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Machine Learning-Based Investigation of Stress in Carbon Fiber Rotating Cylinders

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ABSTRACT

This study analyzed elastic stresses in a rotating cylinder consisting of carbon fiber material using analytical methods and machine learning techniques. Elastic stress ranges were determined according to the Von Mises yield criterion, which provided a comprehensive understanding of the material's behavior under rotational loads. The analytical results were validated and improved through machine learning-based predictions, demonstrating the potential of these approaches in stress analysis. The results are presented graphically for clarity and comparison. The study emphasizes that there is an inverse relationship between the rotational speed parameter and the elastic stress that occurs inside the cylinder. These findings contribute to understanding stress behavior in high-performance composite materials but also demonstrate the effectiveness of machine learning in predicting stress distributions for complex engineering.

1. Introduction

Cylinders are extensively utilized in mechanical components due to their geometric efficiency and functional advantages. Rotating cylinders of various sizes form essential parts of numerous mechanical systems, necessitating accurate evaluation of the stresses and deformations they

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experience, particularly under high-temperature conditions. Understanding stress distributions in these components is crucial for ensuring structural integrity, enhancing operational efficiency, and extending service life. The literature indicates substantial progress in analyzing stresses and deformations in rotating components. For instance,

In recent years, research on plastic deformation of rotating discs has focused on aluminum-based dispersion-hardened alloys. For example, Matvienko et al. (2023) used mechanical tensile tests and optical microscopy methods in their study examining the elastoplastic deformation of rotating discs made of aluminum dispersion-hardened alloys. The study provides a current perspective in understanding the plastic deformation behavior of rotating disks [1]. Similarly, Tutuncu and Ozturk developed a general solution for stress analysis in functionally graded material (FGM) disks, highlighting the benefits of graded materials in reducing stress concentrations [2]. Eraslan and Orcan extended these findings by investigating elastic–plastic deformations in solid disks with variable thickness under external pressure, offering a deeper understanding of the structural response under varying load conditions [3]. Tutuncu and Temel (2009) propose a novel approach for the stress analysis of pressurized functionally graded material (FGM) cylinders, disks, and spheres while Gao and Meguid demonstrated the effects of material gradients on stress distributions in rotating disks [5]. Pooja Rani and Kuldip Singh (2024) investigated the thermoelastic stresses in a functionally graded annular rotating disc subjected to internal and external pressure. The study assumes that the material properties, including elasticity modulus, thermal conductivity, thermal expansion coefficient, and density, vary radially based on three distinct power-law functions, while Poisson's ratio remains constant [6]. Akbari and Ghanbari (2019) developed an analytical exact solution for functionally graded rotating disks subjected to non-symmetric thermal and mechanical loads. Their study provides a detailed analysis of stress distribution, considering material property variations, and offers insights into the behavior of such disks under complex loading conditions [7]. Additionally, Akis and Tekkaya examined stress and deformation in functionally graded hollow cylinders subjected to internal pressure, enhancing the understanding of FGM behavior in pressurized systems [8]. Recent research has focused on specific applications of rotating disks under thermomechanical loading. Nayak and Saha analyzed the elastic limit angular speeds of solid and annular disks, identifying key parameters influencing their strength [9]. Lin conducted an elastic analysis of rotating annular disks made from FGMs with exponentially varying profiles, addressing scenarios where material properties change non-linearly [10]. Numerical analyses by Kayiran assessed the mechanical performance of composite disks based on carbon-aramid/epoxy materials under different loading conditions [11], while Kayiran explored displacements in circular disks composed of various materials, emphasizing their implications for material selection and design [12]. Building on these studies, the current research focuses on the stress analysis of rotating cylinders composed of carbon fiber, a high-performance composite material known for its superior strength-to-weight ratio and thermal resistance. Stresses are examined using both analytical methods and machine learning techniques, particularly artificial neural networks (ANNs), which have been shown to solve complex engineering problems effectively. ANN predictions complement analytical results, offering rapid and accurate stress assessments. This approach bridges the gap between traditional analytical methods and advanced computational techniques, delivering a comprehensive understanding of stress behavior in carbon fiber cylinders under rotational loads. The mechanical properties of carbon fiber used in the analysis are detailed in Table 1, ensuring precise material characterization. Carbon fiber was selected as the most appropriate material for the application due to its exceptional properties.The study investigates the solitary wave solutions for various versions of the fractional 3D-Wazwaz-Benjamin-Bona-Mahony (WBBM) equations, emphasizing the role of fractional derivatives in capturing complex wave phenomena. In a different study, a non-self-adjoint quadratic pencil problem with periodic boundary conditions is considered. The linearly independent solutions of the problem have been determined, and the asymptotic formulas for the eigenvalues and eigenfunctions have been provided [13-14]

1.2. Literature Review Section

Machine learning (ML) and artificial intelligence (AI) are increasingly transforming mechanical engineering and machine systems. These technologies enhance efficiency, reduce costs, and minimize errors in engineering processes. Today, ML and AI methods are widely adopted in production, maintenance, design, optimization, and material development [15]. ML-powered predictive maintenance systems enable early detection of faults by continuously monitoring industrial machines. Through big data analytics and sensor-based monitoring, maintenance operations become more efficient, leading to significant cost savings for businesses [16]. For instance, smart manufacturing systems optimize production lines by leveraging deep learning and neural networks, continuously improving processes [17]. Baduge et al. (2022) provide a comprehensive review of AI, ML, and DL applications in Building and Construction 4.0, covering areas such as architectural design, material optimization, structural analysis, automation, and smart building operations. The study also discusses data collection, processing, storage, challenges in model development, and future research directions [18]. This approach increases the efficiency of production systems while providing more accurate and reliable design processes [19]. Machine learning also plays a crucial role in the development of next-generation materials. Compared to traditional material engineering methods, ML algorithms predict mechanical properties faster and more accurately, optimizing experimental processes [20]. For example, the durability of composite materials and their resistance to environmental effects can be assessed more accurately through AI-driven analyses [21]. AI is also contributing to energy efficiency and sustainable manufacturing. Smart energy management systems optimize factory operations, reducing energy consumption and promoting sustainability [22]. AI-based systems reduce manufacturing defects, minimize waste, and contribute to eco-friendly production methods [23]. Furthermore, ML algorithms are applied to solve optimization problems in mechanical system design. AI-driven engineering solutions assist engineers in making more effective design decisions, resulting in more efficient and durable systems [24]. For instance, AI optimizes aerodynamic analyses and fluid dynamics calculations, leading to faster and more precise results [25]. In conclusion, AI and ML offer a broad range of applications in mechanical engineering. These technologies enhance efficiency in manufacturing, improve fault prediction and maintenance, accelerate material science innovations, and support sustainable manufacturing solutions. The impact of AI and ML on engineering disciplines is expected to grow in the coming years, paving the way for smarter, more autonomous industrial systems [26-27-28-29]. There are also different types of machine learning. These species are given as an example in Figure 1 below.

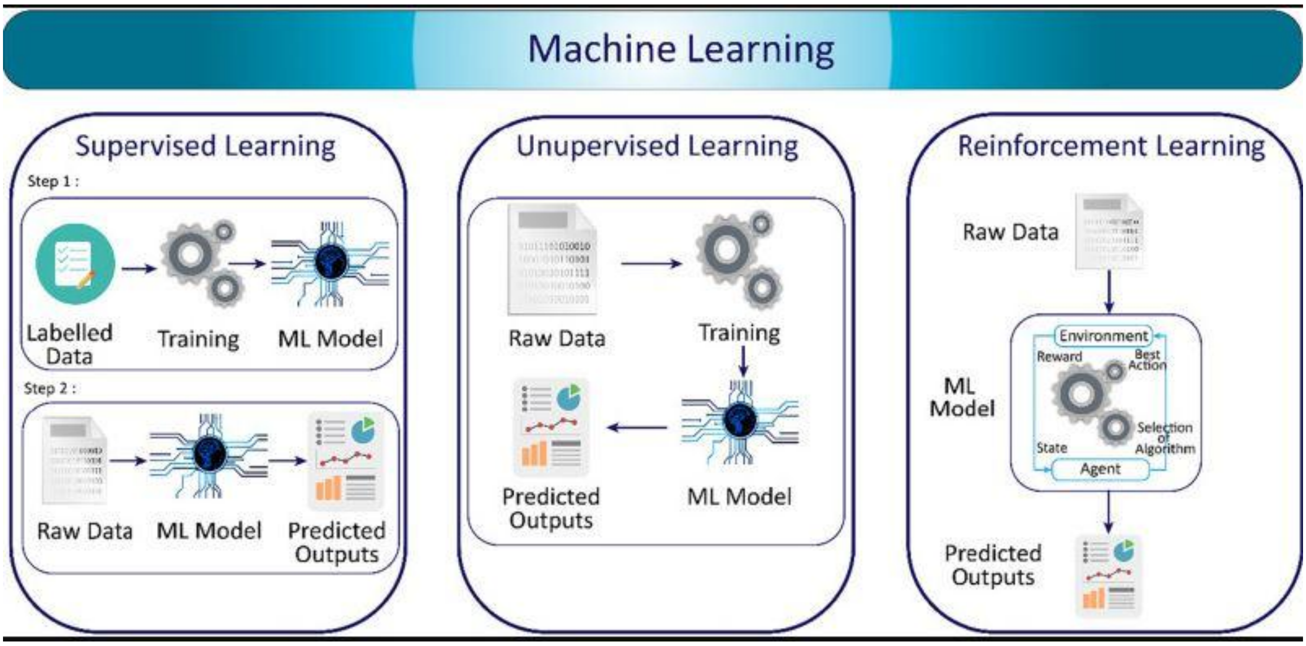


Fig 1. Demonstration of the types of machine learning [18].

2. Material and Method

The numerical results obtained in this study are provided in the formula below:

Two-dimensional equilibrium equation in cylindrical coordinates [30];

$$\frac{d(\sigma_r)}{dr} - \frac{1}{r}\frac{(d\tau_{r\theta})}{d\theta} + \frac{(\sigma_r - \sigma_\theta)}{r} + R = 0 \qquad (1)$$

For the stress analysis equation in rotating cylinders;

$$r^2\frac{d^2F}{dr^2} + r\left[1 - r\frac{E'(r)}{E(r)}\frac{dF}{dr}\right] + \left[v(r)\frac{E'(r)}{E(r)} - 1\right]F = \rho(r)\omega^2 r^3 [r\frac{E'(r)}{E(r)} - \frac{\rho'(r)}{\rho(r)} - 3 - -\frac{v}{1-v} \qquad (2)$$

$$\sigma_r = C_1 r^{(n+k-2)/2} + C_2 r^{(n-k-2)/2} + Ar^{(2+\gamma)} \qquad (3)$$

$$\sigma_\theta\ (\mathrm{MPa}) = \frac{n+k}{2} C_1 r^{\frac{n+k-2}{2}} + \frac{n-k}{2} C_2 r^{\frac{n-k-2}{2}} + (3+\gamma) A r^{(2+\gamma)} + \rho(r)\omega^2 r^2 \quad (4)$$

Radial Displacement U(r);

$$u(r) = \frac{1}{E_{(r)}} + \left\{ \int \sigma_r(r)dr - \nu(r) \right\} \int \sigma_\theta(r)dr \} \quad (5)$$

According to the formulas above; r=et transformation is performed, E_0, modulus of elasticity , ρ_0 density reference value, n and γ are optional constants.C1 and C2 are integral constants. For boundary conditions;

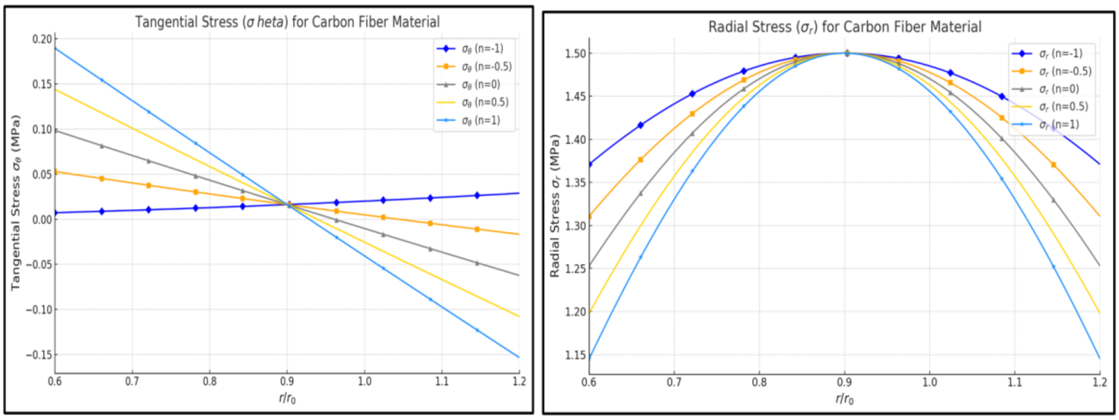
The mechanical properties of carbon fiber are provided in Table 1 below.

Table 1. Mechanical properties of carbon fiber cylinder material [31].

Modulus of elasticity (Gpa))	Angular velocity (rad/sn)	Density (kg/m3)	Inner half diameter (mm)	Outer half diameter (mm)
228	50	1600	60	120

Results

In this study, radial stress, tangential stress and radial displacement were calculated by numerical analysis in a cylinder with carbon fiber material, whose mechanical properties are specified in Table 1 above, rotating at an angular velocity of 50 rad/sec, and the tangential stress results were compared with machine learning, which is a sub-branch of artificial intelligence. The results obtained are shared below with graphs. Below, in Figures 2a and 2b, the tangential and radial stresses obtained at the end of the numerical analysis are given.



(a) (Tangential Stress) (b) (Radial Stress)

Fig. 2. Determination of tangential and radial stresses occurring in a carbon fiber disk rotating at 50 rad/sec

The radial stress distribution shows a significant variation across the radius of the disk. The stress increases from the inner radius (r/r0≈0.6) to the outer radius (r/r0=1) and then slightly decreases beyond the outer radius (r/r0>1). The magnitude of σr is strongly influenced by the parameter n, For n=−1, the radial stress reaches its maximum values throughout the disk. As n increases to n=1n = 1n=1, the overall magnitude of radial stress decreases, particularly at the inner radius. The tangential stress exhibits different behaviors depending on the parameter n; For n=−1, the tangential stress remains nearly constant and close to zero across the disk radius. As n increases, the tangential stress transitions from tensile at the inner radius to compressive near and beyond the outer radius (r/r0>1). The shift becomes more pronounced for higher n values, with n=1 exhibiting the largest tensile and compressive stress gradients. Radial Stress: The maximum radial stress occurs near the outer radius, and its magnitude decreases as n increases. Tangential Stress: Higher n values result in a significant shift from tensile to compressive stresses, highlighting the influence of material properties or loading conditions on the stress distribution. The radial displacement graph is given in Figure 3 below.

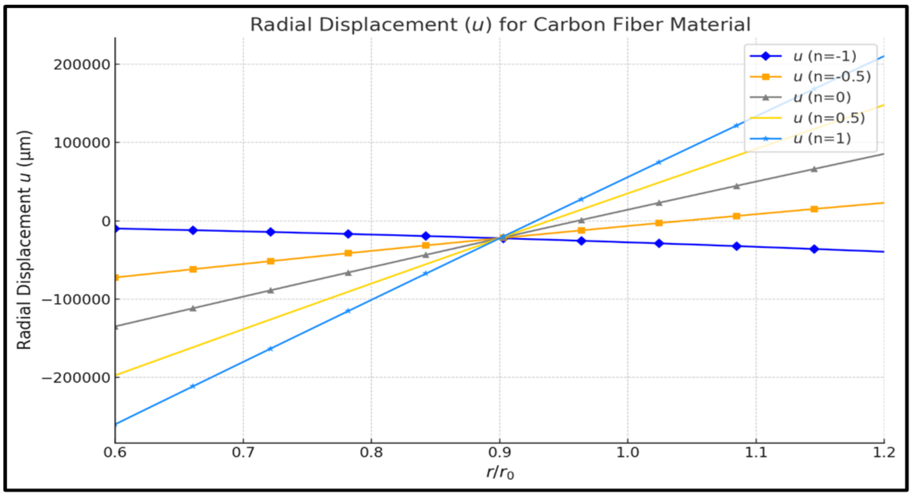


Fig. 3. Determination of radial displacement occurring in a carbon fiber disk rotating at 50 rad/sec

Şekil 3’den görüleceği üzere; For n=−1, the radial displacement remains constant and close to zero throughout the disk. This indicates minimal deformation in this condition.As n increases towards n=1n = 1n=1, the radial displacement becomes significantly larger in magnitude, showing both positive (outward displacement) and negative (inward displacement) values. At r/r0≈1 (outer radius), the displacement trends converge near zero, indicating equilibrium or minimal deformation at this point. For n>0, the displacement shifts predominantly outward (u>0), whereas for n<0, it becomes inward (u<0). Larger n values (e.g., n=1) result in the highest displacement magnitudes, reflecting greater material deformation due to changes in stress distribution and mechanical properties.

Figure 4 below shows the training, validation and test datasets of the Machine Learning model.

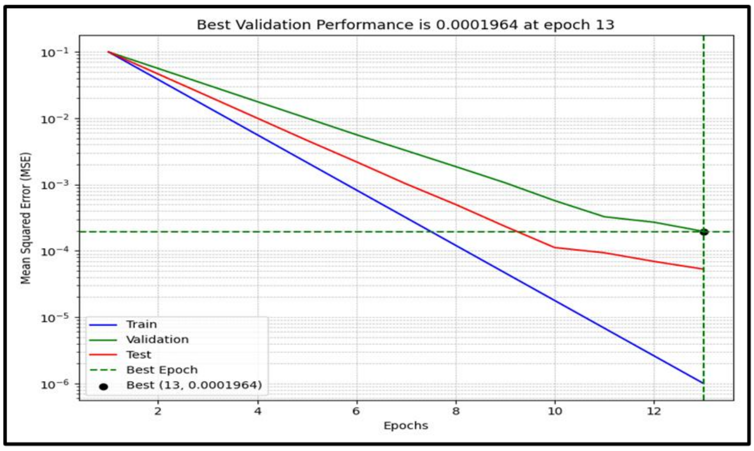
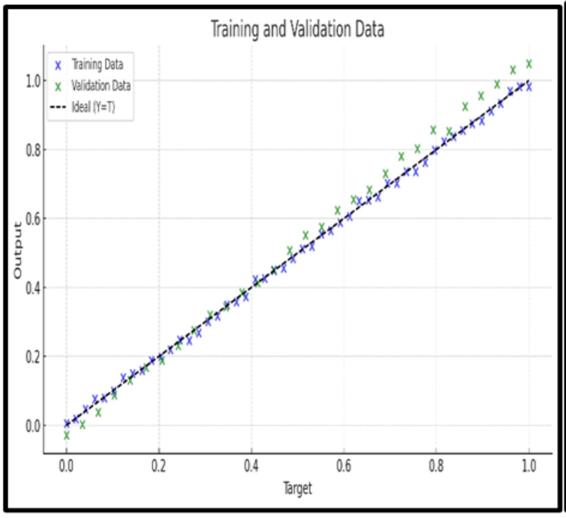
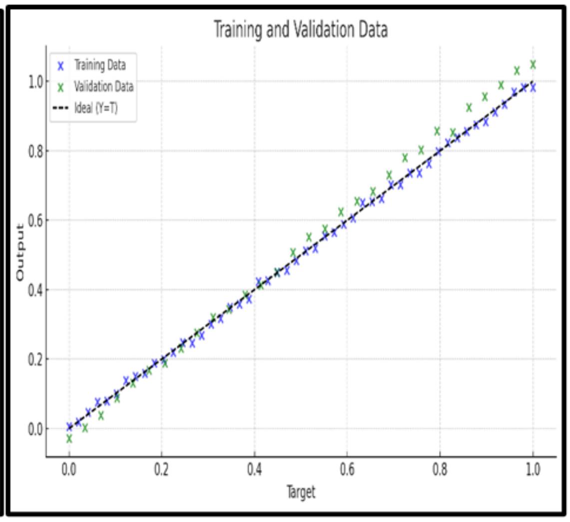


Fig. 4. Mean square error (MSE) for training, validation and test datasets

The best performance in the validation set was achieved at the 13th epoch, so training the model can be terminated from this point on. This is thought to be an efficient choice in terms of both time and resources.Figure 4 shows that the model achieved the best balance between training and generalization in the 13th period, with minimum validation and test error. Below is the training and validation data in Figure 5.



(a) (Traning and validation data)



(b) (Traning and validation data)

Fig. 5. Relationship between the output of the model (predicted values) and the target values for both the training and validation datasets

As can be seen from Figure 5, there is minimal deviation from the ideal line in the graphs in 4a and 4b, indicating that the model achieves high accuracy and exhibits little over or under learning. The graph above shows the training (blue dots) and validation (green dots) datasets generated. Additionally, the dashed black line Y=TY = TY=T represents the ideal linear relationship. The graph shows that both data sets generally produce predictions close to the target. The model performed strongly on the training and validation datasets, producing accurate results with a low error rate.Comparison of tangential stress results with numerical analysis and Machine learning is given in Figure 6 below.

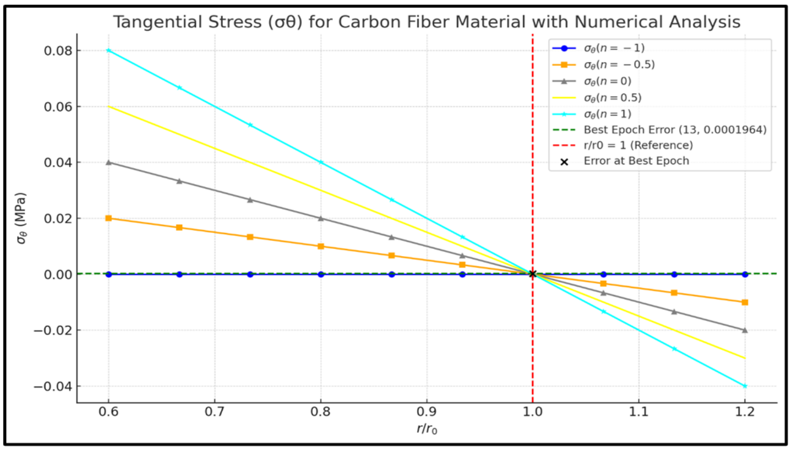


Fig 6. Comparison of tangential stress results with numerical analysis and Machine learning

As can be seen from Figure 5;Tangential Stress Behavior (for n = -1: The tangential stress remains constant and close to zero, which indicates the minimum stress along the radius. (for n > -1): The tangential voltage decreases linearly, starting higher at the inner radius (r / r0 < 1). Then it becomes negative (pressure voltage) at (r / r0 > 1).At higher (n) values, for example, for n = 1, it exhibits the largest stress gradients by switching more sharply from higher tensile stresses to compressive stresses. Lower (n) values indicate, for example, a reduced stress change (n = -1) and a minimal effect on material deformation. In the graph above, the red dashed line shows (r/r0 = 1) and shows the outer radius through which the voltage behavior transitions. The green dashed line highlights the best period error by providing a verification point for numerical accuracy. In general, the tangential voltage distribution reveals the sensitivity of the voltage behavior to the parameter (n). Higher (n) values lead to significant tensile and compressive stress changes, while lower (n) values lead to more uniform stress distributions. This analysis is included in the literature as very important for the design of carbon fiber materials to ensure structural stability under certain processes.

4. Conclusions

In this study, the stresses occurring in a cylinder with carbon fiber material rotating at a hungry speed of w=50 rad/sec were numerically investigated. Carbon fiber radial stresses on the innermost and outermost parts of the cylinder are zero. It was seen that the stresses were inversely proportional to the increase in the rating parameter in the cylinders. For n=−1, the maximum tangential stress (σθ) is in the region of r/r0=0.6. However, since the tangential stress is σθ=0, it is 100% lower compared to the radial stress. This shows that the tangential stress creates a negative difference compared to the radial stress. It has been concluded that the training set created with artificial neural networks, which is a sub-branch of artificial intelligence, for the tangential stresses occurring in the cylinder can be compatible with the numerical analysis results. The anisotropic properties of carbon fiber significantly affect the tangential stress distribution depending on the value of n. The best verification performance (13th epoch) was successfully demonstrated on r/r0 and the error value was proven to be low.

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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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