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Physics-Informed Machine Learning for Predicting Thermomechanical Stress in Rotating Carbon-Aramid Hybrid Composites

Hüseyin Fırat KAYIRAN[1,*]

[1] Provincial Coordinatorate, Agriculture and Rural Development Support Institution, Mersin, Turkey

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ABSTRACT

This work presents a robust analytical and computational framework to investigate the thermomechanical behavior of rotating hybrid composites, specifically PAN-based carbon fiber and aramid subjected to high-speed rotation and extreme thermal gradients. By employing plane strain theory, we modeled the structural response of multilayered cylinders to evaluate how angular velocities and temperature fluctuations interact to influence structural integrity. A distinctive feature of this research is the validation of closed-form analytical solutions against machine learning (ML) predictive models at operational speeds of 100 and 200 rad/s, utilizing the Von Mises yield criterion to delineate elastic-plastic boundaries. The results reveal a significant correlation between rotational-thermal synergies and radial displacement, highlighting the unique load-bearing advantages of the carbon-aramid hybrid. While the PAN-carbon phase provides high specific stiffness, the aramid layer enhances toughness and impact resistance. The integration of physics-based modeling with ML validation confirms the framework's high predictive accuracy and thermal stability. This hybrid approach offers a scalable, intelligent decision-support tool for aerospace and automotive engineering, where lightweight, resilient structural components are paramount for mission-critical performance.

1. Introduction

Rotating cylindrical structures exposed to simultaneous thermal and mechanical effects are critical components in modern aerospace systems, high-speed rotors, turbo-machinery, and lightweight automotive applications. Under such operating conditions, stresses generated by centrifugal forces interact with thermally induced strains, leading to non-uniform and highly coupled stress distributions. Previous studies have demonstrated that thermal gradients, even when moderate, can significantly intensify stress concentrations in rotating components, particularly as angular velocity increases [1]. Analytical approaches remain indispensable for the investigation of thermo-rotational behavior, as they offer direct physical insight into the influence of material properties, geometry, and loading parameters. Closed-form thermoelastic solutions developed for axisymmetric rotating cylinders have been shown to accurately capture radial displacement and stress evolution, while also serving as effective benchmarks for numerical simulations [2]. Moreover,

[*] *Corresponding author.*
E-mail address: huseyinfiratkayiran@gmail.com

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research on layered and functionally graded rotating cylinders indicates that equivalent stress measures, such as Von Mises stress, are strongly governed by material distribution, thermal boundary conditions, and rotational speed [3].

Hybrid fiber-reinforced composite materials have emerged as an efficient strategy to tailor mechanical performance beyond the capabilities of single-fiber systems. Carbon fibers are widely utilized due to their high stiffness-to-weight ratio and excellent load-carrying capacity, whereas aramid fibers are distinguished by their superior toughness, impact resistance, and energy dissipation ability. When combined within a hybrid architecture, carbon and aramid fibers can produce composite systems exhibiting both high stiffness and enhanced damage tolerance, making them particularly attractive for rotating structures subjected to dynamic and thermomechanical loading [4]. Experimental and numerical investigations further reveal that the mechanical response of carbon/aramid hybrids is highly sensitive to stacking sequence and hybrid configuration, with improved strain distribution and delayed failure observed in comparison with non-hybrid laminates [5].

Among various carbon fiber types, PAN-based carbon fibers continue to dominate high-performance structural applications owing to their reliable processing routes and balanced mechanical properties. Recent microstructural studies have confirmed that PAN-based carbon fibers maintain stable strength and stiffness characteristics under elevated temperatures, supporting their suitability for thermally demanding environments [6]. In addition, comparative assessments between PAN-based and pitch-based carbon fibers emphasize the versatility of PAN-based systems for rotating components requiring a combination of stiffness, durability, and thermal resistance [7].

Although extensive research exists on rotating composite cylinders, analytical investigations addressing the coupled thermomechanical response of PAN-based carbon/aramid hybrid composites remain limited. Most available studies focus primarily on numerical simulations or experimental testing, while comprehensive analytical formulations capable of capturing hybrid composite behavior under combined thermal gradients and centrifugal loading are scarce [8]. Furthermore, the influence of thermal boundary conditions and material gradation on stress distributions and safety margins has not been sufficiently clarified for hybrid composite rotating cylinders. In response to these limitations, the present study proposes an analytical framework to evaluate the elastic stress response of multilayer rotating cylinders composed of PAN-based carbon and aramid fiber-reinforced composite layers under coupled thermal and rotational loading. The formulation is established within the plane strain assumption, and the Von Mises yield criterion is employed to assess critical stress states. The analytical results are validated through finite element simulations, and comparisons with existing literature are conducted to demonstrate consistency and reliability. The findings aim to provide design-oriented insight into the role of hybridization, temperature effects, and rotational speed in the structural performance of advanced composite rotating systems.

Recent advances in machine learning (ML) have significantly enhanced the analysis and prediction of complex thermo-mechanical behaviors in composite structures, particularly in cases where strong coupling effects and material heterogeneity challenge purely numerical approaches. Physics-informed and hybrid analytical–ML frameworks have emerged as powerful tools for capturing stress–strain responses governed by partial differential equations, while simultaneously preserving physical consistency and computational efficiency [9,10].

In the context of rotating composite cylinders, ML-based surrogate and validation models have been successfully employed to predict radial and circumferential stress distributions under combined thermal and mechanical loading, demonstrating strong agreement with analytical and finite element solutions [11]. Intelligent decision-support approaches based on data-driven and optimization techniques have also been applied in engineering and transportation systems, demonstrating the growing role of computational intelligence in complex engineering decision processes [12].

Rather than replacing classical elasticity-based formulations, these data-driven techniques serve as robust verification and acceleration tools, enabling rapid assessment of parametric variations such as angular velocity, temperature gradients, and material gradation [13]. Accordingly, integrating closed-form analytical solutions with machine learning-assisted validation provides a reliable and scalable framework for the thermo-elastic assessment of advanced hybrid composite rotating structures. Composite materials have attracted significant attention in recent decades due to their high strength-to-weight ratio, corrosion resistance, and design flexibility. These materials are widely used in aerospace, automotive, marine, and mechanical engineering applications where lightweight structures and high mechanical performance are required. In particular, fiber-reinforced composite cylinders and rotating components have become important structural elements in high-speed mechanical systems. Understanding the stress distribution in such structures is therefore essential for safe design and reliable operation.

Recent studies have investigated the mechanical behaviour of composite structures under different loading conditions. Detailed modelling approaches have demonstrated the ability to capture progressive failure mechanisms in complex composite architectures [14]. Similarly, investigations on sandwich composite structures subjected to impact loading reveal complex deformation patterns depending on core geometry and material configuration [15].

Further studies have analysed the structural response of composite sandwich panels under extreme loading conditions, highlighting the importance of optimized structural design for improving energy absorption capacity [16]. Comprehensive reviews on fiber-reinforced polymer composites have also emphasized their increasing use in modern engineering systems due to their superior mechanical performance and adaptability [17].

Environmental durability has also been examined in several studies. Investigations on carbon fiber reinforced polymer composites exposed to aggressive environments show that environmental conditions can significantly influence long-term mechanical behaviour [18]. Broader assessments of polymer-based materials further highlight their growing importance as alternatives to traditional metallic materials in demanding engineering applications [19].

In structural engineering applications, composite materials have been widely adopted for lightweight structures requiring high stiffness and durability. Reviews on fiber-reinforced composites in marine structures indicate that composite materials can significantly reduce structural weight while maintaining high mechanical performance [20]. Similarly, optimization studies on composite sandwich structures demonstrate that analytical and numerical optimization techniques can effectively enhance the structural performance of lightweight composite systems [21].

The rapid expansion of composite technologies across aerospace, automotive, and energy sectors further illustrates the importance of advanced composite materials in modern engineering design [22]. Recent experimental and numerical investigations have also highlighted the importance of fatigue behaviour and long-term reliability in composite structural connections [23].

Multiscale modelling approaches have been proposed to better understand the mechanical behaviour of hybrid composite systems. Such frameworks demonstrate that microstructural features, such as void defects or porosity, can significantly influence the elastic properties and load-carrying capacity of hybrid composite materials [24].

Parallel to developments in composite materials, machine learning techniques have increasingly been integrated into mechanical analysis and engineering prediction problems, enabling complex physical behaviours to be predicted efficiently using data-driven models.

Recent studies have demonstrated that machine learning models can successfully predict stress behaviour in rotating composite structures when combined with analytical formulations [25]. Similar approaches using Support Vector Regression (SVR) have also shown strong agreement with analytical elasticity solutions in predicting stress distributions in rotating anisotropic composite cylinders [26]. Despite these advances, studies combining analytical elasticity theory with machine learning techniques for rotating composite cylinders remain relatively limited. In particular, the integration of analytical stress solutions with data-driven models for predicting stress behaviour in rotating composite materials still requires further investigation. Therefore, this study aims to analyse elastic stresses in a rotating carbon fiber cylinder using analytical formulations and machine learning-based prediction methods. The results obtained from the analytical solution are evaluated using the Von Mises yield criterion and further validated through machine learning approaches. This combined framework provides a comprehensive methodology for analysing stress behaviour in high-performance composite rotating systems.

2. Methodology

Thermoelastic stress distributions were obtained through numerical simulations over a temperature range varying from 17.5 °C to 105 °C, as illustrated in Figure 1. Due to the small thickness of the layered disk relative to its in-plane dimensions, the mechanical behavior was modeled assuming plane stress conditions, whereby the stresses normal to the disk plane were considered negligible. The coefficients of thermal expansion in the radial and circumferential directions are represented by $\alpha_r$and α_θ, respectively. The thermoelastic constitutive equations were established using elasticity matrix formulations based on engineering material constants, in accordance with classical elasticity principles [27-28].

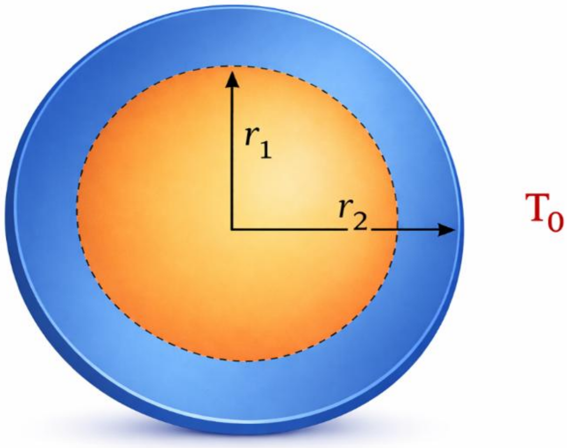

Fig. 1. Numerical representation of the disk geometry considered for thermo-mechanical loading analysis.

Here, $\alpha_r$and $\alpha_\theta$represent the radial and circumferential thermal expansion coefficients, respectively. The elastic behavior is defined through the constitutive matrix components C_{ij}, formulated in terms of Young's modulus and Poisson's ratio for plane stress conditions. To ensure equilibrium and compatibility in the thermoelastic analysis, an axisymmetric stress function $F(r)$is adopted.

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

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

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

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 [27].

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

In this context, the stress function is defined as F, 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.

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

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

Assuming a homogeneous material subjected to a constant angular velocity ω, a particular solution can be obtained. Based on the resulting general solution, the expressions for the radial and circumferential stresses are derived and presented in Eqs. (11) and (12).

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

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

Under the plane strain assumption, the axial strain component is constrained to zero, and the resulting axial stress component $\sigma_z$is expressed in terms of the radial and circumferential strains as: where $\lambda$and $\mu$are the Lamé constants, $\alpha$is the coefficient of thermal expansion, and Tdenotes the temperature change. To evaluate the equivalent stress state considering the three-dimensional stress components, the von Mises stress is computed by incorporating the axial stress $\sigma_z$as

$$\sigma_z = \lambda(\varepsilon_r + \varepsilon_\theta) - (2\mu + 3\lambda)\alpha T \tag{13}$$

$$\sigma_{vm} = \sqrt{\frac{1}{2}[(\sigma_r - \sigma_\theta)^2 + (\sigma_\theta - \sigma_z)^2 + (\sigma_z - \sigma_r)^2]} \tag{14}$$

This formulation enables an effective assessment of the yielding behavior of the material under coupled thermo-mechanical loading, accounting for the combined influence of radial, circumferential, and axial stresses. [29,30]. After establishing the analytical expressions governing the thermo-mechanical response of the multilayer rotating composite cylinder, a machine learning–assisted validation procedure is employed. The analytically computed stress components and von Mises equivalent stress are used as benchmark outputs, while the ML model is trained and tested solely for verification purposes. This hybrid analytical–ML approach allows rapid assessment of parametric variations, such as angular velocity and temperature gradient, and facilitates quantitative error evaluation through loss functions and scatter-based comparisons. Such a strategy ensures that the fundamental physical interpretation remains grounded in classical elasticity theory, while benefiting from the efficiency of data-driven validation [31]. Mean Squared Error (MSE)

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 \tag{15}$$

The schematic architectures of the neural network models used in this study are illustrated in Figure 2, which was adapted from the work of Kim, Park, and Choi [32]. In their study on large eddy simulation of flow over a circular cylinder using a neural-network-based subgrid-scale model, two different neural network structures were presented: a conventional network with two hidden layers (nFU architecture) and a fusion-based architecture (FU) that combines filtered inputs before the final prediction stage.

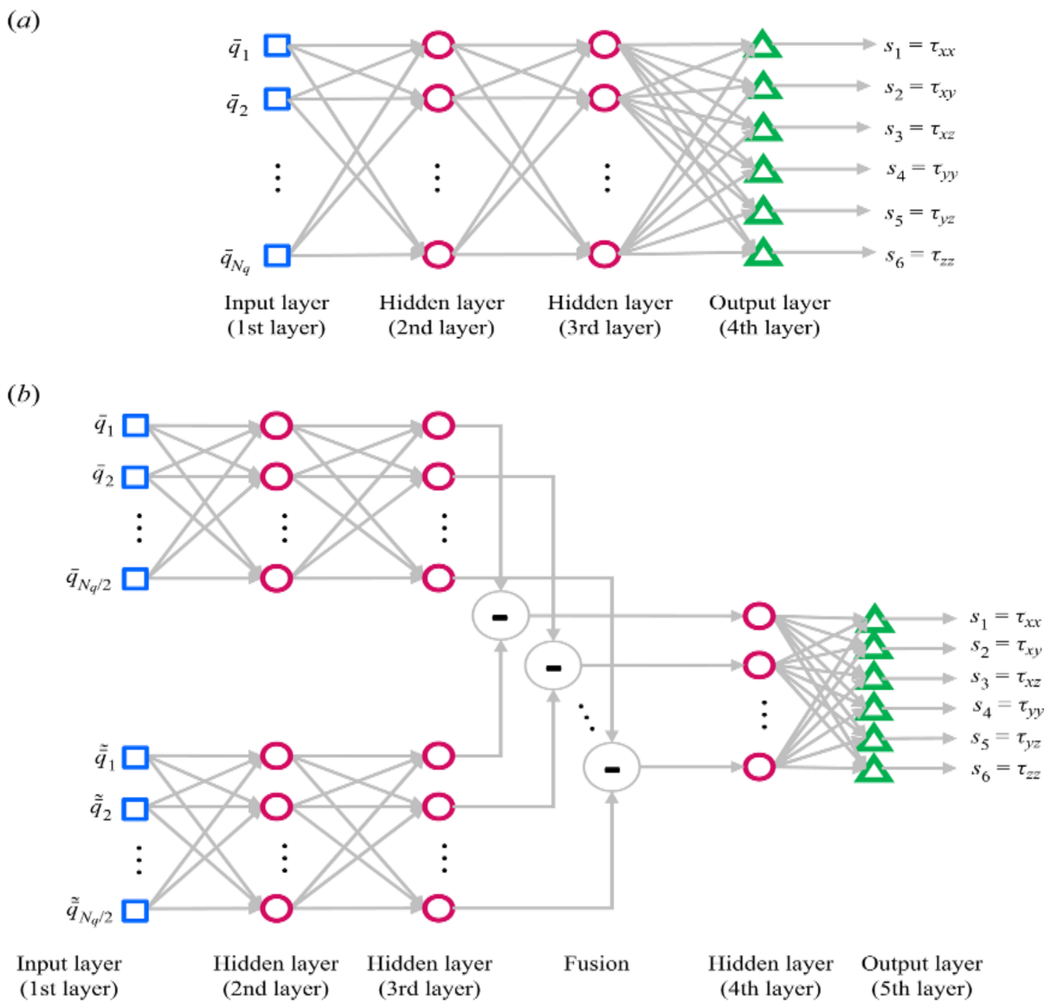

Fig 2. Neural network architectures used for subgrid-scale stress prediction in large eddy simulations: (a) standard neural network with two hidden layers (nFU architecture); (b) fusion-based neural network model (FU architecture). Adapted from Kim, Park, and Choi (32).

3. Results

The elastic stress distributions of a stationary layered structure consisting of partially stabilized zirconia (PSZ) and aluminum were numerically investigated. The model geometry was defined by an inner radius of $a = 25$mm and an outer radius of $c = 65$mm. Thermoelastic analyses were conducted under uniform temperature fields, with temperature levels ranging from 17.5 °C to 105 °C. The mechanical and thermal properties adopted in the numerical simulations are summarized in Table 2.

Table 1. Selected mechanical properties of the composite disk materials [33-34].

Materials	$\boldsymbol{E_\theta}$	$\boldsymbol{E_r}$	$\boldsymbol{k}$	$\boldsymbol{\alpha_r}$	$\boldsymbol{\alpha_\theta}$	$\boldsymbol{v_{\theta r}}$
PAN-based carbon fiber dominated)	135	8,5	4,21	32*10-6	-0.3*10-6	0.28

Table 2. Analytically computed elastic stress components of the disk under plane strain conditions.

Temperature ΔT (°C)	Surface	Tangential Stress (MPa)	Radial Stress (MPa)	σ_{vm} ω=100 (MPa)	σ_{vm} ω=200 (MPa)
12.5	Inner (r=40)	22.14	0	6.48	6.39
	→ Outer (r=80)	-7.48	0	3.42	3.51
25	Inner (r=40)	44.29	0	13.00	12.90
	→ Outer (r=80)	-14.97	0	6.80	6.90
37.5	Inner (r=40)	66.44	0	19.52	19.42
	→ Outer (r=80)	-22.45	0	10.19	10.28
50	Inner (r=40)	88.58	0	26.04	25.93
	→ Outer (r=80)	-29.94	0	13.58	13.67
62.5	Inner (r=40)	110.73	0	32.56	32.45
	→ Outer (r=80)	-37.43	0	16.96	17.06
100	Inner (r=40)	177.17	0	52.11	52.01
	→ Outer (r=80)	-59.88	0	27.12	27.21

Figure 3 shows the radial stress distribution along the disk radius at different temperature levels.

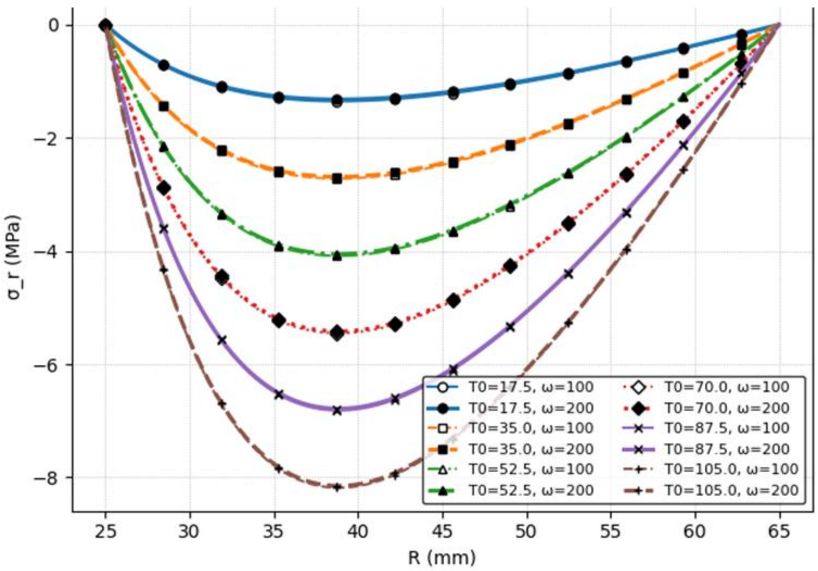

Fig. 3. Radial stress distributions along the disk radius under plane strain conditions for different temperature levels and angular velocities.

Figure 4 illustrates the radial stress (σ_r) distributions under plane strain conditions for different initial temperature levels and angular velocities of $\omega = 100$and 200 rad/s. In all cases, the radial stress approaches zero at both the inner ($R = 25$ mm) and outer ($R = 65$ mm) boundaries, while reaching maximum compressive values within the mid-radius region of the disk. As the temperature level increases, the magnitude of compressive radial stresses becomes significantly higher due to enhanced thermal expansion effects. Moreover, for a given temperature, increasing the angular velocity from $100$to 200 rad/sleads to further amplification of the stress levels, indicating the pronounced contribution of centrifugal forces. These results demonstrate that the combined influence of thermal loading and rotational effects plays a critical role in determining the radial stress response of the disk.

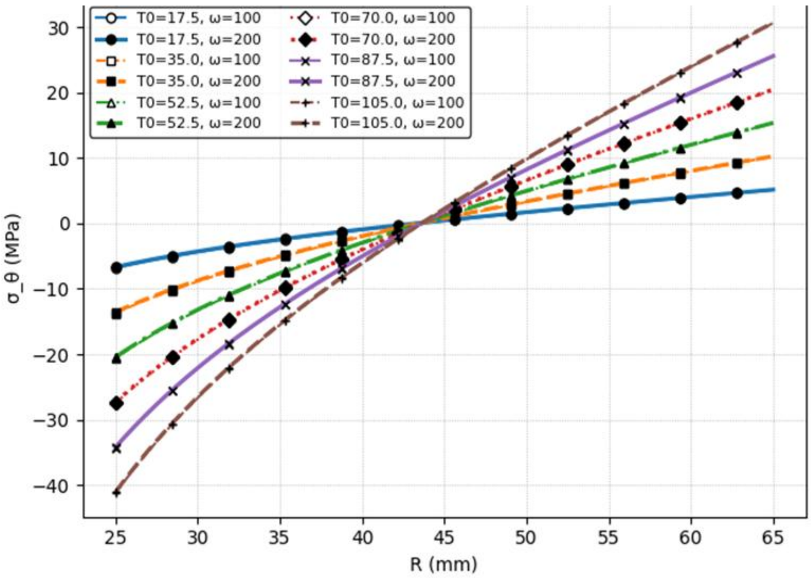

Fig.4. Tangential stress distributions along the disk radius under plane strain conditions for different temperature levels and angular velocities.

Figure 5 illustrates the convergence history of the machine learning model, where a consistent reduction in error is observed throughout training.

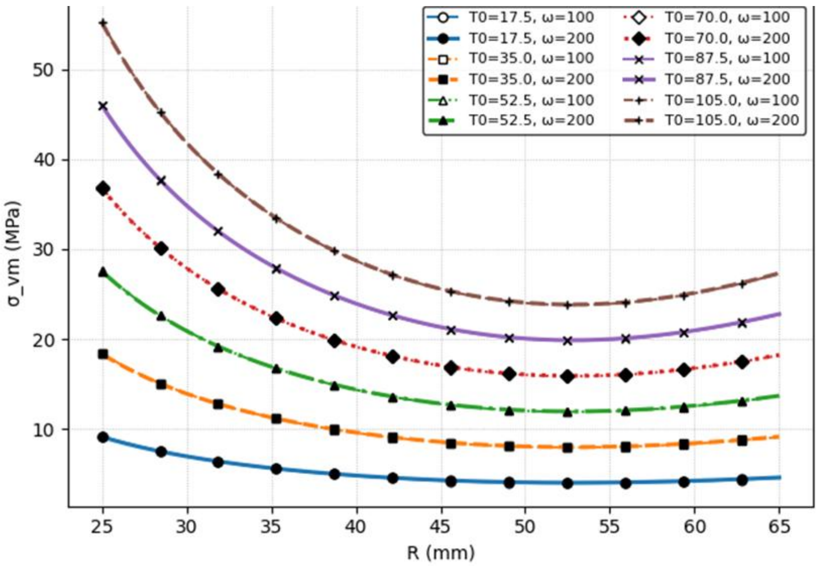

Fig.5. Error convergence of the proposed machine learning model during training, validation, and testing.

Figure 6 presents the error convergence history of the proposed machine learning model in terms of training, validation, and testing mean squared errors across the learning epochs.

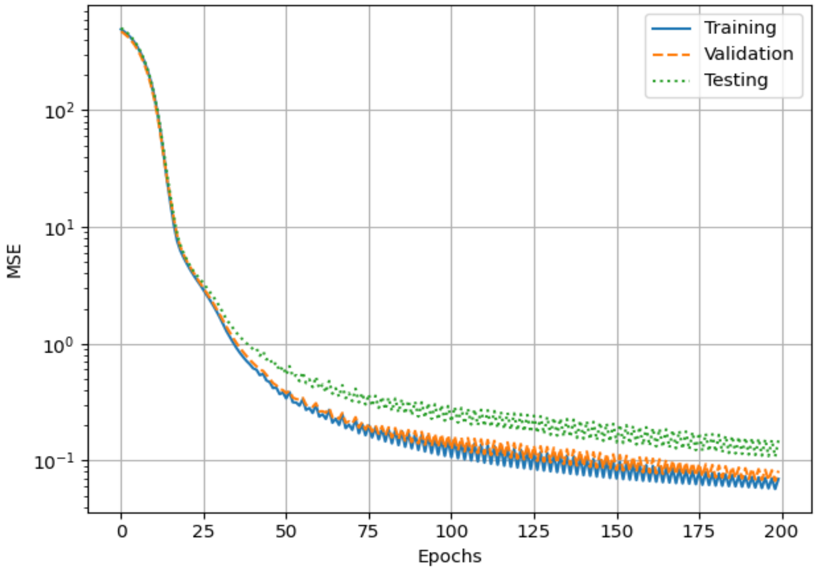

Fig.6. Error convergence history of the proposed machine learning model showing the evolution of training, validation, and testing mean squared errors over the learning epochs.

The comparison between numerical von Mises stress values and machine learning predictions for $\omega = 100$ rad/sis presented in Figure 7

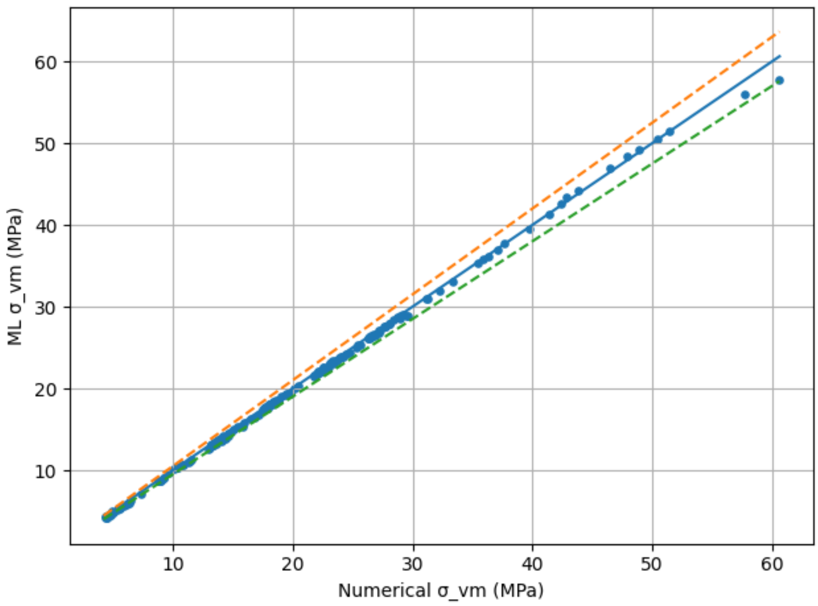

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Fig.7. Comparison between numerical von Mises stress values and machine learning predictions for ω = 100 rad/s.

Figure 8 presents the comparison between numerical von Mises stress values and machine learning predictions for $\omega = 200$ rad/s.

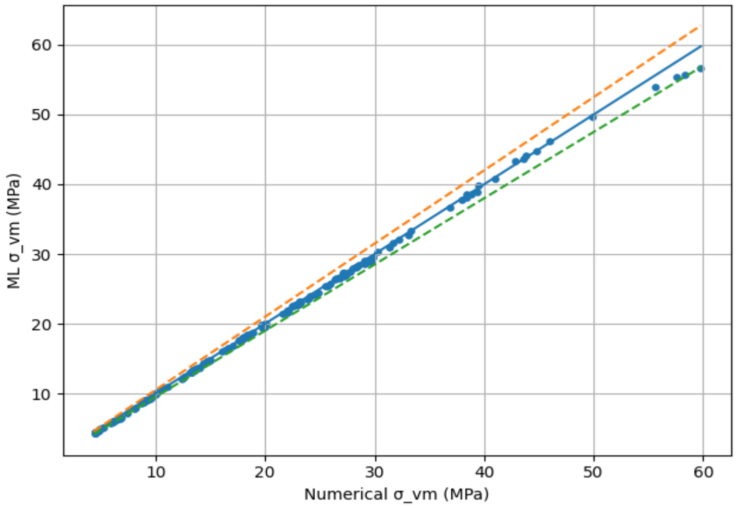

Fig.8. Comparison between numerical von Mises stress values and machine learning predictions for ω = 200 rad/s,

Figure 8 presents the comparison between numerical von Mises stress values and machine learning predictions for $\omega = 200$ rad/s. The predicted results exhibit a close alignment with the ideal $y = x$reference line, indicating a strong level of agreement between the two approaches. Slight deviations observed at higher stress levels remain limited in magnitude and do not alter the overall agreement trend. These findings indicate that the proposed machine learning model maintains its predictive consistency under increased rotational speed, thereby supporting its suitability for validating the analytical stress formulation across different operating conditions. The radial variation of the von Mises stress obtained from the numerical/analytical solution and the corresponding machine learning predictions is presented in Figure 9.

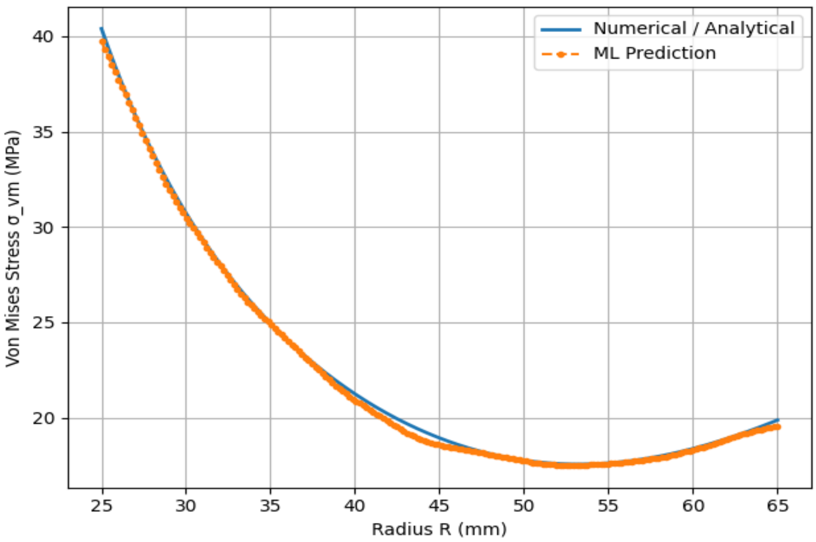

Fig. 9. Radial distribution of von Mises stress obtained from analytical/numerical computation and machine learning prediction at ω = 100 rad/s.

Figure 9 shows a close agreement between the numerical/analytical results and the machine learning predictions along the cylinder radius. Both curves follow a similar trend, with the von Mises stress decreasing from the inner region toward the mid-radius and exhibiting a slight increase near the outer radius. Minor discrepancies remain limited and do not affect the overall stress distribution pattern. This consistency further confirms the capability of the machine learning model to accurately reproduce the analytically derived radial stress behavior. Figure 10 shows the radial distribution of the von Mises stress obtained from the numerical/analytical solution together with the corresponding machine learning predictions.

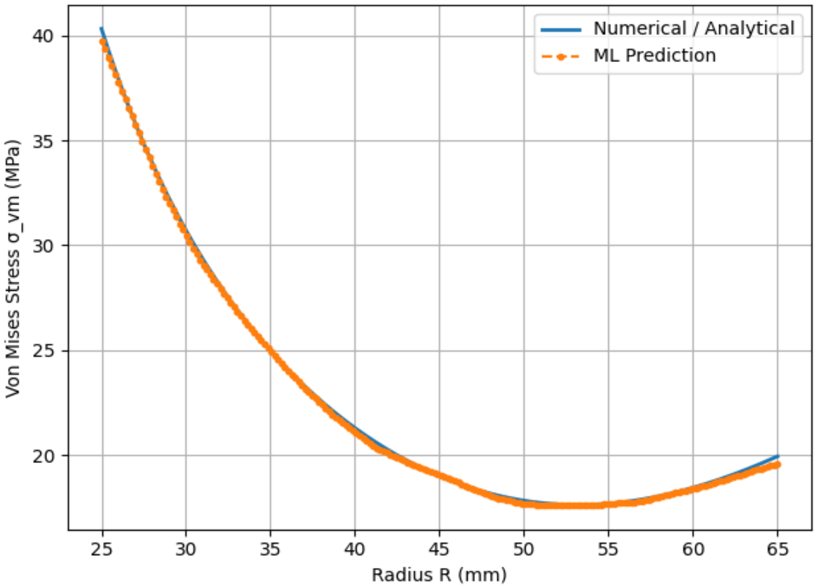

Fig. 10. Radial distribution of von Mises stress obtained from analytical/numerical computation and machine learning prediction at ω = 200 rad/s.

Figure 10 demonstrates a strong consistency between the numerical/analytical results and the machine learning predictions along the cylinder radius. The predicted stress profile closely follows the analytical trend, characterized by a decrease from the inner radius toward the mid-region and a mild increase near the outer radius. The observed differences between the two curves remain small and do not alter the overall stress distribution behavior. This agreement further supports the effectiveness of the machine learning model in reproducing the analytically derived thermo-elastic stress response.

Conclusion

The combined evaluation of tangential and von Mises stress distributions clearly demonstrates the pronounced influence of coupled thermal and rotational loading on the structural response of the layered composite disk under plane strain conditions. As indicated by the analytical results summarized in Table 2, tangential stresses increase monotonically with rising temperature levels and exhibit a distinct sign change across the disk radius, remaining tensile near the inner surface and transitioning to compressive values toward the outer radius. Under the adopted plane strain formulation, the radial stress component remains negligible, confirming that the stress state is predominantly governed by circumferential and equivalent stress responses. The von Mises equivalent stress distributions further reveal that the maximum critical stress levels consistently occur at the inner radius of the disk, identifying this region as the most susceptible to yielding under combined thermomechanical loading. Increasing temperature significantly amplifies the equivalent stress throughout the disk, while higher angular velocity ($\omega = 200$ rad/s) produces systematically higher von Mises stress levels compared to $\omega = 100$ rad/s, in agreement with both analytical predictions and machine learning–based validation results. These observations confirm the synergistic interaction between thermal expansion effects and centrifugal forces, leading to elevated stress concentrations and reduced safety margins. Overall, the results highlight the necessity of simultaneously accounting for thermal loading and rotational speed in the design and assessment of high-performance rotating composite structures. The close agreement between analytical solutions and machine learning predictions, together with the consistent trends observed across varying temperature and angular velocity levels, validates the applicability of the plane strain formulation and the von Mises yield criterion for predicting critical stress states, thereby supporting the reliability and engineering relevance of the proposed analytical framework.

Author Contributions

Conceptualization, Hüseyin Fırat KAYIRAN; methodology, Hüseyin Fırat KAYIRAN; investigation, Hüseyin Fırat KAYIRAN; resources, Hüseyin Fırat KAYIRAN; writing—original draft preparation, Hüseyin Fırat KAYIRAN; writing—review and editing, Hüseyin Fırat KAYIRAN; visualization, Hüseyin Fırat KAYIRAN.

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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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