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Reviewed Paper

Machine Learning-Assisted Prediction of Fatigue Behaviour in Fiber-Reinforced Composites Manufactured via Material Extrusion

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Abstract

The recent advancements in material extrusion (MEX) have expanded the potential use of polymeric and composite structures in a wide range of structural and load-bearing applications. However, cyclic loads can induce fatigue, resulting in the development of structural damage and potentially leading to catastrophic failure at lower stress levels compared to normal mechanical loading. Therefore, it is crucial to thoroughly investigate and understand the fatigue behavior of composite parts manufactured using MEX. Predicting the fatigue life of polymeric composite components poses a significant challenge due to the complex nature of the materials involved. In this research, the aim is to utilize Machine Learning (ML) techniques to predict the fatigue life of fiber-reinforced composites produced through the MEX process. ML focuses on developing models that can learn from data, recognize underlying patterns within the data, and use those patterns to make accurate predictions or decisions.

Keywords: Material Extrusion, Fatigue Prediction, Composites, Machine Learning.

Introduction

MEX is a well-received additive manufacturing (AM) technique used to create 3D objects by extruding semi-molten thermoplastic materials from a heated nozzle or nozzles onto a platform. The filaments used for the process are usually made of polymeric materials such as epoxy, nylon, polycarbonate (PC), polyester, acrylonitrile butadiene styrene (ABS), polylactic acid (PLA), and polyamide (PA) [1]–[3]. MEX has several advantages including the ability to produce complex parts, low cost, minimal material wastage, design flexibility, customization of products for individual consumers, and production of small lots of parts [4]–[8]. Its affordability and accessibility make it popular for both hobbyists and professionals [9], [10]. It offers a wide range of compatible polymeric materials and composites, allowing for different mechanical properties and aesthetic finishes [11]–[14]. MEX finds applications in rapid prototyping, manufacturing tools, and jigs, functional end-use parts, architectural models, customized consumer products, medical and dental applications, and aerospace and automotive parts [15]–[19].

Investigation of the fatigue behavior of composite materials manufactured by MEX has become important due to their applications in the structural field. Fatigue testing encompasses a range of loading conditions, such as tension, compression, torsion, bending, or their combinations which are used to assess the performance and durability of materials under cyclic loading [20], [21]. Various parameters affecting the fatigue life of any fiber-reinforced composites include fiber material, matrix material, volume or weight percentage of fiber in the matrix, fiber type and length, as well as 3D Printing (3DP) parameters such as infill pattern, build orientation, infill density, layer height, printing speed, printing plane, nozzle diameter, bed temperature, etc. as shown in figure 1. Anisotropy induced due to these 3DP parameters makes it very difficult to analytically predict the fatigue behavior of composites. For predicting fatigue life, several researchers have focused on various statistical methodologies. Kakiuchi et al. studied the fatigue strengths of the AM Ti-6Al-4V at room temperature and at elevated temperature evaluated by Murakami's model [22]. In this paper, ML is employed as a statistical method. Bao et al. provided a fatigue life prediction method for SLM (selective laser melting) processed Ti-6Al-4 V parts using ML [23]. This paper presents a fatigue life prediction methodology for composite tidal turbine blades based on combined hydrodynamic and finite element structural models [24].

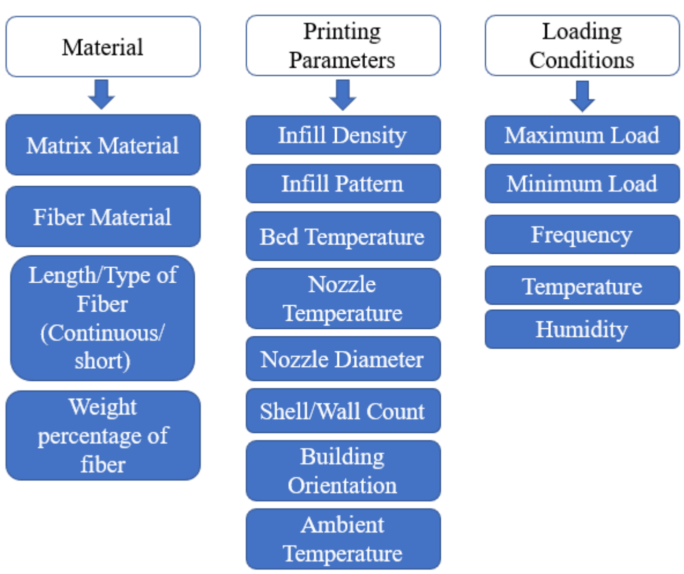

Figure 1: Parameters affecting the fatigue life of AM components

ML is a field of artificial intelligence (AI) that focuses on developing algorithms and models that enable computers to learn and make predictions or decisions without explicit programming. It involves creating systems that can automatically analyze and interpret complex data, recognize patterns, and improve their performance over time through experience. ML algorithms learn from large datasets, extracting patterns and relationships to make predictions or take actions. The learning process involves training the model on the training set, where it learns to recognize patterns and correlations. Once trained, the model can be applied to new, unseen data to make predictions or decisions. There are different types of ML algorithms, as follows:

A) Supervised Learning: In this approach, the algorithm is trained using labeled data, where each data point has a corresponding target or output. The model learns to map input features to the desired outputs and can then predict the output for new, unseen data [25].

B) Unsupervised Learning: Here, the algorithm is trained on unlabeled data, and its task is to find patterns or structures in the data without explicit guidance. Clustering algorithms, such as k-means, are commonly used in unsupervised learning [25].

C) Reinforcement Learning: This type of learning involves training an agent to interact with an environment and learn from the feedback it receives. The agent learns to take actions to maximize rewards and achieve a specific goal through a trial-and-error process [25].

ML has numerous applications across various domains including image and speech recognition, fraud detection, healthcare and medicines, financial forecasting, etc. In recent studies, various researchers have focused on predicting the additively manufactured component's properties such as roughness, porosity, size of voids, etc. by using ML [26], [27]. However, there is no study reported to predict the fatigue behavior of composites manufactured by MEX. This paper presents a novel way of predicting fatigue life with the aid of ML on the experimental data which is available in the journal by Pertuz et. al. [28]. On this collected data, the random forest algorithm which is a type of supervised learning is applied to classify the data. The following sections are divided into Random Forest, Materials and Methods, Results and Discussion, and finally Conclusion.

Random Forest

Random Forest excels in capturing intricate patterns, making it well-suited for materials prediction tasks. Another factor that contributed to selecting Random Forest is its robustness to noisy data and missing values. In materials datasets, incomplete or noisy data are not uncommon due to measurement errors or variations in experimental conditions. Random Forest's inherent resilience to such challenges enhances its suitability for our study's objectives. While other ML algorithms like Support Vector Machines or Neural Networks have their merits, they may require more intricate parameter tuning, larger training datasets, or greater computational resources. Random Forest, on the other hand, strikes a favorable balance between predictive power and ease of implementation, making it an optimal choice for our specific materials prediction study.

Random Forest is a supervised learning algorithm [29]. It falls under the category of supervised learning because it requires labeled data during the training phase. In supervised learning, the algorithm learns from input-output pairs, where the input data is accompanied by corresponding target labels or outputs. In the case of Random Forest, during the training process, each decision tree within the forest is trained on a labeled dataset. The training data consists of input features and their corresponding target values or labels. The algorithm learns to map the input features to the desired outputs based on the provided labels. Once trained, the Random Forest model can make predictions or classify new, unseen data based on the patterns learned from the training data. The generalized form of the random forest decision tree is shown in Figure 2. The precision of a random forest depends on the number of trees. The higher the number of trees in the forest, the higher the accuracy of the outcome. The greater number of trees in the forest also helps in preventing the challenges of overfitting the data set. Jayasudha et. al. [30] in their study used the five predictive models including random forest to estimate the tensile strength of 3DP objects. The results from each ML model were compared using several statistical metrics such as mean squared error (MSE), mean absolute error (MAE), maximum error, and median error.

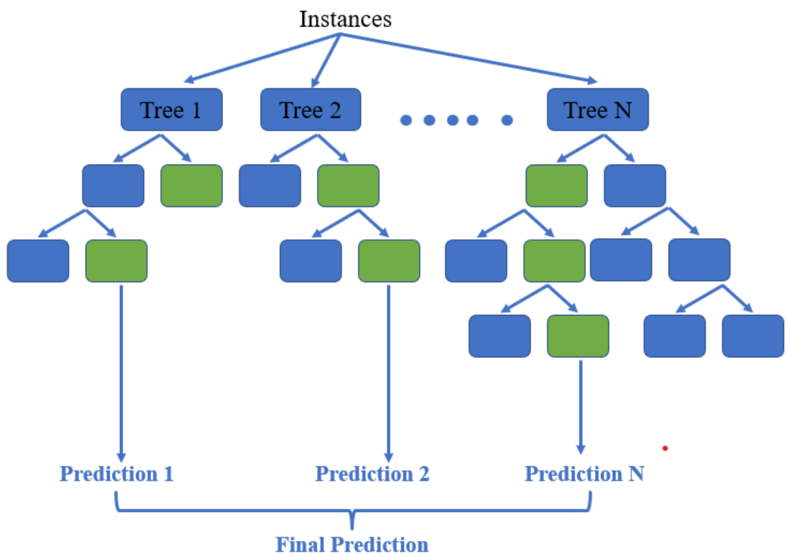

Figure 2: Random Forest decision tree

Materials and Methods

Due to the complex characteristics of the manufactured components and the significant expenses associated with 3DP, it becomes crucial to develop precise prediction models for estimating the fatigue behavior of these parts. The data utilized in this particular case study originates from Pertuz et. al. [28]. They reported the fatigue behavior of continuous fiber-reinforced thermoplastic composites made of a nylon matrix with fiberglass, Kevlar, and carbon fibers. Fatigue tests were conducted following the ASTM D7791 for composite parts, on specimens produced by MEX, under tensile fatigue loading conditions to obtain the S-N curves. Effects of the filling percentage, filling pattern of the nylon matrix, fiber materials, and fiber orientation, as well as the number of concentric rings used in the printing configuration are also reported.

The process workflow of the research is shown in Figure 3. The data is collected and saved in an Excel file and a CSV file is created to give input to WEKA software [31]. The total instances meaning total experimental values obtained are 200 and those are categorized into 8 attributes. Attributes and their assigned values or properties are shown in Table 1. The matrix material for all the data is nylon. Reinforcing materials considered are Carbon Fiber, Kevlar, Fiberglass, and None (for the neat polymer). Infill densities taken into account are 20 and 50. Hexagonal, Triangular, Triangular 2 Layers 4 Rings, and Triangular 4 Layers 2 Rings are assigned for the infill pattern. Infill orientations considered are 0°, 45°, and 60°. For tensile strength and load applied to the specimens are given the numerical values as given in the referred paper. Finally, the fatigue cycles are taken as output and those are categorized as class type 1 and type 2. For type 1, the fatigue cycles are classified as low for 1 to 5000 and high for cycles greater than 5000. For type 2, the fatigue cycles are classified as low for 1 to 250, medium for 251 to 10000, and high for cycles greater than 10000.

Missing data is handled in pre-processing. In feature engineering, output data i.e., fatigue cycles are divided into categories as low and high for type 1 and low, medium, and high for type 2 of the class. The next step is to select a model, for which preliminary tests are conducted to try various algorithms such as bagging, linear regression, etc. with different cross-validations folds. Finally, the random forest tree algorithm is selected because of its efficiency. In the next step, the model is trained on k folds and the value of k varies from 5 to 40. Then, the model is optimized by selecting the optimum value of k, and at the end, the prediction of fatigue life cycles is obtained.

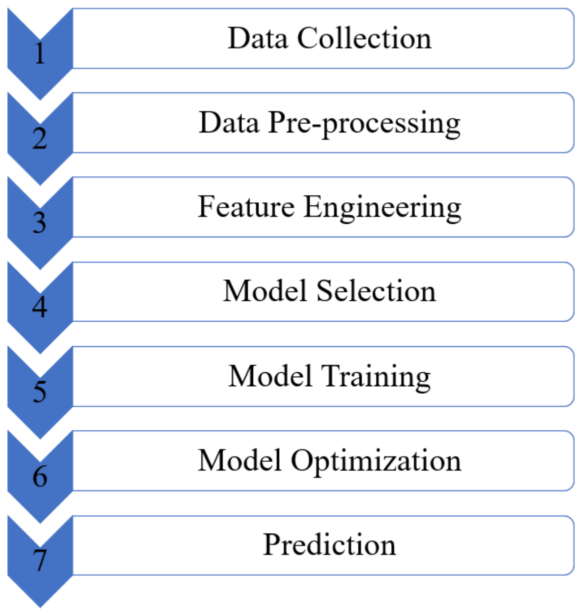

Figure 3: Process workflow of the research

Table 1: Attributes and their assigned values

Sr. No.	Attributes	Values
1	Matrix Material	Nylon
2	Reinforcing Material	Carbon Fiber, Kevlar, Fiberglass, None
3	Infill Density	20%, 50%
4	Infill Pattern	Hexagonal, Triangular, Triangular 2 Layers 4 Rings, Triangular 4 Layers 2 Rings
5	Infill Orientation	0°, 45°, 60°
6	Tensile Strength	Numerical Input from [28]
7	Load	Numerical Input from [28]
8	Class/Output: Fatigue Cycles	Type1: 1 – 5000: Low, >5000: High Type 2: 1 – 250: Low, 251 – 10000: Medium, >10000: High

Result and Discussion

Table 2 represents the results of a ML model based on the Random Forest decision tree algorithm. Here's an explanation of the metrics:

- Class Attribute: This column indicates the variables for the classification task. Here are two types of class attributes labeled as types 1 and 2 [32].
- K-fold: It represents the number of folds used in cross-validation. Cross-validation is a technique to assess the model's performance by splitting the dataset into multiple subsets and iteratively training and evaluating the model on different combinations of these subsets [33]. For type 1, K varies from 10 to 40, and for type 2, K varies from 5 to 30.
- Accuracy: It measures the proportion of correctly classified instances out of the total instances. It is expressed as a percentage [34].
- Kappa Statistics: Kappa statistics measure the agreement between the predicted and actual classifications, considering the agreement that could occur by chance. It ranges between -1 and 1, where 1 indicates perfect agreement, 0 indicates agreement by chance, and negative values indicate worse-than-chance agreement [35].
- MAE: It represents the average absolute difference between the predicted and actual values. It measures the average magnitude of the errors, regardless of their direction. Smaller values indicate better performance [36].
- Root Mean Squared Error (RMSE): It is another metric to evaluate the model's performance, specifically for regression tasks. It calculates the square root of the average of the squared differences between the predicted and actual values. Similar to MAE, smaller values indicate better performance [34].

The table provides a comparison of the model's performance across different configurations, such as the number of folds used in cross-validation (K-fold) and the class attribute. It is evident that the accuracy, kappa statistics, MAE, and RMSE values vary based on these configurations. Generally, higher accuracy, kappa statistics, and lower MAE and RMSE values indicate better model performance.

From the Table, it is observed that the highest accuracy obtained is i.e., 95.5% for class attribute 1 and 30-fold cross-validation. The Lowest MAE and RSME are 0.0696 and 0.2045 respectively for class attribute 1 and 30-fold cross-validation. After 30 Folds for class attribute 1, the accuracy saturates at 95.5%. For class attribute 2, the highest accuracy obtained is 83.49% for 5-fold cross-validation. For class attribute 2 and 5-fold cross validation MAE and RSME are 0.1375 and 0.284 respectively.

Table 2: Results for random forest algorithm

Attribute	K-fold	Accuracy	Kappa Statistics	MAE	RMSE
Type 1	10	94.5%	0.7979	0.0703	0.2045
Type 1	20	95%	0.827	0.0736	0.211
Type 1	30	95.5%	0.8387	0.0696	0.2045
Type 1	40	95.5%	0.8424	0.7505	0.206
Type 2	5	83.49%	0.7296	0.1375	0.284
Type 2	10	82.54%	0.7128	0.1338	0.02811
Type 2	20	82.54%	0.7142	0.137	0.2874
Type 2	30	81.13%	0.689	0.138	0.2875

Conclusion and Future Scope

In this paper, one case study was considered wherein various process parameters of the 3DP were treated as the inputs to an ML-based prediction system, which then predicted the fatigue behavior of the part. Based on the elaborate analysis, the following conclusions can be drawn:

- Random forest algorithm is applicable to predict the fatigue behavior of composite materials with good accuracy.
- Accuracy is dependent on a number of folds in K-fold cross-validation and varies extremely based on the classification of class attributes.
- One limitation of this study is that it does not provide an exhaustive comparison. Numerous other ML algorithms, including support vector regression, multi-layer perceptron regression, hist gradient boosting regression, and more, have not been considered in this study. Additionally, the study lacks the utilization of global optimization algorithms when searching for optimum hyperparameters. In the future, the study aims to address these limitations by incorporating additional ML algorithms and exploring other case studies. The anticipated outcomes of this extended research are expected to offer valuable insights to practitioners seeking to implement ML for enhancing machining or manufacturing processes.

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Conflicts of Interest

The authors declare no conflict of interest.

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