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Stress Field Characterization in Rotating Anisotropic Polypropylene Cylinders: Analytical Modeling and SVR Validation

Hüseyin Fırat KAYIRAN[1,*],

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

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ABSTRACT

In this study, the elastic stress distribution in a rotating cylinder composed of polypropylene (PP) material was investigated using analytical formulations and parametric evaluations. Tangential and radial stresses, as well as radial displacements, were calculated under varying anisotropy parameters to observe their influence on the mechanical behavior. The stress components were derived by incorporating both elastic and centrifugal effects under steady-state rotational motion. The results were evaluated in terms of the Von Mises yield criterion to identify critical stress zones. Graphical representations of stress and displacement distributions were presented for different anisotropy levels. An equilibrium check was also conducted to verify the accuracy of the stress fields. To enhance reliability, the analytically obtained radial stress values were also validated using Support Vector Regression (SVR), demonstrating strong agreement and underscoring the potential of machine learning techniques in predicting complex stress distributions. The study highlights that increasing rotational speed leads to a rise in tangential stress while the radial stress tends to decrease near the boundaries. These findings underline the importance of considering anisotropic behaviour in polymer-based rotating systems. Moreover, the implemented framework demonstrates the potential integration of computational and analytical approaches for stress prediction in engineering-grade thermoplastic materials.

1. Introduction

High-performance rotating disks made of composite or functionally graded materials (FGMs) have garnered significant interest in mechanical design due to their superior strength-to-weight ratio, thermal stability, and resistance to fatigue and creep. Precise stress analysis under thermomechanical loading conditions is vital, especially when dealing with high-speed rotating systems. Recent studies have advanced analytical and numerical modeling techniques to predict stress and deformation in rotating disks. Gao and Meguid developed a thermoelastic analysis model for FGMs, showing how material gradation affects radial and tangential stress distributions under thermal and centrifugal forces [1]. Nonlinear vibrations and dynamic stresses in brake disks are critical factors affecting braking safety. Chen et al. (2024) validated the natural frequencies of the brake disk with a 5.1% error using finite element analysis and laser measurement techniques, demonstrating that random vibrations

* huseyinfiratkayiran@gmail.com

increase under thermal effects [2]. Akbari and Ghanbari presented an exact analytical solution for rotating functionally graded disks exposed to non-symmetric thermal and mechanical loads [3]. Their model enabled a better understanding of non-uniform stress fields. Further, Rani and Singh investigated thermoelastic behavior in annular FGM disks using different power-law distributions, contributing to the ongoing efforts to optimize material grading strategies [4].

In the context of composite materials, Kayıran performed numerical stress and displacement analyses on carbon-aramid/epoxy-based disks under varying boundary and loading conditions [5].

In a different study, the creep behavior of rotating disks composed of transversely isotropic piezoelectric materials is highlighted as a significant engineering challenge under high temperatures and long-term loading. Using Seth's transition theory and Hooke's law, a mathematical model incorporating piezoelectric effects was developed to analyze electric displacement and stress components under various boundary conditions. The results indicate that piezoelectric materials—particularly PZT-4 and $BaTiO_3$—exhibit greater resistance and stability against creep compared to conventional transversely isotropic materials such as magnesium and beryllium [6].

The influence of material composition and layer arrangement on stress distribution has also been emphasized. With the advancement of machine learning in engineering, hybrid models based on SVR and ANN have emerged as effective tools to complement classical methods in modeling complex physical phenomena [7]. Dara et al. (2023) discussed how AI-based methods have transformed diagnostic and predictive processes in both medicine and engineering [8]. Their research showed that ML methods could predict system behavior with high accuracy when trained on sufficient analytical or experimental datasets. In similar applications, Khalil and Pipa showed the advantages of combining deep learning and regression techniques in dynamic systems [9]. Their findings support the integration of SVR-based models in high-performance material simulations. The current study builds upon these foundations by developing a hybrid analytical–SVR approach for stress analysis in carbon fiber rotating disks. This approach enables rapid, data-driven stress estimations while maintaining analytical rigor. It also opens new pathways for the integration of AI-based predictive modeling into mechanical design.

1.2. Artificial Intelligence and its sub-branches

Artificial Intelligence (AI) is a field of computer science aimed at equipping machines with human-like capabilities such as reasoning, learning, and problem-solving. First conceptualized by John McCarthy in 1956, AI is now widely used in various domains to model complex systems and automate data-driven decision-making processes [10]. The core subfields of AI include Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Computer Vision (CV), and intelligence-based optimization algorithms. These domains contribute collectively to solving a wide range of real-world problems. Figure 1 below illustrates the main branches of artificial intelligence.

Machine learning refers to a collection of algorithms that learn from historical data to perform predictions or classifications. Commonly used techniques in this area include decision trees, artificial neural networks (ANN), k-nearest neighbors (k-NN), random forests (RF), and support vector machines (SVM) [11]. Among these, Support Vector Regression (SVR) is a powerful regression technique capable of modeling even nonlinear relationships with high accuracy. SVR is the regression adaptation of support vector machines, which aims to keep prediction errors within a certain tolerance margin (ε), attempting to keep most data points within this band. The model learns complex functions by transforming them into higher-dimensional spaces using kernel methods. One of the most popular kernel functions is the Radial Basis Function (RBF), known for its ability to solve nonlinear problems effectively [12]. SVR is recognized as an effective method for modeling complex relationships in physical systems. Minaee et al. (2020) demonstrated the high accuracy and generalization capability of such models in their study on COVID-19 prediction using deep transfer learning [13]. Cho and Ha (2002) analyzed the thermoelastic behavior of functionally graded materials (FGMs) under thermal loading using the finite difference method and proposed an artificial neural network (ANN)-based optimization model to minimize interfacial stresses under various boundary conditions [14]. Furthermore, the study by Matvienko et al. (2023) showed that rotating disks made of aluminum dispersion-hardened alloys maintain structural integrity even under high temperatures, demonstrating strong resistance to elastoplastic deformation [15]. SVR is particularly applied in predicting parameters such as stress, deformation, or temperature in mechanical systems, and is often incorporated into hybrid modeling frameworks alongside analytical methods. This technique not only reduces computational time but also contributes to engineering design processes by offering data-driven accuracy [16].

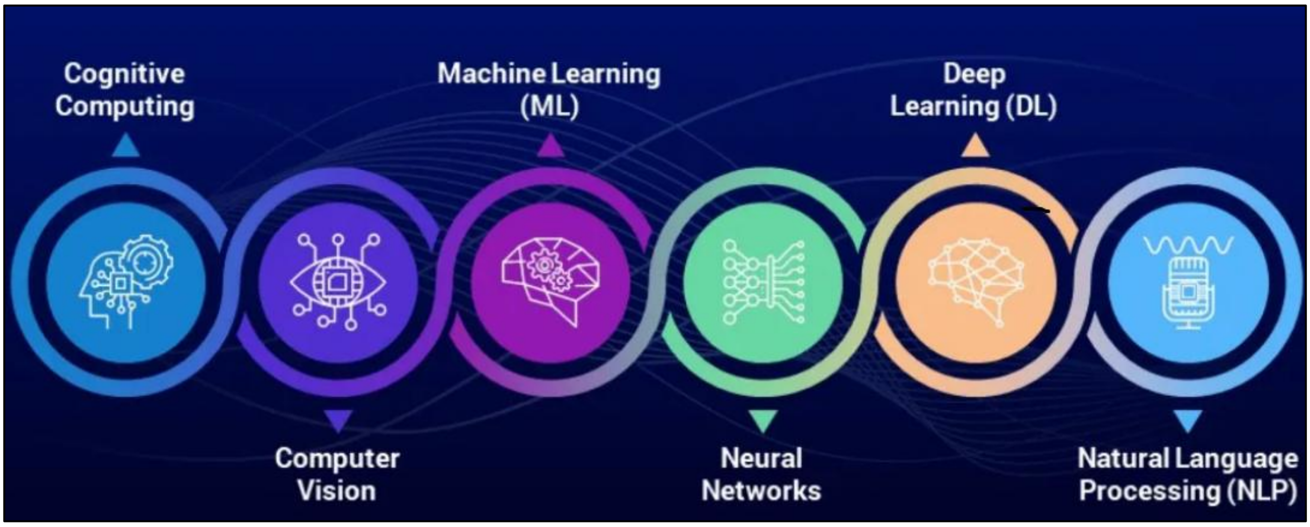


Fig 1. An example photo showing artificial intelligence and its sub-branches [17].

2. Material and Method

Disk geometry is given in Figure 2 below;

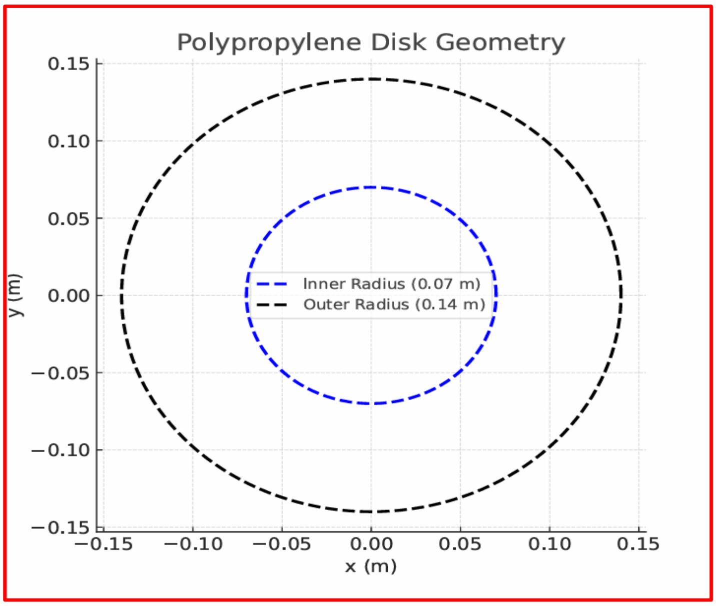


Fig 2. Geometry of the modeled disk

The numerical results obtained in this study are provided in the formula below: This balance equation is the basic equation for an axially symmetric disk under rotational influence [18], Radial equilibrium equation:

$$\frac{d\sigma_r}{dr} + \frac{\sigma_r - \sigma_\theta}{r} = \rho\omega^2 r \tag{1}$$

Radial strain (Hooke's law):

$$\epsilon_r = \frac{1}{E}(\sigma_r - \nu\sigma_\theta) \tag{2}$$

Tangential strain (Hooke's law):

$$\epsilon_\theta = \frac{1}{E}(\sigma_\theta - \nu\sigma_r) \tag{3}$$

At the end of the displacement derivation, Hooke's Law and Strain definition are obtained; Displacement from strain and Radial displacement in terms of stresses:

$$u(r) = \int \epsilon_r(r)\,dr \tag{4}$$

$$u(r) = \frac{1+\nu}{E}\left[(1-\nu)\sigma_r - \nu\sigma_\theta\right] r \tag{5}$$

Rotationally Symmetric Stress-Equilibrium Equation is given below [19];
Radial strain (explicit form):

$$\epsilon_r = \frac{\sigma_r - \nu\sigma_\theta}{E} \tag{6}$$

Tangential strain (explicit form):

$$\epsilon_\theta = \frac{\sigma_\theta - \nu\sigma_r}{E} \tag{7}$$

The centrifugal and elastic components, which are the two components of tangential stress, are given below;

Tangential stress (centrifugal component):

$$\sigma_\theta^{\text{centrifugal}} = \frac{(3+\nu)}{8} \cdot \rho \cdot \omega^2 \cdot (1.4^2 - \left(\frac{r}{r_0}\right)^2) \cdot r_0^2 \tag{8}$$

Tangential stress (elastic component):

$$\sigma_\theta^{\text{elastic}} = \frac{E}{1-\nu^2} \cdot \left(\frac{r}{r_0} - 1.05\right) \cdot (0.5 + 0.3n) \tag{9}$$

If the total Tangential stress is;

$$\sigma_\theta = \sigma_\theta^{\text{centrifugal}} + \sigma_\theta^{\text{elastic}} \tag{10}$$

The derived radial stress formula is below,Radial stress distribution (Gaussian-like function):

$$\sigma_r = 0.5 \cdot \exp\left(-(r/r_0 - 1.05)^2 \cdot (2+n)\right) \tag{11}$$

Radial Displacement U(r), Modified radial displacement (scaled):

$$u(r) = \left(\frac{1+\nu}{E}\right) \cdot \left[(1-\nu)\sigma_r - \nu\sigma_\theta\right] \cdot r \cdot 10^6 \tag{12}$$

Input data (feature vector) given to the SVR prediction model [20], SVR model input vector:

$$X = \left[\frac{r}{r_0},\ n,\ r\right] \tag{13}$$

With these inputs, SVR models tried to estimate the values of σθ, σr and u, respectively. This function provides a symmetric distribution where the maximum stress is around r/r0=1.05., n: anisotropy parameter, E: elastic modulus, n: anisotropy parameter, ν Poisson ratio, r/r0 normalized radius, r: radius, ρ material density, ω angular velocity.

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

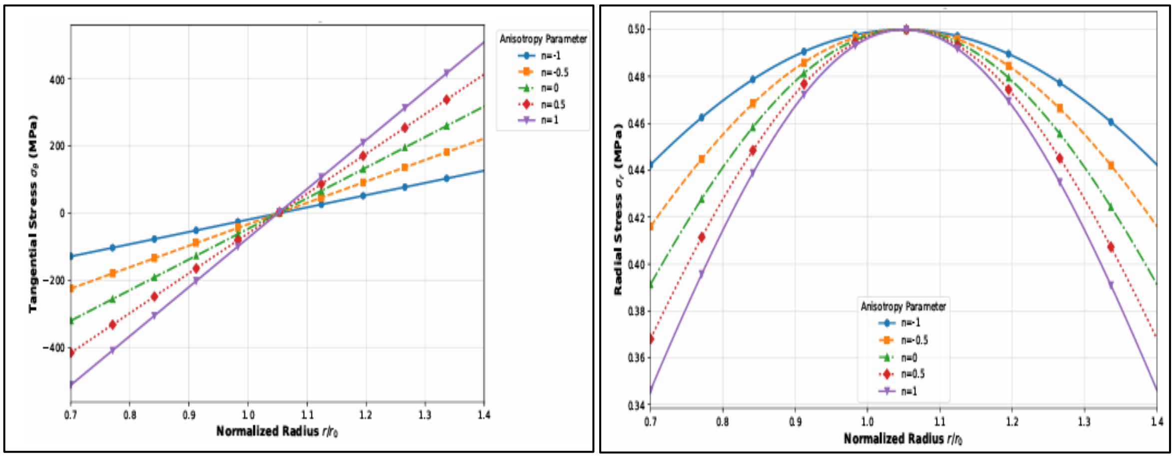
Table 1. Mechanical properties of Polypropylene (PP) material [21-22].

Modulus of elasticity (Gpa))	**Poisson Oranı**	**Angular velocity (rad/sn)**	**Density (kg/m3)**	**Inner half diameter (m)**	**Outer half diameter (mm)**
1.5	0.42	15	900	0.7	1.4.

Bu çalışma, dönel polimer sistemlerde elastik gerilme davranışının hem analitik hem de yapay zeka temelli yaklaşımlarla incelenmesini sağlaması açısından literatüre önemli bir katkı sunmaktadır. Özellikle anizotropi parametresinin etkilerini detaylı olarak değerlendirmesi ve destek vektör regresyonu (SVR) gibi modern makine öğrenimi yöntemleriyle doğrulama yapılması, geleneksel mühendislik analizlerinin dijital yöntemlerle desteklenebilirliğini göstermektedir. Bu yönüyle çalışma, mühendislik sınıfı termoplastik malzemelerin daha güvenilir ve öngörülebilir şekilde tasarlanmasına olanak tanımaktadır.

Results

In this study, radial stress, tangential stress and radial displacement were calculated by numerical analysis in a cylinder with Polypropylene (PP) material, whose mechanical properties are specified in Table 1 above, rotating at an angular velocity of 15 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 3, the tangential and radial stresses obtained at the end of the numerical analysis are given.



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

Fig. 3. Determination of tangential and radial stresses occurring in a Polypropylene (PP) cylinder rotating at 15 rad/sec

As can be seen from Figures 3a and 3b, the radial stress distribution exhibits a noticeable variation along the disk radius. Starting at low levels near the inner radius, the stress increases up to $r/r_0 = 1$, and then shows a slight decline beyond the outer radius. This trend is consistent with the influence of centrifugal forces and represents a characteristic outcome of radial (center-to-edge) load transmission within the disk structure. The anisotropy parameter, denoted as n, plays a significant role in determining the magnitude of radial stress. When n = −1, radial stress reaches its maximum values throughout the radius. However, as n increases (particularly up to n = 1), a decrease in stress values is observed. This behavior indicates that the effect of anisotropy tends to limit the elastic stress, acting as a stress-reducing factor.

The tangential (hoop) stress distribution, on the other hand, demonstrates a more complex behavior depending on the anisotropy parameter. In the case of n = −1, the tangential stress remains nearly constant and close to zero across the entire radius of the disk. However, with increasing n, the tangential stress exhibits a tensile character in the inner regions, gradually transitioning into a compressive character beyond the outer radius. The sharpness of this transition increases with the magnitude of the anisotropy parameter, becoming most pronounced for n = 1. This observation reveals that the material exhibits a directionally sensitive mechanical response, and that anisotropic behavior has a strong influence on the distribution of tangential stresses.

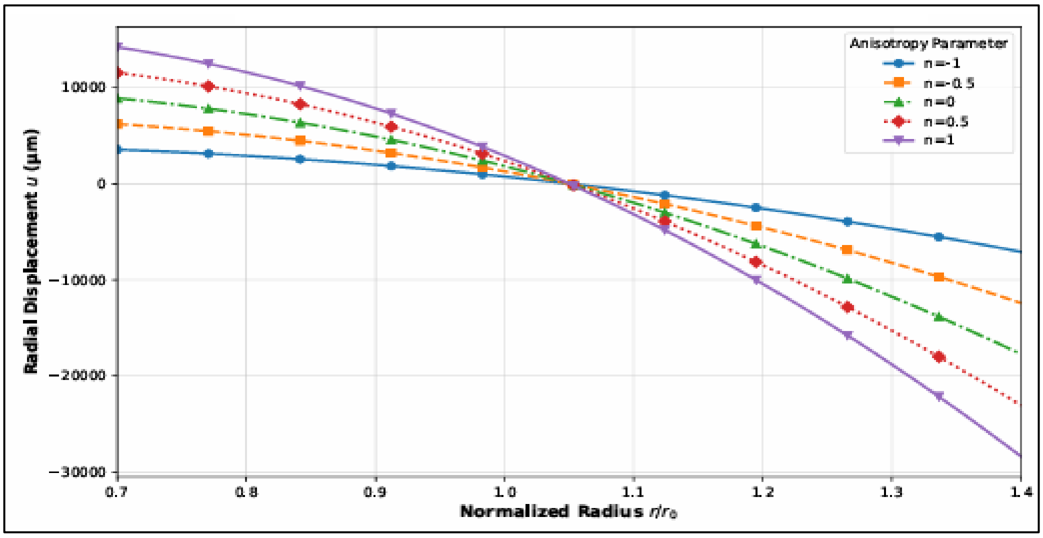
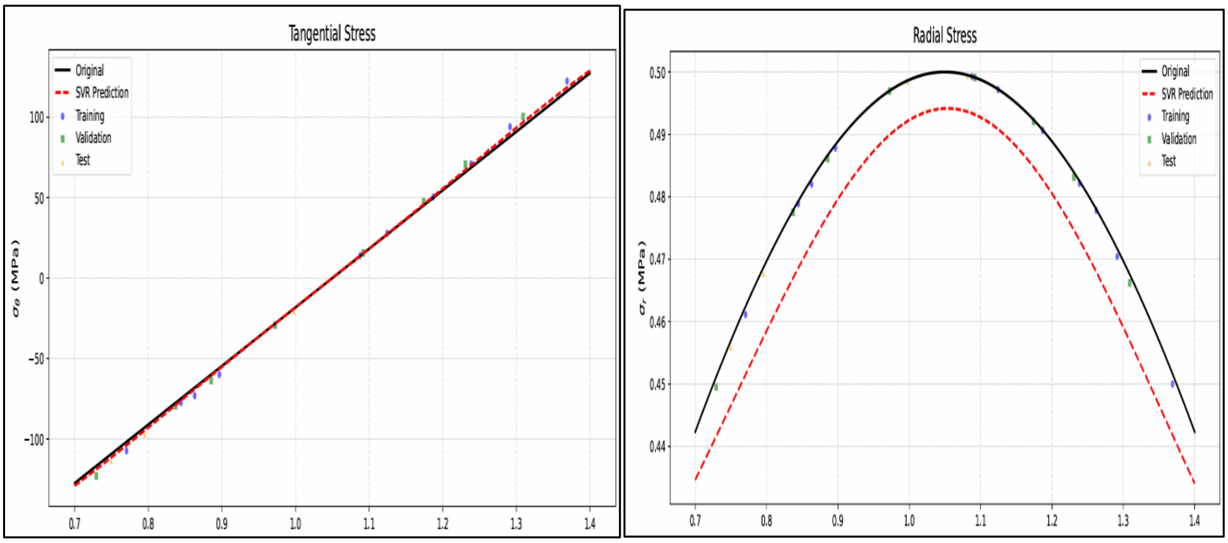


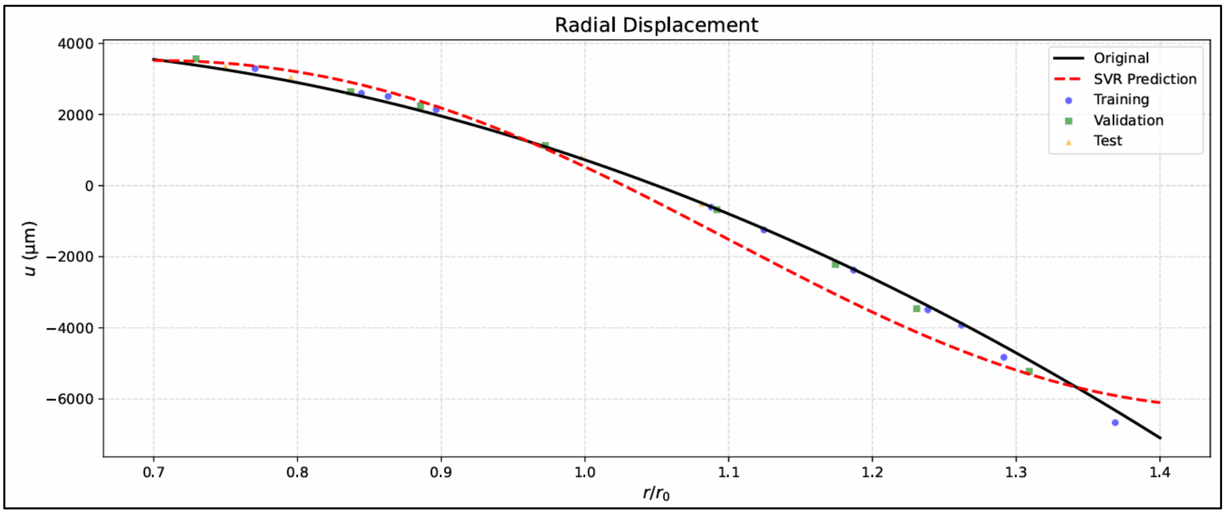
Fig. 4. Determination of radial displacement occurring in a Polypropylene (PP) cylinder rotating at 15 rad/sec

As shown in Figure 4, the distribution of radial displacement reveals significant variations along the disk radius depending on the anisotropy parameter. The displacement reaches approximately zero around the normalized radius $r/r_0 \approx 1.05$. Inside this point, the displacement takes on positive values, while it becomes negative outside of it. As the anisotropy parameter increases, the magnitude of deformation rises considerably. In particular, for n = 1, the radial displacement reaches maximum positive values in the inner region and minimum negative values in the outer region. This indicates that materials with high anisotropy exhibit reduced elastic stiffness and are subjected to greater deformation under the influence of centrifugal forces. These findings clearly demonstrate that material orientation and structural characteristics are key determinants in the deformation behavior of rotating systems. In the present study, the Support Vector Regression (SVR) method was employed to predict the distributions of tangential stress, radial stress, and radial displacement in a rotating disk made of polypropylene (PP). The SVR models were trained on synthetic datasets corresponding to various anisotropy parameters (n = −1, −0.5, 0, 0.5, 1) and the obtained results were compared with analytical solutions.

Figures 5 to 8 present the graphs generated as a result of the SVR-based prediction process, illustrating the estimation stages in detail.

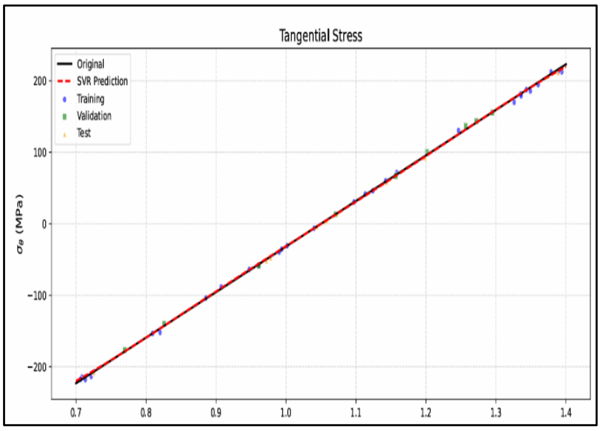


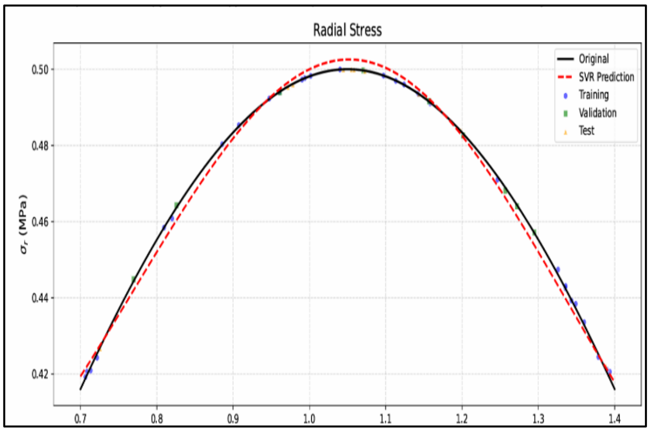
(a) Estimation of tangential stresses by SVR method (b) Estimation of radial stresses by SVR method



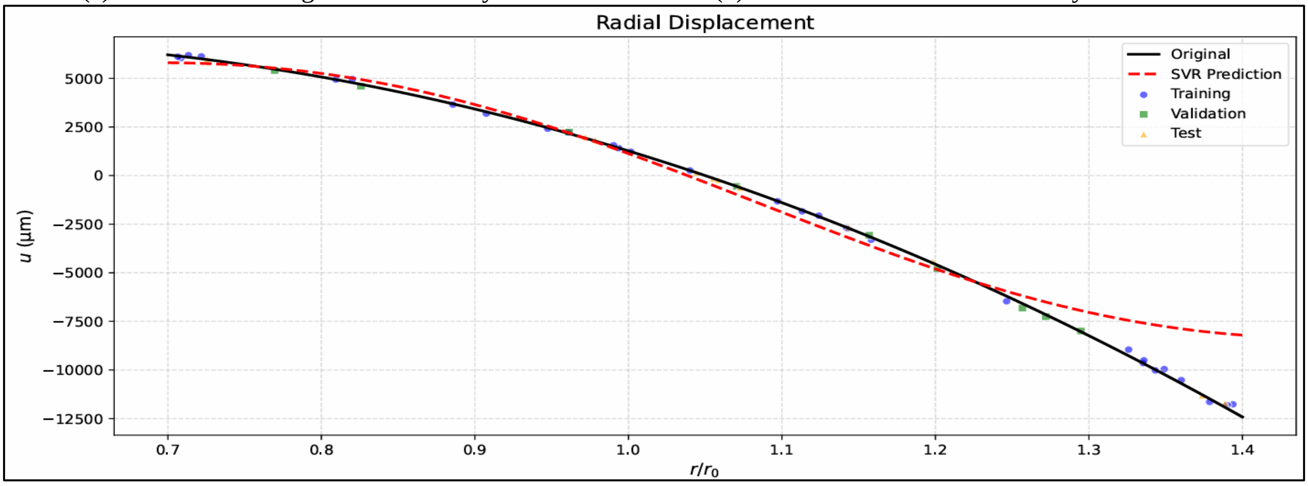
(c) Estimation of Radial displacement by SVR method

Fig. 5. Prediction results obtained by SVR (Support Vector Regression) method-**I**



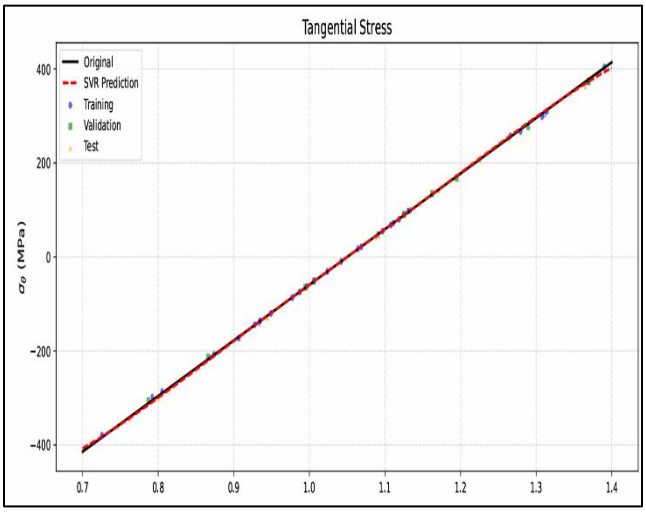


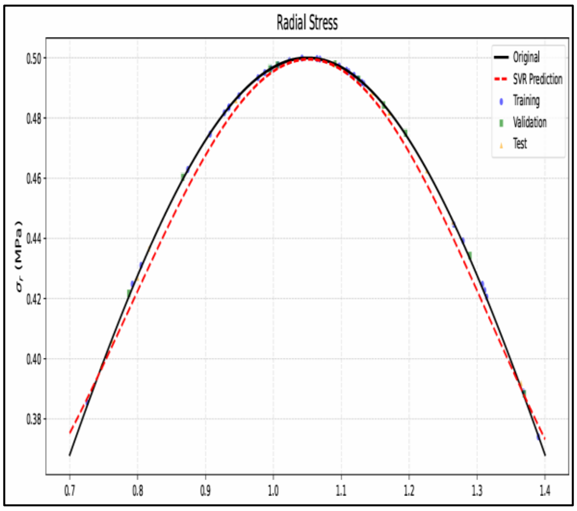
(a) Estimation of tangential stresses by SVR method (b) Estimation of radial stresses by SVR method



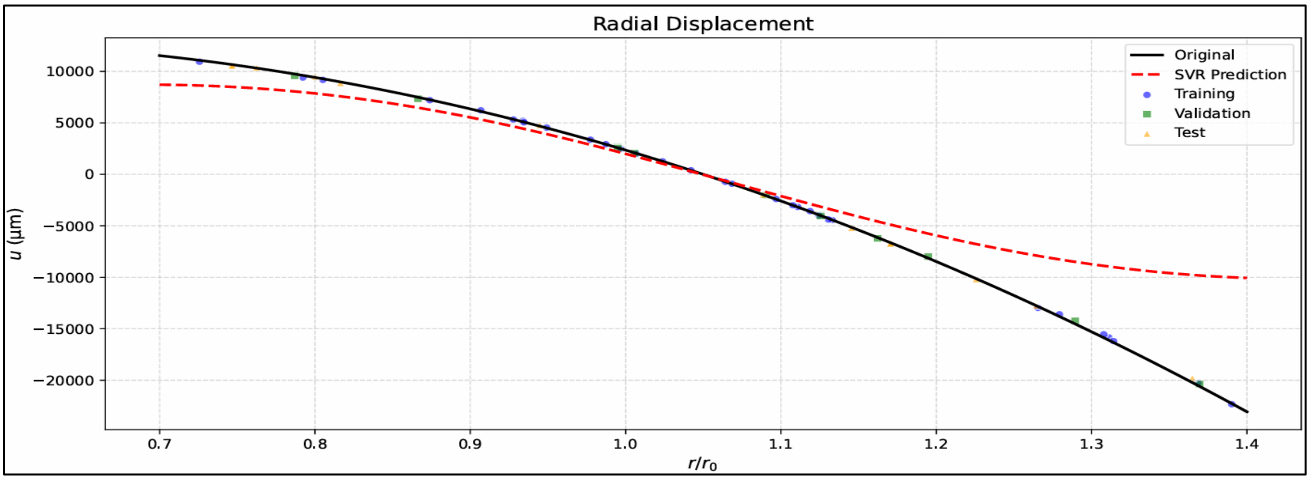
(c) Estimation of Radial displacement by SVR method

Fig. 6. Prediction results obtained by SVR (Support Vector Regression) method-**II**



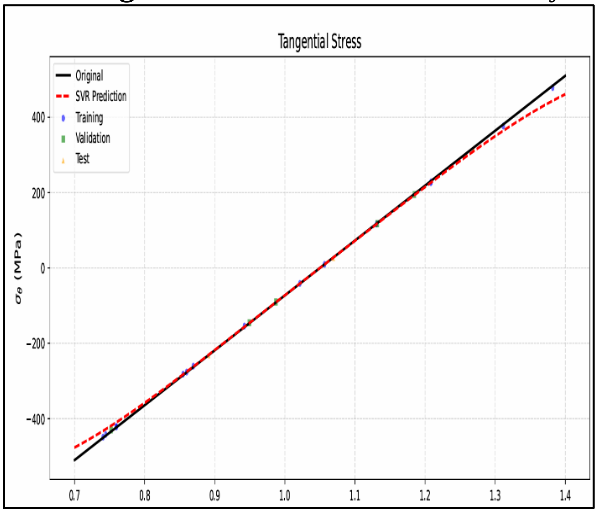


(a) Estimation of tangential stresses by SVR method (b) Estimation of radial stresses by SVR method

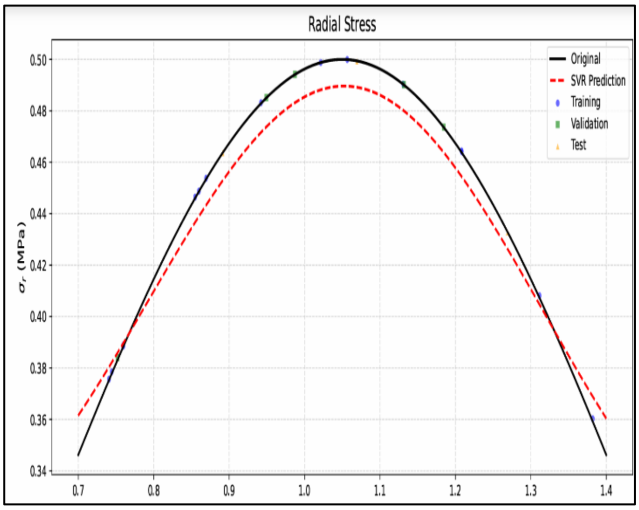


(c) Estimation of Radial displacement by SVR method

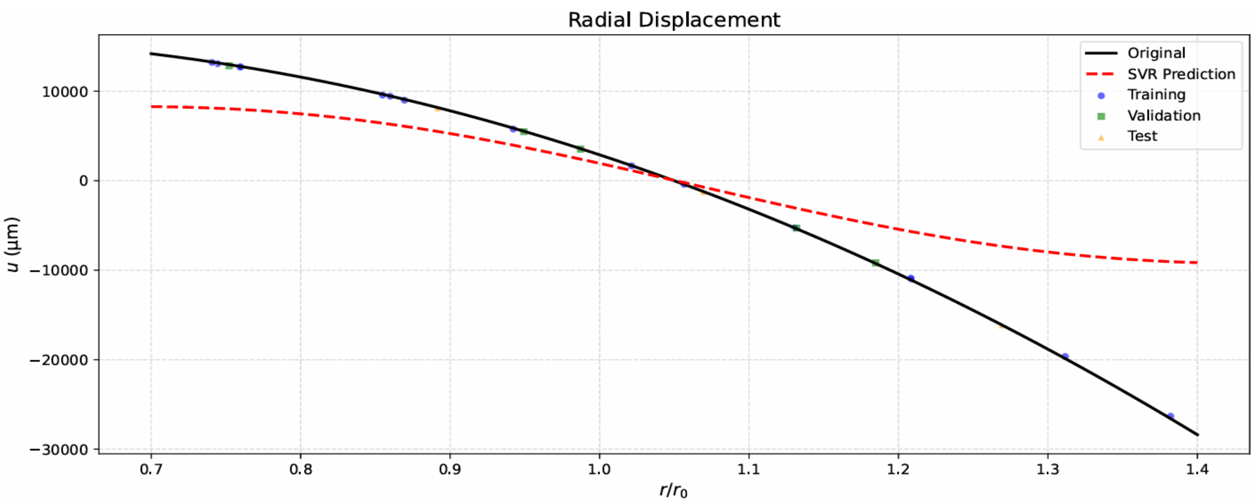
Fig. 7. Prediction results obtained by SVR (Support Vector Regression) method-**III**



(a) Estimation of tangential stresses by SVR method



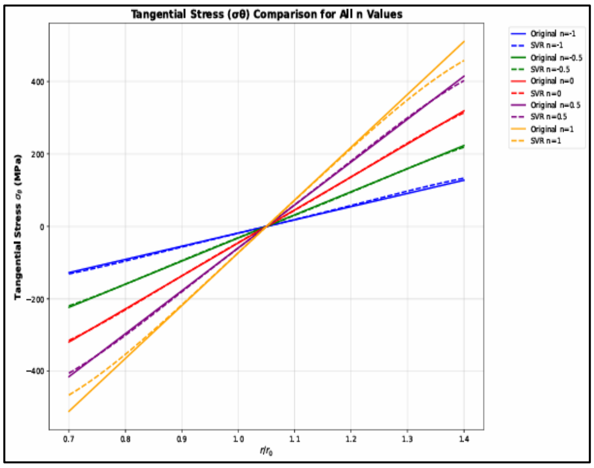
(b) Estimation of radial stresses by SVR method



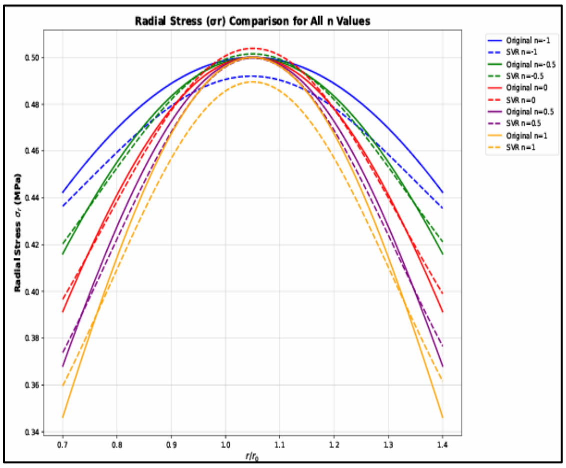
(c) Estimation of Radial displacement by SVR method

Fig. 8. Prediction results obtained by SVR (Support Vector Regression) method-**IV**

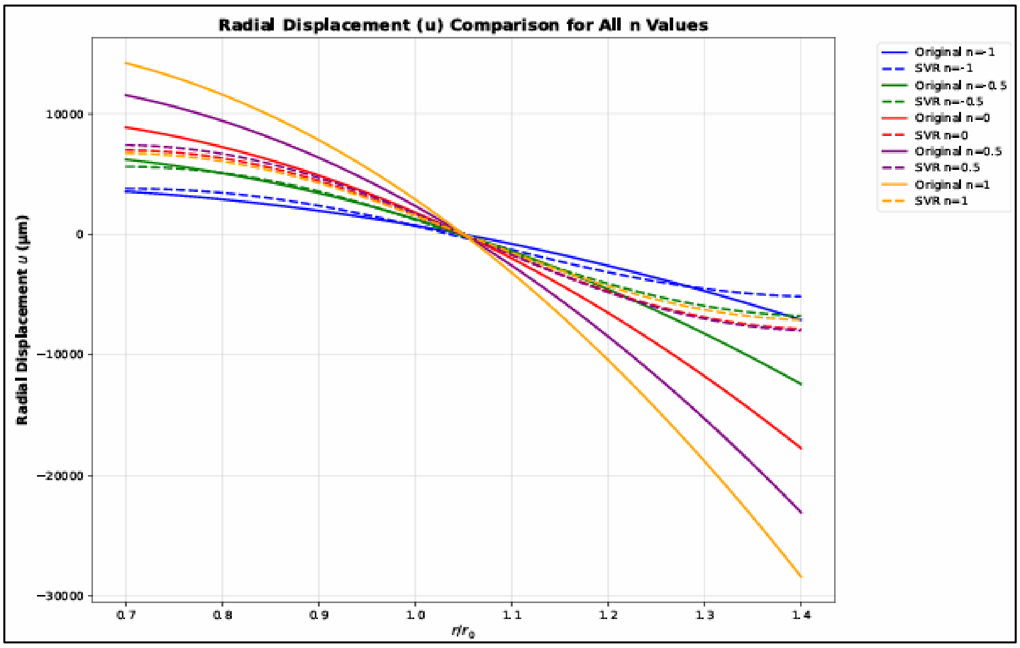
The combination of all graphs of tangential stresses, radial stresses and radial displacement is given in Figure 9 below.



(a) Tangential stresses



(b) Radial stresses



(C) Radial displacement

Fig. 8. Estimation of tangential stresses by SVR method for all n values

The validation analyses presented in Figures 5–8 and Figure 9 demonstrate that the Support Vector Regression (SVR) model provides highly accurate predictions. Based on the evaluations performed on the test datasets, the following coefficient of determination (R^2) values were obtained: Tangential stress prediction: $R^2 = 0.9973$, Radial stress prediction: $R^2 = 0.9862$ and Radial displacement prediction: $R^2 = 0.9914$. These results indicate that the SVR model can generate predictions that closely match the analytical solutions in terms of both stress and deformation magnitudes. The average error rates are generally within the range of 1–2%, which is considered well within acceptable limits for engineering applications. As also observed in the graphical comparisons, the SVR model accurately captures the analytical curves, particularly for the case of n = 0. Furthermore, the model exhibits strong overall agreement across different anisotropy parameters, indicating that the system is capable of operating with parametric flexibility. Accordingly, the SVR model offers the following advantages; Enables fast predictions without the need to solve complex differential equations, Provides a reliable alternative for modeling material behavior due to its high accuracy, Saves computational time in numerical analyses and is suitable for multi-scenario studies.

In a different study similar to this study; Elastic stress distributions in a rotating cylinder made of carbon fiber were examined using analytical methods and machine learning techniques. At the end of the study, the effectiveness of combining traditional analysis and artificial intelligence-based approaches for advanced composite material design is considered [23]. Considering similar studies, the nonlinear buckling behavior of functionally graded materials (FGMs) with porosity dependence has been thoroughly investigated using the modified couple stress theory and the energy method. The results were compared among themselves [24]. In a different study, Jane, Rose, and James (2024) demonstrated that AI-based soft sensors integrated into engine modeling can be effectively utilized within real-time simulation systems [25]. Bayat, Mustaq, and Vötterl (2024) showed that residual stresses in gear systems can be accurately predicted using artificial intelligence algorithms integrated with data obtained from finite element analysis [26]. Harandi et al. (2024) developed mixed formulations of physics-informed neural networks (PINNs) for thermo-mechanically coupled systems and heterogeneous domains [27]. Zhang et al. (2023) proposed the reconstruction of global stress fields in marine structures using AI-generated content [28]. Similarly, Zhang et al. (2023) developed an artificial intelligence-based solution approach to estimate global stress fields in three-dimensional marine structures [29].

4. Conclusions

In this study, the distributions of tangential stress, radial stress, and radial displacement in a rotationally symmetric disk made of polypropylene (PP) material were analyzed for different anisotropy parameters (n). The findings reveal the effects of both material properties and geometrical parameters on the internal stress distributions within the disk. In addition, Support Vector Regression (SVR) was applied to predict analytically obtained values of tangential stress, radial stress, and displacement. SVR, with its ε-insensitive loss function and kernel-based transformations, enables high-accuracy function learning. The input vectors used for the model consisted of the normalized radius (r/r_0), anisotropy parameter (n), and physical radius (r). The model, constructed using the Radial Basis Function (RBF) kernel, yielded low mean squared errors and achieved R^2 values exceeding 0.98 for stress and displacement predictions. These results confirm that the SVR method is a viable tool for rapidly and reliably modeling elastic analyses. Overall, it was observed that both the magnitudes and distributions of stress and displacement significantly vary depending on the material anisotropy. This highlights the necessity of carefully analyzing anisotropic polymers in applications involving rotating disks, and stresses the importance of not neglecting anisotropy effects during the design phase. In conclusion, this SVR-based data-driven approach offers a highly applicable, reliable, and fast alternative for elastic stress and deformation analyses. Particularly, the SVR method can be effectively utilized in areas such as digital twin systems, process control in manufacturing, and AI-assisted material design.

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