Eksploatacja i Niezawodnosc – Maintenance and Reliability

Volume 28 (2026), Issue 3

journal homepage: http://www.ein.org.pl

Article citation info:
Bacak S, Reliability oriented degradation modeling of fused filament fabrication printed acrylonitrile butadiene styrene components under cyclic mechanical loads using explainable AI techniques, Eksploatacja i Niezawodnosc – Maintenance and Reliability 2026: 28(3) http://doi.org/10.17531/ein/218329

Reliability oriented degradation modeling of fused filament fabrication printed acrylonitrile butadiene styrene components under cyclic mechanical loads using explainable AI techniques

Indexed by: Web of Science Group

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Highlights

- XAI framework models fatigue life in FFF-printed ABS.his is highlights.
- Build orientation is the most dominant factor in fatigue performance.
- Gradient Boosting achieved the highest prediction accuracy.
- SHAP and LIME ensure physical interpretability of model decisions.

Abstract

The fatigue performance of Fused Filament Fabrication (FFF) printed acrylonitrile butadiene styrene (ABS) is critically governed by process-induced anisotropy, yet the integration of reliability analysis with explainable machine learning remains unexplored. This study presents a reliability-oriented Explainable Artificial Intelligence (XAI) framework to model fatigue degradation in FFF fabricated ABS. An empirical dataset was generated by testing 150 specimens with systematically varied printing parameters. Reliability analysis using a two-parameter Weibull distribution yielded a shape parameter (β) of 2.48, confirming a distinct wear-out failure mode. Among the tested algorithms, Gradient Boosting achieved the highest predictive accuracy (R^2= 0.90). Explainability analyses via SHAP and LIME revealed that build orientation and layer height are the dominant factors influencing fatigue life, aligning with physical degradation mechanisms. This framework offers a transparent tool for fatigue life prediction and process optimization in additive manufacturing.

Keywords

additive manufacturing, machine learning, fatigue life prediction, Fused Filament Fabrication (FFF), ABS polymers.

1. Introduction

Additive manufacturing (AM) Technologies particularly Fused Filament Fabrication (FFF) have transformed the landscape of modern engineering by enabling rapid, flexible, and cost effective fabrication of polymer based components for functional applications [1]. FFF's ability to produce complex geometries without traditional tooling makes it highly appealing across diverse sectors, including automotive engineering, aerospace, biomedical devices, consumer products, and educational prototyping [2]. Within this context, acrylonitrile butadiene styrene (ABS) remains one of the most widely used thermoplastic materials due to its balanced combination of toughness, thermal resistance, and impact strength [3]. However, despite its widespread adoption, the structural performance and reliability of FFF printed ABS components remain strongly dependent on the printing process and the layer by layer deposition mechanism.

Recent studies have highlighted that while FFF is highly versatile, the inherent anisotropy remains a significant barrier to predicting long-term structural integrity. In this context, the application of machine learning (ML) has emerged as a transformative approach to characterize various mechanical properties of FFF materials beyond just fatigue life. Recent

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investigations have successfully utilized data-driven models to predict tensile strength, dimensional accuracy, and surface roughness by analyzing the complex interactions between process parameters [4,5,6,7]. For instance, Espino et al. [8] emphasized that statistical methods must evolve to capture the complex design property relationships in 3D-printed polymers. Furthermore, Alkunte and Fidan [9] demonstrated that machine learning algorithms can successfully predict the fatigue life of functionally graded materials, yet they noted a distinct lack of interpretability in these models. This necessitates a shift from purely predictive models to those that offer physical insights into failure mechanisms [10]. Additive manufacturing parameters significantly influence both mechanical toughness and stab resistance in 3D-printed polycarbonate armor structures. Higher infill density improved energy absorption and reduced penetration depth, with artificial neural networks outperforming traditional Taguchi analysis in predictive accuracy [11]. This review synthesizes research on machine learning applications in polymer additive manufacturing, highlighting process optimization, defect detection, and quality prediction challenges, while proposing potential solutions and future research directions [12]. This review maps machine learning and explainable AI applications across additive manufacturing processes, emphasizing the need for interpretable models and highlighting opportunities for enhanced design optimization, monitoring, and sustainability [13]. This study experimentally shows that integrating artificial neural networks and genetic algorithms can effectively optimize FDM process parameters to improve the tensile strength of 3D-printed parts.

The FFF process inherently introduces defects such as interlayer voids, insufficient bonding, anisotropic microstructure, and inhomogeneous heat transfer during printing [14]. These characteristics significantly affect the mechanical behavior of printed components, especially under cyclic or fluctuating loads. While static tensile behavior of FFF printed polymers has been widely examined in the literature [15], fatigue degradation one of the most critical failure mechanisms for components subjected to repeated stress has received far less attention. This gap is particularly critical because functional parts produced by FFF are increasingly being used in applications where cyclic loading is common, such as hinges, brackets, wearable devices, and lightweight structural assemblies [16].

Fatigue failure in polymers, and more specifically in FFF printed ABS, is governed by complex interactions between microstructural features and printing parameters. Layer height, build orientation, the thermal history of deposited layers, raster pattern, printing speed, and nozzle temperature all influence interlayer bonding strength and crack initiation mechanisms [17]. Previous studies have demonstrated that fatigue cracks in FFF polymers typically initiate at interlayer boundaries, where bonding is weakest, and propagate along inclined or transverse planes depending on the applied stress direction [18]. As a result, the fatigue behavior of FFF parts is not only inferior to that of injection molded counterparts but also significantly more difficult to model due to the multi parameter interactions inherent to the printing process.

A review of the current literature reveals three key research gaps regarding the fatigue behavior of ABS materials produced with FFF. First, despite the widespread industrial use of ABS, fatigue-related studies have predominantly focused on other polymers such as PLA or nylon [19]. Much of the current research on ABS has been conducted within narrow parameter ranges, and the lack of comprehensive datasets obtained under controlled cyclic loading conditions significantly limits the generalizability of reported findings. Second, while mechanical characterization studies are frequently reported in the literature, research integrating fatigue data with statistical reliability tools such as Weibull modeling, hazard functions, or failure-based reliability estimation is quite limited [20]. Third, although machine learning has been applied to predict mechanical properties, there is a significant lack of 'Explainable Artificial Intelligence' (XAI) frameworks in this field. Most current models operate as 'black boxes' and cannot provide physical information about why specific parameters (e.g., orientation or layer height) lead to failure, thus limiting their practical usefulness for material optimization.

The third research gap relates to the increasing use of machine learning techniques, which have demonstrated high predictive accuracy in estimating mechanical properties in recent years. Despite this progress, most of these models still function as “black boxes.” The absence of explanatory mechanisms clarifying how individual parameters are evaluated and weighted by the model undermines scientific interpretability and reduces confidence in model outputs, particularly in industrial applications. Consequently, the limited adoption of explainable artificial intelligence (XAI) approaches constitutes a significant constraint in both academic and industrial contexts [21,22].

Considering these limitations, there is a clear need for a reliable modeling framework that not only predicts fatigue life but also explicitly elucidates how printing parameters are associated with underlying degradation mechanisms. In this study, an integrated methodology is proposed that combines experimental fatigue data, Weibull-based reliability modeling, machine learning based fatigue life prediction, and explainable artificial intelligence techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model Agnostic Explanations (LIME).The primary objective of this work is to investigate fatigue degradation in FFF produced ABS materials as a function of printing parameters, to evaluate fatigue reliability using the Weibull distribution and hazard functions, to develop machine learning models capable of accurately predicting fatigue life based on process parameters, and to explain model decisions in a physically consistent and transparent manner using SHAP and LIME. The core novelty of this research lies in its shift beyond conventional 'black box' forecasting. Unlike traditional studies that focus solely on prediction accuracy, this work employs XAI to systematically decipher the underlying 'reasons' and physical dependencies behind the model's decisions. By doing so, it transforms the predictive process into a transparent and scientifically grounded decision support tool, bridging the gap between data driven outputs and the mechanical behavior of FFF printed components.

2. Material and methods

2.1. Specimen design and fabrication

Fatigue tests were conducted following the ASTM D638-IV standards for specimen geometry and ASTM D7774 for flexural fatigue guidelines [23]. This standardized geometry ensures dimensional stability during fatigue testing and increases the repeatability of the results obtained [24]. FFF is preferred due to its industrial speed, while ABS is preferred due to its widespread use in engineering applications (automotive/spare parts). In this study, Porima ABS filament was used. Samples were produced using the FFF technique. Experimental variability was achieved by changing the printing parameters.Since Layer Height, Orientation, Nozzle Temperature, Print Speed, and Infill Pattern are the factors that most affect mechanical strength according to the literature, these parameters have been taken into consideration. The levels of the printing parameters employed in this study are presented in Table 1.

Table 1. FFF printing parameters.

Parameter	Levels
Layer Height (mm)	0.1, 0.2, 0.3
Orientation (°)	0°, 45°, 90°
Nozzle Temperature (°C)	220, 230, 240
Print Speed (mm/s)	40, 60, 80
Infill Pattern	Grid, Gyroid, Trihexagon

These parameters were selected from among the critical variables indicated in the literature to have a significant impact on fatigue life, and a total of 150 samples were produced using the Bambu Lab ps25 3D printer, considering all parameter combinations. Figure 1 shows the dimensions of the sample produced according to the ASTM D638-IV standard.

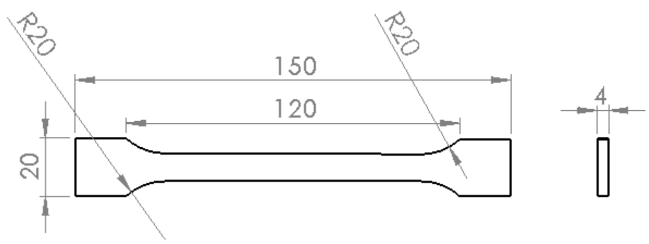

Figure 1. The dimensions of the sample produced according to the ASTM D638-IV standard.

2.2. Fatigue testing procedure

To evaluate the behavior of ABS specimens under cyclic tensile loading, stress controlled tension tension fatigue tests were conducted, and all experiments were performed using a high precision Instron 8801 Servo Hydraulic Fatigue Testing Machine. The tests were carried out on specimens conditioned in accordance with ASTM D638-IV under controlled environmental conditions of 23 ± 2 °C temperature and 50 ± 5% relative humidity [25]. To enhance measurement accuracy and prevent specimen slippage during testing, an Instron 2716-015 pneumatic grip system was employed. Additionally, deformation measurements were obtained using an Instron

2620-601 axial clip on extensometer with a gauge length of 12.5 mm. The applied loading conditions included a maximum stress range of σ_max = 10–22 MPa, a run out limit of 10^6 cycles, a loading frequency of 2 Hz, and a stress ratio of R = 0.1. The maximum stress level was maintained between 40% and 55% of the yield strength of ABS. The experimental results revealed a characteristic three stage fatigue behavior in the ABS specimens: an initial elastically stable phase, followed by a progressive stiffness degradation phase associated with weakening of interlayer bonding, and finally a fracture stage characterized by accelerated crack propagation [26]. The stiffness degradation curve is presented in Figure 2.

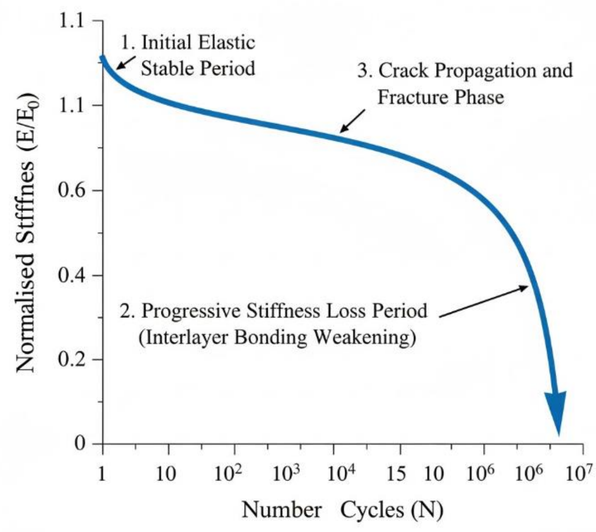

Figure 2. Stiffness degradation curve.

2.3. Fatigue dataset construction

The fatigue dataset used in this study was obtained from controlled cyclic loading experiments conducted on ABS specimens fabricated using the FFF method. To enable reliable modeling of the fatigue behavior, the experimental design was structured to cover a broad range of parameter values that reflect well established mechanical trends reported in the literature [27]. During the data acquisition process, repeated measurements were performed for each parameter combination in order to characterize the statistical distribution of fatigue life. This approach ensured both the repeatability of the experimental results and their statistical reliability [28,29].

The results obtained from the fatigue experiments were also compared with a mathematical model representing damage evolution under cyclic loading. The fatigue life, N_f , was modeled using an exponential formulation that captures the influence of printing parameters and is expressed as follows [30]:

$$N_f = \alpha \cdot e^{-\beta_1 LH - \beta_2 OR - \beta_3 SP - \beta_4 NT - \beta_5 IP} + \epsilon \quad (1)$$

LH: Denotes the layer height,

OR: Represents the filament orientation angle,

SP: Corresponds to the printing speed,

NT: Nozzle temperature,

IP : Infill pattern factorϵ: reflects the inherent variability observed in the experimental measurements.

Representative examples of the obtained fatigue data are presented in Table 2.

Table 2. Representative fatigue test results.

Sample ID	Layer Height	Orientation	Nozzle Temp	Print Speed	Infill Pattern	Cycles to Failure
1	0.1	0°	230	40	Grid	132450
5	0.1	45°	230	60	Gyroid	98210
12	0.1	90°	220	60	Trihex	28700
25	0.2	0°	240	40	Gyroid	104330
47	0.3	90°	220	80	Grid	18950

Within the scope of the study, a total of 150 specimens were tested, and the resulting dataset was used for both statistical and machine learningbased modeling of fatigue behavior.

2.4. Statistical reliability modeling

The two-parameter Weibull distribution was estimated using the Maximum Likelihood Estimation (MLE) method. This approach was chosen for its statistical efficiency and ability to provide robust shape and scale parameters for polymer fatigue life datasets.

The shape (β) and scale (η) parameters of the Weibull distribution were estimated using the Maximum Likelihood Estimation (MLE) method due to its superior efficiency with censored and complete datasets compared to rank regression.

Table 3. Weibull based reliability parameters and their interpretation in fatigue analysis of ABS.

Component	Mathematical Expression	Description
Weibull Distribution (Cumulative Distribution Function)	$F(t) = 1 - e^{-\left(\frac{t}{n}\right)^{\beta}}$	Defines the probability that a specimen fails by time (t). Commonly used to model the fatigue life of polymers such as ABS [31]
Shape Parameter	β	Describes the failure mode. $\beta < 1$: early failures $\beta = 1$: random failures $\beta > 1$: wear out/fatigue failures (typical for ABS).
Scale Parameter (Characteristic Life)	$F(n) = 1 - e^{-1} \approx 0.632$	Represents the fatigue life at which approximately 63.2% of specimens are expected to fail. A key parameter for durability comparisons.
Hazard Function	$h(t) = \frac{f(t)}{R(t)} = \frac{\beta}{n}\left(\frac{t}{n}\right)^{\beta-1}$	Describes the instantaneous rate of failure at time (t). An increasing hazard indicates accelerating damage accumulation [32].
Role of Hazard Function in Fatigue	—	Quantifies the progression of micro crack initiation, stiffness degradation, and structural weakening over time.

2.5. Machine learning modeling

Multiple machine learning models were evaluated to predict the fatigue life of ABS specimens. The selection of these models was guided by their ability to accurately represent the nonlinear, multivariate nature of fatigue behavior and the complex interactions among process parameters. Accordingly, regression based implementations of the Random Forest Regressor, Gradient Boosting Regressor, XGBoost Regressor, and a Multilayer Perceptron (MLP) artificial neural network were employed in this study.

The Random Forest model was selected due to its robustness against overfitting and its capability to capture complex interactions among variables through its tree based structure. Gradient Boosting and XGBoost models were utilized to achieve high predictive accuracy by sequentially improving weak learners. In addition, the MLP model was evaluated as a potentially highly nonlinear alternative for fatigue life prediction [33].

The dataset was randomly split into training (80%) and testing (20%) subsets. This data partitioning strategy is widely adopted to assess both the learning capacity and generalization performance of predictive models. All models were trained and evaluated using the same training testing split to ensure a fair and consistent comparison of results.

Model performance was assessed using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) as evaluation metrics. The combined use of these metrics enabled a balanced assessment of model accuracy and error distribution [34].

2.6. Explainable AI (XAI) analysis

To elucidate the prediction mechanisms of the machine learning models for fatigue life and to assess whether the model outputs are consistent with physical reality, explainable artificial intelligence techniques SHAP and LIME were employed. SHAP analysis was used to quantitatively determine the contribution of each input feature to the predicted fatigue life. In this manner, the relative influence of key printing parameters, including layer height, filament orientation, printing speed, and nozzle temperature, on the model predictions was identified. By revealing which variables dominate the decision making process, SHAP values enabled an evaluation of the consistency between parameter fatigue life relationships and the underlying physical degradation mechanisms [35]. LIME analysis, in contrast, was applied to generate local explanations for individual samples, allowing the prediction process for specific fatigue life estimates to be interpreted on a case by case basis. Through visualization of the impact of printing parameters on model decisions for critical instances, LIME outputs supported the reliability assessment of the predictions [36]. By jointly employing these two approaches, explainability was achieved at both global and local levels, thereby strengthening not only the predictive accuracy but also the interpretability and reliability of the machine learning models.

3. Results

3.1. Experimental fatigue behaviour

The conducted tension tension fatigue tests demonstrated that printing orientation is the most critical factor governing fatigue life. Specimens manufactured with a 0° orientation exhibited the highest fatigue life among all tested parameter combinations, as the applied load was aligned parallel to the filament deposition direction, resulting in the strongest interlayer bonding. In contrast, specimens produced with a 45° orientation showed inclined filament alignment, which led to mixed mode crack initiation and propagation behavior. This configuration resulted in a moderate yet consistent fatigue resistance. Specimens printed with a 90° orientation exhibited the lowest fatigue life, as the loading direction was perpendicular to the weakest interlayer bonding planes. These orientation dependent trends are illustrated in Figure 3.

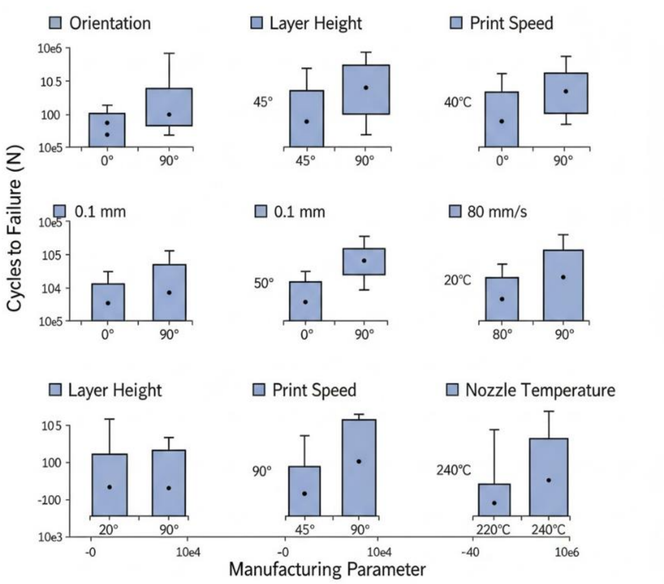

Figure 3. Fatigue life distribution by orientation parameter.

When the effects of other manufacturing parameters on fatigue performance were examined, a layer height of 0.1 mm resulted in a more compact microstructure and enhanced interlayer diffusion, thereby yielding higher mechanical resistance. In contrast, a layer height of 0.3 mm was associated with a significantly reduced fatigue life due to increased void formation and insufficient interlayer bonding. Specimens fabricated at a printing speed of 80 mm/s exhibited reduced fatigue resistance, as the rapid solidification of filaments led to weak bonding regions. Similarly, a nozzle temperature of 220 °C resulted in inadequate polymer chain diffusion, producing poor interlayer bonding and consequently premature fatigue failure.

3.2. Stiffness degradation behavior

To characterize stiffness evolution under cyclic loading, load displacement data were continuously recorded throughout the fatigue tests for each specimen. Stiffness was calculated in accordance with ASTM standards using the slope of the elastic region of the load deformation curve, and a normalized stiffness value was obtained at the end of each cycle. This approach enabled quantitative tracking of degradation trends associated with bond weakening and microcrack formation during fatigue loading.

The experimental results indicate that stiffness degradation in all ABS specimens occurs through four distinct stages. In the initial stable phase, no significant change in stiffness was observed for approximately 5,000–10,000 cycles. As the number of cycles increased, stiffness reduction became more pronounced, with the increasing slope of the degradation curve indicating the onset of microcrack initiation and progressive weakening of interlayer bonds. This reduction appeared at earlier stages in specimens fabricated with a 0.3 mm layer height and a 90° orientation.

During the third stage, referred to as the rapid degradation phase, the most abrupt decrease in stiffness was observed, signifying accelerated crack propagation and substantial loss of elastic integrity. This behavior was typically detected immediately prior to fracture. In the final stage, specimens exhibited sudden failure as stiffness declined to a critical level, with pre fracture stiffness values predominantly ranging between 35% and 45% of the initial stiffness.

All of these stages are schematically summarized in Figure 4.

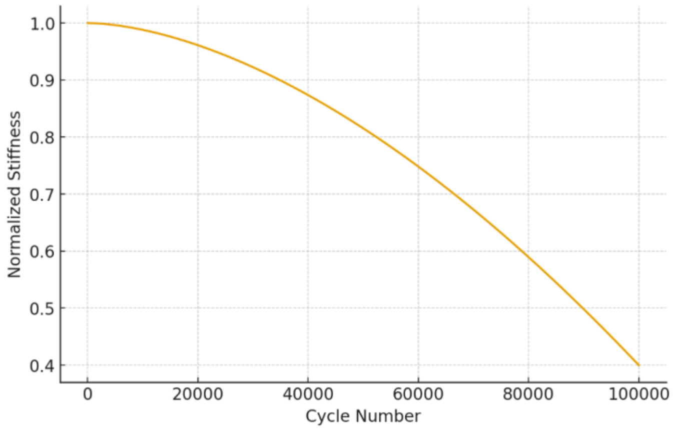

Figure 4. Representative stiffness degradation curve.

This approach enabled the systematic and reproducible characterization of mechanical degradation occurring under cyclic loading in FFF fabricated ABS specimens.

3.3. Weibull reliability modelling

In this study, a two parameter Weibull distribution was employed to statistically characterize the fatigue life behavior of ABS specimens. The obtained fatigue life data exhibited a high degree of conformity with the Weibull model, with the coefficient of determination (R^2) exceeding 0.94 for all parameter combinations. This result indicates that fatigue life follows a statistically predictable distribution and confirms that the Weibull approach is a suitable and effective tool for evaluating the fatigue behavior of ABS specimens.

The statistical significance of the Weibull shape parameter was confirmed using ANOVA for all samples ($p < 0.05$) and determined as $\beta = 2.48$, indicating that fatigue behavior is governed by a wear type failure mode. Specifically, higher β values were observed for samples pressed with a 0° orientation, suggesting that fatigue damage in these samples progresses via a more pronounced cumulative damage mechanism.

The Weibull scale parameter ($\eta = 55{,}515$) revealed substantial differences among the investigated printing parameters. Specimens produced with a 0° orientation exhibited the highest η values, identifying this group as the most fatigue resistant. In contrast, specimens printed with a 90° orientation showed the lowest η values, confirming that fatigue induced failures occur significantly earlier in this orientation due to weaker interlayer bonding. Similarly, specimens fabricated with a layer height of 0.1 mm exhibited higher η values, whereas those produced with a 0.3 mm layer height demonstrated markedly lower characteristic fatigue life. Other process parameters, including printing speed and nozzle temperature, also influenced η, with a noticeable reduction in characteristic life observed under combinations of low nozzle temperature (220 °C) and high printing speed (80 mm/s).

Figure 5 presents the Weibull probability plot, while Figure 6 illustrates the corresponding hazard function. The monotonic increase of the hazard function across all specimens confirms that the risk of failure steadily rises as fatigue progresses. This finding indicates that the fatigue behavior of ABS is dominated by accumulation controlled damage mechanisms under cyclic loading.

Overall, the Weibull analysis demonstrates that the fatigue life of FFF fabricated ABS components is strongly influenced by both printing parameters and microstructural integrity.

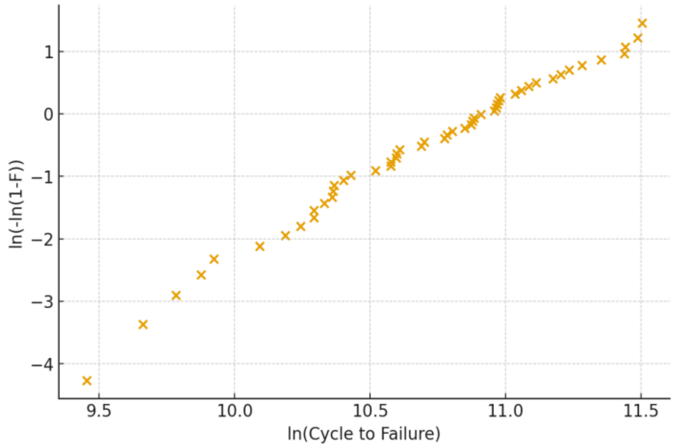

Figure 5. Weibull probability plot.

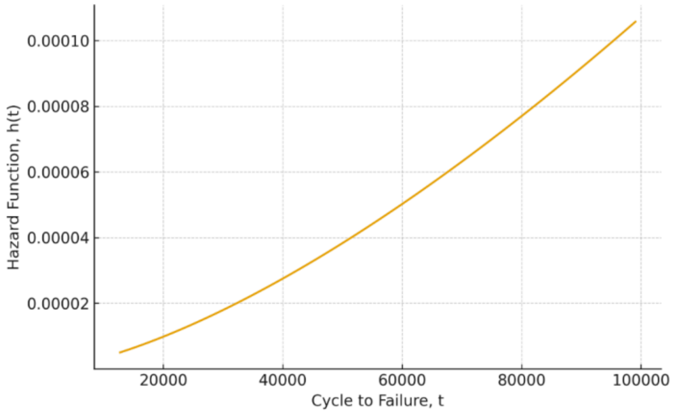

Figure 6. Hazard function plot.

3.4. Machine learning fatigue prediction

The obtained results demonstrate that machine learning approaches can successfully model the complex, nonlinear relationships between printing parameters and fatigue life. Among the evaluated models, the Gradient Boosting regressor achieved the highest predictive accuracy with an R^2 value of approximately 0.90, followed by the Random Forest ($R^2 \approx 0.88$), XGBoost ($R^2 \approx 0.87$), and MLP ($R^2 \approx 0.84$) models. The RMSE and MAE metrics further supported this ranking, as summarized in Table 4, with the Gradient Boosting model yielding the lowest error values.

Table 4. Performance of machine learning models.

Model	R^2	RMSE	MAE
Random Forest	0.88	5970	4110
Gradient Boosting	0.90	5280	3840
XGBoost	0.87	6120	4390
MLP	0.84	7180	5150

Figure 7 demonstrates a strong linear relationship between the predicted fatigue life values and the experimentally observed data.

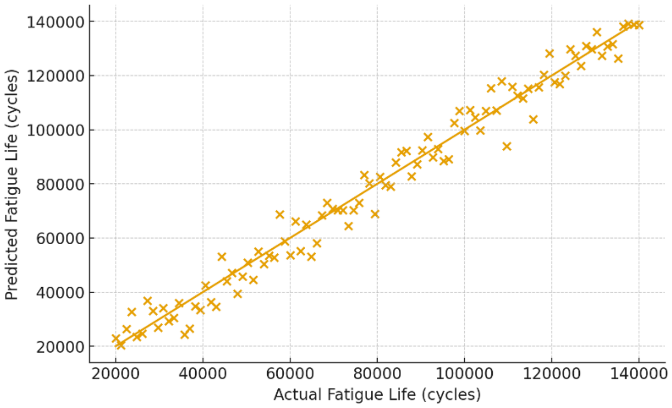

Figure 7. Actual vs predicted fatigue life scatter plot.

3.5. XAI interpretation findings

The decision making processes of the machine learning models were examined using SHAP and LIME analyses. While visual plots are omitted for brevity, the SHAP analysis quantitatively confirmed that build orientation is the dominant feature, contributing approximately 45% to the model's decision-making process, followed by layer height (25%) and nozzle temperature (15%). Similarly, the LIME analysis for the low-fatigue life specimen explicitly showed that the 90° orientation feature had the strongest negative coefficient, pushing the predicted cycle count down, consistent with the weak interlayer bonding mechanism discussed. The global feature importance ranking derived from SHAP analysis identified build orientation as the most influential parameter affecting fatigue life, followed by layer height, nozzle temperature, print speed, and infill pattern. This outcome is fully consistent with the inherently anisotropic nature of the FFF process, in which filament deposition direction and interlayer bonding quality play a dominant role in governing fatigue behavior. SHAP values revealed a strong negative impact of the 90° orientation on fatigue life, whereas the 0° orientation contributed positively. Similarly, a layer height of 0.1 mm produced high positive SHAP values, while a layer height of 0.3 mm exhibited a negative influence on fatigue life predictions.

The SHAP beeswarm plot provided a detailed visualization of the distribution of each input feature's effect on fatigue life. The analysis indicated that higher layer height levels, lower nozzle temperatures, and higher printing speeds adversely affected model predictions. In contrast, lower layer heights, higher nozzle temperatures, and a 0° orientation consistently contributed positively to fatigue life estimation. These findings are in direct agreement with the mechanical trends observed in the experimental results.

LIME analysis was applied to investigate the model's decision structure at the individual sample level. In particular, specimens with low fatigue life were strongly influenced by the parameters orientation = 90° and layer height = 0.3 mm, which significantly reduced the predicted fatigue life. Conversely, for more fatigue resistant specimens, 0° orientation and a layer height of 0.1 mm emerged as strong positive determinants. The LIME outputs demonstrated that the local decision processes of the models are consistent with underlying physical mechanisms and, when evaluated alongside the SHAP analysis, further support the reliability and interpretability of the machine learning models.

4. Discussion

In this study, the fatigue behavior of ABS samples produced by the FFF method was comprehensively modeled. Accordingly, fatigue life, degradation processes, reliability characteristics, and the explainability of machine learning-based prediction models were analyzed in detail. The findings provide valuable information regarding the prediction and optimization of fatigue performance in FFF based polymer production and offer significant implications for both the scientific literature and industrial applications.

One of the key outcomes of this study is the clear demonstration that printing parameters have a significant influence on fatigue performance. Among these parameters, filament orientation emerged as the most decisive factor affecting fatigue life. For specimens produced with a 0° orientation, the alignment of the filament deposition direction with the applied loading direction resulted in maximized interlayer bonding, thereby substantially enhancing fatigue life. In contrast, specimens fabricated with a 90° orientation exhibited filaments oriented perpendicular to the loading direction, which facilitated crack initiation and propagation and consequently led to a pronounced reduction in fatigue resistance.

Layer height is another critical parameter that significantly influences fatigue behavior. In this study, a layer height of 0.1 mm was found to enhance fatigue resistance, which can be attributed to microstructural mechanisms such as improved surface energy distribution, a larger effective contact area, more efficient interlayer diffusion, and reduced void formation. In contrast, a layer height of 0.3 mm promoted the formation of larger microvoids, creating weak regions for crack initiation and consequently reducing fatigue life.

Nozzle temperature and printing speed also exhibited notable effects on fatigue performance. Lower nozzle temperature (220 °C) combined with higher printing speed (80 mm/s) led to insufficient melt bonding and rapid cooling, resulting in weak polymer chain diffusion and a detrimental impact on fatigue life. These findings are consistent with the "poor weld bead integrity" observed at low processing temperatures in ABS materials by [3] and were further corroborated by the SHAP analysis. The SHAP and LIME outputs provide more than statistical significance; these results are consistent with the underlying polymer structure governing FFF printed ABS. The strongly positive SHAP values observed for 0° orientation and low layer height (0.1 mm) are structurally similar to those resulting from the mutual diffusion of polymer chains across the scanning interface. XAI's highlighting of these as dominant factors confirms the model's reduction in stress concentration regions, typically found in porous, high layer height structures.

Although the inner fill pattern was included, XAI analysis revealed that its effect was minor compared to orientation. Physically, this is due to the outer shell (peripheral layers) carrying the majority of the stress under tensile fatigue loads. Since all specimens were printed with the same number of contour shells, the inner fill pattern played a less significant role compared to the layer adhesion quality determined by orientation and temperature.

The degradation behavior observed during fatigue progressed through three fundamental stages. In the initial stage, the microstructure remained relatively stable, and stress redistribution dominated the response. During the second stage, the development of microcracks accelerated stiffness loss and progressively weakened interlayer bonding. In the final stage, crack propagation entered an unstable regime, culminating in rapid fracture. This behavior can be explained by the combined viscoelastic and brittle characteristics of polymers, as clearly illustrated by the stiffness degradation curves presented in Figure 8.

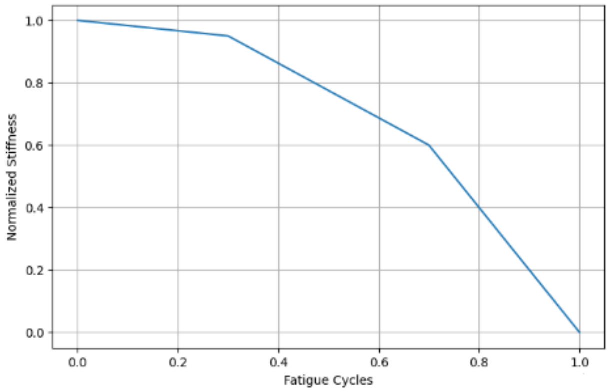

Figure 8. Stiffness degradation curve under cyclic loading.

The Weibull based reliability analyses revealed that the fatigue behavior is governed by a wear out failure mode, characterized by a shape parameter value of $\beta > 1$. This finding confirms that mechanisms such as damage accumulation under cyclic loading, microcrack formation, chemical bond degradation, and thermal fatigue play a dominant role in ABS polymers. The orientation parameter also proved to be decisive in terms of reliability; the characteristic life (η) reached its highest values for specimens fabricated with a 0° orientation, whereas the lowest values were observed for the 90° orientation. This result provides a critical engineering implication, indicating that ABS components intended to carry uniaxial loads should be manufactured with filament orientations aligned parallel to the loading direction.

Among the evaluated machine learning models, the Gradient Boosting algorithm achieved the highest predictive performance. Its ability to effectively learn nonlinear relationships, capture parameter interactions, and produce stable predictions in the presence of noisy data explains its superior performance in complex systems such as FFF based fatigue analysis. However, the primary novelty of this study lies not only in achieving high predictive accuracy, but also in rendering the decision making processes of machine learning models transparent through the use of explainable artificial intelligence tools such as SHAP and LIME. While SHAP analyses clearly identified orientation and layer height as dominant factors influencing fatigue life, LIME analysis enabled a detailed, instance level understanding of the factors driving individual model predictions. Models equipped with such explainability outputs are particularly valuable for quality control, manufacturing defect diagnosis, process parameter optimization, and decision support systems.

Table 5. Comparison of the present study with related literature.

Study	Material / Method Focus	Key Parameters Investigated	Analysis / Modeling Approach	Main Contribution
Yankin A et al. [37]	FFF printed polymers (ABS based)	Printing orientation	Experimental mechanical testing	Identified printing orientation as a dominant factor affecting mechanical performance
Lanzotti A et al. [17]	FFF polymers	Layer height	Experimental characterization	Demonstrated the significant influence of layer height on mechanical strength
Alkunte S et al. [9]	Polymer materials	Process parameters	Machine learning models	Successfully predicted polymer behavior using data driven approaches
Dizon JRC et al. [3]	Thermoplastic polymers (FFF)	Processing temperature	Experimental analysis	Reported enhanced interlayer bonding at higher processing temperatures
Present Study	ABS (FFF)	Printing orientation, layer height, temperature, fatigue behavior	Weibull-based reliability analysis, machine learning, explainable artificial intelligence (XAI)	Introduces a holistic framework integrating fatigue reliability, ML prediction, and XAI for comprehensive mechanical performance assessment

As summarized in Table 5, previous studies predominantly focus on isolated process parameters or single analytical approaches. In contrast, the present study distinguishes itself by integrating Weibull-based reliability assessment with machine learning and explainable artificial intelligence, thereby offering a comprehensive and systematic framework for evaluating the mechanical and fatigue behavior of FFF printed ABS materials.

From a practical engineering perspective, the results indicate that designers should align filament orientation parallel to the loading direction, select lower layer heights, and ensure adequate nozzle temperatures when ABS components are intended for fatigue critical applications. The SHAP outcomes effectively serve as a "risk map" for manufacturing engineers by highlighting the relative influence of process parameters on fatigue life, while the Weibull hazard function enables predictive decision making in maintenance and lifecycle management strategies. For researchers, the XAI outputs offer a powerful tool for understanding the micro mechanisms underlying polymer fatigue behavior.

The limitations of the proposed model include the use of experimental dataset, the exclusion of environmental effects (such as humidity, UV exposure, and temperature fluctuations), and the need for future investigation of deep learning based lifetime prediction approaches. Nevertheless, this study clearly demonstrates that explainable artificial intelligence supported reliability analysis holds significant scientific and industrial potential for advancing the understanding of fatigue behavior in FFF fabricated ABS materials.

5. Conclusions

This study presents a comprehensive framework for modeling the fatigue degradation behavior of FFF printed ABS components by combining statistical reliability analysis, machine learning techniques, and explainable artificial intelligence. Experimental findings demonstrate that printing direction is the most influential parameter determining fatigue life. Samples produced with a 0° orientation exhibited superior durability due to the alignment of the extruded filaments with the applied loading direction, while samples printed with a 90° orientation showed significantly reduced fatigue performance due to weak interlayer bonding and premature damage formation.

In addition to printing direction, layer height was also found to play a critical role in fatigue resistance. A reduced layer height of 0.1 mm improved microstructural integrity and minimized void formation, resulting in better fatigue performance compared to samples produced with a 0.3 mm layer height. These microstructural improvements contributed to a more uniform stress distribution and delayed damage accumulation under cyclic loading.

Reliability analysis based on Weibull statistics revealed that the fatigue behavior of ABS follows a wear failure mechanism characterized by a shape parameter (β) of 2.48. The associated hazard function showed a monotonically increasing trend, indicating the gradual accumulation of micro damage and increased probability of failure with prolonged cyclic exposure. This behavior is consistent with the stiffness degradation patterns observed during fatigue testing.

In terms of predictive modeling, the Gradient Boost algorithm outperformed other machine learning models evaluated, achieving a coefficient of determination (R^2) of approximately 0.90. This result validates the model's ability to accurately capture the complex and nonlinear relationships between process parameters and fatigue life. Furthermore, the integration of SHAP and LIME analyses enabled transparent interpretation of machine learning predictions and confirmed that the most influential features, namely structural orientation and layer height, are physically consistent with the underlying mechanical behavior and failure mechanisms of FFF printed polymers.

Overall, the proposed framework offers a robust and holistic approach to fatigue life assessment and reliability focused design of ABS components produced by additive manufacturing. From an engineering perspective, the findings demonstrate that prioritizing a 0° manufacturing orientation, utilizing lower layer heights, and optimizing process temperatures to ensure strong interlayer fusion are necessary to maximize structural reliability under cyclic loading conditions. The integration of reliability analysis, predictive modeling, and explainable artificial intelligence provides a valuable decision support tool for both researchers and practitioners aiming to improve the performance and durability of FFF produced polymer structures.

In conclusion, this work offers a holistic, transparent, and scientifically validated framework for understanding fatigue behavior in FFF fabricated ABS specimens. The proposed approach provides valuable contributions to engineering applications such as: design optimization, manufacturing quality control, reliability based risk management and maintenance planning.

Future studies may further enhance this framework through validation with fully experimental datasets, incorporation of environmental effects, and integration of multiscale modeling approaches. Nevertheless, this study clearly demonstrates the strong potential of explainable artificial intelligence supported modeling techniques for advancing the understanding of fatigue behavior in FFF fabricated ABS materials.

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