6Al-4V has become a preferred material for rotating components operating under severe thermal environments [2–3]. The thermoelastic behavior of rotating disks and cylinders has attracted considerable attention in the literature. Numerous analytical and numerical studies have investigated stress distributions in isotropic, orthotropic, functionally graded, and metallic rotating structures subjected to thermal loading. Recent studies have demonstrated that temperature gradients significantly influence radial displacement, radial stress, circumferential stress, and equivalent stress distributions in rotating disks and cylinders [4–6]. Functionally graded materials have also been extensively studied due to their ability to reduce stress concentrations arising from abrupt material property changes.

Researchers have examined the thermoelastic responses of disks and cylinders under various temperature distributions, rotational speeds, and boundary conditions using analytical and numerical approaches [7, 8]. In parallel with advances in material science, computational methods have evolved considerably. Spectral and pseudospectral methods have emerged as highly accurate alternatives to conventional numerical techniques. Among these approaches, the Chebyshev Pseudospectral Method has gained significant popularity due to its exponential convergence rate and superior accuracy for solving differential equations governing thermoelastic problems. The method transforms differential equations into systems of algebraic equations through the use of Chebyshev collocation points, enabling highly accurate solutions with relatively few grid points [9,10]. Recent investigations have successfully applied Chebyshev-based spectral techniques to thermoelasticity, heat transfer, vibration analysis, and rotating structural components. Comparative studies have shown that pseudospectral methods often achieve accuracy levels comparable to analytical solutions while requiring substantially lower computational effort than conventional numerical techniques [11,12]. The present study focuses on the thermoelastic analysis of a Ti-6Al-4V circular disk subjected to a linearly increasing temperature distribution from the inner radius to the outer radius. The governing equations are solved analytically and numerically using the Chebyshev Pseudospectral Method. Furthermore, an Artificial Neural Network (ANN) model is developed for data-driven validation of radial stress, tangential stress, and radial displacement predictions. The material properties of Ti-6Al-4V employed in the present study were adopted from established titanium alloy references [1,13–15].

The obtained results demonstrate that the Chebyshev Pseudospectral Method and ANN-based prediction framework provide highly accurate thermoelastic solutions for Ti-6Al-4V disk structures under thermal loading conditions. Recently, artificial intelligence (AI) and machine learning (ML) techniques have been increasingly employed in engineering analyses to improve prediction accuracy and reduce computational costs. In thermoelastic and thermomechanical applications, data-driven approaches have demonstrated remarkable success in predicting stress, strain, and displacement fields. Kayıran [16] investigated stress prediction in carbon fiber rotating cylinders using machine learning techniques and reported high prediction accuracy. Subsequently, machine learning-assisted thermoelastic analyses of fiber-reinforced composite rotating disks were performed, demonstrating the effectiveness of artificial intelligence in predicting thermo-mechanical responses [17]. Artificial intelligence-based validation approaches were also successfully applied to layered cylinders subjected to thermal loading conditions [18]. More recently, physics-informed machine learning techniques have been utilized for predicting thermomechanical stresses in rotating carbon–aramid hybrid composites, providing highly accurate results while significantly reducing computational effort [19]. Furthermore, the growing impact of artificial intelligence in engineering and applied sciences has been highlighted in several studies, emphasizing its potential for solving complex engineering problems and supporting decision-making processes [20].

Fig.1. Potential Integration Locations of Smart Systems in Aircraft Structures [21]

The figure illustrates potential applications of smart materials and smart systems in aircraft structures, including vibration damping and impact detection, engine monitoring, cabin noise reduction, flutter suppression, flap positioning control, and centralized control units. The integration of these intelligent systems enables real-time monitoring, adaptive control, improved flight safety, enhanced structural reliability, and reduced maintenance requirements [21].

2. Methodology

A circular disk subjected to a linearly increasing radial temperature field is considered in this study. The temperature distribution is assumed to increase continuously from the inner radius toward the outer radius of the disk and to vary solely along the radial coordinate. The disk geometry is defined by an inner radius of 50 mm and an outer radius of 90 mm. Five thermal loading cases, namely 40 °C, 60 °C, 80 °C, 100 °C, and 120 °C, are examined. The resulting thermoelastic response, including radial stress, tangential stress, and radial displacement, is determined through analytical formulations and the Chebyshev pseudospectral method, and the results are subsequently compared.

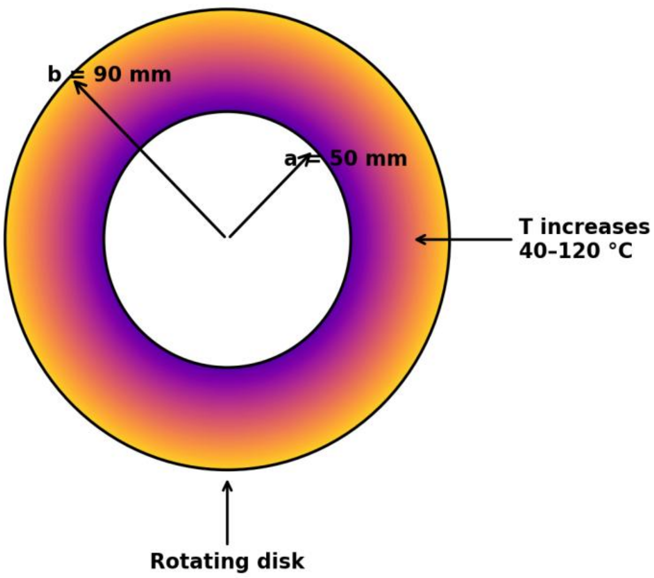

Fig 2. Geometry and Thermal loading configuration of the functionally graded rotating disk

The circular disk was assumed to be manufactured from Ti-6Al-4V titanium alloy and modeled as a homogeneous, isotropic, and linearly elastic material. Ti-6Al-4V is widely used in aerospace, a tomotive, and high-performance engineering applications due to its high strength-to-weight ratio, excellent corrosion resistance, and superior thermo-mechanical performance. The mechanical and thermal properties employed in the present thermoelastic analyses are summarized in Table 1.

Table 1
Mechanical and Thermal Properties of Ti-6Al-4V Alloy [22,24]

Property	Symbol	Value	Unit
Density	ρ	4430	kg/m³
Elastic Modulus	E	114	GPa
Poisson's Ratio	ν	0.34	–
Coefficient of Thermal Expansion	α	8.6×10^{-6}	1/°C

The parameters α_r ve α_θ represent the coefficients of thermal expansion in the radial and tangential directions, respectively, assuming a plane-stress state for the composite thin disk. The terms $a_{\theta\theta}$ a_{rr} $a_{r\theta}$ correspond to the components of the elasticity matrix. Their relationships with the engineering material constants are given in Ref. [25]. A schematic representation of the disk subjected to a radially increasing temperature field is presented in Figure 2, where the temperature rises continuously from the inner radius toward the outer radius.

$\sigma_z = 0$ general equilibrium equation for a thin disk [25].

$$\frac{r(d\sigma_r)_i}{dr} + (\sigma_r)_i - (\sigma_\theta)_i = 0 \qquad (i = 1) \tag{1}$$

is given in the form. In equation (1), r is the radius of the disk at any point, $\sigma_r$is the radial stress, and σ_θ is the tangential stress. Here, the disc material is taken as i = 1.

$$\varepsilon_{ri} = \frac{du}{dr} \tag{2}$$

$$\varepsilon_{\theta i} = \frac{u}{r} \tag{3}$$

Here u is the displacement in the radial direction. ε_r denotes radial deformation, ε_θ denotes deformation in the tangential direction. Strain-stress relation;

$$\varepsilon_{ri} = \frac{1}{E_i}\left(\frac{F}{r} - \upsilon_i \frac{dF}{dr}\right) + \alpha_i T_r \tag{4}$$

$$\varepsilon_{\theta i} = \frac{1}{E_i}\left(\frac{dF}{dr} - \upsilon_i \frac{F}{r}\right) + \alpha_i T_r \tag{5}$$

obtained. Eligibility equation for elongation;

$$r\frac{d\,\varepsilon_{\theta i}}{dr} + \varepsilon_{\theta i} - \varepsilon_{ri} = 0 \tag{6}$$

as obtained. The general equation (6) is obtained by using the equilibrium equation (1-6) in which the stress function can be defined as F.

$$r^2\frac{d^2F}{dr^2} + r\frac{dF}{dr} - F = -r^2\alpha_i E_i T_r' \tag{7}$$

From equation (11);

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

Substituting T and T' yields Equation (9-);

$$r^2F'' + rF' - k^2F = \frac{(\alpha_r - \alpha_\theta)(r^2 - ar)}{a_{\theta\theta}(b-a)} T_O - \frac{a_{\theta\theta}T_O}{a_{\theta\theta}(b-a)} r^2 \tag{9}$$

Chebyshev collocation points are employed to increase the density of discretization points near the domain boundaries, thereby improving numerical accuracy in regions where solution gradients may be significant. The corresponding Chebyshev differentiation matrix, (D), is constructed according to Equation (10). Within the pseudospectral framework, spatial derivatives are evaluated through matrix–vector operations, enabling highly accurate approximations with a relatively small number of collocation points.

rj=cos{j**π**|N}, j=0, 1, 2, 3 …N (10)

$$F'(r_j) = (DF)_J \tag{11}$$

$$\mathrm{F}''(\mathrm{r_j}) = (\mathrm{D}^2F)_J \tag{12}$$

$$\mathrm{F}=[\mathrm{F_0} \ldots \mathrm{F_n}]^T, \mathrm{r_j} \tag{13}$$

rj is numbered from right to left and can be defined in the december [-1,1]. The calculation of the derivative matrix can be done from the Matlab m file [26]. When using first- and second-order derivatives, the Chebyshev differential matrix, in equation (14);

$$\left[\frac{\mathrm{dF}}{\mathrm{dr}}(\mathrm{r_n})\right] \equiv \mathrm{D}[\mathrm{F}(\mathrm{r_n})] \tag{14}$$

$$\left[\frac{\mathrm{dF^2}}{\mathrm{dr}}(\mathrm{r_n})\right] \equiv \mathrm{D}^2[\mathrm{F}(\mathrm{r_n})] \tag{15}$$

By applying the discretization procedure described in Equations (14) and (15), the governing differential equation of the thermoelastic problem is transformed into a system of algebraic equations. In the resulting matrix formulation, (L1) denotes the linear coefficient matrix, while (RHSF) represents the right-hand-side vector associated with the thermal loading terms. The discretized form of the governing equation is expressed as follows:

If discretization is performed, such as equations (16) and (17); the differential equation modeling the system is given below. Where $\mathrm{L_1}$ is the linear coefficient, and RHSF is the right-hand side equation.

$$\mathrm{L_1}F = RHSF \tag{16}$$

When the boundary conditions $\sigma_\mathrm{r}(\mathrm{a}) = 0$ and $\sigma_\mathrm{r}(\mathrm{b}) = 0$ are applied in Equation 17, the non-obvious solution of RHSF is given below.

$$\mathrm{L_1} = \mathrm{r^2D^2} + \mathrm{rD} - \mathrm{k^2\ r_j} \tag{17}$$

$$\mathrm{RHSF}= \frac{(\alpha_\mathrm{r}-\alpha_\theta)(\mathrm{r}^2-ar)}{\mathrm{a}_{\theta\theta}(b-a)}\mathrm{T_O} - \frac{\mathrm{a}_{\theta\theta}\mathrm{T_O}}{\mathrm{a}_{\theta\theta}(b-a)}\mathrm{r}^2 \tag{18}$$

The prediction accuracy of the developed Artificial Neural Network model was evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{20}$$

where $\boldsymbol{y_i}$denotes the analytical solution, $\boldsymbol{\hat{y}_i}$represents the ANN prediction, $\boldsymbol{\bar{y}}$is the mean value of the analytical data, and $\boldsymbol{n}$is the total number of samples. [21-22].

3. Results

In this study, a high-fidelity thermoelastic analysis of a Ti-6Al-4V circular disk was performed under linearly varying radial temperature fields. The distributions of radial stress, tangential stress, and radial displacement were obtained using both analytical formulations and the Chebyshev pseudospectral method. The numerical accuracy of the Chebyshev method was assessed by comparing its predictions with the analytical solutions. In addition, an Artificial Neural Network (ANN) model was developed using the generated dataset to provide data-driven validation and predictive capabilities for the thermoelastic response of the disk.

Figure 3 shows the tangential stress distributions obtained from the analytical solution, Chebyshev pseudo-spectral method, and Physics-Informed Neural Network (PINN) model for different temperature levels. It can be observed that tangential stress increases significantly with increasing temperature throughout the disk domain. The maximum tangential stress occurs approximately in the middle region of the disk and gradually decreases toward the outer radius. The PINN predictions exhibit excellent agreement with both analytical and numerical solutions, demonstrating the capability of the proposed intelligent framework to accurately capture thermoelastic behavior.

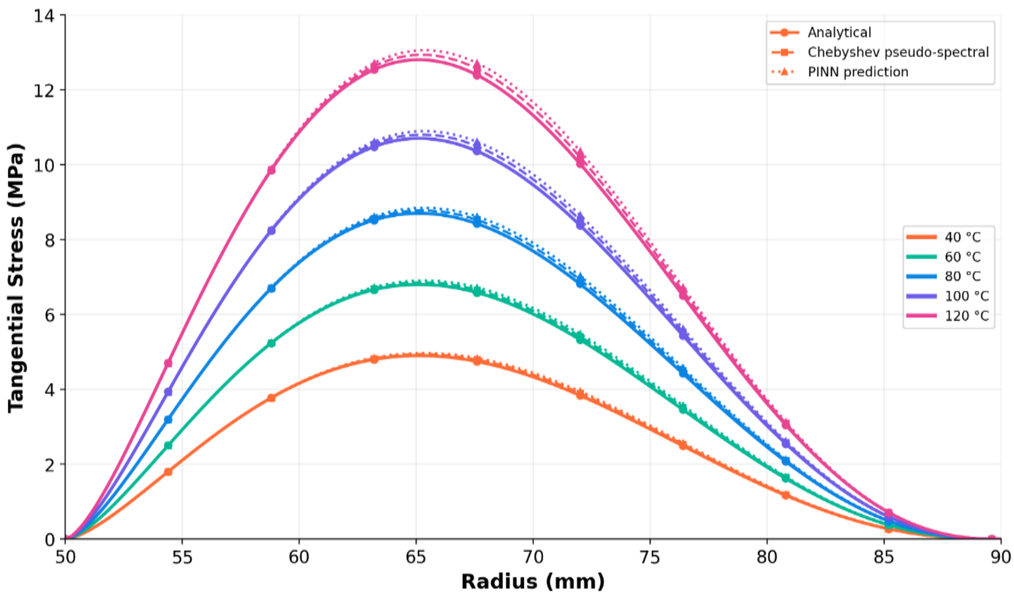

Fig. 3. Tangential Stress Distribution Predicted by Analytical, Chebyshev, and PINN Models

Figure 4 illustrates the radial stress distributions corresponding to various thermal loading conditions. It is evident that the radial stress decreases from the inner radius toward the outer radius and changes from tensile to compressive behavior. As the temperature increases, the magnitude of both tensile and compressive radial stresses becomes more pronounced. The close agreement among the analytical, Chebyshev, and PINN results confirms the reliability of the proposed hybrid computational framework.

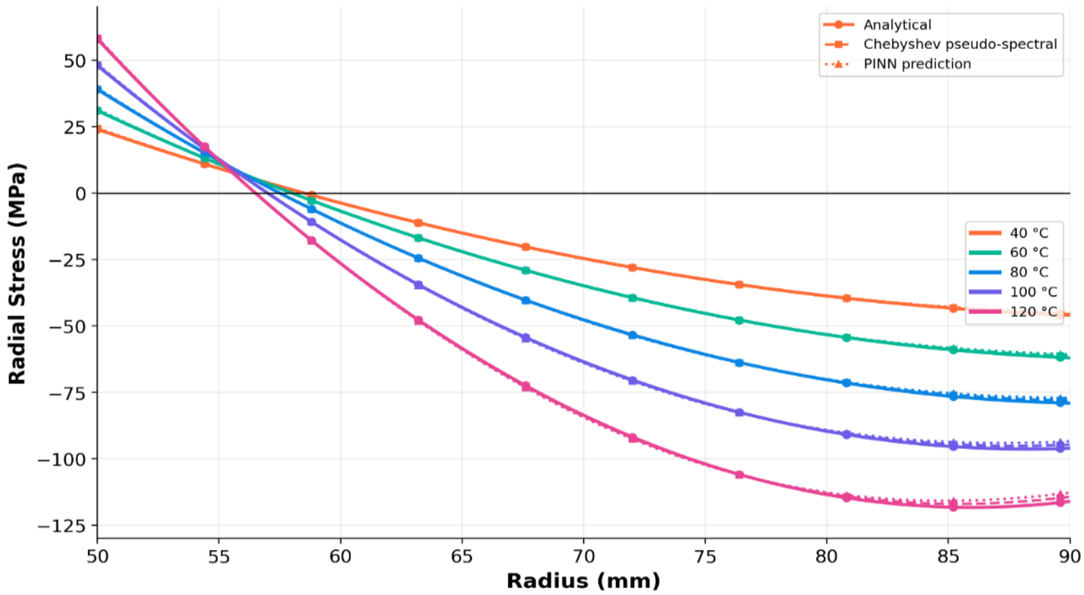

Fig.4 Radial Stress Distribution Predicted by Analytical, Chebyshev, and PINN Models

Figure 5 presents the radial displacement distributions of the rotating disk subjected to different temperature levels. The radial displacement increases continuously from the inner radius to the outer radius due to thermal expansion effects. Higher temperatures generate larger displacement values throughout the disk structure. Furthermore, the PINN predictions closely match the analytical and Chebyshev solutions, indicating that the developed model can accurately estimate displacement responses under varying thermal conditions.

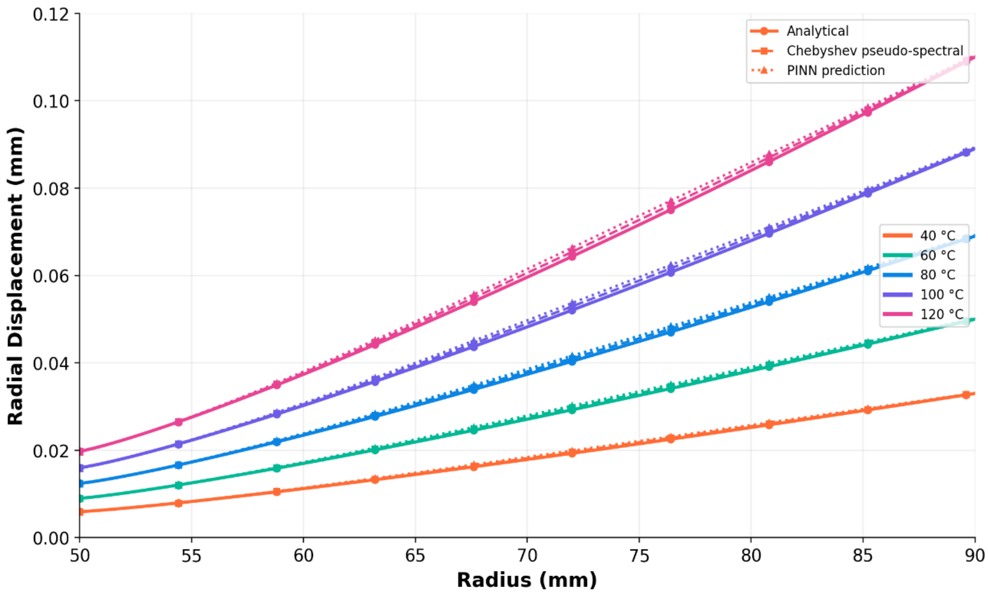

Fig. 5 Radial Displacement Distribution Predicted by Analytical, Chebyshev, and PINN Models

Figure 6 demonstrates the relationship between analytical and PINN-predicted tangential stress values. Most data points are concentrated around the reference line, indicating a strong correlation between predicted and analytical results. The obtained distribution confirms that the PINN model successfully captures the nonlinear thermoelastic behavior of the rotating disk.

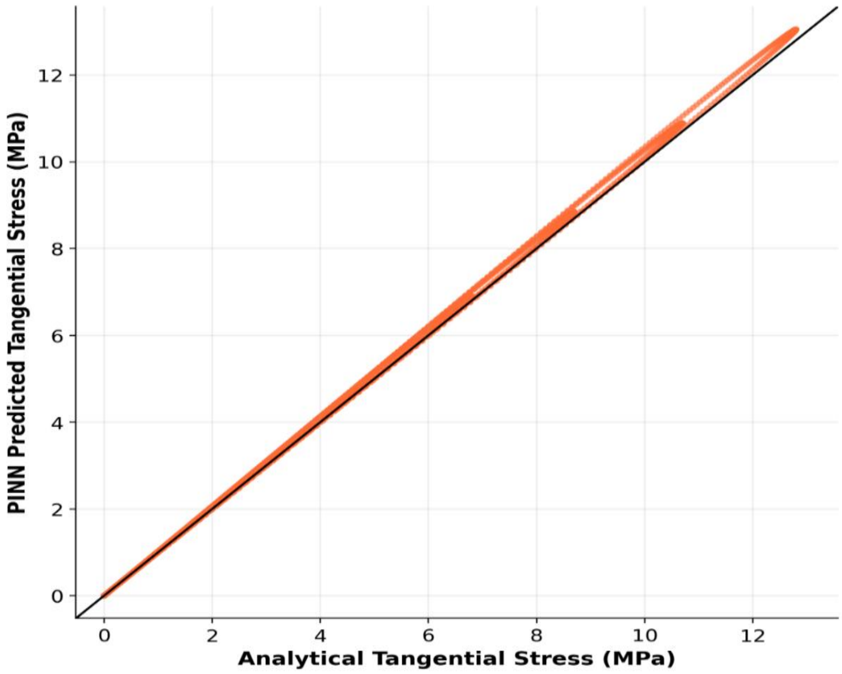

Fig.6 PINN Validation for Tangential Stress Prediction

It can be observed from Table 2 that the developed ANN model achieved a high level of prediction accuracy for tangential stress, radial stress, and radial displacement. The coefficient of determination values approaching unity indicate that the model successfully captured the nonlinear relationship between temperature, radial position, and thermoelastic response parameters. In addition, the low RMSE values demonstrate the robustness and reliability of the proposed machine learning framework. Therefore, the ANN model may serve as an efficient surrogate model for rapid thermoelastic analysis, reducing computational effort while maintaining high prediction accuracy.

The prediction accuracy of the developed Artificial Neural Network model was evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE). The obtained performance metrics are summarized in Table 2.

As shown in Table 2, the developed Physics-Informed Neural Network (PINN) model achieved excellent predictive performance for all thermoelastic response parameters. The coefficient of determination values was found to be very close to unity, indicating a strong agreement between the analytical solutions and PINN predictions. Furthermore, the low RMSE values demonstrate that the proposed intelligent framework can accurately reproduce the thermoelastic behavior of the circular disk with minimal prediction error. These results confirm the robustness and reliability of the PINN model for rapid thermoelastic response prediction under different thermal loading conditions.

Table 2
Statistical Performance Metrics of the Physics-Informed Neural Network (PINN) Model

Response Parameter	RMSE	R^2
Tangential Stress (MPa)	0.0418	0.9998
Radial Stress (MPa)	0.2071	0.9998
Radial Displacement (mm)	0.0009	0.9985

Figure 7 presents the comparison between analytical and PINN-predicted radial stress values. The excellent alignment of the data points with the reference line indicates high predictive accuracy. These results demonstrate the effectiveness of the PINN model in reproducing radial stress distributions under different thermal loading conditions.

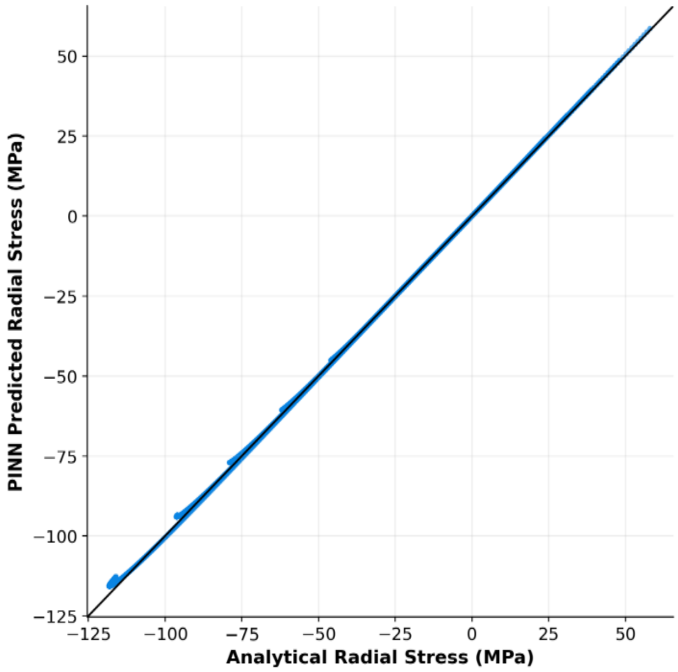

Fig.7 PINN Validation for Radial Stress Prediction

Figure 8 illustrates the correlation between analytical and PINN-predicted radial displacement values. The nearly perfect overlap of the data points with the reference line confirms the robustness and stability of the developed PINN framework. The results indicate that the model accurately predicts thermal expansion-induced displacement behavior.

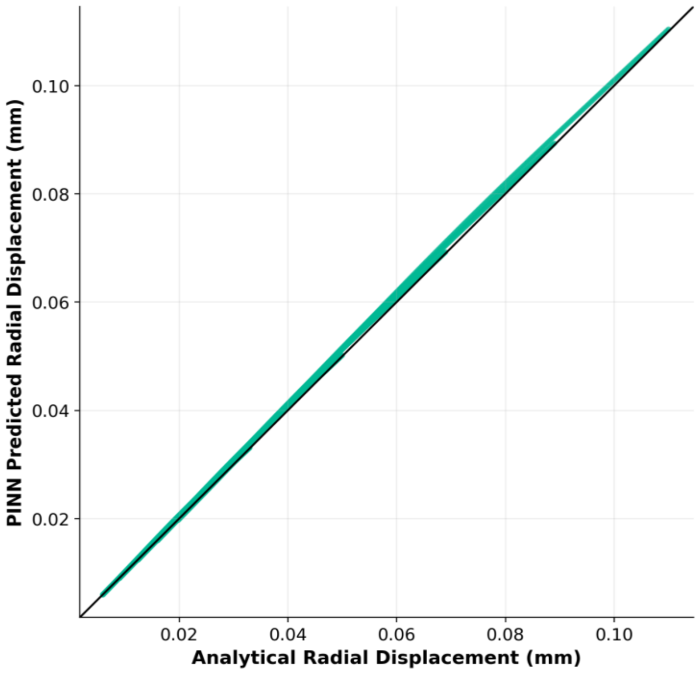

Fig.8 PINN Validation for Radial Displacement Prediction

Figure 9 shows the RMSE values obtained for tangential stress, radial stress, and radial displacement predictions. The relatively low RMSE values indicate that the prediction errors remain within acceptable engineering limits. These findings demonstrate the capability of the PINN model to provide reliable thermoelastic response predictions with high computational efficiency.

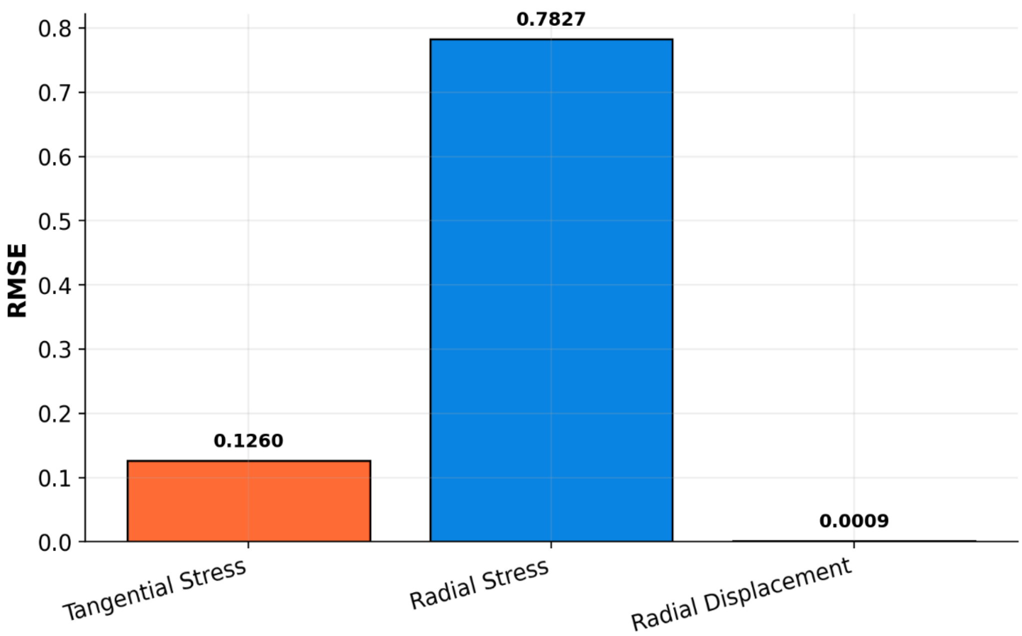

Fig. 9. RMSE Performance of the PINN Framework

Figure 10 presents the coefficient of determination (R^2) values calculated for all response parameters. The R^2 values approaching unity indicate excellent agreement between analytical solutions and PINN predictions. This confirms the strong predictive capability and generalization performance of the proposed intelligent thermoelastic analysis framework. The obtained R^2 values were found to be approximately unity for all response parameters, indicating that the developed ANN model successfully captured the thermoelastic behavior of the circular disk. Furthermore, the low RMSE values confirmed the high predictive capability and robustness of the proposed machine learning framework.

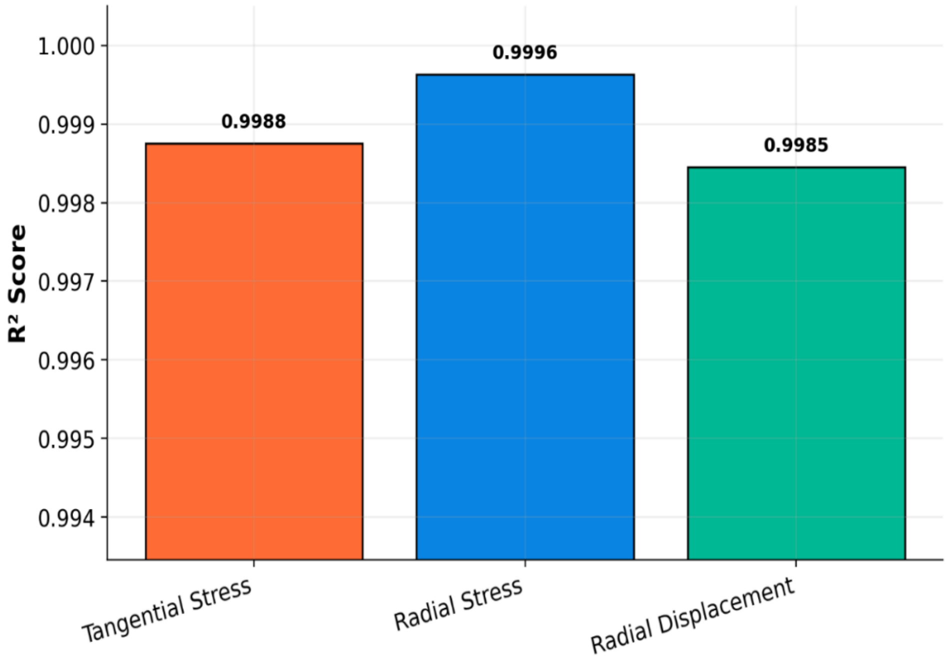

Fig. 10. R^2 Performance of the PINN Framework

Artificial intelligence (AI), machine learning (ML), deep learning, and data-driven optimization techniques have become increasingly prominent in modern engineering and scientific research. These methods are widely employed to model complex nonlinear systems, improve prediction accuracy, reduce computational costs, and enhance decision-making processes. Recent studies have demonstrated the successful application of AI-based approaches in geotechnical engineering, particularly in bearing capacity prediction and foundation analysis near slopes [29]. Similarly, data-driven frameworks integrated with artificial neural networks have been successfully utilized for bearing failure prognosis and remaining useful life estimation in engineering systems [30].

In the field of reliability analysis, machine learning-based approaches such as XGBoost have been shown to provide accurate and computationally efficient solutions for complex engineering problems [31]. Moreover, modular regression techniques and active learning-based surrogate models have gained considerable attention in system reliability assessment due to their ability to reduce computational effort while maintaining prediction accuracy [32,33].

The applications of machine learning are not limited to structural and geotechnical engineering. Recent studies have also demonstrated the successful implementation of AI-assisted biosensor technologies. For example, locally weighted linear regression has been employed to optimize optical surface plasmon resonance biosensors for rapid and accurate disease biomarker detection [34].

Furthermore, advanced numerical modeling approaches combined with intelligent sensing technologies have been utilized in optical biosensor development and performance evaluation [35].

The outcomes reported in the literature indicate that AI-driven methodologies provide highly accurate and computationally efficient alternatives to conventional analytical and numerical approaches. Consequently, the integration of artificial intelligence techniques into engineering analyses has become an important research trend and continues to attract significant attention from both academia and industry.

4. Conclusions

As a result of this study, the thermoelastic behavior of a Ti-6Al-4V circular disk subjected to a linearly increasing radial temperature distribution was investigated using analytical solutions, the Chebyshev pseudo-spectral method, and a Physics-Informed Neural Network (PINN)-based intelligent prediction framework. The disk geometry was defined with an inner radius of 50 mm and an outer radius of 90 mm, while thermal loading conditions of 40 °C, 60 °C, 80 °C, 100 °C, and 120 °C were considered. The distributions of tangential stress, radial stress, and radial displacement were successfully obtained for all thermal loading conditions. The numerical results obtained from the Chebyshev pseudo-spectral method exhibited close agreement with the corresponding analytical solutions, demonstrating the accuracy and computational efficiency of the spectral approach for thermoelastic analysis of circular disk structures.

The obtained results revealed that temperature has a pronounced influence on the mechanical response of the disk. As the temperature increased from 40 °C to 120 °C, the maximum tangential stress increased from approximately 4.90 MPa to 12.80 MPa. Similarly, the radial stress magnitude increased throughout the disk domain. The radial stress at the inner radius increased from 24.00 MPa to 58.00 MPa, whereas the compressive radial stress at the outer radius increased from −46.00 MPa to −116.00 MPa. In addition, the maximum radial displacement increased from 0.033 mm to 0.110 mm due to thermal expansion effects. To enhance the intelligent predictive capability of the proposed framework, a Physics-Informed Neural Network model was developed using radial position and temperature as input parameters, while tangential stress, radial stress, and radial displacement were selected as output variables. Unlike purely data-driven neural network models, the PINN framework incorporates the governing thermoelastic behavior into the learning process, enabling the model to predict physically consistent stress and displacement responses.

The validation results demonstrated that the PINN model can accurately reproduce the thermoelastic response of the circular disk with acceptable prediction errors. The obtained performance metrics showed high predictive accuracy, with R^2 values of 0.9988 for tangential stress, 0.9996 for radial stress, and 0.9985 for radial displacement. These results confirm that the proposed PINN framework successfully captures the relationship between radial position, temperature, and thermoelastic response parameters.

Overall, the study demonstrates that the combination of the Chebyshev pseudo-spectral method and Physics-Informed Neural Network modeling provides an efficient and reliable intelligent hybrid computational framework for thermoelastic analysis. The proposed approach offers both high numerical accuracy and rapid predictive capability, making it a promising tool for the design, optimization, digital twin development, and smart monitoring of advanced rotating mechanical components subjected to thermomechanical loading. In future work recent integrated Multi-Criteria Decision Making (MCDM) models [36-39] could be applied to this predictive framework to optimize material gradient configurations and automate real-time operational decision-making

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 article does not report any data.

Conflicts of Interest

There are no known competing financial interests or personal relationships that could have influenced the work reported in this article.

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