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Research Progress on Fatigue Life Prediction of Machine Learning-Assisted Additive Manufacturing Titanium Alloy

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Abstract. Titanium alloys are crucial for aerospace and advanced industries due to their lightweight and high-strength properties. Additive manufacturing (AM) enables the near net shape fabrication of complex titanium components, breaking the limitations of traditional manufacturing designs. However, rapid cooling rates and large local temperature differences during AM titanium processes inherently introduce defects such as gas pores and lack of fusion. These internal defects significantly degrade the high-cycle fatigue performance of AM titanium components, restricting their wide application in safety-critical areas, and also pose great challenges for fatigue life prediction. In recent years, the rapid development of machine learning has provided new solutions to related complex problems. This paper reviews the latest progress in fatigue life prediction of AM titanium alloys based on machine learning. The models proposed based on artificial neural network, support vector machine, random forest and other systems have successfully revealed the relationship between defect, microstructure and fatigue performance. Finally, the future challenges and development directions of fatigue life of AM titanium alloys are discussed.

Keywords: machine learning, artificial intelligence, additive manufacturing, fatigue life prediction, titanium alloys

1. Introduction

The rapid development of advanced industries places ever-increasing demands on the performance of structural materials. As a lightweight and high-strength material, titanium alloy is widely used in aerospace, biomedical, automotive energy and other fields. Additive manufacturing (AM) technology, relying on its "near-net-shape" advantage, can accurately fabricate titanium alloy components with complex structures, which is expected to break through the design limitations of traditional manufacturing and become one of the core technologies promoting the upgrading of high-end manufacturing. However, due to the inherent characteristics of AM processes such as large local temperature differences and fast cooling rates, intrinsic defects, such as gas pores and lack of fusion (LOF) are prone to occur inside AM titanium alloys [1-3]. These defects substantially affect the fatigue failure behavior of AM titanium components, resulting in a significant difference between their actual service life and that of traditional forged titanium components, which seriously restricts the large-scale application of AM titanium alloys in key safety-critical components [4-6]. Therefore, accurately predicting the fatigue performance of AM titanium components is essential to

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ensure their structural integrity and to support design optimization. Classical fatigue prediction models for metallic materials are generally based on the assumption of microstructural homogeneity, which is difficult to adapt to the heterogeneous microstructure and defect distribution inherent in AM titanium alloys, leading to large deviations between prediction results and actual conditions. Therefore, establishing a fatigue performance prediction model that considers defect effects, microstructure evolution and load conditions for the characteristics of AM titanium alloys has become a key breakthrough direction in the interdisciplinary field of materials science and manufacturing engineering.

With the development of artificial intelligence (AI), the new paradigm of material science research, data-intensive scientific discovery, has emerged [7]. Among the related research in AM, machine learning (ML) has become a research hotspot in the extended application of AI, and is widely used to solve complex multi-dimensional problems [8, 9]. With the emergence of ML, the trial and error thinking in material design and performance optimization can be changed, and the expensive cost of fatigue test can be reduced, so that researchers can find relevant laws in fatigue life data and form data-based models and design principles. Wang et al. [10] described the two-way prediction process of additive manufacturing process-structure-performance based on ML life prediction model, as shown in Fig.1. The fatigue life prediction of AM components can be effectively improved by machine learning, which provides a new path for the reliability research of AM components. Therefore, ML is a subject with great research potential in predicting the fatigue life of AM parts.

In summary, ML provides a new solution for studying the influencing factors and prediction models of AM titanium alloys fatigue life. This paper compares the research status of fatigue life prediction based on different machine learning systems, and discusses the potential factors affecting fatigue life. In addition, the challenges and problems in the ML fatigue life prediction of AM titanium alloy are reviewed, and some suggestions for improving its performance are put forward.

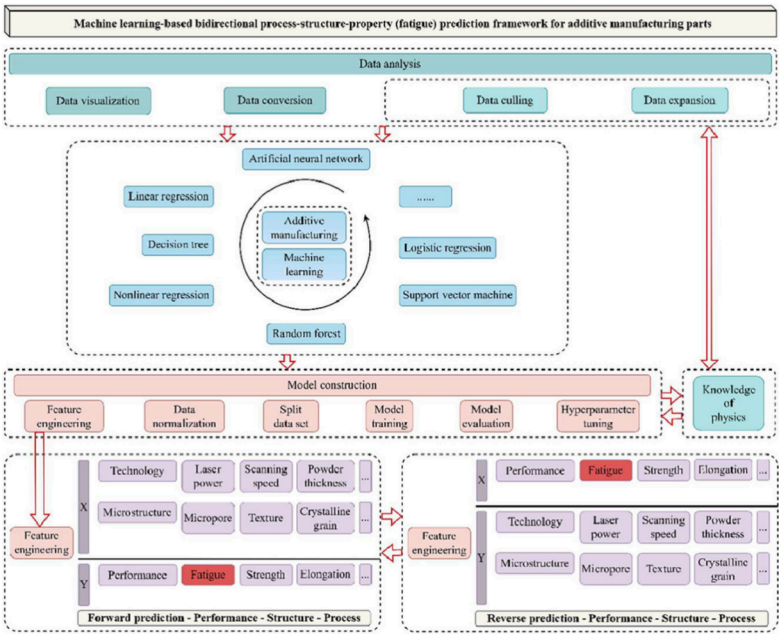

Figure 1. ML model technology roadmap for fatigue life prediction of additive manufacturing components [10]

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2. Fatigue life prediction of AM titanium alloys with ML

ML is a data-centric discipline whose fundamental logic involves constructing predictive models by extracting statistical patterns from data. This technology enables computer systems to automatically discover the mapping relationship between inputs and outputs through learning from training datasets, thereby making accurate inferences and decisions for unknown data. This data-driven modeling approach does not rely on prior knowledge of underlying physical mechanisms, but instead automatically identifies statistical correlations between variables through algorithms, thereby enabling effective description and prediction of complex systems [11, 12].

In terms of fatigue performance prediction of AM components, according to the form of data processed by machine learning and the degree of integration of knowledge, existing research can be summarized into three major technical paths: data-driven methods based on feature engineering, deep learning methods based on microscopic images, and modeling methods that integrate physical information. These methods reflect the technical evolution from pure data-driven to physical fusion.

2.1. Data-driven method based on feature engineering

For AM titanium alloys, its fatigue life is affected by the coupling of various factors including defect geometric characteristics, printing parameters, surface roughness and load conditions. Establishing a quantitative mapping between these complex input variables and fatigue life is the key to data-driven models. This section summarizes the research status of data-driven methods based on feature engineering.

Fatigue performance prediction based on data-driven is widely carried out at home and abroad. For example, Liu et. al. [13] collected more than 150 sets of fatigue test data to train the ML model. Through the sensitivity coefficient analysis, it was determined that the defect size and the maximum stress were the parameters with the strongest correlation with the fatigue life. The results show that the prediction accuracy of the ML model is better than that of the classical Murakami model, and it has high prediction accuracy in the range of 106 ~ 1010 cycles. Early research mainly relied on extracting the most relevant feature description of fatigue life from measurable physical quantities. Xie et. al. [14] used the area square root, depth, angle, aspect ratio and roundness of pores as input features, analyzed the correlation between each parameter and fatigue life, and found that depth, area square root, roundness and angle are the core influencing factors. Based on this, they used random forest algorithm to construct a fatigue life prediction model. The results of the model are mostly in the 1.5 times error band, and the prediction accuracy is high. Konda et. al. [15] used energy density as a single parameter to evaluate AM printing parameters (laser power, layer thickness, scanning speed, scanning spacing, etc.). Then, the energy density and stress amplitude are normalized, and different ML models of logarithmic fatigue life are established on the same data set. The results show that the XGBoost algorithm performs best in prediction accuracy.

However, due to the high cost and long experimental period of fatigue test of AM titanium alloys, effective data are scarce, which is one of the serious problems faced by data-driven machine learning models. To this end, researchers have proposed different data enhancement methods to expand the original fatigue data. Li et al. [16] constructed a fatigue life model by using artificial neural network model (ANN), and studied the coupling effects of defect size, depth, position and configuration direction on the fatigue life of AM titanium alloys. In order to overcome data sparsity, they expanded the size of the data set through Monte Carlo simulation (MCS). The results show that the quality of the original data set limits the accuracy of the ML prediction model. In fact, when the data set size of the ML model is insufficient, the change or dispersion of fatigue performance often

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leads to a misunderstanding of the relationship between performance influencing factors, which makes it difficult to obtain accurate prediction results through algorithms.

In summary, the data-driven method provides an efficient solution for predicting the fatigue performance of AM titanium alloys, and can also reveal the dominant factors of defect influence through feature analysis. However, although such methods can achieve high-precision prediction under small sample conditions through data augmentation techniques, they still have certain limitations in characterizing the coupling relationship between complex nonlinear processes, structures and properties, and rely heavily on database quality. Therefore, the evolution to a model with stronger learning ability has become an inevitable trend in the field of machine learning assisted additive manufacturing titanium alloy fatigue research.

2.2. Deep learning method based on microscopic image

Microstructure determines the properties of materials. In the process of establishing fatigue life prediction model, it is necessary to take microstructure as an important reference object. With its advantages in unstructured data processing and automatic extraction of high-dimensional features, the deep learning model provides a new technical path for identifying structural defects from microscopic images and perceiving fatigue life, and provides a new paradigm for constructing more complex 'process-defect/microstructure-performance' relationships. Different from the aforementioned ML methods that rely on artificial feature analysis, the deep vision model can directly process unstructured data such as original images and sequences, showing unique advantages in the prediction of fatigue performance of AM titanium alloys.

Aiming at the problem that it is difficult to accurately quantify the small defects inside the additive manufacturing titanium alloy, which limits the accuracy of fatigue prediction, Pan et al. [17] proposed a hybrid fatigue life prediction framework combining deep learning and physical driven model. This framework realizes a complete process from micro-defect identification to macro-life prediction. Firstly, the improved deep convolutional neural network is used to process the high-resolution CT images of SLM Ti1-6AI-4V alloy. By introducing cropping, under sampling strategy and category weighted loss function, the problem of extreme imbalance of samples and small target recognition in defect detection is overcome, and the pixel-level segmentation accuracy is as high as 98.2%. Secondly, based on the binary mask obtained by segmentation, the key morphological features of defects (such as equivalent size, sphericity and position parameters) are automatically extracted and quantified, so as to obtain high-fidelity defect geometric data. Finally, these defect characteristic parameters accurately captured by machine learning are taken as input variables and substituted into the physical model based on effective strain energy density to calculate the fatigue life. The results show that this deep learning prediction method based on microscopic images can effectively capture the performance differences of different batches of materials, and the error dispersion band between the predicted life and the experimental data is controlled within ± 2.2. In addition, in order to further explore the intrinsic relationship between image features and fatigue performance, Templeton et al. [18] developed a generative learning architecture combining regression network and variational autoencoder architecture. This method can automatically identify the key defect morphology that affects the fatigue behavior of additively manufactured titanium alloys from optical micrographs. By simultaneously learning the microscopic defect image features and the joint distribution with the life label, the correlation modeling between the defect image and the fatigue life is realized. The strong potential of deep visual network in revealing the inherent law between microstructure and properties of AM titanium alloys is further verified.

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Although deep learning shows great potential to construct complex ' process-defect / microstructure-performance ' correlations in the prediction of fatigue properties of additively manufactured titanium alloys. However, the excellent performance of this method relies heavily on large-scale data and considerable computing power, and the 'black box' feature of the model seriously affects its credibility: although some ML models can obtain life prediction results through high-precision fitting data, they cannot clearly explain the key issues such as 'which features (such as grain size, load amplitude, etc.) dominate fatigue life attenuation' and 'what is the contribution weight of different features'. These factors seriously restrict its application in practical engineering.

2.3. Interpretability modeling of fused physical information

Faced with the problem of insufficient generalization ability and poor physical consistency of prediction results, machine learning methods that integrate physical information provide new solutions. By introducing the known physical laws in fatigue (such as fracture mechanics and damage accumulation rule) into the model training process, the prediction results with more physical meaning and extrapolation ability can be obtained under the condition of limited data, so as to effectively improve the interpretability of the model.

Feng et al. [19] integrated physical knowledge such as stress concentration caused by cracks and defects in fracture mechanics and fatigue life following logarithmic normal distribution into the loss function. In the framework of multi-task physical information branch neural network, PyTorch automatic differentiation is used to calculate the first derivative of the mean and standard deviation of fatigue life to the maximum stress, which is incorporated into the loss function as a physical constraint. This method effectively deals with the problem of fatigue life dispersion caused by micro-defects in additive manufacturing parts, improves the reliability and accuracy of model prediction, and overcomes the limitations of traditional data-driven methods. Liao et al. [20] focused on the prediction of residual life of fatigue crack propagation. This work is based on the Paris law of linear elastic fracture mechanics, and integrates the relationship between crack growth driving force and fatigue crack growth rate into the loss function. The neural network is obtained by automatic differentiation to predict the gradient of fatigue cycle number to crack length, and the total loss function including data loss and physical knowledge loss is constructed respectively. This not only uses the physical model to directly constrain the network gradient, but also reversely identifies the physical model parameters in training to improve the accuracy of fatigue crack growth residual life prediction and the extrapolation ability of the model, providing a more reliable method for fatigue crack residual life prediction.

The physical information machine learning strategy has become a key path to break through the bottleneck of fatigue prediction of additive manufacturing titanium alloys. These methods are no longer limited to data fitting, but embed knowledge such as fracture mechanics and semi-empirical models into the data-driven framework, which realizes the leap from the 'black box' to the physical interpretable model, improves the generalization and extrapolation ability of the model in the sparse data region, and provides a new perspective for understanding the 'defect-fatigue' nonlinear relationship.

3. Discussions and outlooks

This paper reviews the latest progress in the prediction of fatigue life performance of AM titanium alloys. Due to the complex physical and metallurgical processes experienced during the preparation process, the characteristics of AM titanium alloys such as defects, ultra-fine structure and residual

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stress are the essential reasons for their poor fatigue performance and large life dispersion. At the same time, these characteristics also bring difficulties to the accurate prediction of the high-cycle fatigue performance of AM titanium alloys. At present, several classical fatigue performance prediction models proposed based on metals prepared by traditional processes have shortcomings in predicting the performance of AM titanium alloys, and need further modification or optimization. In recent years, the development of AI and ML has provided a new path for fatigue life assessment: it is expected to improve the accuracy, efficiency and generalization ability of fatigue life prediction by integrating process parameters, defect morphology, microstructure characteristics and loading conditions, and combining data-driven models and physical information models.

For the fatigue performance prediction model of AM titanium alloys, the theoretical model combined with physical characteristics can better reflect its fatigue failure mechanism and has a better prediction effect. In the future, artificial intelligence methods should be further combined with mechanism-based models and high-quality fatigue databases to establish a more reliable prediction framework for multi-factor coupling, small-sample learning and cross-process generalization. Specifically, when establishing a high-cycle fatigue life prediction model for additive manufacturing titanium alloys, it is essential to further consider the local characteristics between structure and defects as well as their coupled competitive relationships.

4. Conclusion

In the present work, we review the research progress of machine learning in fatigue life prediction of additive manufacturing titanium alloys. ML approaches provide powerful tools for predicting the fatigue life of additive manufacturing titanium alloys. However, challenges remain, including data scarcity, the need for high-quality annotated datasets, and ensuring physical interpretability. Future work should focus on integrating physics-based knowledge, developing open datasets, and leveraging transfer learning to achieve model generalization across different materials and manufacturing platforms.

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