AM Design Tool for Rapid Structural Assessment of Aerospace Components

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ABSTRACT

A recent focus on attritable/expendable technologies in the aerospace community has highlighted a need for new, streamlined design tools and a potential re-assessment of current design requirements. Additive Manufacturing (AM) technology offers design flexibility and innovative potential; however, for AM materials, internal voids and surface features drive component failure and produce significant scatter in stress-life (S-N) data. AM scatter reduction is often achieved through process optimization; however, this approach requires specific AM process knowledge and significant amounts of material data. A defect-informed design approach identifies specific inspection requirements, minimizes the amount of data to characterize material performance, and reduces the need for substantial process development to minimize defects because the effects of defects are specifically included in the design. Therefore, defect-informed design effectively drives down the cost of AM process development.

The current work leverages small crack growth modelling and experimental defect observations to develop a defect-informed S-N equivalent model which accurately predicts component life based on the initiating defect stress intensity factor (K). This K-N approach reduces the scatter observed in S-N data and minimizes the training data required for the model. The result of this investigation is a versatile design tool for AM applications and a quantitative understanding of material testing requirements for uncertainty quantification. The insights found here reveal opportunities for improving designs in the attritable/expendable product space and promote cost-savings in the AM supply chain for the benefit of a wide array of industries.

1.0 INTRODUCTION

Additive manufacturing (AM) is an exciting technology that has potential applications in numerous industries. The opportunities for flexible and novel designs are facilitated with this “ground-up” approach. Traditional fatigue life evaluation techniques have focused on characterization of fatigue limit behavior which is important for defect tolerant design frameworks, however with a push toward low-cost, attritable systems, more specific efforts toward finite lifing methods are needed to drive cost down and push the design envelope for future systems. Additionally, material characterization and statistical evaluation techniques must be developed to specify the type and minimize the quantity of data required to certify AM material at a rate amenable to the fast-paced, low-throughput AM process.

The United States (US) Department of Defense (DoD) recently published DoD Instruction (DoDI) 5000.93 which outlines guidance for the implementation and use of AM components within the DoD (OUSDR&E, 2021). This document directs USDoD components to “take a risk-informed approach to AM and have policies that define the level of qualification, certification, risk evaluation, and approval authority required to use an AM part.” In the context of AM fatigue life, it is crucial to understand defects and failure mechanisms in order to quantify risk for AM components. As failure mechanisms are better understood, methods for qualifying material and processes with minimal material data can be developed. DoDI 5000.93 also instructs DoD entities to “carry out material and process characterization research that increases reliability of AM process and part quality to speed up the qualification and certification processes.” Currently, industry process qualification and component certification standards (NASA, 2017; ASTM International Committee F42, 2021; ASTM International Committee F42, 2014) are available and provide guidelines for characterizing AM material. Often standards and industry best practices work to minimize defect occurrence rates by continually developing process parameters, however these practices drive costs higher and require further experimental work to increase confidence in the resulting components. Additionally, Air Force standards such as MIL-HDBK-1783B (Engine Structural Integrity Program) and MIL-HDBK-1530 (Aircraft Structural Integrity Program) establish best practices and guidelines for current implementation of structural materials (Air Force Life Cycle Management Center/EZSS, 2016; Air Force Life Cycle Management Center/EZFP, 2004). For low-cost, attritable systems, many of the current guidelines impose restrictive benchmarks which add to the cost of the overall system. In order for the AM community to pursue the goals and directives established in DoDI 5000.93, it is imperative that methods for quantifying risk while minimizing the time and expense required to characterize component performance be developed and proven. The development of these methods may also inform current design practices for low-risk implementation of AM components into legacy aircraft. To this end, a physics-based modelling approach is being proposed to quantify material/component behavior in a rapid, cost-efficient manner. This approach may help the USDoD community to tailor its material qualification procedures to take advantage of the rapidity and the low-throughput advantages of AM processes.

One of the most common failure mechanisms for AM materials is structural fatigue which is driven by several common mechanisms including internal defects (gas pores, keyhole pores, and lack of fusion), surface defects (surface roughness, surface porosity, etc.), and microstructural features (twins, detrimental phases, etc.). The stochastic nature of each of these defect types often results in significant scatter in fatigue data even from components within the same AM build. Several fatigue models have been proposed in the literature to characterize the fatigue behavior of AM material and provide insight into the fatigue scatter behavior of which the most basic is the traditional stress-life (S-N) diagram which portrays the fatigue lives of numerous components compared to the stress that was applied to observe that particular life. For many traditionally manufactured materials, the S-N diagram often follows a bi-linear trend with a steep negative sloped line representing finite life fatigue behavior and an almost horizontal sloped line representing the fatigue limit of the material. For AM material, the material fatigue limit is very difficult to find because defects in the material either obscure it due to scatter or lower it below the minimum tested stress. Design using this approach is often difficult because the average AM fatigue behavior trend does not portray the scatter in the fatigue data. Some work has been performed to characterize lower design limits of AM material using fracture mechanics based calculations, however building confidence in these approaches requires large datasets that are both expensive and time consuming to test and analyze. A pertinent question then is, “How much fatigue data is necessary to provide accurate confidence in the model?”

Another common approach to characterize the fatigue limit of materials is the Kitagawa-Takahashi (K-T) diagram (Kitagawa & Takahashi, 1976) which uses material fatigue limit behavior and linear elastic fracture mechanics (LEFM) assumptions to predict the fatigue limit behavior of a material with a known initial crack size. El-Haddad introduced a small crack correction to the K-T Diagram framework which has been leveraged heavily in the AM literature for fatigue limit characterization of AM materials in the presence of small defects (El-Haddad, et al., 1979). One weakness of the El-Haddad model is that it neglects finite life behavior and models only fatigue limit behavior. Furthermore, for AM alloys, the processing that the materials undergo often results in different microstructure compared to traditionally manufactured materials. Since microstructure is a significant driver of fatigue properties, identifying defect free fatigue limit properties that are analogous to AM material is difficult, so in some cases assumptions must be made in constructing El-Haddad’s model which may or may not be accurate representations of actual material behavior.

Finally, statistical approaches to fatigue characterization have been developed such as Extreme Value statistics (Romano, et al., 2017; Beretta, 2021; Sanaei & Fatemi, 2021) and equivalent initial flaw/defect size (EIFS/EIDS) (Johnson, 2010; Fawaz, 2000). For extreme value statistical methods, failure defects across a wide quantity of specimens are identified and a statistical distribution is defined. Random samples can be obtained from this distribution and applied to crack growth calculations to determine the probability of failure of a component at a specific location or to determine the life distribution of a component. As mentioned for the other fatigue modelling approaches, this model has proven to be effective; however, it requires a significant amount of data to use for accurate modelling. The EIFS approach characterizes a sample of observed cracks and back-calculates the initial flaw size that must have been present assuming known crack growth behavior in order for the observed crack to grow to the final length. This approach can be used for numerous components and an EIFS distribution can be constructed and sampled for use in forward calculations. In this way, an unknown life distribution can be estimated for the component population based on a sample population. The accuracy of the EIFS approach is reliant on accurate fatigue crack growth properties which may or may not change in components spread throughout the build chamber or even through the height of each part. Therefore significant amounts of location and build specific crack growth data is required to accurately obtain EIFS data for future use.

A significant weakness of each of the fatigue modelling approaches mentioned above is the requirement of large amounts of data to accurately construct and use the model. This high-throughput output is in opposition to the low-cost, low throughput cost-modelling paradigm of the AM process. Additionally, the AM process' heavy dependence on atmospheric conditions, stock material quality, machine location, etc. means that different machines may produce components that exhibit slightly different fatigue behavior and that even the same machines in the same locations may produce fluctuations or degradation in material properties over time. Therefore, a physics-based model that lends itself to rapid characterization of fatigue behavior with minimal input data is needed to complement the fast-paced environment of AM processing.

2.0 METHODOLOGY

2.1 Addressing Scatter in AM Fatigue Data

Stress and defects play a collaborative role in dictating fatigue life of AM components. Therefore, for life prediction, it is critical to take both applied stress and defect size into account. The S-N approach to fatigue life prediction only accounts for the applied stress in the material. A sample set of AM superalloy 718 fatigue data was collected as described in (Sheridan, et al., 2020; Sheridan, et al., 2021) and the corresponding S-N diagram can be observed in Figure 1

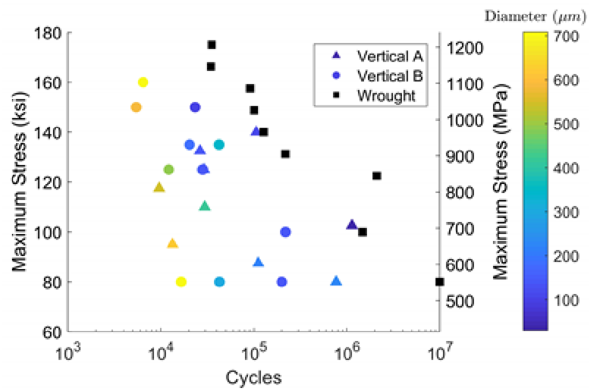


Figure 1 – S-N diagram of AM superalloy 718 showing two different lots of AM material and the size of the failure defect. Black squares represent wrought material S-N behavior.

A metric that is commonly used in LEFM to characterize the elastic stress field surrounding a crack is the stress intensity factor (K) which is defined as

$$K = Y\sigma\sqrt{\pi a} \qquad (1)$$

Where Y is the stress intensity shape factor, σ is the applied stress and a is the crack size. Small defects in AM material such as LOF and porosity are often considered to be small cracks with K-values calculated based on a characteristic crack size ($\sqrt{A}$) which is the square root of the transverse projected area of the defect in the stress-plane (Murakami & Endo, 1980; Murakami & Endo, 1994). Failure defects are often found at the surface of a component, and the shape factor for this crack configuration is often approximated as 0.65.
When the applied stress and defect size are combined using Eq. (1), the scatter observed in the resulting K-N plot is greatly reduced and the life of a component with a known initial K value can be predicted with some accuracy (Figure 2).

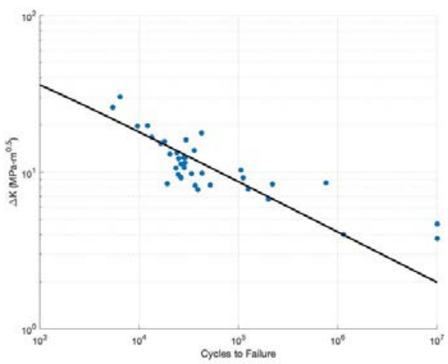


Figure 2 – Fit K-N model for AM superalloy 718 using Paris crack growth model

An equation can be derived for the K-N curve using basic crack growth behavior as summarized below. A more thorough look into this derivation and its application to extending the El-Haddad fatigue limit model to finite life behavior may be found in (Sheridan, 2021). Beginning with the common Paris Law for stable crack growth, the crack growth rate of a material can be modelled as:

$$\frac{da}{dN} = C(\Delta K)^n \qquad (2)$$

This equation can be integrated analytically through separation of variables and solved for the initial crack size (a_N) so that

$$a_N = \left[a_c^{1-\frac{n}{2}} - N_f\left(1 - \frac{n}{2}\right)C\left(Y\Delta\sigma\sqrt{\pi}\right)^n\right]^{\frac{1}{1-\frac{n}{2}}} \qquad (3)$$

Eq. (1) be applied such that

$$\Delta K_{N,\Delta\sigma} = Y\Delta\sigma\sqrt{\pi\left[a_c^{1-\frac{n}{2}} - N_f\left(1 - \frac{n}{2}\right)C\left(Y\Delta\sigma\sqrt{\pi}\right)^n\right]^{\frac{1}{1-\frac{n}{2}}}} \qquad (4)$$

which represents a family of curves that is dependent on applied stress and number of cycles to failure. This equation can be reduced to a function of a single variable N_f by substituting the Basquin Equation ($\Delta\sigma_N$) for $\Delta\sigma$ which characterizes the S-N behavior of the material with no defects.

$$\Delta K_N = Y\Delta\sigma_N \sqrt{\pi \left[a_c^{1-\frac{n}{2}} - N_f \left(1 - \frac{n}{2}\right) C\left(Y\Delta\sigma_N\sqrt{\pi}\right)^n \right]^{\frac{1}{1-\frac{n}{2}}}} \tag{5}$$

where

$$\Delta\sigma_N = AN^b \tag{6}$$

The scatter in AM S-N data is often too wide for the Basquin equation to predict the S-N behavior of an AM material, however the Basquin equation can be applied for defect-free wrought S-N material. If the wrought Basquin model is used, the resulting a_N will be inaccurate compared to experimentally observed initiating defect sizes, however when the calculated a_N and the Basquin $\Delta\sigma_N$ are used to calculate ΔK_N (Eq. (5)) the calculated ΔK value will generally reflect the experimentally observed stress intensity value. This behavior is expected because while the dimensionality of Eq. (4) is reduced using the Basquin law for the wrought material, the actual crack growth model is that of the AM material. Therefore, as long as two independent initial stress intensity values are the same, the corresponding lives of the components will be the same. Thus, a physics-based model has been developed to characterize component life with respect to both initial flaw size and applied stress.

2.2 Predicting material growth behavior

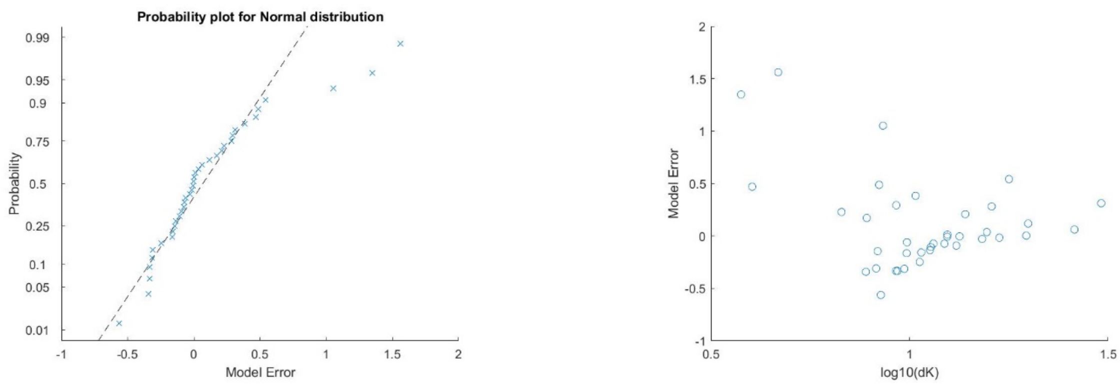
Often, axial fatigue data obtained via (ASTM International Committee E08, 2021) can easily be collected, however without foreknowledge of material crack growth behavior, predicting fatigue life with respect to applied stress and defect content is very difficult. While standard crack growth tests can be performed (ASTM International Committee E08, 2015), these tests often require more AM material and more tests to identify the local crack growth behaviour and the global variation in AM fatigue crack growth material behavior. However, if after performing axial fatigue tests, the applied stress, failure defect size, and number of cycles to failure is known, the average crack growth behavior of the AM material can be estimated using the above model. This can be performed by adjusting the material crack growth constants for the Paris law so that the K-N prediction matches the experimental data. Visual fitting of a K-N model for alloy 718 material has been performed in (Sheridan, 2021). Numerical optimization can also be performed to minimize a cost function such as the sum of the squared error between the K-N model and the experimental data. This methodology will not be discussed here.

As described above, in prior work the authors have developed a physics-based model that accurately predicts fatigue life of AM components containing defects. While this approach reduces the amount of scatter in fatigue data, stochastic variations in crack growth properties and other unknown variables prevent perfect correlation of experimental data with the model therefore uncertainty quantification is important to understand the variability in the predicted response. Additionally, since the AM process is a low-throughput manufacturing method, model training data reduction is critical to more efficient modelling and characterization of AM material behavior. Therefore, a study that quantifies model uncertainty with respect to training dataset size will be performed and a series of prediction curves will be generated for the reduced data models and compared with each other. A novel method will then be proposed to generate minimum design curves in S-N space based on the generated prediction curves which can be used in future design efforts to design confidently for AM fatigue.

3.0 RESULTS AND DISCUSSION

3.1 Uncertainty Quantification

Since the assumptions provided in section 2.1 were that the crack growth of a material followed a power law behavior, the model can be considered linear under a log-log transformation. Therefore, linear analysis and statistical methods can be performed. If the crack growth model has been appropriately fit by the least squares method using the K-N methodology above, the model residuals should form approximately a normal distribution and the range of the residuals across every observation should not follow any trend. While the first assumption is proven to be true in Figure 3a, Figure 3b shows that for small ΔK values, the range of error increases. This is because at small ΔK values, the crack growth threshold begins to dominate, and the linear assumption of the Paris Law is no longer valid. A more complex model that includes threshold effects should be implemented in the future, however, for the sake of the current analysis, the linear case is considered conservative.



(a) *(b)*

Figure 3 – (a) Normal probability plot showing that residuals follow an approximately normal distribution; (b) Residuals vs. ΔK observations showing that the range of residuals is approximately constant for a majority of observations.

For a linear model with normal residuals, general prediction bounds can be calculated as defined below:

$$y_p = \hat{y}_h \pm t_{(\alpha, n-2)} * \sqrt{MSE\left(\frac{1+\frac{1}{n}+(x_h-\bar{x})^2}{\Sigma(x_i-\bar{x})^2}\right)} \qquad (7)$$

Where y_p is the prediction curve dependent variable, $\hat{y}_h$ is the model dependent variable, t is the student t-distribution, n is the number of observations used to make the model, α is the significance level required, x_h is the model independent variable, and $\bar{x}$ is the mean of all independent variable observations (x_i). MSE is the mean square error and is calculated as

$$MSE = \sum_{i=1}^{n} \frac{(y_i-y_h)^2}{n-2} \qquad (8)$$

In terms of the K-N model developed above, Eq. (7) is transformed to:

$$log10(N_p) = log10(\widehat{N}_h) \pm t_{(\alpha, n-4)} * \sqrt{MSE\left(\frac{1+\frac{1}{n}+(\Delta K^*-\overline{\Delta K}^*)^2}{\Sigma(\Delta K^*-\overline{\Delta K}^*)^2}\right)} \qquad (9)$$

and

$$MSE = \frac{\left(N_i^*-N_h^*\right)^2}{n-4} \qquad (10)$$

where the asterisk represents the base-ten logarithm of the variable (e.g. $N_i^* = \log_{10} N_i$).
Note that for this formulation, the initial stress intensity factor (i.e. the applied stress and failure defect size) is known, and the component life is being predicted. This formulation is actually the inverse problem to that

presented in section 2.1, which assumes that the desired life is known and the quantity that is being calculated is the stress intensity factor. While the former situation is valid and may be desired for targeted life applications, the traditional design case, where the loading and defect size are known, will be examined more thoroughly here.

If Eq. (9) is plotted and overlaid at a confidence level of 99.99% on the entirety of the data (as shown in Figure 4), it may be seen that all of the data falls well within the prediction bounds. However, as the confidence level (α) decreases to 0.95, 0.9, and 0.75, more and more data falls outside of the prediction curves. The confidence level represents the percentage of future predictions which will lie inside the bounds. Therefore, to ensure that future predictions are accurate, it is important to maximize the confidence level of the prediction. For mission success prediction, this parameter can be tailored in the model depending on the desired success rate of the mission where successful missions experience behaviour that lies within the prediction bounds whereas unsuccessful missions will experience behaviour that lies outside the prediction curves. Therefore, with the collection of axial K-N data, a worst-case design criteria can be identified which can provide conservative material performance predictions quickly and efficiently for new AM materials.

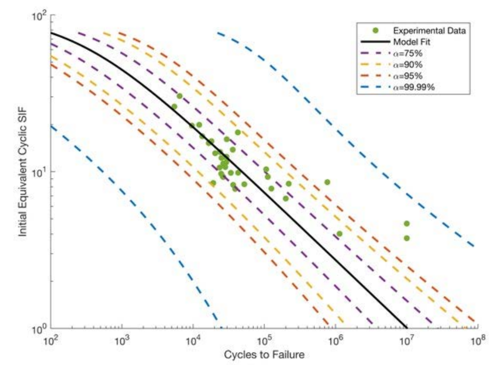


Figure 4 – K-N plot showing experimental data compared to prediction bounds at four different confidence levels (Purple – 75%, Yellow – 90%, Red – 95%, Blue, 99.99%).

3.2 Identifying Minimum Design Criteria

In Section 3.1, the spread of K-N fatigue data was approximated using the prediction bounds construct. In most situations, the lower bound is of most interest because it defines the lowest stress intensity that will cause failure at a given number of cycles. Therefore, the lower prediction bounds can be used as a design criteria for AM materials. Often, however, designing in terms of stress intensity is undesirable because the defect content is stochastic at every location and relatively unpredictable. Additionally, inspection for many AM components is difficult, so designing based on stress intensity can be very difficult. A minimum stress design criteria can be defined, however using the K-N modelling technique.

Once axial fatigue tests have been performed and the K-N model has been trained, an extreme value distribution may be constructed of failure-inducing defect diameters. From this distribution, a maximum defect size (a_m) can be inferred at a specified probability level (e.g. 99th percentile). Once the worst-case defect has been determined, the K-N lower bound can be converted to an S-N lower bound by converting each stress intensity value along the lower prediction bound to applied stress as shown:

$$\Delta\sigma = \frac{\Delta K}{Y\sqrt{\pi a_m}} \tag{11}$$

The resulting curve in relation to the experimental S-N data is shown in Figure 5.

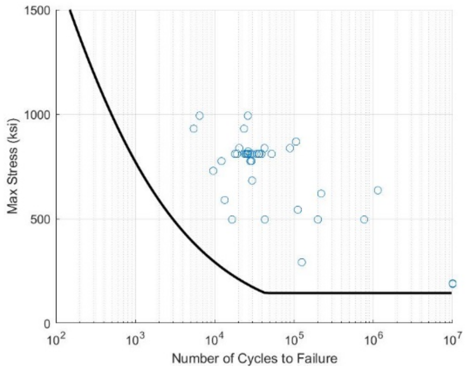


Figure 5 – S-N diagram with minimum design criteria identified

Identifying this minimum design curve is crucial for the implementation of AM components into fatigue critical applications. The S-N tool is well established for traditional materials, but applying S-N methodologies to material datasets with high levels of scatter (such as AM materials) is challenging. The systematic approach presented here leverages fracture mechanics and probability theory to confidently approximate the minimum fatigue behavior of AM materials with significantly fewer input data points than traditionally sought for full qualification of AM materials. This risk-informed approach to AM material characterization is a crucial step toward rapid AM material and process qualification and certification efforts for fatigue critical aerospace components.

4.0 Conclusions and Future Work

The work described herein identifies a statistically informed method for characterizing scatter in AM materials and defining minimum design criteria for future AM alloys. The approach takes into consideration the low-cost, low-throughput characteristics of AM processes and identifies appropriate data size requirements for characterizing an AM material in fatigue. The approach presented actively pursues goals set forth in DODI 5000.93 and may serve as the baseline for future efforts to certify AM processes and qualify AM components. The results of this work are as follows:

1) A stress intensity based fatigue life model has been presented; the model error has been quantified, and statistically determined predictive bounds have been implemented for future AM fatigue specimens. These predictive bounds can be tailored to account for mission or part criticality.
2) A method for identifying a stress-based minimum design criteria from the proposed K-N model has been outlined which can facilitate a quicker turnaround for machine qualification and material characterization. This rapid assessment also opens doors for characterizing build to build variation and performing active trending of AM machines which to date has not been possible due to the number of specimens and amount of time required to confidently characterize the fatigue performance of a material from a given machine.

The framework developed here promotes rapid characterization of AM materials and is agnostic to material type or process configuration. While this framework is a significant starting point for rapid AM process qualification, there are still several avenues to improve and optimize the proposed methods. Future work includes:

1) Minimize specimen and testing requirements through statistical analysis and by combining standard crack growth testing for model identification and standard axial fatigue tests for scatter characterization.

2) Development of a standard AM characterization build and specimen suite for characterization of AM fatigue behavior and identification of minimum design criteria using the results from Future Work bullet number 1.
3) Incorporate failure defect size rate of occurrence into the above framework to account for changes in material volume from the specimen level to the component level to promote further confidence in model predictions.
4) Demonstrate capability of statistical predictive models against a large specimen dataset to verify approximate results obtained above match experimental observations.

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