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LCF AND TMF OF SINGLE-CRYSTAL AND DIRECTIONALLY-SOLIDIFIED Ni-BASE SUPERALLOYS PREDICTED USING A PROBABILISTIC PHYSICS-GUIDED NEURAL NETWORK

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Abstract

Predicting the life under thermomechanical fatigue (TMF) is challenging because there are several parameters defining the mechanical and thermal cycles including dwell periods within the cycle that can impact life. The relationships between these TMF history parameters and fatigue life are not always clear. A probabilistic physics-guided neural network was developed and trained to learn these relationships and predict the cycles to failure for a wide range of possible creep-fatigue and TMF histories using life data extracted from the literature.

1. Introduction

Gas turbine blades and vanes are subject to complex thermomechanical loading conditions. Today's most advanced turbines used in jet engines and power generation utilize single crystal (SX) or directionally-solidified (DS) Ni-base superalloys to enhance high-temperature performance. In addition to creep, thermomechanical fatigue (TMF) is often cited as an operative damage mechanism in these systems, particularly at cooling holes and platform areas of blades and vanes. Fatigue life data under a wide variety of TMF conditions is necessary to evaluate component designs and predict the life performance.

Using an extensive compilation of LCF, creep-fatigue and TMF data extracted from the open literature, a probabilistic physics-guided neutral network (PPgNN) was developed and trained to generate strain-life curves for any input of creep-fatigue and TMF conditions. Physics-guided constraints are applied during training to force the PPgNN to adhere to known physics-informed trends, such as the flattening of the slope of the strain-life curve as the strain range decreases. This helps the model conform to known physics and be robust as opposed to letting the NN depend solely on the statistical relations it learns solely from the data. The PPgNN uses inputs of strain range, maximum and minimum temperature, the phasing between the thermal and mechanical cycles, cycling frequency, and dwell time in either tension or compression. The model predicts both the mean fatigue life and its confidence intervals (CI). The model is evaluated in several ways to determine the success of learning the relationship between the TMF conditions and cycles to failure.

2. Results

During the training of the PPgNN, there can exist an element of randomness defined by the initial training data selected and the initial randomly selected biases and weights. To account for this randomness affecting the trained model, the NN model was trained 10 times using different randomly selected biases and weights each time. An example of a strain-life prediction showing the mean and 95% CI curves is shown in Fig. 1. The bolder curves in this plot represent the mean of 10 predictions. This figure shows an OP TMF case with experimental points covering a number of blade and vane alloys tested under comparable conditions. These plots show that the sensitivity to the initial biases and weights is about a factor of two on fatigue life. Samplings of predictions made by the trained model are given in Figs. 2 and 3.

3. Conclusions

The evaluation of the PPgNN model serves to confirm the value of the PPgNN architecture for extending strain-life predictions to an extraordinary wide range of TMF and creep-fatigue conditions. The model captures the essential life behaviors typically observed in this class of alloys and provides a measure of confidence in the prediction.

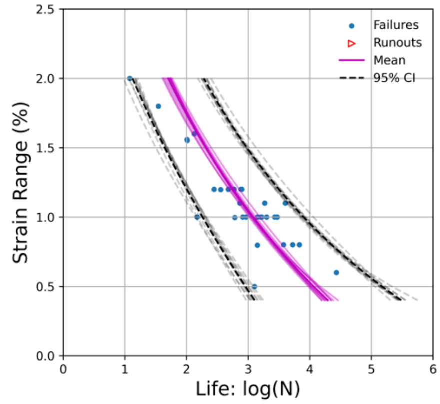

Fig.1 – Ten predictions of the strain-life curve for OP TMF, 400°C-900°C, 5 min. cycle compared to experimental data extracted from literature (SX loaded in [001] and DS loaded in longitudinal direction).

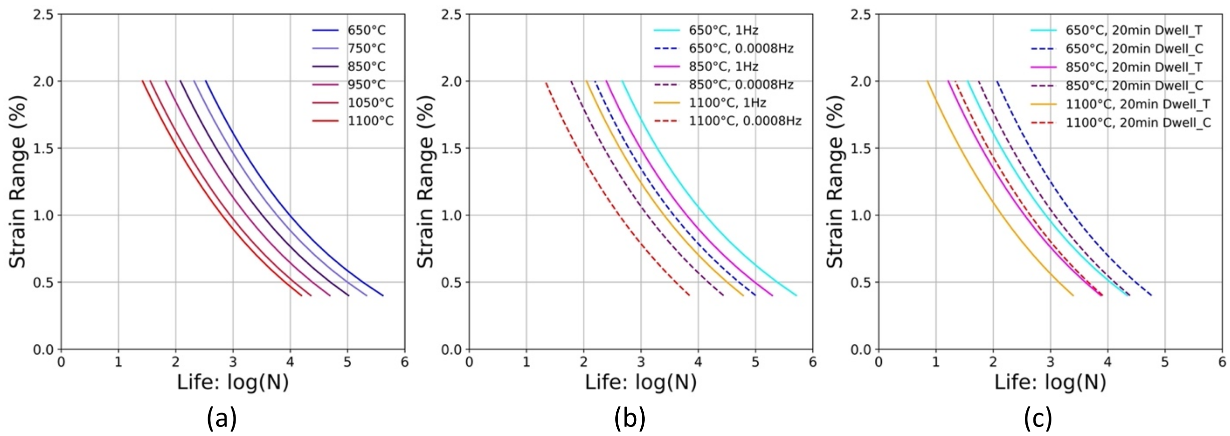

Fig.2 – Isothermal fatigue mean life predictions for SX loaded in [001] and DS loaded in longitudinal direction showing (a) influence of temperature at f = 0.01 Hz, (b) influence of frequency at three temperatures, and (c) influence of 20 min. dwells, comparing tensile vs. compressive dwells.

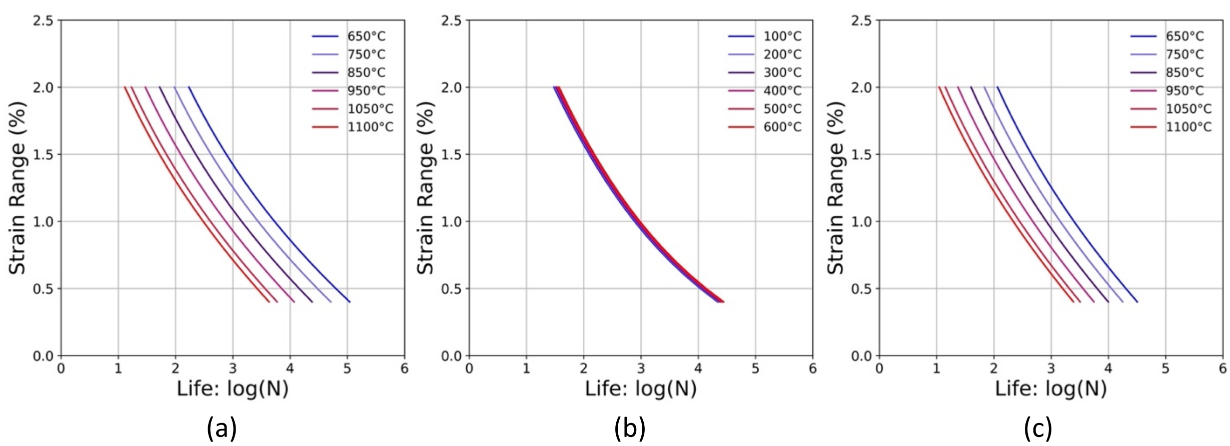

Fig.3 – OP TMF mean life predictions for SX loaded in [001] and DS loaded in longitudinal direction showing (a) influence of T_{max} with T_{min} = 100°C, 5 min. cycle, (b) influence of T_{min} for with T_{max} = 950°C, 5 min. cycle, and (c) influence of T_{max} with T_{min} = 100°C, and 20 min. compressive dwell.